Neural Net Methodology in the Context of Evolving Economic Systems[1]

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ABSTRACT. **Five neural nets relate macro-economic input variables to macro-economic output variables. Three nets for the United States (US) and two nets for the Japanese economy were computed to model the production systems of the two most advanced economies in the world. When the Japanese input vector was used through a US net, gross domestic product (GDP), and GDP per capita, and GDP per person employed are reduced in the same order, -0.38, -0.37, and -0.39% per year. Similarly, when the US input vector is passed through the Japanese neural net each of the three measures of gross domestic product drops in the same order -0.22, -0.22 and -0.23% per year. All of the 20 output measurements used in the analysis have similar results when an alien input vector is used. The model presumes that the determinants of growth are implicit in the neural net (black box), and that the determinants of growth have been culturally shaped through adaptation to the norms and values reflected in the input vectors. A neural net could not be obtained using inputs from all G7 nations as a single group. Convergence of predicted outputs with observed outputs required the use of same-nation data in the iterations.**

OHIO J SCI 101 (3/4):57–64, 2001

INTRODUCTION

The context in which economic growth occurs is one of continuous change and constant evolution. All variables in a system are simultaneously undergoing incremental changes in value that impinge upon and cause changes in all other variables of the system (Table 1). The natural condition of any real system can be conceptualized as a set of all-system variables related by a corresponding system of differential equations with all variables changing and simultaneously interacting (Blauberg and others 1977). Neural net methodology can address a problem of this complexity in a real dynamic system by relating a set of outputs to a set of inputs.

The neural net is a mathematical construct (Haykin 1999) developed from a data set of real measurements of inputs and a corresponding data set of real measurements of outputs. Internal variables within the net (between the inputs and the outputs) are incrementally changed over and over through many iterations until a computed vector of outputs is very close to the observed vector of outputs, providing convergence actually occurs. When the difference in the error is sufficiently small in a least sum of squares sense, the net has been trained and can be used for analysis and prognosis. If the observation of inputs and outputs used to train the net are not used again as inputs through the net, the network weights are unbiased and the results are therefore immediately available for insights of analysis and statistical manipulation using other input vectors.

The neural nets developed in this research are equivalent to templates for market based, capitalist economies. The global system captured by the nets represent the highest levels of economic output for contemporary, market based, money exchange economies. All of the 26 member states of the Organization for Economic Cooperation and Development (OECD) fit the criteria for market based, capitalist economies. The neural nets for US and Japan correspond to highly efficient systems for economic growth. Neural nets developed for other nations are simply less efficient in the economic process. Putting a given input vector through the US net and putting the same input vector through some other nation-state's net, Japan, for example, results in a different output vector. The differences in the output vectors are the metrics for comparing efficiencies of the systems.

The input structure varies from nation to nation because of differing historical evolution. Customs, religious belief structures, military conquest, language, taboos, prejudice, legal systems, and the way of life are specific to each nation-state. The 7 most advanced nations in an economic sense, the so-called G7 nations (United States, Japan, Germany, France, Italy, United Kingdom, Canada), establish a multinational basis for evaluating the status of other nations in their quest for advanced economic status and the associated high living standards. The analysis permits evaluation and implications for policy directions for other nation-states willing to make changes in their input structures and in their economic organizations to achieve the desired outcomes (Janson 1993).

Input vectors correspond to observed choices by a society for the deployment of societal resources (Table 2). The structures of the input variables are quantitative measures of corresponding cultures. By using a focal nation's input structure through the US net the computed output vector measures the economic potential based on the US production system. The difference between the potential outputs and the outputs actually realized by the focal nation is a measure of economic

[1]Manuscript received 3 June 1999 and in revised form 15 September 2000 (#99-14).

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outputs foregone or outputs enhanced in the output vectors.

The outputs in an evolving economic system feedback to control or regulate the inputs. For example, as prejudice declines and opportunities increase for women and minorities, a consequential increase in demand occurs. As demand increases the wage rises and more women and minorities are induced to enter the labor market. At the same time these new factors of production substitute and complement other factors of production with ripple effects that course through the entire system like waves that reflect, reinforce and cancel other waves. Keeping the labor force disaggregated by sex and ethnicity, for example, permits analyses that are impossible otherwise. The procedure is similar to input-output methodology in this sense: The all-economy variables are kept disaggregated on the input side and are also kept disaggregated on the output side (Janson and others 1992). Much potential for understanding is lost the moment variables are lumped together. Variables are allowed to vary, *mutatis mutandis.* In much

TABLE 1

Some of the determinants of growth for four macro factors of production.

	Capital
K_1	Increase saving
K_2	Increase investment
K_3	Reduce inflation
K_4	Subsidies to promote investment
K_5	Subsidies to private investment
K_6	Transparency & widening of global capital markets
K_7	Adequate return on investment
K_8	Create enterprise zones
	Labor
L_1	Education of work force
L_2	Participation of workforce
L_3	Skill development
L_4	Incentives to workforce
L_5	School enrollment
L_6	Increased labor force
L_7	Immigration of skilled people
L_8	Improve educational system
L_9	Strengthen female participation
L_{10}	Strengthen minority participation
	Technology
T_1	New technologies available
T_2	Rate of innovation
T_3	Protection of intellectual property
T_4	Research and development investments
T_5	Rapid technology adoption
T_6	Strengthen graduate schools
	Environment
E_1	Political stability
E_2	Rule of law
E_3	Free market policy
E_4	Promotion of competition
E_5	Reduce defense expenditure
E_6	Lower interest rates
E_7	Open the economy
E_8	Reduce government spending
E_9	Reduce barriers to trade
E_{10}	Adequate returns expectation
E_{11}	Assure property rights
E_{12}	Market friendly policies
E_{13}	Economic freedom
E_{14}	Eliminate central planning
E_{15}	Reduce taxes
E_{16}	Promote exports
E_{17}	Eliminate corruption

Source: OECD 1995 Historical Statistics 1960-1963, Section 1.

TABLE 2

The vector of inputs.

	Structure of Population and Labour Force
2.1	Population from 15 to 64 as a percentage of total population
2.2	Total labour force as a percentage of total population
2.3	Female labour force as a percentage of total labour force
2.4	Male labour force as a percentage of male population
2.5	Female labour force as a percentage of female population
2.6	Total labour force as a percentage of male population from 15 to 64
2.7	Male labour force as a percentage of male population from 15 to 64
2.8	Female labour force as a percentage of female population from 15 to 64
2.9	Employment in agriculture as a percentage of civilian employment
2.10	Employment in industry as a percentage of civilian employment.
2.11	Employment in manufacturing as a percentage of civilian employment
2.12	Employment in services as a percentage of civilian employment
2.13	Government employment as a percentage of total employment
2.14	Total employment as a percentage of population from 15 to 64
2.15	Unemployment as a percentage of total labour force
2.16	Male unemployment as a percentage of male labour force
2.17	Female unemployment as a percentage of female labour force
2.18	Male unemployment as a percentage of total unemployment
2.19	Youth unemployment (less than 25) as a percentage of total unemployment
2.20	Standardized unemployment rates

Source: OECD 1995 Historical Statistics 1960-1963, Section 2.

multivariate analysis a set of independent variables determines a single dependent variable. In neural net analysis a set of inputs may be specified to determine an entire set of outputs. In most multivariate analyses the relationship specified in the mathematical model is linear because linear systems are more tractable to solution. In neural net analysis the relationships are non-linear and the solutions (if the system converges) are far superior in accuracy measured *ex post facto.*

There is no one-to-one correspondence between an entire input vector of variables and a single selected output variable. The correspondence is between an entire vector of input variables and the entire vector of output variables. The quantity of inputs in the input set can differ from the quantity of outputs in the output set, and the entities being measured can be diverse. There is no commensuration of units in a fungible sense. Outputs represent joint products of the production system, for example, the value of agricultural products, value of manufactured products, value of private final consumption, and value of government final consumption (Table 3). Outputs not usually considered in economic literature, although replete in the literature of sociology, are such things as human longevity, infant mortality, leisure time, and similar variables that are clearly outputs from the economic-social-political system, but are not amenable to most analyses. We have made no effort in this paper to include these outputs in this analysis, but the output vector could be lengthened to include them. Development economists usually prefer the value of gross domestic product per capita, or per person employed, as the most significant criterion for an economy's performance. Nevertheless all variables in the output vector are as characteristic of the system as GDP per person employed. Outputs can have either positive implications (output per person employed) or negative implications (pollution outputs, for example).

Denison first used the phrase, determinants of growth, to explain the secular growth in real income over a 40 year period characterized by more than a doubling of real income, per person employed (Denison 1974). Hours of labor and hours of capital equipment became more productive over the decades. The explanation to some extent (say 25%) was the result of higher quality labor measured by education, and to new knowledge, especially new technical knowledge (say 50%). New knowledge was computed as a residual, required to explain the greater than expected increments of income. Innovation, applied new technology, was and is the prime mover of economic growth (Battelle 1999).

Many of the determinants of growth are captured in the neural net as intermediate variables that can be altered by government policy. For example, science education in elementary schools can be strengthened; girls can be targeted for mathematics and science in high school; engineering schools can be strengthened; mathematics can become a core requirement throughout the school years. For the corporate sector, research and development expenditures can be expanded by tax incentives; foreign trade can be facilitated; collaboration in research within an industry can be encouraged; collaboration with foreign research centers can be subsidized; partnering with universities can be funded. In a thousand creative ways the determinants of growth can be targeted to promote growth. These are the target variables that can change the productivity of the production system; these are the policies that can transform poor nations into rich nations.

TABLE 3

The vector of outputs.

	Growth of Real GDP and Productivity
3.1	Gross domestic product (GDP)
3.2	GDP per capita
3.3	Value added in agriculture
3.4	Value added in industry
3.5	Value added in manufacturing
3.6	Value added in services
3.7	GDP per person employed
3.8	Value added in agriculture per person employed
3.9	Value added in industry per person employed
3.10	Value added in manufacturing per person employed
3.11	Value added in services per person employed
	Growth in Real Final Expenditure
4.1	Private final consumption expenditure
4.2	Private final consumption expenditure per capita
4.3	Gross fixed capital formation (GFCF)
4.4	GFCF: Residential construction
4.5	GFCF: Non-residential construction
4.6	GFCF: Machinery and equipment
4.7	Government final consumption expenditure
4.8	Exports of goods and services: volume
4.9	Imports of goods and services: volume

Source: OECD 1995 Historical Statistics 1960-1963, Sections 3 and 4, Outputs 1 through 20.

The neural net contains many interior variables that have unknown functional relationship to the determinants of growth. These interior variables map to determinants of growth in an overall sense. The significant changes in the determinants of growth occur within the social system (Table 1). The hallmark of a growing economy is adaptability and robustness of the system. Dissemination of job opportunities, ease of entry into jobs by the labor force, and encouragement of new entry into product markets, are obvious policies that facilitate adaptability. Over regulation and bureaucratic inertia vary widely among nations, but are clearly impediments to adaptability.

Development economics includes many growth models, nearly all of which are based on static equilibrium analysis (Miller and Blair 1985) to which an element of compound growth has been grafted (real capital investment for each period incrementally increasing the rate of output from period to period). Neural net analysis can finesse this problem. The elegance of the neural net, even though it is a black-box approach, is the fact that all of these issues are subsumed within the black box.

Only an input vector is required to compute the output vector, once the neural net has been trained.

The first purpose of this networks study was to test the assumption that all G7 nations behave in a similar manner so far as their economies are concerned, even though inputs and outputs vary considerably, and input ratios and output ratios also vary over considerable ranges. This notion of similarity of economic behavior is widely accepted among international economists and sociologists. Economists go so far as to predict convergence, the narrowing of the wage and income gaps among the nations with advanced economies. This assumption of similarity is made in spite of historical, cultural, legal, and language differences. The ideas are in consonance with the contemporary notion of global products, global competition, and transnational corporate structures. All of the G7 are late twentieth century democracies with advanced market economies, although the path to this status is unique and as varied as their separate histories. The research question addressed was whether a neural net can be trained using input data from all G7 countries. The mathematical requirement is convergence of the observed output vector and the computed output vector.

The second purpose of this networks study was to compare the outputs of the US net with the outputs of the Japanese net. Both US inputs and Japanese inputs were used through the US net (Figs. 1,2,3) and then both US inputs and Japanese inputs were used through the Japanese net (Figs. 4,5). The objective was to establish which input structure provides the most desirable output structure, and which neural net (US or Japanese) was most efficient in converting input vectors to desired output vectors.

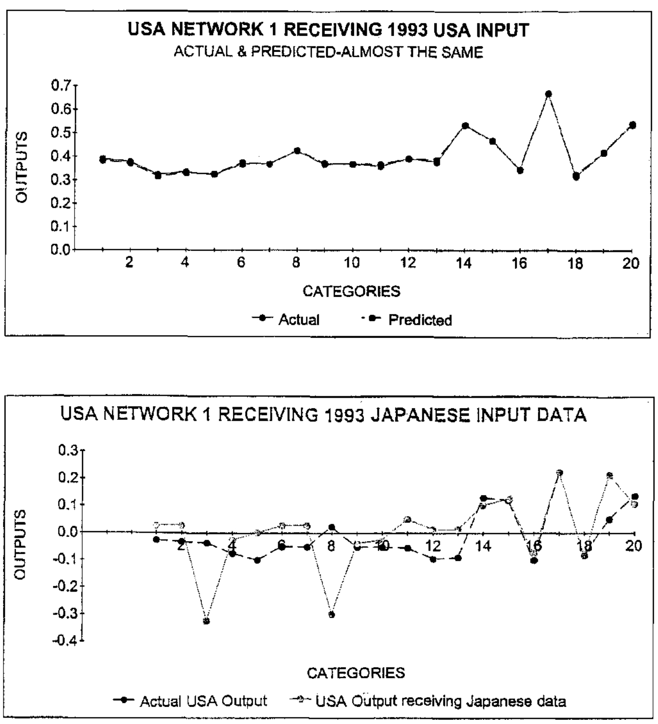

FIGURE 1. Top graph: USA 1993 input data was passed through USA Network 1. Bottom graph: Japanese 1993 input data was passed through the USA Network 1. Note vertical scale change. Heavy line is top graph arbitrarily imposed on Y-axis to compare cross-national output vectors. Source: Authors.

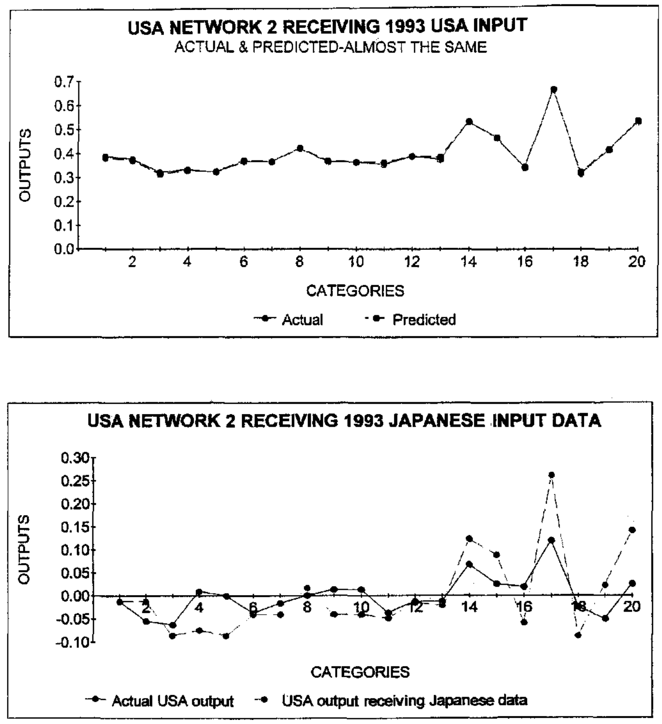

FIGURE 2. Top graph: USA 1993 input data was passed through USA Network 2. Bottom graph: Japanese 1993 input data was passed through the USA Network 2. Note vertical scale change. Heavy line is top graph arbitrarily imposed on Y-axis to compare cross-national output vectors. Source: Authors.

MATERIALS AND METHODS

An artificial neural network is a parallel distributed processing structure that can be expressed mathematically or graphically. That includes units (neurons) that allow a single output value to be exported to a finite number of interconnected neurons (nodes). The output signal exported is the same value to all of the interconnected nodes. Within the neuron processing element the input signal is transformed through a chosen mathematical function usually sigmoid in shape. The transformed value is then added to the internal value already stored in the neuron. If the aggregated value exceeds a threshold the neuron fires and the aggregated transformed signal is passed undirectionally (forward) to all connected neurons. The mathematical representation mimics the real neural network within the brain. A simplified drawing illustrates the point (Fig. 6).

The neuron in the brain is a cell with a nucleus (the soma) with dendrites that receive the signals, and an axon to channel the signal being exported to dendrites of other brain cells (Simpson 1990). Simpson and Haykin illustrate the neuron as a simplified processing unit (Figs. 7A,B). The brain operates with massive parallel processing (say 10,000 synapse connections between the axon in one cell and dendrites of other brain cells). For this reason the brain has far fewer steps between input

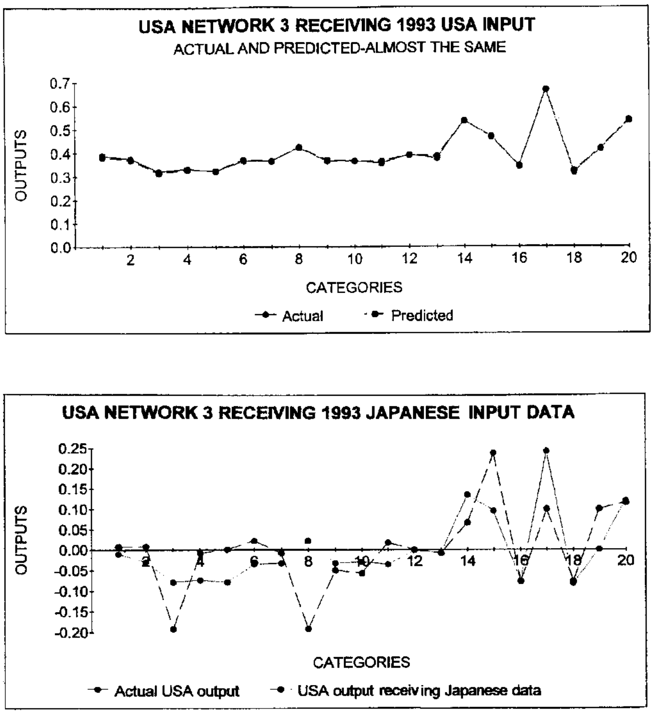

FIGURE 3. Top graph: USA 1993 input data was passed through USA Network 3. Bottom graph: Japanese 1993 input data was passed through the USA Network 3. Note vertical scale change. Heavy line is top graph arbitrarily imposed on Y-axis to compare cross-national output vectors. Source: Authors.

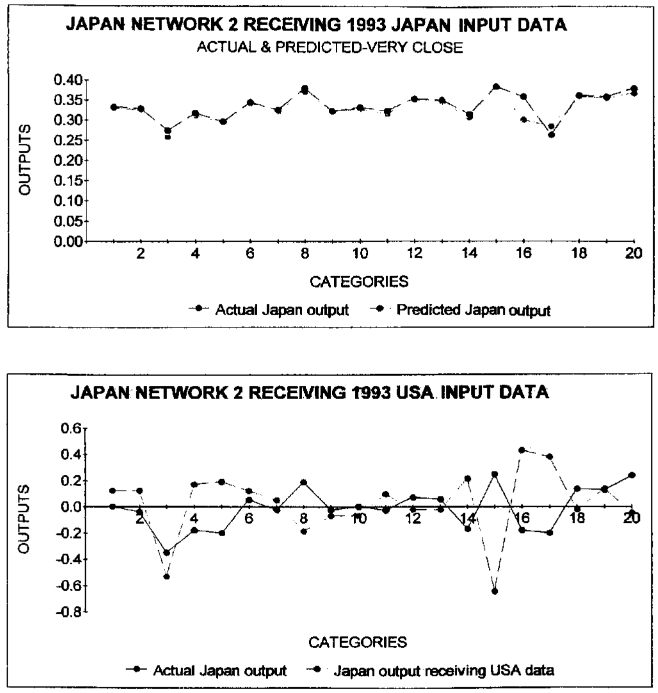

FIGURE 5. Top graph: Japanese 1993 input data was passed through Japan Network 2. Bottom graph: USA 1993 input data was passed through the Japan Network 2. Note vertical scale change. Heavy line is top graph arbitrarily imposed on Y-axis to compare cross-national output vectors. Source: Authors.

and output than the most advanced computers today. This is one major reason for the superior performance of the brain over a serial digital computer, even though the serial digital computer processes each step some million times faster. Another reason is the fact that storage of information learned through a lifetime accrues in the brain, whereas it is replaced in storage areas of the serial computer. Information placed in an addressed memory location destroys previous information stored there. The brain is adaptive and completely anarchic, whereas the computer is controlled by total autocratic direction. In parallel networks all of the information required for processing incoming signals is local. There is no reference to global information stored elsewhere and the signal is passed on after threshold processing to connected neurons.

The processing elements (PE, the neuron node) are impinged by signals from many upstream (backward) PEs.

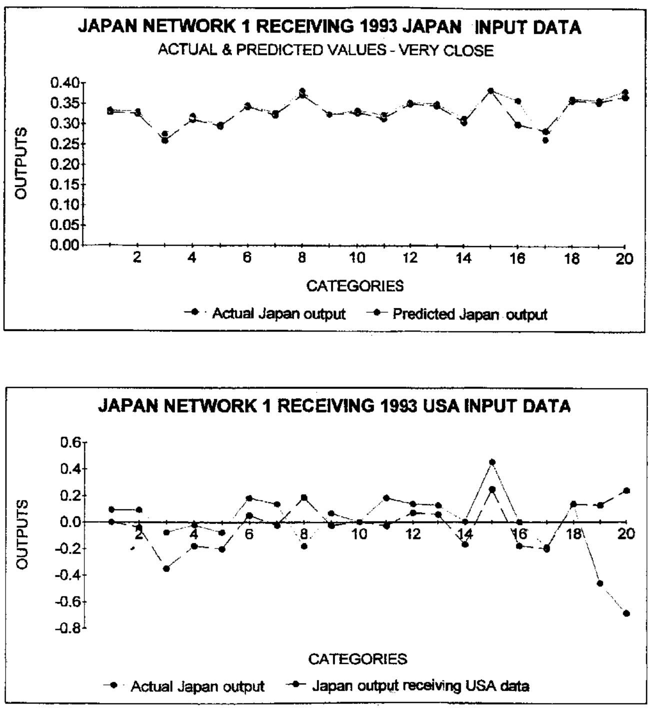

FIGURE 4. Top graph: Japanese 1993 input data was passed through Japan Network 1. Bottom graph: USA 1993 input data was passed through the Japan Network 1. Note vertical scale change. Heavy line is top graph arbitrarily imposed on Y-axis to compare cross-national output vectors. Source: Authors.

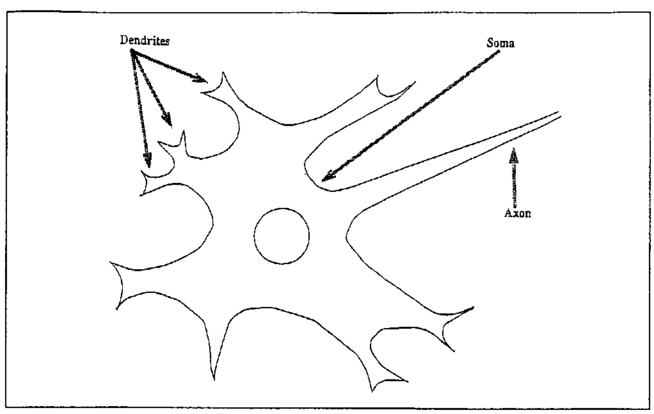

FIGURE 6. Simplified representation of a neuron. The neuron has a cell body with a nucleus, called the soma, an axon that carriers the signal away from the neuron, and dendrites that receive the signal from other neurons.

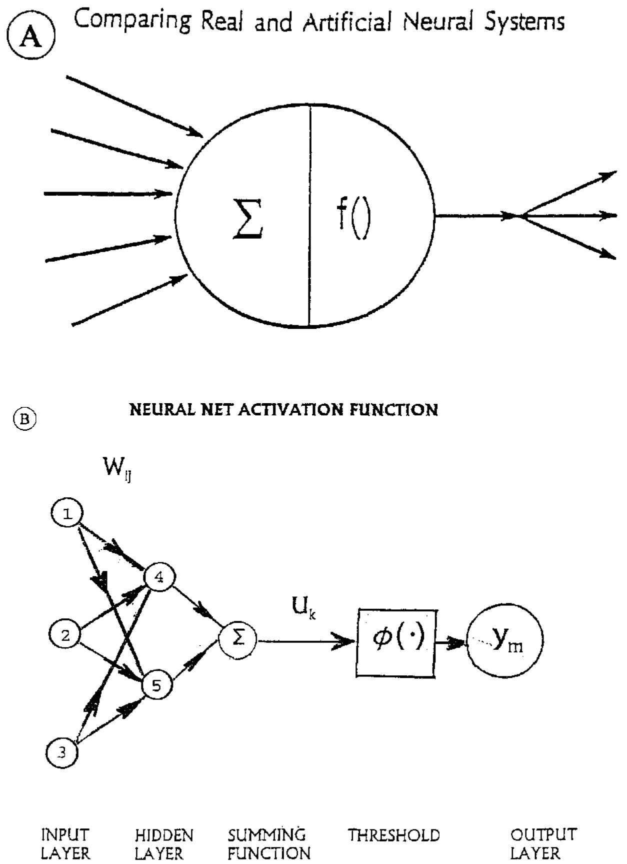

FIGURE 7. (A) A neuron as a simple threshold unit. The incoming lines represent dendrites. Each line carriers a signal that is added, Σ, together. After the addition, the signal is processed through a threshold function f (), which produces the output signal. Source: Simpson. (B) Non linear model of a neural net activation function. Source: Haykin.

Each upstream neuron is associated with an output and an adjustable value, w_i (weight). The input to a neuron is the dot product of the weights and the corresponding outputs from upstream neurons. Each weight is a measure for the connection strength between the neurons.

A neuron output, z, is expressed as

$$z = h\left(\sum_{i=1}^{m} w_i u_i\right) \qquad ,i = 1,2,\ldots,9 \qquad \text{Eq. 1}$$

Note that u_i is the output of the upstream (backward) neuron and w_i is the weight or strength associated with the corresponding connection, and m is the number of input neurons. Using a sigmoid function for h of the form shown next has several advantages. Note that λ is the steepness factor.

$$h(s) = \frac{1}{1+\exp(-\lambda s)} \; , \lambda > 0 \qquad \text{Eq. 2}$$

The function is bounded and derivatives in terms of h can be evaluated (Janson and others 1994). The neuron will fire to the next downstream (forward) layer of neurons providing that the value exceeds a threshold. When the neuron does fire, the same signal is sent to all connected forward (downstream) neurons. A simplified model of a neural network is illustrated (Fig. 8). The functional relationship between input x and output y is expressed as follows:

$$y = f(x_1,x_2) \qquad \text{Eq. 3}$$

The estimated value of y is a function of the inputs and the weights.

$$\hat{y} = g(x_1,x_2,w_1,w_2,\ldots,w_9) \qquad \text{Eq. 4}$$

The difference between y and $\hat{y}$ is the modeling error.

$$e = f(x_1,x_2) - g(x_1,x_2,w_1,w_2,\ldots,w_9) \qquad \text{Eq. 5}$$

A loss function is defined to minimize the error.

$$p_j = \sum_{i=1}^{m} (e_i^2)_j \; , \text{ where } m \text{ is the number of outputs and } j \text{ is the iteration number} \qquad \text{Eq. 6}$$

An algorithm to minimize $\sum e^2$ was used that incorporates backward propagation learning methodology. At each interation the weights are adjusted as follows (Janson and others 1994).

$$(w_i)_{j+1} = (w_i)_j - \mu\left(\frac{\partial p}{\partial w}\right)_j , \quad i = 1,2,\ldots,9 \qquad \text{Eq. 7}$$

μ is the learning rate specified and $\frac{\partial p}{\partial w}$ is the gradient of the loss function evaluated at w_j. One of the advantages of neural net methodology is that the estimate is bias free, providing that data for the year(s) being estimated are not incorporated into the learning phase of the procedure. Also the data points available for the learning phase can be used over and over again with hundreds of thousands of iterations. If a functional relationship between the inputs and outputs exists then convergence between y and $\hat{y}$ will be achieved. If convergence does not occur then the theory that relates the vector of outputs to the vector of inputs is simply not valid. Note that each backward layer of neurons is a proportionally weighted sum of the errors produced in the neighboring forward layer of neurons. The algorithm to reduce $\sum e^2$ makes incremental changes in all of the weights between each iteration. The algorithm used to compute the weights within the neural net is a commercial program provided to the researchers by the software firm Neural Ware and is the back propagation method familiar to neural net practitioners (Neural Ware 1999).

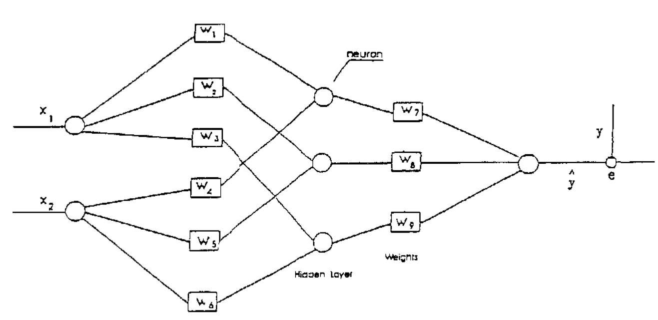

FIGURE 8. A neural network model with three layers and nine weights. Source: Authors.

A trained validated neural net for the United States was computed using a set of data consisting of 20 input variables (Table 2) and 20 output variables (Table 3) for each of 10 years (1983 through 1992) (OECD 1995). In a similar manner a trained neural net was obtained for the nation state of Japan. For each single country the vector for each successive year was used in the iterations. For the G7, as a group, the same procedure was used except the input vector for each of the G7 nations for a selected year was used in each iteration. The data was used over and over, many thousands of iterations. The input categories selected establish some of the economic and demographic structures of the economy (Table 2). The output categories measure the performance of the economy in terms of categories such as gross domestic product per person employed, and the value added in agriculture, manufacturing, services, and gross fixed capital formation (Table 3).

The theoretical basis for favoring this methodology has been discussed in an earlier paper (Janson and others 1994). The fundamental reason for confidence in this approach is that neural net learning mimics learning by trial and error. Any neural net, complex enough in the sense of many redundant paths between inputs and outputs, may have the capability to record weights in the line segments of the net that will produce a unique output vector in a one-to-one association with a unique input vector. The justification of the methodology is the success of the method. In cases where convergence of measured and computed output occurs, a functional relationship is presumed.

RESULTS AND DISCUSSION

The effort to get a neural net for the G7 nations as a group by using input vectors for all of the G7 countries for the entire 10 year period was not successful. On the other hand, convergence was successful for the United States and also for Japan, using same nation data. An inference seems appropriate: Neural nets that plumb the deep sociological systems that characterize a nation-state are a function of the unique historic-geographic trajectory corresponding to the particular country. It is likely that similar countries such as the US and Canada could be used together to train a net, but the G7 are too divergent in their several systems (such as economic, sociological, and political systems) for participation in the same neural network.

Cross-National Comparison of Output

The neural networks were used for cross comparison of the economic performance of the Japanese production system with the United States production system. Of course the computed output vector for the same-country network using same country inputs was virtually identical to the observed output vector for the corresponding year. The computed output vector corresponding to the cross-country output vector is substantially different. The difference between the output vectors are metrics that measure the likely results of transforming the set of inputs to the corresponding outputs using two alternative production systems.

Note that all 20 inputs are measured as percentages; for example, the first input cell is the population from 15 to 64 as a percentage of total population (Table 2). The specific ith cell in the input vector is directly comparable to the ith cell across nations. The cells are not commensurable among or between different inputs in the input vectors. Likewise the outputs are measured as percentage changes in real gross domestic product and productivity, and percentage changes in real final expenditure. Again, cross-national comparisons for the ith output are valid, but units are not commensurable among the cells in the output vector.

Three neural networks were trained for the United States production system based entirely on United States data. When the Japanese input vector was used through these nets the absolute magnitude of output cells was always less (by some proportion of 1%) per year than the output values for the United States using a corresponding US input vector (Figs. 1,2,3). The outputs were measured as average values for the networks available. Two neural networks were trained for the Japanese production system with similar results (Figs. 4,5). Outputs were always less using alien input vectors (Table 4). Several general statements follow that reflect the findings summarized in Table 4.

TABLE 4

The vector of outputs using alien inputs (percent change per year).

Output Measured	US Net Japan Inputs	Japan Net US Inputs
Gross Domestic Product		
1. Gross domestic product (GDP)	-0.38	-0.22
2. GDP per capita	-0.37	-0.22
3. GDP per person employed	-0.39	-0.23
Agriculture		
4. Value added in agriculture	-0.52	-0.57
5. Value added in agriculture per person employed	-0.53	-0.56
Industry, Manufacturing, and Services		
6. Value added in industry	-0.34	-0.24
7. Value added in manufacturing	-0.32	-0.24
8. Value added in services	-0.36	-0.19
9. Value added in industry per person employed	-0.39	-0.33
10. Value added in manufacturing per person employed	-0.39	-0.37
11. Value added in services per person employed	-0.35	-0.18
Consumption		
12. Private final consumption expenditure	-0.39	-0.29
13. Private final consumption expenditure per capita	-0.38	-0.30
14. Government final consumption expenditure	-0.38	-0.30
Gross Fixed Capital Formation		
15. Gross fixed capital foundation (GFCF)	-0.45	-0.20
16. GFCF: Residential construction	-0.34	-0.55
17. GFCF: Non-residential construction	-0.38	-0.22
18. GFCF: Machinery and equipment	-0.52	-0.29
Exports and Imports		
19. Exports of goods and services: volume	-0.33	-0.52
20. Imports of goods and services: volume	-0.45	-0.74

Consider the important macro variables of gross domestic product (GDP), GDP per capita and GDP per person employed. The cross-national input vector is significantly more deleterious to US output than to Japanese output regardless of which measure of output is used (Table 4). Categories of agricultural output are especially vulnerable in both nations. The cost of alien inputs in the output measures of industry, manufacturing, and services are similar in both nations. Real consumption drops somewhat more in the US than in Japan. In the area of gross fixed capital formation (GFCF) the effect is more negative in the US than in Japan, except for the drop in GFCF in residential construction, which is more severe in Japan. Finally, using the alien input vector reduces both exports and imports. Globalization processes are diminished markedly, significantly more so in Japan than in the US.

The result of the comparison between the US production system and the Japanese production system, the two most advanced economies in the world, is clear and unambiguous. There is a drop of gross domestic product, productivity, and real final expenditure when cross-national inputs are used in lieu of same-nation inputs. The drop in value of outputs, however defined, is a significant proportion of 1% per annum. These are strong values in growth economics (Table 4).

Input Structures Compared

Striking differences emerge when the input values are compared. (1) The US utilizes substantially more of the female labor force (ages 15 to 64) as a percentage of the female population. (2) Japan has a much higher percentage of people working in agriculture. (3) The US has a much larger percentage of government employment as a percentage of total employment. (4) The unemployment rates in the United States are significantly higher in all unemployment categories.

Several comments are advanced as possible explanations. The participation of women in the US workforce contrasted with traditional Japanese societal norms is well known. Obviously taboos that limit participation by a large segment of any group restrict talent and introduce inefficiencies into the system. The efficiency of US agricultural methods are also well known and the Japanese pattern of protecting small agricultural landholders comes at a dear price in efficiency. The fact that the US has substantially more of the workforce in government may require a new appreciation of the contributions of this sector to efficiency. The higher rates of unemployment in the US curtail potential output, but the higher rates of unemployment may also increase efficiency and production by facilitating job changing as the economy adjusts to the potential of computers and telecommunications (the digital information revolution). Competition within the labor force combined with easy job changing is a mainspring of US adaptation to changing conditions.

Determinants of Growth

The implicit presumption underlying this neural net approach is that nations condemn themselves to reduced output by pursuing wrong-headed policies or policies constrained by cultural mores. The output performance of nation-states varies widely. In some nations policies consistent with large incremental output changes require bold initiatives to alter the composition of input streams or the structure of the production system. Interventionist government policy is appropriate for nations if the agreed goal is to achieve output similar to that of the US or Japan. Developing nation comparisons are beyond the scope of this paper but the neural nets can be applied directly to developing nation inputs. The authors acknowledge a recent *Economist* article (Economist 1995) that discussed some of the issues of this paper. Growth economists are preoccupied with the transition from current levels of economic output to higher levels of output, and usually the focus is on higher levels of output per person employed. Suboptimal equilibrium can be caused by many factors including resistance to downward wage remuneration discussed by Keynes. Rigidities in economic organization will also cause a similar outcome. Other examples are barring of investment, such as proscription against foreign investment or almost feudal rules that limit the pool of investors. The restrictions to free markets and the opening of markets are political issues that are addressed as public policy.

The reason nations are dissimilar in the realm of economic performance is because the determinants of growth are dissimilar, being adaptations to differing input factors that reflect the diverse social and cultural systems of each nation. The determinants of growth are the pervasive shapers of the production system modeled by the neural nets. The United States production system and the systems of G7 nations are not perfect but they represent the most efficient organizational structures to add value in the economic production process. The systems represent attainable benchmarks for nations willing to undertake the reforms required to promote the determinants of growth.

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