FEASIBILITY STUDY OF DESIGNING POST-MODERN MARKETING MODEL FOR CREATING GLOBAL MARKET

[1]REZVAN POURMANSOURI, [2]REZA SEDDIGHI CHAHARBORJ, [3]ZAHRA MOVAFEGH DEHDASHTI, [4]ABBAS HOSSEINPOUR

Research Branch Tehran
E-mail: R_seddighi2008@yahoo.com

Abstract - In this research, our goal is to examine the feasibility of providing a method for postmodern marketing. We used this model in Iran to predict criminal behavior, and we got good results. In this paper, we try to answer the question of whether an artificial intelligence model can be used to predict consumer behavior in postmodern markets. The proposed model is presented as a theory, and after the implementation of the model in postmodern markets, it can be stated about its correctness.

Key words - Feasibility , Postmodern , Artificial Intelligence , Marketing

I. INTRODUCTION

Modernity reasoning in political, social, psychological and other aspects stresses on self-regulation and personal functionality. The most characteristic feature of human beings in modern attitude is keeping independence and rational actions. In this attitude, it is assumed that people act on scientific awareness and rational thought. This aspect of modernity is inspired through democracy logic, human being functionality, people tendency to act and react, individual's attempt in forming his own destiny and life. Post-modern has challenged this novel position and people. Two major theories are discussed and criticized here which are the foundations of all rule-makings regarding human ones; that is, segregation of subjectivity from objectivity, and separating individual from society. Further, due to exploitive view on individuals, modern marketing and advertisements are reprimanded. Marketing concept and attitude emphasizes that the consumer is fundamentally a subjective creature who could be surrounded by objective suggestions and receive service. New postmodern perspectives approve that marketing cannot be apart from people's tendencies and mind. In fitting , marketing accompanies building a complex of desires and consumers' knowledge. In postmodernism, marketing helps consumer build communities and assemblies, and makes him capable of improving the concept and materials of his life. With the emergence of this constructive style regarding consumption, the notion of postmodern consumer has been brought to life. Therefore, postmodernism aims at providing various requisites which makes the postmodern consumer socialized (SeddighiChaharborj , 2017).

II. STEPS OF THE PROPOSED MODEL

A. Explaining the plan for:

1. Concept of abstraction and scaling of postmodern marketing model:

An important decision in modeling is choosing the appropriate level of details for the problem under consideration and then knowing what level of detail is required for the companion model. This process is called abstraction and typically requires a thoughtful approach to identifying the phenomena we want to focus on, which answers the basic question why we are looking for a model or developing it.
In addition to this, as we are concerned with finding the right level of abstraction or appropriate level of data, we simultaneously discuss an appropriate scale of a model being developed for intelligent postmodern marketing.

B. Explaining principles of preservation and equilibrium in postmodern marketing:

When developing mathematical models, we often begin with statements representing some features of an object or system that are retained. For example, we can analyze customer tendency for ideal market, a friction path that retains consumer's inclination. Sometimes, when we model total population of consumers, we need to maintain a balance in the maximum numbers and values of those are willing to buy, which delineates the boundary of the defined market system. We apply principles of equilibrium or preservation in order to assess the effect of maintaining or controlling level of important physical properties. Equations of preservation and equilibrium are interrelated. As a matter of fact, rules of particular case preservation are rules of equilibrium.

C. Where did we elicit the idea of equilibrium?

Mathematics of equilibrium and preservation rules are simple at this level of abstraction. Representing physical properties as Q(t) and the time of independent variable as t are controlled and we can write an equilibrium rule for time rate or time change, in that the characteristics of market system boundary are shown in the following equation:

$$\frac{dQ(t)}{dt} = q_{in}(t) + g(t) - q_{out}(t) - c(t)$$

Where $q_{out}(t)$and $q_{in}(t)$represent flow rate of $Q(t)$ to (tendency to buy in the market) and (flow) of system boundary, $g(t)$is the rate at which Q is generated within the boundary, and c(t) is the rate at which Q is consumed at the boundary. Note that the above equation is called a rate equation, because each statement has two meanings and dimensions of time change rates are quantitative Q (t).

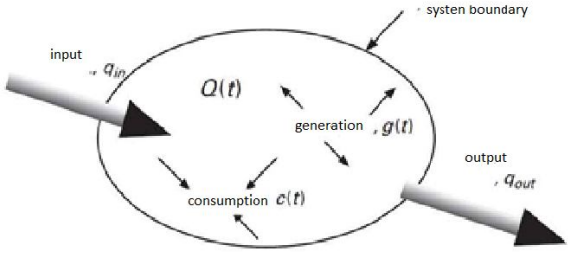


Fig: system boundary around object or a modeling system. Input $q_{in}(t)$, and output $q_{out}(t)$, generation $g(t)$, and consumption $c(t)$, affect the rate, while the desired quality $Q(t)$, is aggregated on the boundary (Cha, Rosenberg, and Dam, 2000).

In cases where there is no generation and consumption at system boundary (say, when $g = c = 0$), equilibrium law in equation (2.1) becomes a preservation law:

$$\frac{dQ(t)}{dt} = q_{in}(t) - q_{out}(t)$$

Here, following this, the rate at which $Q(t)$ is aggregated on the boundary is equal to the difference between in $q_{in}(t)$and out $q_{out}(t)$.

D. discussion on construction of linear models for postmodern marketing:

Linearization is an important concept in mathematical modeling. Modeling a linear device or system is said to be basic-algebraic, differential, or integral equations, as their behavior or response directly leads to proportional stimulation. Even when devices like pendulum are completely introduced as non-linear models, their behavior can often be approximated by a linear model in linear systems.

E. essential instruments for developing postmodern marketing model and process of deriving Jacobian matrix for a the thesis proposed to university:

This section examines the concept of dynamic and stable systems, in that a number of definitions and theorems related to the sustainability of market equilibrium points are expressed. Linear and nonlinear systems are also taken into consideration. We present a method of deriving the application of linear equations in order to explain postmodern marketing model below;

Dynamic Systems

Dynamical systems can be built on models of mathematics and other sciences. Mathematically, these systems can be described using differential equations.

A continuous dynamical system with finite dimensions can be described by a first-order differential equation.

$$\frac{dx}{dt} = f(t, x(t)),$$

Where $x(t)$ is the value of an n -dimensional state vector at t time, $x(t) = \left(x_1^{(t)}, x_2^{(t)}, \dots, x_3^{(t)}\right)^T$and n is system degree.

Solving this system is shown by the initial assumptions x_0 at $t = t_0$with $x(t; x_0, t_0)$and sometimes by $x(t)$. This solution is also called a trajectory, motion, path, or a circuit.

Wing dynamical system is called purchase tendency in equilibrium state, if the vector function f does not depend explicitly on time, such a system is called "autonomous" and is examined under the following equation:

$$\frac{dx}{dt} = f(x(t))$$

Motion of an autonomous system toward time variations will be non-variable, i.e., if $x(t; x_0, t_0)$ is a first equation motion, then,

$$x(t; x_0, t_0) = x(t + T; x_0, t_0 + T)$$

For all $t; x_0, t_0$and Ts.

A dynamical system is called linear if f is linear with respect to x. In this case, the system of equations is equal to $\frac{dx}{dt} = J(t)x(t)$.

If for all Ts,

$$f(x_e, t) = 0,$$

Then for each t_0, we have $x(t; x_e, t_0) = x_e$. A $x_e$point that applies to the equation is called a market equilibrium point, or a critical point in market, or a buyer's desire, or a state of equilibrium in the market. Therefore, a solution that passes through $x_e$at t time will remain zero for all times. This solution is called an equilibrium solution or a constant path. If $x_e = 0$, it is called null solution.

Definition 1: assume x_e is an equilibrium point of dynamical system, i.e. $\frac{dx}{dt} = f(t, x(t))$and for all ts, $f(t, x_e) = 0$. The equilibrium point $x_e$or the equilibrium solution $x(t) = x_e$will be called stable if for every given $t_0$and the positive number ϵ ε there exists a positive number $\delta(\epsilon, t_0)$ such that $\|x_0 - x_e\| < \delta$ means that,

$$\|x(t;x_0,t_0) - x_e\| < \epsilon$$

For all $t \geq t_0$

Definition 2: The equilibrium point x_e of is a covert convergence with pseudo-asymptotic stability if for each t_0 there exists $\delta_1(t_0)$, such that $\|x_0 - x_e\| < \delta_1$ means that for all $t \geq t_0 + T$:

$$\lim_{t\to\infty} x(t;x_0,t_0) = x_e$$

Definition 3: Market equilibrium point x_e is said to have asymptotic stability if it is convergent and stable.

Definition 4: It is said that market equilibrium point x_e has an asymptotic stability or global asymptotic stability if it is stable and if, as long as t tends to infinity, each trajectory converges to a point of equilibrium.

idea of linearization in proximity to market equilibrium point autonomous system state

$$\frac{dx}{dt} = f(x(t))$$

points of equilibrium are defined by deleting vector field; that is,

$f(x) = 0$.A

position in state space in which this condition holds is called singularity. At such a point, trajectory or integral curve of the vector field f will coincide with the market equilibrium point itself.

Suppose $x_e$is the solution of market equilibrium equation, i.e., the point of system equilibrium with tendency variable and is desired to be zero or infinite just like the above equations. To determine the stability of new market equilibrium point, we insert a small perturbation u on it and obtain:

$$x(t) = u(t) + x_e$$

By this insertion we have:

$$\frac{du(t)}{dt} = f(x_e + u(t))$$

Note that the system point $x = x_e$ is converted to the equilibrium point $u = 0$ in the system. We assume that each of the scale components f has at least two differentiation capability with respect to the scale component x. By generalizing the system as a Taylor series around x_e and maintaining a linear expression in the perturbation, we will have:

$$\frac{du}{dt} = f(x_e) + D_x f(x_e)u(t) + O(\|u\|^2),$$

or

$$\frac{du}{dt} \approx D_x f(x_e)u \equiv Ju$$

Where J, first-order partial derivative matrix, is called the Jacobian matrix. This procedure is also known as methods of parameter changing. If components of f include:

$$f_1(x_1,x_2,\dots,x_n), f_2(x_1,x_2,\dots,x_n),\dots$$
$$,f_n(x_1,x_2,\dots,x_n)$$

Then

$$J = \begin{bmatrix} \frac{df_1}{dx_1} & \frac{df_1}{dx_2} & \cdots & \frac{df_1}{dx_{n-1}} & \frac{df_1}{dx_n} \\ \frac{df_2}{dx_1} & \frac{df_2}{dx_2} & \cdots & \frac{df_2}{dx_{n-1}} & \frac{df_2}{dx_n} \\ \vdots & \vdots & \cdots & \vdots & \vdots \\ \frac{df_{n-1}}{dx_1} & \frac{df_{n-1}}{dx_2} & \cdots & \frac{df_{n-1}}{dx_{n-1}} & \frac{df_{n-1}}{dx_n} \\ \frac{df_n}{dx_1} & \frac{df_n}{dx_2} & \cdots & \frac{df_n}{dx_{n-1}} & \frac{df_n}{dx_n} \end{bmatrix}$$

Characteristic values of the Jacobian matrix J yield information on the local stability of the market equilibrium point x_e. We say market stability, because we considered only a small perturbation and linearized the vector field.

E. Stability of linear dynamical systems

We consider a n-th order homogeneous linear system with constant coefficients:

$$\frac{dx(t)}{dt} f(x(t)) = Ax(t)$$

where$A$ is a constant matrix $n \times n$ and x is a column vector $n \times 1$. Keep in mind that we are looking for solutions for market adjustments with the following equation:

$$x(t) = \lambda e^{rt}.$$

After substituting the equation in the system, we find that

$$(A - rI)\lambda = 0.$$

Therefore,r must be a characteristic value for the market and λ a counterpart characteristic value of matrix coefficient A for market in equilibrium. Characteristic values include roots of polynomial equations or characteristic equations,

$$\det(A - rI) = 0,$$

And characteristic vectors are determined up to an arbitrary constant coefficient. We assume that the matrix is non-singular $\det(A) \neq 0$. As a result, according to linear algebra, it is concluded that $x = x_e = 0$ is the only market equilibrium point and is called a single equilibrium point.

Definition: The matrix $A \epsilon \mathbb{R}^{n\times n}$ is irreducible if there is no permutation matrix P and an integer r with $1 \leq r \leq n-1$ in that:

$$P^T AP = \begin{bmatrix} B & C \\ 0 & D \end{bmatrix}$$

Where B, D, C and 0 are matrices $r \times r$, $n - r \times n - r$, $r \times n - r$ and $n - r \times r$, respectively.

Note that if all non-diagonal entries of A are non-zero, then A is irreducible.

Definition: assume that the matrix $A \epsilon \mathbb{R}^{n\times n}$ has characteristic values of $\lambda_1, \lambda_2, \dots, \lambda_n$, then, the spectral radius A, which is represented as $\rho(A)$, and the spectral horizontal dimension (spectral range) A, represented as $s(A)$, are defined as follows:

$$\rho(A) = \max_{i=1,\dots,n} \left|\lambda_i\right|, s(A) = \max_{i=1,\dots,n} Re\left(\left|\lambda_i\right|\right).$$

Definition 7: assume $B = [b_{ij}] \in R^{n\times n}$. If $A = kI - B$, where I is the identity matrix $n \times n$, $k > 0$, $b_{ij} \geq 0$ and $k \geq \rho(B)$, then A is called a M matrix. If $k > \rho(B)$, then A is said to be a non-singular M matrix.

Theorem: If $= [a_{ij}]$ is a non-singular irreducible M matrix, then A has a positive inverse (as input), that is, $A^{-1} = [k_{ij}]$ and $k_{ij} > 0$.

Theorem: If A is a M matrix, then $s(-A) \leq 0$. If A is a non-singular M matrix, then s (-A) <0.

Theorem: assume that $A = [a_{ij}] \in R^{n\times n}$ has $a_{ij} \leq 0$ for $i \neq j$. If the sum of entries in each column is positive, then A is a non-singular M matrix.

Theorem: assume that $A = [a_{ij}]$ with $a_{ij} \geq 0$ is irreducible, then

$$\min_i s_i \leq \rho(A) \leq \max_i s_i$$

Where s_i represents the sum of the column entries of the i-th A column.

Theorem: if F is a non-negative matrix and V is a non-singular M matrix, then:

$s(F - V) < 0 (> 0) \Leftrightarrow \rho(FV^{-1}) < 1 (> 1)$.

Theorem: consider the following system,

$\dot{u} = g(u)$,

With $g \in C^1[\mathbb{R}^n, \mathbb{R}^n]$ and $g(u_0) = 0$, suppose A is Jacobian $g(u)$ in u_0, then, the equilibrium point u_0 have local asymptotic stability, if $s(A) < 0$ and it will be unstable if $s(A) > 0$.

Theorem: every usual differential equation in $C[\mathbb{R}^n, \mathbb{R}^n]$,

$$\dot{u} = f(t, x),$$

is called asymptotic autonomous, with limit equation

$$\dot{u} = h(y),$$

If $f(t, x) \to h(x)$, while $t \to \infty$, it is local integrable in $x \epsilon \mathbb{R}^n$; i.e., for x in each compact subset of $\mathbb{R}^n$.

F. Description of the dynamic neural network model proposed for the university proposal:

Dynamic Artificial Neural Networks (NARX) are an important category of nonlinear Recurrent Neural Networks. In this category of neural networks, memory units that store the past information exist between output layer and the input layer, as well as in input layer. Therefore, in NARX dynamic artificial networks, using input delays we use some kind of static memory, as do we some kind of dynamic memory using output delays. Thus, NARX artificial neural network is a recurrent dynamic network with feedback connections, in that output layer connects to input layer with time delay. The NARX neural network model is based on the ARX linear model, which is commonly used in time series modeling. The governing equation for the NARX model is as follows;

$$y(t) = f\{y(t-1), y(t-2), \dots, y(t-d_y), u(t), u(t-1), u(t-2), u(t-d_u)\}$$

where $d_y \geq 1$ is the number of delays at the output and $d_u \geq 1$ is the number of delays in the input. It is important to note that the inputs of the model can be without delay as well. U(t) is the input value of the network at t time.

Y (t) is the expected output value at t time, which depends on the previous values (whether purchase tendency was in the past, or data such as amount of sales in the past or satisfaction, etc.), or previous input values. F is a nonlinear function that is approximated by using artificial multilayer perceptron artificial neural network (MLP), which will be fully described in the next section. Moreover, fig. 5.3.illustrates the structure of the NARX Dynamic Artificial Neural Network, which z^{-1} is unit of time delay in inputs and outputs (Jose Maria et al, 2008). In the present study, time unit is year. Hence, according to what argued for above, it can be concluded that recurrent neural networks are capable of expressing desired nonlinear dynamical mappings that can be of great help in predicting time series such as time series. The advantage of recurrent neural networks that can use previous output values as model input can be very effective in long-run time series predictions. It should be noted that the NARX artificial neural network has two parallel and parallel-series structures, which is laid down in what follows (Matlab 2011, User's Guide).

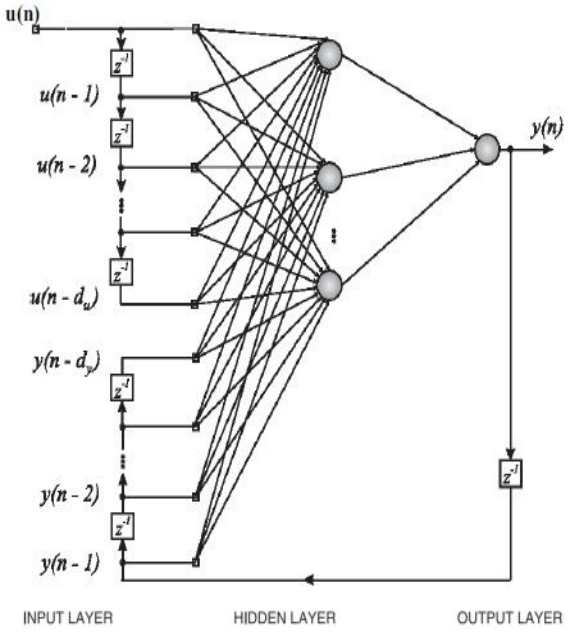


Fig. 3.6. Dynamic Artificial Neural Network structure of NARX with d_y number of output delay and number of input delays

Idea of multilayer perceptron network and back propagation algorithm

As described in the NARX Artificial Neural Network, according to the above equation, the NARX artificial neural network uses a nonlinear function called f in its structure, which is approximated using the multilayer perceptron network (MLP). As such, it is necessary to lay out the multi-layered perceptron network.

In many complex mathematical problems that lead to a solution of nonlinear equations, a multi-layer perceptron network can simply be used to define appropriate weights and functions. Different activity functions are used in neurons as per problem pattern. In these types of networks, an input layer is used to apply problem entries, as well as a hidden layer, and an output layer that ultimately present problem responses. The training of these networks is undertaken by using error-back propagation algorithm. The error-back propagation algorithm is essentially composed of two main flows; the first flow is known as forward flow, input vector is applied to MLP network and its effects spread through the hidden layer through output layer. In this path, network parameters that include the matrix of weights and bias vector are considered constant and unchanged. The second flow is called back flow. In this flow, the parameters of the network are changed and adjusted as opposed to forward flow. This adjustment is achieved in accordance with error correction learning rule. The error signal is formed in the network output layer. The error vector, which is equal to the difference between optimal response and real network response, is formed in the output layer. Following calculation, error value is distributed in the whole network in back flow from output layer and through the network layers, and as this latter distribution is performed on the contrary to weight connection path, the term "error back-propagation" is chosen to account for the correction of the network behavior. Network parameters are adjusted in such a way that genuine network response gets closer to the optimal response as much as possible. This will continue until error value reaches an acceptable level. Here network learning phase is over, and if the network is set to the input vector not being already seen, it can display an appropriate output.
Parameters of learning algorithm for the proposed idea:
Learning algorithm with Levenberg-Marquart function contains several elements. Some of these parameters are empirically set and initial values were proposed for them. These parameters are:

Epoch: The largest value of the iteration number of the learning loop, i.e. how many times correction of weights and bias should be iterated.

Goal: The sum of squared acceptable errors that a network must reach and its value is set as per user's intended precision. If the network reaches this precision before epoch, the training stops.

Min-Grad: minimum gradient to continue learning process,
Mu: initial learning coefficient,
Mu-inc: a coefficient for increasing learning rate,
Mu-dec: a coefficient for decreasing learning rate,
Mu-max: Maximum amount of learning factor,

Another feature developed to determine the amount of network training is the simultaneous observation of the average errors of the test set and training during learning process. In this case, the end of the network training should be considered when the average error of the test set has reached its minimum. Accordingly, network weights and bias at that point are optimal network response. Learning factor is the amount calculated by the program (according to golden search rule). Learning factor represents the size of the variation that must be created in every iteration in terms of weights and biases. Small learning factor will prolong training time, but it ensures that no jump has been reached according to values of minimum errors.

G. How the number of neurons is determined in the proposed model:
The number of necessary neurons in the secret layer for solving a problem in neural networks should be determined experimentally rather than universally. Yet it can be held that if the number is less than a limit, learning may not be completed. This state is known as under fitting, which means that the weights and biases by which network can produce logical outputs close to correct responses are not available.

H. How initial values are selected
The initial selection of weights and biases has been considered autonomous in this present study.

Size of network training
The power of the network to correctly respond to learning instances is called memorization. The more this feature, the larger number of learning instances network will correctly respond to. As opposed to the power of network generalization, the network's ability lies in responding correctly to instances not being trained. These two network capabilities work against each other, and both capabilities cannot be increased at the same time; If the power of memorization and learning goes up, the power of generalization goes down and vice versa.

CONCLUSION

According to the method presented in the article, which was first used to investigate criminal behavior,

we have optimized the above equations to examine the behavior of consumers in postmodern markets. The matured model was first introduced in marketing, and in later papers we will try to implement it in postmodern markets.

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