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Application of Artificial Neural Networks to Food and Fermentation Technology

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1. Introduction

Every system is controlled by certain parameters and works at its best for a certain combination of the values of these parameters Input parameters of the system are defined as the independent variables or causes, which affect the values of output parameters commonly identified as effects. The relationship in many case is typically nonlinear, and complex. Different input parameters –apart from their individual influences – may affect the output parameter in synergistic or antagonistic way.

The knowledge of cause-and-effect relationships is important in the solution of problems in all fields of endeavor. In the simplest of cases, these relationships may take on a linear form, while in others, highly nonlinear and complex, relationships may be appropriate. Some relationships are static, while others involve dynamic or time varying elements.

A complex system like thermal processing requires maximum destruction of undesirable microorganisms with minimum loss of freshness, taste, texture and flavor as the outputs, with time temperature, can size, etc. as extrinsic causes, along with the composition, viscosity, and thermal properties of food material as intrinsic causes. Product development happens to be an equally complex system where level and proportion of ingredients are the inputs, which determine the sensory parameters, cost and marketability. Modeling of bioprocesses for engineering applications is equally challenging task, due to their complx nonlinear dynamic behaviour.

The conditions of best functioning are called optimum operating / functioning conditions. Large number of experiments need to be performed under certain set of conditions, for obtaining these optimum parameters. Still, the results at selected data points need not necessarily represent the optimum functioning of a process, specially for typical nonlinear systems. Performing permutations and combination with experimental parameters till the optimum combination of parameters is achieved is not only time consuming and laborious, but also contributes to increased expenses, hazard possibility and error incorporations. In such situation, several structured and unstructured models can be developed from the available data, and the possible outputs can be successfully predicted at any combination of values, within the frame work. Artificial Neural Network (ANN) is one such tool for prediction of outputs for nonlinear systems at various combinations. The process is based on learning of the network with the experimental values, thus knowing the system behavior, & then predicting the output values of the desired set of parametric combinations. Food

science and technology represents a potential area for application of ANN. Critical review by Huang et al. (2007) discusses the basic theory of the ANN technology and its applications in food science, providing food scientists and the research community an overview of the current research and future trend of the applications of ANN technology in the field.

2. What is Neural Network?

Mother nature's most complex creation, the human brain has evolved over million of years and has very complex and powerful architecture. It consists of large number of nerve cells called neurons. The axon or output path of a neuron splits up and connects to dendrites or input paths of other neurons through a junction known as a synapse (Fig.1) The transmission across this junction is chemical in nature, and the amount of signal transferred depends on the amount of chemicals (Acetylchloline) released by the axon and in turn received by the dendrites. This synaptic strength is modified when the brain learns. Each neuron will have of the order of 10,000 dendrites through which they accept inputs.
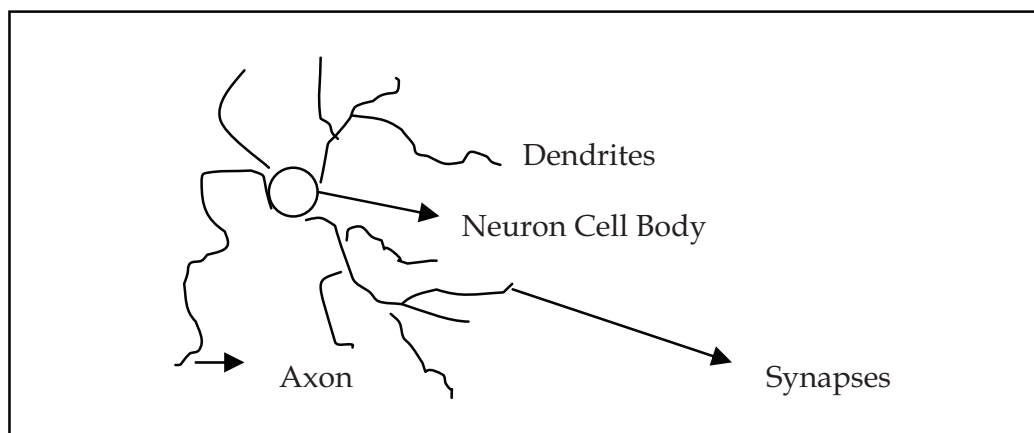

Fig. 1. Biological Neuron

2.1 Artificial Neural Network (ANN)

An artificial neural network (ANN) is a data processing system based on the structure of the biological neural simulation by learning from the data generated experimentally or using validated models.

Some terms required to be defined for ANN users are:

- ANN: A neural network is a processing device, either an algorithm, or actual hardware, whose inspired by the design in and functioning of animal brains and components thereof. It is computer program designed to simulate the brain neurons.
- Processing element: In an ANN, the unit analogous to the biological neuron is a processing elements (PE). Each PE has many inputs and outputs. The network consists of many units or neurons, each possibly having a small amount of local memory. The unit by undirectional communication channels "connections" which carry numeric data. The units operate only on their local data and on the inputs they receive connection.
- Connection weight: The output path of a processing element is connected to input paths of other PEs through connection weights, analogous to the synaptic strength of neural connections.

- Input, output and hidden layers: A network consists of a sequence of layers with connections between successive layers. Data to the network is presented at input layer and the response of the network to the given data is produced in the output layer. There may be several layers between these two principal layers, which are called hidden layers.
- Training: Most neural networks have some sort of "training" rule whereby the weights of connection are adjusted on the basis of presented patterns. In other words, neural network patterns "learn from example".
- Error: It is defined as the total sum of the difference between desired output and output produced by the network for the set of inputs.
- Learning rate: A learning rule, which changes the connection weights of the network in response to the example inputs and desired output to those inputs. The training of neural network model is similar to the way humans or animals are trained by reinforcement technique, where certain synapses that connect the neurons selectively get strengthened leading to increase in the gain.
- Recall: Recall refer to how the network processes a data set presented at its input layer and produces a response at the output layer. The weights are not changed during the recall process.
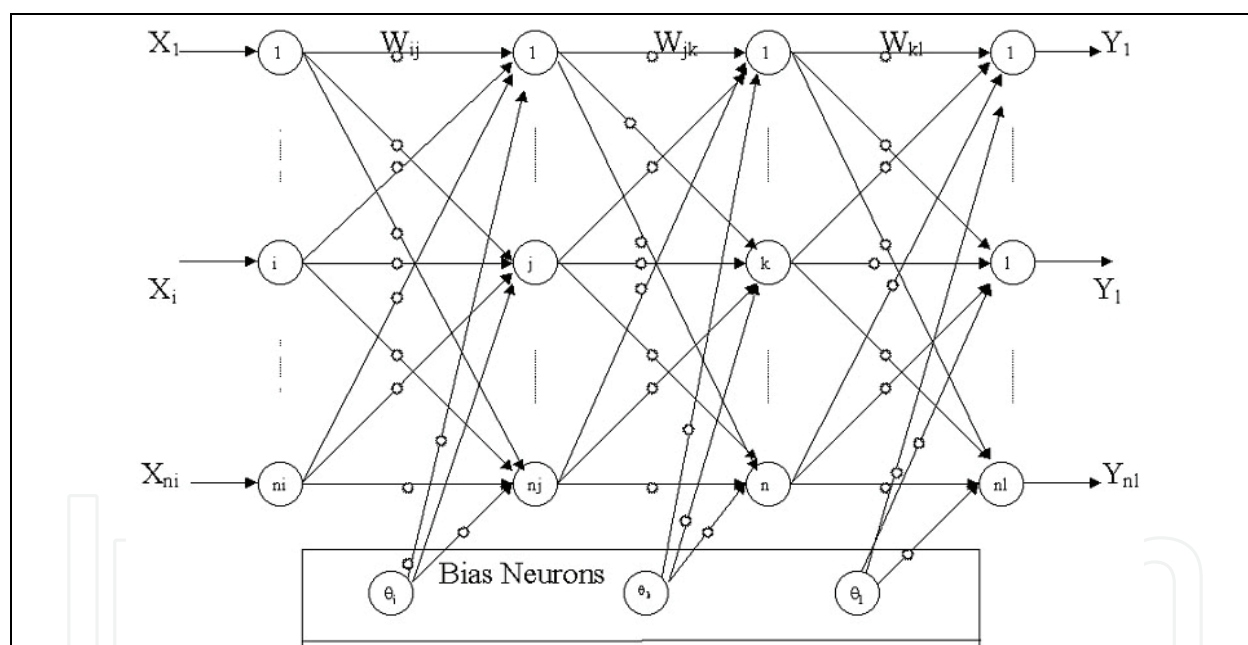

Fig. 2. Artificial Neural Network : A Multilayer Perceptron

Derived from their biological counterparts, ANNs are based on the concept that a highly inter-connected system of simple processing elements can learn complex inter relationships between independent and dependent variables. ANNs offer an attractive approach to the black-box modeling of highly complex, nonlinear systems having a large number of inputs and out puts in the form of massively connected parallel structures. It has three-layered system, an input layer, and intermediate layer called hidden layer, and an output layer (Fig.2). Each layer contains a number of neurons. The number of neurons in the input layer equals the number on inputs to the neural network while the number of neurons in the output layer equals the number outputs in the system. Although numerous guidelines have

been proposed for selecting the number of units in the hidden layer, they do not work in all situations, and the number is often determined heuristically. Each neuron is connected to all the neurons in the next layer by means of a "connection weight". The output from neurons can be calculated by suitable "transform equations" provided the inputs and the connection weights are known.

The sequence of neural network modeling is to assume a set of weights initially, compute the outputs and the predict error, and then adjust the weights according to an error minimization technique until the prediction error falls to an acceptable level. This activity of finding optimal weight is called network training. Once the network is so trained, the black –box model is ready, and may be used to predict outputs for a set of new inputs, not originally part of those used in training.

2.2 Types of ANN
1.   Back Propogation Network (BPN)
Back Propogation Network has been extensively studied, theoretically, and has been the most successful. The BPN is usually built from a three layered system consisting of input, hidden, and output layers. An equation in the hidden layers (transfer function) determines whether inputs are sufficient to produce an output (Hornik et al 1989). There are several kinds of transfer functions, e.g. threshold or sigmoid functions. In training a NN, the values predicted by the net work are compared to experimental values using the delta rule, an equation which minimizes error between experimental values and net work predicted values. The errors are then back propagated to hidden and input layers to adjust weights. This is repeated many times until errors between predicted and experimental values are minimized. General reviews, and references of NN procedure are discussed by Eberhart and Dobbins (1990) .
2.   General Regression Neural Network (GRNN)
General Regression Neural Network are memory based feed forward networks meaning that all the training samples are stored in the network. It possess a special property that they do not require iterative training.

3. Neural network vs statistical regression

In statistical regression, the parameters or constants of the equation are determined for a given mathematical equation, which relates the inputs to the output(s), so that the difference between the desired output and the output of the equation for the set of inputs is a minimum. Here the type and nature of the equation relating the inputs with the output has to be initially formulated clearly. Neural Network (NN) doesn't require such explicit relationship between the inputs and the output(s). In Neural network parameter values cannot be extracted after the simulation. In statistics the analysis is limited to a certain number of possible interactions. However, more terms can be examined for interaction and included in Neural Network. By allowing more data to be analyzed at the same time, more complex and subtle interactions can be determined. Fuzzy and not so clear data sets can also be analyzed and their interaction studied with Neural Network, whereas statistical regression analysis will fail in such situation.

It can perform better than statistical regression analysis for prediction, modeling & optimization even if the data is noisy and incomplete. It is also ideally suited when the inputs are qualitative in nature and when the inputs or the output can not be represented as

mathematical terms (Pandharipande, 2004). Unlike other modeling such as expert system, an ANN can use more than two parameters to predict two or more parameters. In addition, ANN differs from traditional methods due to their ability to learn about the system to be modeled without a prior knowledge of the process parameter. ANN results are straight forward and do not need any transformations. ANN is amongst various intelligent modeling methods which are able to solve a very important problem –processing of unstructured ,scarce and incomplete numerical information about nonlinear and non stationary systems , as well as biotechnological processes (Vassileva et al, 2000).. ANN has the ability for relearning according to new data., and it is possible to add new observations at any time. Unlike ANN, when new observations are added to the data set in PCR, principal components have to be calculated before regression analysis is applied (Vallejo-Cordoba et al ,1995)

4. Applications of ANN in food technology

Artificial Neural Networks (ANNs) have been applied in almost every aspect of food science over the past two decades, although most applications are in the development stage. ANNs are useful tools for food safety and quality analyses, which include modeling of microbial growth and from this predicting food safety, interpreting spectroscopic data, and predicting physical, chemical, functional and sensory properties of various food products during processing and distribution. ANNs hold a great deal of promise for modeling complex tasks in process control and simulation and in applications of machine perception including machine vision and electronic nose for food safety and quality control.

4.1 ANN for prediction of food quality, properties and shelf life

Quality of food is complex term, and is assessed by suitable combination of physical, chemical and organoleptic tests. Physical / chemical parameters- though convenient to measure - do not always have straightforward correlations with the sensory evaluation results. However, frequent sensory evaluation is restricted due to the availability of trained judges, and proper ambience. Several investigators have attempted to apply ANN models for prediction of food properties, and changes during processing and storage of foods.

Zhang and Chen (1997) introduced a method of food sensory evaluation employing artificial neural networks. The process of food sensory evaluation can be viewed as a multi-input and multi-output (MIMO) system in which food composition serves as the input and human food evaluation as the output. It has proved to be very difficult to establish a mathematical model of this system; however, a series of samples have been obtained through experiments, each of which comprises input and output data. On the basis of these sample data, the back-propagation algorithm (BP algorithm) is applied to "train" a three-layer feed-forward network. The result is a neural network that can successfully imitate the food sensory evaluation of the evaluation panel. This method can also be applied in other fields such as food composition optimizing, new product development and market evaluation and investigation.

Lopez et al (1999) have applied ANN for identification of registered designation of origin areas of portugese cheese defined by microbial phenotypes and artificial neural networks.

The human sense of smell is the faculty which has very important role to play in industries such as beverages, food and perfumes. Studies have been carried out to construct an instrument that mimics the remarkable capabilities of the human olfactory system (Gardner et al 1990). The instrument or electronic nose consists of a computer-controlled multi-sensor

array, which exhibits a differential response to a range of vapors and odors. The authors report on a novel application of artificial neural networks (ANNS) to the processing of data gathered from the integrated sensor array or electronic nose. This technique offers several advantages, such as adaptability, fault tolerance, and potential for hardware implementation over conventional data processing techniques. Results of the classification of the signal spectra measured from several alcohols are reported and they show considerable promise for the future application of ANNs within the field of sensor array processing. Electronic/artificial nose, developed as systems for the automated detection and classification of odors, vapors, and gases is generally composed of a chemical sensing system (e.g., sensor array or spectrometer) and a pattern recognition system (e.g., artificial neural network). Electronic noses for the automated identification of volatile chemicals for environmental, medical and food industry applications are being developed

A similar report on application of electronic nose for classification of pig fat has been reported by Carrapsio et al. (2001). Fatty acid analysis is frequently performed in fat and other raw materials to classify them according to their fatty acid composition, but the need to carry out online determinations has generated a growing interest in more rapid options. This research was done to evaluate the ability of a polymer-sensor based electronic nose to classify Iberian pig fat samples with different fatty acid compositions. Significant correlations were found between individual fatty acids and sensor responses, proving that sensor response data were not fortuitously sorted. Significant correlations also appeared between some sensors and water activity, which was considered during the sample classification. Two supervised pattern recognition techniques were attempted to process the sensor responses: 85.5% of the samples were correctly classified by discriminant analysis, but the percentage increased to 97.8% using a one-hidden layer back-propagation artificial neural network.

An artificial olfactory system based on Gas Sensor Array and Back-Propagation Neural Network is constructed to determine the individual gas concentrations of gas mixture (CO and H_2) with high accuracy. Back-Propagation (BP) neural network algorism has been designed using MATLAB neural network toolbox, and an effective study to enhance the parameters of the neural network, including pre-processing techniques and early stopping method is presented in this paper. It is showed that the method of BP artificial neural improves the selectivity and sensitivity of semiconductor gas sensor, and is valuable to engineering application (Tai et al., 2004). The electronic nose (sensor responses analyzed by a neural network) achieved success similar to that obtained using the more usual fatty acid analysis by gas chromatography. Similar application in fatty acid analysis of soyabean oil is reported by Kovalenko et al (2006).

An artificial neural network model is presented for the prediction of thermal conductivity of food as a function of moisture content, temperature and apparent porosity. (Sablani and Rahman, 2003).The food products considered were apple, pear, corn starch, raisin, potato, ovalbumin, sucrose, starch, carrot and rice. The thermal conductivity data of food products (0.012-2.350W/mK) were obtained from literature for the wide range of moisture content (0.04-0.98 on wet basis fraction), temperature (-42-130°C)and apparent porosity(0.0-0.7). Several configurations were evaluated while developing the optimal ANN model. The optimal model ANN consisted two hidden layers with four neurons in each layer. This model was able to predict thermal conductivity with a mean relative error of 12.6%,a mean absolute error of 0.081 W/mK. The model can be incorporated in heat transfer calculations during food processing. Rahman's model (at 0°C) and a simple multiple regression model predict thermal conductivity with mean relative error of 24.3%.

An interesting application of ANN for identification of organically farmed atlantic salmon from wild salmon is by analysis of stable isotopes and fatty acids is discussed by Molkentin et al (2007). Using isotope ratio mass spectrometry (IRMS), the ratios of carbon (δ ^{13}C) and nitrogen (δ ^{15}N) stable isotopes were investigated in raw fillets of differently grown Atlantic salmon (*Salmo salar*) in order to develop a method for the identification of organically farmed salmon. IRMS allowed to distinguish organically farmed salmon (OS) from wild salmon (WS), with δ ^{15}N-values being higher in OS, but not from conventionally farmed salmon (CS). The gas chromatographic analysis of fatty acids differentiated WS from CS by stearic acid as well as WS from CS and OS by either linoleic acid or α-linolenic acid, but not OS from CS. The combined data were subjected to analysis using an artificial neural network (ANN). The ANN yielded several combinations of input data that allowed to assign all 100 samples from Ireland and Norway correctly to the three different classes. Although the complete assignment could already be achieved using fatty acid data only, it appeared to be more robust with a combination of fatty acid and IRMS data, i.e. with two independent analytical methods. This was also favorable with respect to a possible manipulation using suitable feed components. A good differentiation was established even without an ANN by the δ ^{15}N-value and the content of linoleic acid. The general applicability in the context of consumer protection is recommended be checked with further samples, particularly regarding the variability of feed composition and possible changes in smoked salmon.

Experimental measurements of the variation in the solid fraction during crystallization of lipid mixtures are often correlated in terms of the so-called Avrami model. Jose et al (2007) employed above model to describe measurements taken during the crystallization of blends of tripalmitin in olive oil at high concentrations. Although the blends appeared to behave ideally, the Avrami model failed to describe the experimental results over the entire range of tripalmitin concentration investigated. As an alternative to the description of lipid crystallization experiments, the use of continuous-time artificial neural network (ANN) approximators is proposed. ANN successfully reproduced the experimentally observed behavior for all temperatures and tripalmitin concentrations used.

ANN based automatic grading and sorting systems for fruits and vegetables have been developed by various investigators. Saito et al (2003) have developed eggplant grading system using image processing and artificial neural network. The lighting conditions are discussed for taking color components of the eggplant image effectively. The shape parameters such as length, girth, etc. are measured using image processing. On the other hand, bruises of the eggplants are detected and classified based on the color information by using artificial neural network. Development of electronc nose for determination of fruit ripeness has been reported by Salim et al. (2005).

A combination of machine vision and artificial neural network model for guava sorting which classify from size, weight and defect of guava has been described by Chokananporn and Tansakul (2008) and the system was evaluated by comparing with human sorting. Furthermore, the surface area of guava could be estimated from the artificial neural network model. The major diameter, intermediate diameter, minor diameter, and sphericity were used to classify the shape and used as the input parameters of the network. The sorting process was controlled by computer software which was well designed and created on visual basic 6.0. The experiments were carried out with fresh guava. The results from machine vision system were compared with those from human classifying capability. One hundred percent coincidence for the extra size and 73.3 percent coincidence for the class I and II size were obtained. For surface area estimation, the predicted surface area was found

to be nearly the same as that from the standard method. The lowest mean relative error (MRE) and mean absolute error (MAE) values were 0.15% and 0.39 cm^2, respectively. Similar combination system for classification of beans is reported by Kilik et al (2007).

Prediction of Milk shelf – life based on Artificial Predicting Neural networks and head space gas chromatographic data has been reported by Vellejo-Cordoba et al. (1995 **).** Pasteurized milk was sampled during refrigerated storage at 4°C until termination of shelf life, as determined by sensory evaluation, sub samples were incubated at 24 $\pm$1°C for 18 hours prior to detection of volatiles by dynamic head space gas chromatograph (Cordoba & Nakai, 1994)). Several volatiles consisting mainly of aldehydes, ketones & alcohols were identified in milk. Not only increased peak areas of the compounds already present appeared in poor-quality milk, new volatiles were also detected, including esters. Cross validation was used with 113 training sets, and 21 test sets. In PCR, the independent variables were the first 30 principal components and the dependent variable was flavor – based shelf life in days. The shelf life predictability of ANN was superior to PCR as indicated by carrying out regression analysis for experimental vs predicted shelf life and the squared correlation (r^2) and the standard error of the estimate (SEE).

The power of computational neural networks (CNN) for growth prediction of three strains of *Salmonella* as affected by pH level, sodium chloride concentration and storage temperature was evaluated by Herv's et al (2001). The architecture of CNN was designed to contain above three input parameters and growth as output parameter. The standard error of prediction (%SEP) obtained was under 5% and was significantly less than the one obtained using regression equations. Similar study by Zurera-Cosano et al (2005) reported an Artificial Neural Network-based predictive model (ANN) for *Leuconostoc mesenteroides* growth in response to temperature, pH, sodium chloride and sodium nitrite, was validated on vacuum packed, sliced, cooked meat products and applied to shelf-life determination. Lag-time (*Lag*), growth rate (*Gr*), and maximum population density (*yEnd)* of *L. mesenteroides*, estimated by the ANN model, were compared to those observed in vacuum-packed cooked ham, turkey breast meat, and chicken breast meat stored at 10.5°C, 13.5°C and 17.7°C. From the three kinetic parameters obtained by the ANN model, commercial shelf-life were estimated for each temperature and compared with the tasting panel evaluation. The commercial shelf life estimated microbiologically, i.e. times to reach 10$^{6.5}$ cfu/g, was shorter than the period estimated using sensory methods.

Application of ANN for prediction of shelf life of green chilli powder (GCP) is reported by Meshram (2008).Green Chilli Powder (GCP) prepared by dehydration of *Jwala* variety of chilli in air–Radio Frequency (RF) combo dryer had 1.13% moisture content with 19% ERH. Danger and critical points were identified at 60.5 % and 63% ERH corresponding to 7.12% and 8.0% moisture content respectively. Storage study was carried out under ambient (25°C, 65% RH) and accelerated (38°C, 90% RH) conditions for GCP packed in Laminated aluminium foil (LAM) and Polypropylene (PP). Half Value Period (HVP) and shelf life at different combinations of temperature (T) and relative Humidity (RH%) for 100 g GCP pack was calculated based on WVTR (LAM =2.35, PP =4.16 units at 38°C,90% RH) and packaging constant.(Ranganna). Application of Artificial Neural Network (*elite-ANN $^{\copyright}$*) for prediction of shelf life as function of T and RH% gave R^2 value >0.99 for both packings.

4.2 ANN in food processing

Various processing parameters are required to be monitored and controlled simultaneously, and it is quite difficult to derive classical structured models, on account of practical

problems in conducting required number of experiments and lack of sufficient data. Possibility for application of ANN for optimizing the process parameters is an interesting area, with many potential applications.

The effect of agglomerate size and water activity on attrition kinetics of some selected agglomerated food powders was evaluated by Hong Yan and Barbosa-Canovas (2001) by application of ANN. Investigation of the attrition of agglomerates is very important for assessing the agglomerate strength, compaction characteristics, and quality control. A one-term exponential attrition index model and the Hausner ratio were used to study the effects of agglomerate size and water activity on the attrition kinetics of some selected agglomerated food powders. It was found that the agglomerate size and water activity played significant roles in affecting the attrition: the larger the agglomerate size and higher the water activity, higher was the attrition index under the same tap number. The Hausner ratio was well correlated with the attrition index at high tap numbers and might be used as a simple index to evaluate attrition severity for agglomerates. Knowing the effects of agglomerate size and water activity is very useful to minimize the attrition phenomenon during the handling and processing of agglomerated powders.

Modeling and control of a food extrusion process using artificial neural network and an expert system is discussed by Popescue et al. (2001). A neural network model is proposed and its parameters are determined. Simulation results with real data are also presented. The inputs and outputs of the model are among those used by the human operator during the start-up process for control. An intelligent controller structure that uses an expert system and "delta-variations" to modify inputs is also proposed.

A hypothesis on coating of food is put forward by Bhattacharya et al (2008), who have also discussed development of a system analytical model based on simulation studies and artificial neural network The process of coating of foods is a complex process due to the presence of a large number of variables, and unknown relationship between the coating variables and coating characteristics. Needs exists to develop a model that can relate the important variables and coating parameters that would be helpful in developing coated products. A system analytical model for coating of foods has been hypothesized. The model relates influencing variables to derived parameters that in turn relates the target coating parameters. The concentration of solids and temperature of coating dispersions are the examples of the influencing variables, whereas rheological parameters (apparent viscosity, yield stress, flow and consistency indices) are the derived parameters that finally decide the coating parameters such as total uptake, solid uptake and dimensionless uptake according to the hypothesized relations $y = f(x)$ and $z=g(y)$. The proposed hypothesis was initially examined by performing simulation studies conducted on steel balls (small and big) using sucrose solution and malt – maltodextrin dispersions at different concentrations (20-60%) and temperatures (5-80°C), and applying the theory of artificial neural network (ANN) for prediction of target parameters. The hypothesis was tested in actual system using corn balls and sucrose solution. The proposed analytical model has been employed to develop sweetened breakfast cereals and snacks.

Application of ANN in baking has been studied out by few investigators. The bake level of biscuits is of significant value to biscuit manufacturers as it determines the taste, texture and appearance of the products. Previous research explored and revealed the feasibility of biscuit bake inspection using feed forward neural networks (FFNN) with a back propagation learning algorithm and monochrome images (Yeh et al 1995). A second study revealed the existence of a curve in colour space, called a baking curve, along which the

bake colour changes during the baking process. Combining these results, an automated bake inspection system with artificial neural networks that utilises colour instead of monochrome images is evaluated against trained human inspectors .

Comparison of Neural Networks Vs Principal component regression for prediction of wheat flour loaf volume in baking tests has been reported by Harimoto et al. (1995). The objective here was to determine values of four parameters which minimize the standard error of estimate (SEE) between prediction of NN & actual, measured remix loaf volumes of the flour. Two hundred patterns (i.e. quality test results of 200 flours) were used for training the NN. The training tolerance specifies how close each output (remix loaf volume) of the network must be to the empirical response to be considered "correct" during training. The training tolerance is a percentage of the range of the out put neuron. Net works with smaller tolerances require longer time to train. If a network is slow in learning, it is sometimes helpful to begin with a wide tolerance and then narrow tolerance. A back-propagation neural network has been developed by Ruan et al (1995) to accurately predict the farinograph peak, extensibility, and maximum resistance of dough using the mixer torque curve. This development has significant potential to improve product quality by minimizing process variability. The ability to measure the rheology of every batch of dough will enable online process control through modifying process conditions.

Razmi Rad et al (2007) have shown the ability of artificial neural network (ANN) technology for predicting the correlation between farinographic properties of wheat flour dough and its chemical composition. With protein content, wet gluten, sedimentation value and falling number as input parameters six farinographic properties including water absorption, dough development time, dough stability time, degree of dough softening after 10 and 20 min and valorimeteric value as output parameters. The ANN model predicted the farinographic properties of wheat flour dough with average RMS 10.794. indicating that the ANN can potentially be used to estimate farinographic parameters of dough from chemical composition. A neural network based model was developed for the prediction of sedimentation value of wheat flour as a function of protein content, wet gluten and hardness index (Razmi et al 2008). The optimal model, which consisted of one hidden layer with nine neurons, was able to predict the sedimentation value with acceptable error. Thus, ANN can potentially be used to estimate other chemical and physical properties of wheat flour.

Ismail et al (2008) have compared chemometric methods including classical least square (CLS), principle component regression (PCR), partial least square (PLS),and artificial neural networks (ANN) for estimation of dielectric constants (DC) dielectric loss factor (DLF) values of cakes by using porosity, moisture content and main formulation components, fat content, emulsifier type (Purawave™, Lecigran™), and fat replacer type (maltodextrin, Simplesse). Chemometric methods were calibrated firstly using training data set, and then they were tested using test data set to determine estimation capability of the method. Although statistical methods (CLS,PCR and PLS) were not successful for estimation of DC and DLF values, ANN estimated the dielectric properties accurately (R^2, 0.940 for DC and 0.953 for DLF). The variation of DC and DLF of the cakes when the porosity value, moisture content, and formulation components were changed were also visualized using the data predicted by trained network ANN is applied for prediction of temperature and moisture content of frankfurters during thermal processing (Mittal and Zhang, 2000). Lou, and Nakai (2001). Have discussed application of artificial neural networks for predicting the thermal inactivation of bacteria as a combined effect of temperature, pH and water activity.

Linear Regression, NN & Induction Analysis to determine harvesting & processing effects on surimi quality is reported by (Peters et al 1996). Surimi production is highly technical process requiring considerable skill.   Harvesting & Processing input combinations and product quality attributes for the pacific writing surimi industrial were collected and analyzed. Multiple linear regression (MLR), NN, & MS – Induction were used to determine significant variables in the industry. MLR incorporated time, temperature and date of harvest as the variables, whereas ANN could incorporate other significant variable factors intrinsic to the fish (moisture content, salinity, pH , length, weight) and processing variables (processing time, storage temp, harvest date, wash time, wash ratios) in addition to the above three variables. Most variables were highly interactive and non linear. The back propagation NN algorithm was used to relate the influences of the variables (inputs) and their effects on quality (output) as defined by gel strength the NN model was trained so that the model predication was = 10% of the actual value for all data points.

Comparison of three analytical systems, MLR, NN, & MS –I showed that time from capture to final production, temp of storage and date of harvest were indicated to be critical to get desired gel strength by all systems. ANN & MS-I also identified fish weight and length, salinity & moisture of flesh as important processing parameters. In addition, NN analysis indicated flesh pH, wash ratios and geographic location were important factors that affect quality. NN and MS-I were effective computer based methods for analyzing large data sets of complex biological system. They were especially useful for determining factors that affect final product quality in a multi-process operation.

A three-layer feed forward neural network was successfully applied by Paquet et al (2000) to model and predict the pH of cheese curd at various stages during the cheese-making process. An extended database, containing more than 1800 vats over 3 yr of production of Cheddar cheese with eight different starters, from a large cheese plant was used for model development and parameter estimation. Very high correlation coefficients, ranging from 0.853 to 0.926, were obtained with the validation data. A sensitivity analysis of neural network models allowed the relative importance of each input process variable to be identified. The sensitivity analysis in conjunction with a prior knowledge permitted a significant reduction in the size of the model input vector. A neural network model using only nine input process variables was able to predict the final pH of cheese with the same accuracy as for the complete model with 33 original input variables. This significant decrease in the size of neural networks is important for applications of process control in cheese manufacturing.

Optimization of the process of extraction of soy-fiber from defatted soy-flour is reported by Gupta and Shastri (2005). Defatted soya flour (DSF) is a good source of proteins, which are extracted in alkaline medium. The concept of integrated processing of DSF involves simultaneous recovery of soya proteins and fiber, which find use in dietetic foods. Process needs to be optimized to solubiise maximum protein, which is recovered afterwards as Soya Protein Isolate (SPI), with minimum fiber disintegration, and maximum recovery. DSF (obtained from Rasoya Ltd. Nagpur) contained 40.3% protein and 25% fiber. Extraction of soy-fiber was carried out by alkaline extraction at 11 different concentration-time combinations with alkali concentration (range 0.1-0.5N) as variable I, and extraction time (range 0.5-1.5 hours) as variable II. Maximum recovery of the fiber after protein solubilization was the required output. ANN [elite]; software (Pandharipande &. Badhe,2003) was applied by selecting three hidden layers with 5 neurons, 0.9 learning rate and 0.001 back propagation error. Learning of the network was carried out using 9 data points from the

experimental data, whereas remaining two data points were used for assessment of the learning status of the network. The comparison between the experimental and predicted results is given in Fig. (3)
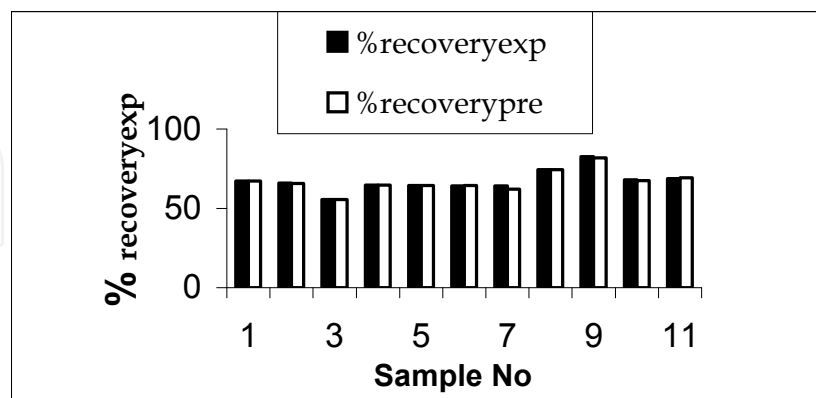

Fig. 3. Experimental and predicted values for recovery of fiber from DSF

The optimum conditions predicting maximum percentage recovery under the above consideration were found to be 0.5 hrs extraction time with 0.5 N alkali(condition I) and 0.35N alkali for 60 minutes (condition II). Validity of the model was established by confirming the recovery under the selected combinations of alkali concentration and time which showed excellent correlation (R^2=0.998) with the predicted values, Thus, it can be concluded that the developed Artificial Neural Network model has been used effectively as a tool in optimizing the process parameter for removal of fiber from DSF.

5. ANN in the field of biotechnology

ANN can be a boon in the field of biotechnology in view of the complex nature of biocatalysts and microorganisms and their interactions with the environment. Prediction of models is usually very difficult on account of the lack of information about the physiological and biochemical constraints of biocatalysts, and their effect on physical phenomena like solubility of nutrients, oxygen transfer, and availability of water. ANN has the advantage that it can make accurate forecast even when the process behavior is non linear and data is unstructured. Since network training is fast, the method is suitable for on-line forecasting.

Characteristic of the beer production process is the uncertainty caused by the complex biological raw materials and the yeast, a living organism. Thus, predicting the speed of the beer fermentation process is a non-trivial task. Data sets from laboratory-scale experiments as well as industrial scale brewing process were used to develop the neural network and descision tree. Simple decision trees were able to predict the classes with 95%–98% accuracy. Utility of these methods was checked in a real brewery environment. The neural network could, on average, predict the duration of the fermentation process within a day of the true value; an accuracy that is sufficient for today's brewery logistics. The accuracy of the decision tree in detecting slow fermentation was around 70%, which is also a useful result. (Rousu et al 1999). Beluhan and Beluhan (2000) describe estimation of yeast biomass concentration in industrial fed-batch yeast cultivation process with separate arificial neural networks combined with balance equations. Static networks with local recurrent memory structures were used for on line estimation of yeast biomass concentration in industrial

bioreactor , and the inputs were standard cultivation state variables: respiratory quotient, molasses feed rate, ethanol concentration, etc. This hybrid approach is generally applicable to state estimation or prediction when different sources of process information and knowledge have to be integrated.

Multivariate statistical methods namely, principal component analysis (PCA) and partial least squares (PLS), which perform dimensionality reduction and regression, respectively, are commonly used in batch process modeling and monitoring. A significant drawback of the PLS is that it is a linear regression formalism and thus makes poor predictions when relationships between process inputs and outputs are nonlinear. For overcoming this drawback of PCA, an integrated generalized regression neural networks (GRNNs) is introduced for conducting batch process modeling and monitoring. The effectiveness of the proposed modeling and monitoring formalism has been successfully demonstrated by conducting two case studies involving penicillin production and protein synthesis.(Kulkarni et al 2004). Application of neural network (ANN) for the prediction of fermentation variables in batch fermenter for the production of ethanol from grape waste using *Saccharomyces cerevisiae* yeast has been discussed by Pramanik (2004). ANN model, based on feed forward architecture and back propagation as training algorithm, is applied in this study. The Levenberg- Marquardt optimization technique has been used to upgrade the network by minimizing the sum square error (SSE). The performance of the network for predicting cell mass and ethanol concentration is found to be very effective. The best prediction is obtained using a neural network with two hidden layers consisting of 15 and 16 neurons, respectively.

Online biomass estimation for bioprocess supervision and control purposes is addressed by Jenzsch et al (2006), for the concrete case of recombinant protein production with genetically modified *Escherichia coli* bacteria and perform a ranking. As the biomass concentration cannot be measured online during the production to sufficient accuracy, indirect measurement techniques are required. At normal process operation, the best estimates can be obtained with artificial neural networks (ANNs). Simple model-based statistical correlation techniques such as multivariate regression and principle component techniques analysis can be used as alternative. Estimates based on the Luedeking/Piret-type are not as accurate as the ANN approach; however, they are very robust. Techniques based on principal component analysis can be used to recognize abnormal cultivation behavior. All techniques examined are in line with the recommendations expressed in the process analytical technology (PAT)-initiative of the FDA.

Badhe et al (2002) extended application of ANN to study hydrolysis of castor oil by Pancreatic lipase *(Biocon India Ltd.)* at 35 °C at pH 7.5 in immobilized membrane bio reactor to investigate the application of free and immobilized lipase for oil hydrolysis. Effect of three variables, e.g. enzyme concentration (range 0.1-0.5 ml), substrate concentration (Range 0.25 to 2.0g) and reaction time (range 2 –8 hours) on percent hydrolysis was investigated. Total 30 data points in the above mentioned range were subjected to training and validation using *eliteANN* software (Pandharipande & Badhe, 2003) with feed forward, sigmoidal activation function & delta learning rule. The topology of the system is described as in Table 1. ANN predictions were accurate (R^2 =0.998) for predicting the percentage hydrolysis of castor oil by lipase enzyme as a function of enzyme concentration, ratio of substrate to buffer concentration and reaction time.

Number of neurons	input	3
	Output	1
First hidden layer		15
Second hidden layer		07
Training data points		26
Test		04
Learning rate		0.8

Table 1. Topology of the ANN network applied for prediction for hydrolysis of castor oil using pancreatic lipase.

Cheese whey proteolysis, carried out by immobilized enzymes, can either change or evidence functional properties of the produced peptides, increasing the potential applications of this byproduct of the dairy industry. However, no information about the distribution of peptides' molecular sizes is supplied by the mass balance equations and Michelis Menten like kinetics. Sousa et al (2003) present a hybrid model of a batch enzymatic reactor, consisting of differential mass balances coupled to a "neural-kinetic model," which provides the molecular weight distributions of the resulting peptides.

6. ANN for prediction of enzyme production

Mazutti et al (2009) have studies production of inulinase employing agroindustrial residues as the substrate to reduce production costs and to minimize the environmental impact of disposing these residues in the environment. This study focused on the use of a phenomenological model and an artificial neural network (ANN) to simulate the inulinase production during the batch cultivation of the yeast *Kluyveromyces marxianus NRRL Y-7571,* employing a medium containing agroindustrial residues such as molasses, corn steep liquor and yeast extract. It was concluded that due to the complexity of the medium composition it was rather difficult to use a phenomenological model with sufficient accuracy. For this reason, an alternative and more cost-effective methodology based on ANN was adopted. The predictive capacity of the ANN was superior to that of the phenomenological model, indicating that the neural network approach could be used as an alternative in the predictive modeling of complex batch cultivations.
SSF is defined as cultivation of microorganisms on a moist insoluble substrate, which binds sufficient water to solubilize the nutrients. The desirable a_w is 0.88 to 0.85 and the amount of water to be added is determined by the water binding capacity of the solid substrate. Although wheat bran is widely recommended ingredient in SSF, several other lignocellulosic agrowastes may be incorporated as inducers for specific products. (Deshpande et al 2008). On account of difference in water binding capacity of such varied substrates, it becomes necessary to optimize the amount of water for achieving maximum productivity. The system can be described as a unstructured model, on account of several undefined parameters and interactions. Possibility of application of ANN for prediction of extracellular enzyme production under SSF conditions was examined for several systems, specially to define optimum level of water in combination of solid substrate containing components with different water binding properties.
Production of Pectin Trans Eliminase (PTE) by *Penicillium oxalicum* was carried out on wheat bran medium by incorporation of de-oiled orange peel (DOP), which was incorporated at

different levels (range 25 – 75%) as first input parameter and levels of substrate: moisture ratio (range 2-3) as second input variable. Enzyme activity units /ml of crude enzyme extract (CEE) was first output parameters and specific activity (enzyme activity units/mg proteins) was second output parameter. ANN topology employed for the study had three hidden layers, each with 10 neurons, learning rate 0.9 and back propogation error =0.0014.

The model was used for prediction of experimental conditions within the system framework for optimum enzyme production and the output predicted by ANN showed excellent concurrence with experimental results (Fig.4). Results clearly indicate that DOP is a good inducer, because increase in orange peel % increases the enzyme activity but to enhance the activity, it is necessary to increase moisture content simultaneously since orange peel has more moisture binding capacity. Optimum combination for high productivity as per the ANN analysis was found to be 60-65% DOP, with 90% moisture. (Yadav et al. 2003).
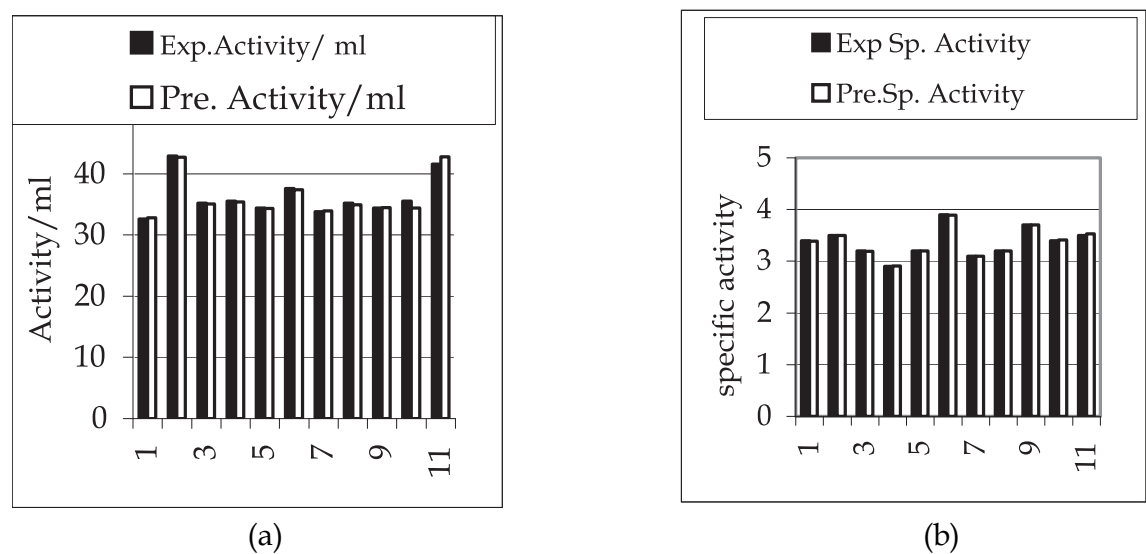

(a)   (b)

Fig. 4. Experimental and predicted values for production of Pectin Trans Eliminase by *Penicillium oxalicum* on Wheat bran : Deoiled Orange Peel medium under SSF conditions
(a) Enzyme units /ml of Crude enzyme extract
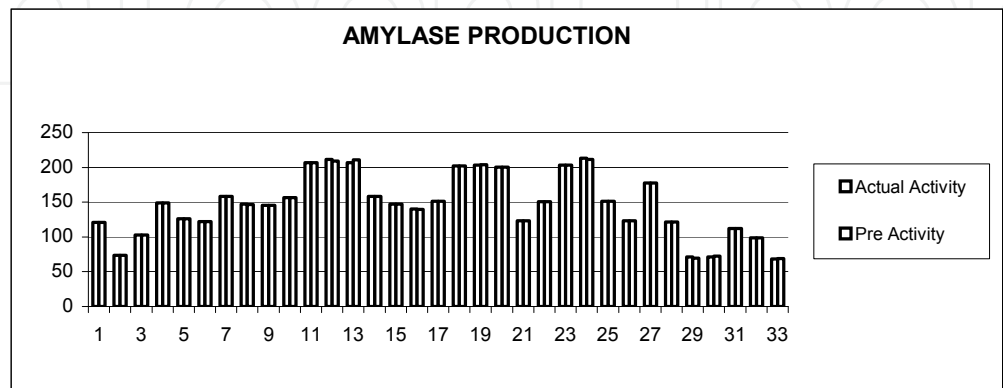(b) Specific activity

Fig. 5. Experimental and predicted values for specific activity of Amylase produced by *Aspergillus oryzae* on sorghum grit and sorghum stalk medium under SSF conditions

Similar Study was carried out for production of amylase by *Aspergillus oryzae* by using combination of sorghum stalk and sorghum grits as substrate (Pandharipande et al. 2003). Sorghum stalk content varied between 0-100%, and the level of moisture varied between (30-70%) with total 33 data sets. Amylase activity units/ml in CEE, as well as the specific activity were the output parameters. The data was processed by *elite^ANN* software (Pandharipande and Badhe, 2003), with three hidden layers of 20 neurons each, learning rate of 0.9, and back propogation error 0.0001. The experimental results are shown in Fig. 5.

It was observed that the amount of inducer influenced the amount of water to be added. The optimum specific activity was obtained at inducer level 70% and moisture level 65% experimentally as against the predicted values of 85% inducer and 60% moisture.

Application of ANN for prediction of cellulase and xylanase production by Solid State Fermentation (SSF) was studied using microorganisms *Trichoderma reesei* and *Aspergillus niger* (Singh et al. 2008, 2009). Experiments were performed with three variables on the production of xylanase and cellulase enzyme by *T.reesei* and *A.niger* by SSF. Total 60 different combination of wheat bran-sugarcane bagasse composition, water: substrate ratio and incubation time were selected as shown in Table 2.

Variable	Range	
	Low	High
1. Bran%	0	100
2.Water Substrate Ratio(v/w) W:S	1.875	3.125
3.Time of Incubation (hrs)	24	168

Table 2. Range of variables selected for study of cellulase & xylanase production

Experimental data was divided into two data series. First set, consisting of about 75-80% of the data points, named as 'Training Set'. It was used for training of ANN to develop independent models for xylanase and cellulase production, each containing three inputs (%wheat bran, W:S Ratio, and Hours of incubation) and one output (IU/ml), three hidden layers (10 nodes each) , learning rate 0.6 and final error 0.002. Adequacy and predictability of the model was tested by giving input parameters for the second data set named as 'Test set' and comparing the predicted and experimental values for *T. reese* (Fig. 6a & 6b,) and *A.niger* (Fig. 7a & 7b) respectively by using *elite-ANN^©* software.
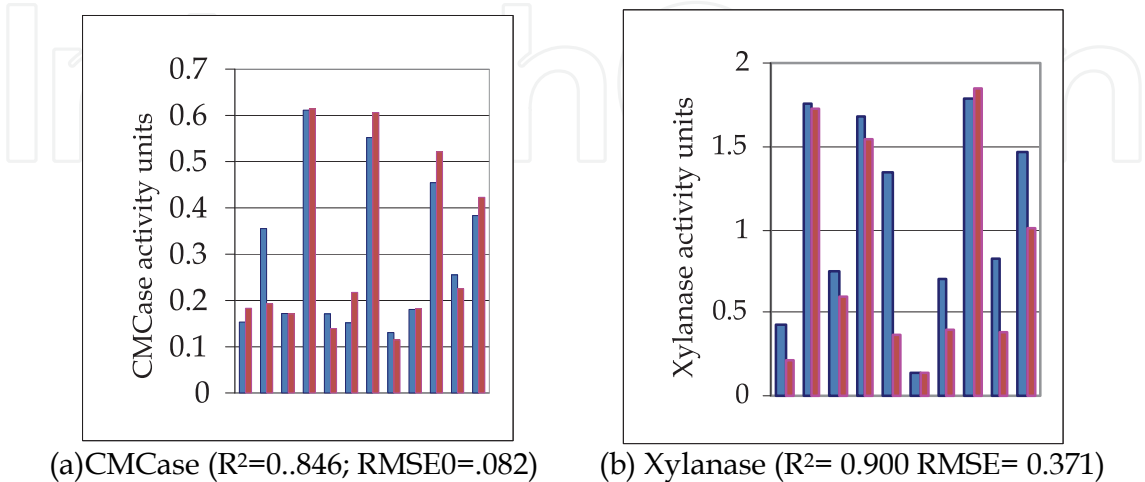

(a)CMCase (R²=0..846; RMSE0=.082)   (b) Xylanase (R²= 0.900 RMSE= 0.371)

Fig. 6. Comparison between actual and predicted values of enzyme production for test data set of *T.reesei* (a) CMCase (b) Xylanase

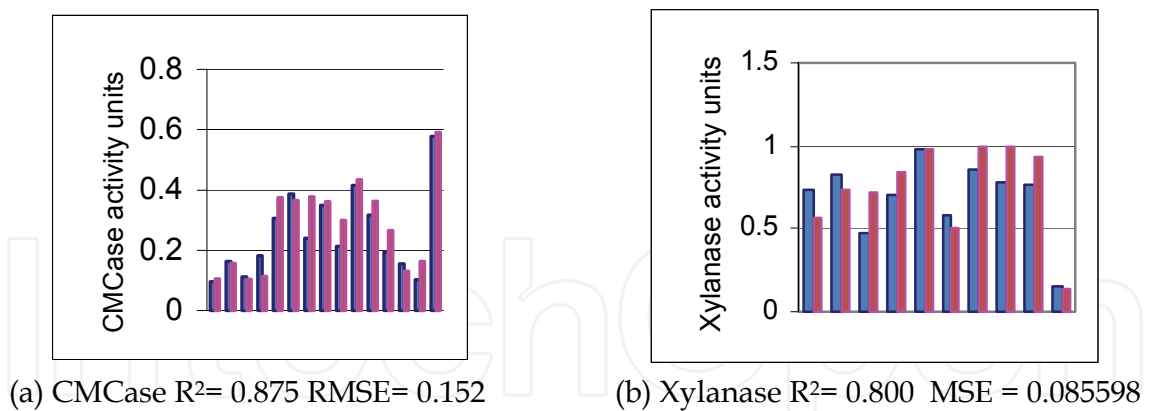(a) CMCase R²= 0.875 RMSE= 0.152   (b) Xylanase R²= 0.800 MSE = 0.085598

Fig. 7. Comparison between actual and predicted values of enzyme production for test data set of *A niger* (a) CMCase (b) Xylanase

Adequacy and predictability of the developed ANN mode l is judged by the comparison of the actual and the predicted values (Fig.6 &7), which show a satisfactory match as indicated by the correlation coefficients (0.0.90 & 0.81 for xylanase and 0.85 & 0.87 for cellulase) and root mean square error (0.35 & 086 for xylanase and 0.082 & 0.15 for cellulase) for *T.reesei* and *A. niger* respectively. Minor variations in the prediction may be due to complexity and inherent variability of biological system. (Pandharipande et al. 2007)

Production of CMCase and Xylanase by *A.niger* and *T.reesei* under SSF condition is a function of %baggasse (which acts as an inducer) and a_w (which supports the growth). Since wheat bran and baggasse differ in their water absorption capacity (WAC), proportion of water required to achieve desirable a_w in combined substrate needs to be predicted. The observations indicate that CMCase and Xylanase production is optimum (>0.6 units) with greater than 50% baggasse, and ratio of water to substrate being 2.0. Thus it can be concluded that the model developed is validated for the given set & range of process conditions and can be used for the prediction of the enzyme activity at different combinations of parameters and selection of most appropriate fermentation conditions.

Xylanase				Cellulase			
Wheat Bran %	W : S Ratio	Hours	PredictedActivity IU/ml-	Wheat Bran %	W : S Ratio	Hours	Predicted Activity IU/ml-
90	2.75	168	1.769	55	2.5	120	0.527
65	2.5	156	1.491	50	2.25	144	0.497
60	2.5	168	1.387	45	2.25	120	0.443
55	2.25	120	1.524	40	2.75	120	0.426

Table 3. ANN based predicted combinations for optimized production of enzymes by *T. reesei*

Xylanase				Cellulase			
Wheat Bran %	W : S Ratio	Hours	Predicted Activity IU/ml	Wheat Bran %	W : S Ratio	Hours	Predicted Activity IU/ml
90	1.875	108	0.9503	80	1.750	108	0.5489
80	1.750	144	0.9741	75	1.875	120	0.5483
75	2.259	120	0.9027	70	2.000	136	0.4315
60	2.000	136	0.8836	65	2.250	144	0.4832

Table 4. ANN based predicted combinations for optimized roduction of enzymes by *A.niger,*

Above data was subjected to Response Surface Methodology, for Box Behnken model using second order regression equation obtained for the model expressed as follows:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_{11} x_1^2 + \beta_{22} x_2^2 + \beta_{33} x_3^2 + \beta_{12} x_1 x_2 + \beta_{23} x_2 x_3 + \beta_{31} x_3 x_1$$

where x_1, x_2, and x_3 are inputs, y is the output, The Statistical analysis was done using Minitab1511. The correlation coefficient and MSE obtained by these two models is compared in Table 3 indicating suitability of both models.

Parameter	T.reesei		A,niger	
	Xylanase	CMCase	Xylanase	CMCase
R^2 by ANN	0.9	O.846	0.8	0.875
R^2 by RSM	0.987	0.79	0.99	0.87
MSE ANN	0.371	0.082	0.856	0.152
MSE RMS	0.034	0.028	0.06	0.076

Table 5. Comparison of ANN and RSM for prediction of cellulase and xylanase production by Solid State Fermentation (SSF)

7. Future prospects

Modern systems with diverse application areas demand expert & accurate calculations within a nick of time. For Such diverse and cutting-edge technology conventional systems have proved expendable and arduous. It is when the Artificial Neural Networks and Fuzzy Systems have proved their speed competitive potentials and expandability. In the last years several propositions for hybrid models, and especially serial approaches, were published and discussed, in order to combine analytical prior knowledge with the learning capabilities of Artificial Neural Networks (ANN). The intelligent modeling approach of models employing Artificial Neural Network in combination with other data analysis systems is able to solve a very important problem - processing of scarce, uncertainty and incomplete numerical and linguistic information about multivariate non-linear and non-stationary systems as well as biotechnological processes (Vassileva et al ,2000, Beluhan and Beluhan, 2000).

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Artificial neural networks may probably be the single most successful technology in the last two decades which has been widely used in a large variety of applications. The purpose of this book is to provide recent advances of artificial neural networks in industrial and control engineering applications. The book begins with a review of applications of artificial neural networks in textile industries. Particular applications in textile industries follow. Parts continue with applications in materials science and industry such as material identification, and estimation of material property and state, food industry such as meat, electric and power industry such as batteries and power systems, mechanical engineering such as engines and machines, and control and robotic engineering such as system control and identification, fault diagnosis systems, and robot manipulation. Thus, this book will be a fundamental source of recent advances and applications of artificial neural networks in industrial and control engineering areas. The target audience includes professors and students in engineering schools, and researchers and engineers in industries.

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