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SOFT COMPUTING APPLICATIONS IN FOOD TECHNOLOGY

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Abstract

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This paper describes the potentials of the application of modern soft computing techniques into development stage of contemporary food products. Recently, soft computing has been extensively studied and applied for scientific research and engineering purposes. In biological and food engineering, researchers have developed methods of fuzzy logic, artificial neural networks, genetic algorithms, decision trees, and support vector machines to study complex characteristics of many products in order to be adopted cost effective measures satisfying the production constraints and consumer expectations.

Key words: soft computing, neural networks, fuzzy systems, food, food mycology, food composition

Introduction

Soft computing is a set of computing techniques, such as Fuzzy Logic (FL), Artificial Neural Networks (ANNs), and Genetic Algorithms (GAs). These computing techniques, unlike hard computing, which refers to a huge set of conventional techniques such as stochastic and statistical methods, offer somewhat "inexact" solutions of very complex problems through modeling and analysis with a tolerance of imprecision, uncertainty, partial truth and approximation. In effect, soft computing is an integration of biological structures and computing techniques. FL developes multi-valued, non-numeric linguistic variables for modeling human reasoning in an imprecise environment. ANNs provides configurations made up of interconnecting artificial neurons that mimic the properties of biological neurons. GAs are a way of solving problems by mimicking the same processes nature uses through selection, recombination and mutation. Soft computing is used to achieve tractability, robustness, and provide a low cost solution with a tolerance of imprecision, uncertainty, partial truth, and approximation. This makes soft computing capable of solving problems that more conventional methods have not yet been able to provide in a cost-effective, analytical or complete manner.

Among soft computing techniques, FL appears to be the first one that has established fundamental ideas of soft computing The established basic ideas have influenced other techniques that arrived later. In recent years, there is greater interest inusing neural networks as problem solving algorithms which can perform mapping, regression, modeling, clustering, classification and multivariate data analysis (Marini et al., 2008; Basheer et al., 2000). The flexibility of neural network predestines them to deal with highly non-linear problems and any kind of data. The artificial neural networks are applicable also, to a number of types of food products quality control (Brodnjak-Voncina et al., 2005; Liu et al., 2009). Genetic algorithms differ from other search techniques in that they search among a population of points and use probabilistic rather than deterministic transition rules. They find also a wide application in food technology (Osnsivialai et al., 2009; Enitan et al., 2007).

Currently, soft computing techniques are successfully applied in the areas of agricultural, biological and food engineering. This paper provides a brief review of some practical applications of soft computing methodologies in food processing and food safety in order to emphasize their potentials to solve many practical problems.

Forecasting in Food Production

For each modern for company is very useful to have a good estimate of how key indicators are going to behave in the future, a task that is fulfilled by forecasting. An efficient forecasting system can improve machine utilization, reduce inventories, achieve greater flexibility to changes and increase profits. In particular, sales forecasting is very important, as its outcome is used by many functions in the organization (Mentzer et al., 1998). Production, needs a long-term forecast for planning the development of the plant and equipment and a more detailed short-term forecast for arranging the production plan. Marketing needs a view of the future market in order to plan its actions and assess the impact of changes in the marketing strategy on sales volumes. Food companies are more concerned with sales forecasting due to their special characteristics, such as the short shelf-life of their products, the need to maintain high product quality and the uncertainty and fluctuations in consumer demands. As products can only be sold for a limited period of time, both shortage and surplus of goods can lead to loss of income for the company. The variations in consumer demand are caused by factors like price, promotions, changing consumer preferences or weather changes (Van der Vorst et al., 1998). A recent initiative of several large companies in the food industry, which aimed to improve forecasting practice, identified that 48% of food companies are poor at forecasting (Adebanjo et al., 2000). The methodologies that have been used in sales forecasting are typically time series algorithms that can be classified as linear or nonlinear, depending on the nature of the model they are based on. Linear models, like autoregressive moving average (ARMA) and autoregressive integrated moving average (ARIMA) (Box et al.,1994) are the most popular methodologies, but their forecasting ability is limited by their assumption of a linear behavior and thus, it is not always satisfactory (Zhang, 2003). In order to address possible nonlinearities in time series modeling, researchers introduced a number of nonlinear methodologies. Their main drawback is that the type of nonlinearity is not known in advance and the the structure of the model must be selected by trial and error. Advanced artificial intelligence technologies, like artificial neural networks (ANNs) and fuzzy logic systems use more sophisticated generic model structures that can incorporate the characteristics of complex data and produce accurate time series models, by eliminating the time consuming trial and error procedure.

Obviously, the key question concerns the accuracy of each modeling method. To this end, a number of studies have been conducted to compare the aforementioned methods and the results are not clearly in favor of one particular method. ANNs have been applied successfully to problems concerning sales of food products, such as predicting the impact of promotional activities and consumer choice on the sales volumes (Agrawal et al., 1996) and were found to perform better than linear models. Another interesting example is by (Ainscough et al., 1999) that compared ANNs to linear regression for studying the same effects on yogurt. (Zhang et al., 1998) did a comprehensive review of the literature concerning the utilization of ANNs in forecasting problems in various areas. ANNs performed equally well with linear methods in 30% and better in 56% of the cases reviewed. In a subsequent study by (Stock et al.,1999) linear and nonlinear methods were compared and it was found that in terms of forecasting performance, combinations of nonlinear methods are better than combinations of linear methods. Additionally, feedforward neural networks (FNNs) that constitute a special ANN architecture performed equally well or better than traditional methods in more than half of the cases. (Zhang, 2003) pointed out that no single method is best in every situation and that combining different models is an effective and efficient way to improve forecasting accuracy, giving examples of previous work in hybrid methods that use neural networks.

Optimum Operating Conditions in Food Drying

Drying is an essential procedure in food processing industries. Food drying process involves simultaneous heat and mass transfer, which have been modeled with different levels of complexity (Zogzas et al., 1996; Hernndez-Perez et al., 2000; Xueqiang et al., 2007). In order to obtain, the optimum operating conditions in the drying process on-line, mathematical description of heat and mass transfer during the drying process is required. There are some works that permit to calculate optimum operating conditions using different mathematical models. For example (Elustondo et al., 2002) evaluated the optimum operating conditions in drying foodstuff with superheated steam. The authors solved the mass and energy balance equations and converted them into a general initial drying rate equation, where all dryer characteristics were grouped into one dimensionless parameter. However, the calculation of optimal parameters gets sometimes difficult and requires special software, especially when the complexity of the drying process is considered. Empirical models are used to control on-line, the drying process. For instance, artificial neural networks models are developed for a rapid calculation of the drying rates (Islam et al., 2003) as well as to predict the temperature and moisture content on line, during the drying process (Hernandez-Perez et al., 2004). At present, they have a large number of applications in food industry (Boillereaux et al., 2007; Chaoxin et al., 2006; Qiao et al., 2007) and notably in the speciality of drying process (Lertworasirikul et al., 2008; Goni et al., 2008). The advantage of this class of models lays on simple arithmetic operations with well-known input parameters. However, in many cases, when we want to have an optimum output, the optimal input parameters are unknown. Consequently, the aim of this very relevant work is to develop a strategy to obtain, on-line, the optimum operating conditions in the drying process from artificial neural networks.

Determination of the Optimal Set Points in Food Processing Taking into Account the Sensory Analysis

Sensory characteristics are often the ultimate measures of food product quality. Food manufacturing processes, however, must be regulated by controlling instrumentally measurable variables and manipulated process variables. To produce food products with desired sensory quality, an effective method is required to convert sensory quality targets into instrumental process set points. (Kupongsak et al., 2004) discussed various cases and issues related to mapping between the sensory and the instrumental domains, and proposed different strategies for determining process set points based on sensory quality evaluations under the conventional framework of sensory data analysis. An important issue in controlling food processes based on sensory quality is how to quantify and interpret sensory evaluations. (Tan et al., 1999) show that the conventional ways to quantify and analyze sensory responses are not reliable because the underlying assumptions are unreasonable and unverifiable. Since human thinking and reasoning are naturally fuzzy, the fuzzy set concept (Zadeh, 1965) has been applied by a number of researchers in conducting and analyzing human sensory evaluations. (Westerberg et al., 1989) used fuzzy sets and fuzzy logic inferences in classifying a fat spread product. A fuzzy questionnaire on the basis of a truth scale was used. Each trained panelist was asked to indicate whether a statement about a sample was considered to be "true", "borderline" or "false". The panelist responses to the statement were tallied in the form of fractions and used as membership grades to classify a sample by fuzzy logic inferences. (Tan et al., 1999) demonstrated how fuzzy sets would lead to a natural method for interpretation of sensory evaluations.

Sensory scales were formulated as fuzzy sets, sensory attributes as fuzzy variables, and sensory responses as sample membership grades. Multi-judge responses were represented as fuzzy histograms of responses. A maximum method of defuzzification was used to give a crisp grade of the majority opinion. Neural networks were then used to predict the sensory responses of beefsteak muscle color and marbling abundance based on instrumental measurements. The fuzzy membership vector could represent multi-judge responses in an untainted manner, avoiding the unreasonable and unverifiable assumptions embedded in the conventional numerical scoring. (Perrot et al., 2000) applied fuzzy set and fuzzy logic techniques for feedback control of a biscuit-baking process. Fuzzy membership functions were established by associating the sensory judgment of an expert operator with physical measurements. Fuzzy logic rules were then applied in implementing a closed-loop control system for the process.

Modeling in Food Mycology

Growth-predictive models are currently accepted as informative tools that assist in rapid and cost-effective assessment of microbial growth for product development, risk assessment, and education purposes (Ross et al., 1994). More recently, predictive microbiology has been used to forecast the growth of spoilage micro-organisms in order to study the shelf life of a food product. Fungal spoilage of food commodities causes significant economic losses and although industrial standards have been greatly improved in the last years, food spoilage by fungi is still a major concern for both food producers and regulatory agencies. Today, there is need for understanding fungal growth in foods, particularly those factors associated with new manufacturing processing and packaging techniques. Fungal presence on food may adversely affect not only the organoleptic value of the commodity, due to the appearance of visible mycelium and off-flavour development, leading to consumer rejection, but most importantly its nutritional value by producing toxic metabolites that may be carcinogenic, posing thus a public health risk (Murphy et al., 2006). Improvement of food quality and safety demands the development of appropriate tools allowing prediction of fungal growth. In the last years, predictive microbiology has been focused on food-borne pathogens, whereas predictive modelling of filamentous fungi had not received the same level of attention (Dantigny et al., 2005). Recently, the situation has changed and a growing number of studies are available in the literature dealing with the predictive modelling approach of fungi (Parra et al., 2004; Patriarca et al., 2001). Polynomial models have been widely used in predictive microbiology for the quantitative assessment of the effects of various environmental factors on fungal growth. They are usually determined using multiple linear regression analysis and allow any of the environmental parameters and their interactions to be taken into account. Once the model is developed, microbial growth under various conditions within the experimental range of variables employed to develop the model can be constructed. However, there are certain disadvantages of these models, such as; they are developed from linear and quadratic combinations of variables where linearity may not be justified; collinearity problems among variables may exist; sensitivity analysis of input variables is difficult due to the presence of cross-interactions (Lou et al., 2001). Artificial Neural networks have been employed in recent years as an alternative to conventional regression models, due to their ability to describe highly complex and non-linear problems in many fields of science. The ANNs-based methodologies have been initially reviewed in predictive food microbiology (Hajmeer et al., 1997). A NN normally has no restriction on the type of relationship between the growth parameters (input patterns) and the desired output, whereas regression-based models require the order of the model to be stated beforehand. In contrast, ANNs directly explore the knowledge contained in the input–output patterns by adjusting the parameters of the non-linear ANN topology, as the input–output patterns are repeatedly presented to the network (Ham et al., 2001). When the system is supervised trained using an appropriate training data set, it can then be used to predict growth kinetic values for different growth conditions within the initial experimental range. Several published works indicate that neural network based models produce better estimation of kinetic parameters of micro-organisms than response surface models. In a recent study, ANNs have been compared with response surface models in the study of the growth rate of L. Plantarum and E. coli, respectively and it was reported that the ANN approach outperformed the statistical models based on its lower SEP term, despite the fact that ANNs models had higher degree of complexity (Garcia-Gimeno et al., 2005). Jeyamkondan et al. (2001) have developed a general regression neural network to model the growth of Aeromonas hydrophila, S. Flexneri and Brochothrix thermosphacta and reported better predictions to statistical models based on lower values of RMSE, MRPE and MAPE. (Lou et al., 2001) have studied the effect of temperature, water activity and pH on the thermal inactivation of Listeria monocytogenes using response surface methodology, Cerf's model and an artificial neural network and reported higher accuracy of the network-based approach based on RMSE and R2 values. (Geeraerd et al., 1998) developed a low-complexity neural network to model the effect of temperature, pH and NaCl on microbial activity and reported better prediction performance compared with classical predictive microbiology models.

Conclusions

Different applications of soft computing methodologies in food technology have been presented in this paper. The achieved results show the potential applicability of modern artificial intelligence methods to solve a wide variety of scientific and production problems in the field of food technology. Using such methods may influence the development of more efficient, safe and consumer satisfying products as well as the diminishing the production costs.

References

Adebanjo, D. and R. Mann, 2000. Identifying problems in forecasting consumer demand in the fast moving consumer goods sector. *Int. Journal of Benchmarking*, **7** (3): 223–230.

Agrawal, D. and C. Schorling, 1996. Market share forecasting: Anempirical comparison of artificial neural networks and multinomial logit model. *J. Retailing*, **72:** 383–407.

Ainscough, T. and J. Aronson, 1999. An empirical investigation and comparison of neural networks and regression for scanner data analysis. *Journal of Retailing and Consumer Services*, **6** (4): 205–217.

Basheer, I. and M. Hajmeer, 2000. *Journal of Microbiological Methods*, **43:** 3–31.

Boillereaux, L., C. Cadet and A. Le Bail, 2007. Thermal properties estimation during thawing via real-time neural network learning. *J. of Food Engineering*, **57** (1): 17–23.

Box, G., G. Jenkins and G. Reinsel, C., 1994. Time seriesanalysis: Forecasting and control (3rd ed.). *Englewood Cliffs, Prentice-Hall*.

Brodnjak-Voncina, D., **Z. Cencic-Kodba and M. Novic,** 2005. *Chemometrics and Intelligent Laboratory Systems*, **75:** 31–43.

Chaoxin, Z., **S. Da-Wen and Z. Liyun,** 2006. Correlating colour to moisture content of large cooked beef joints by computer vision. *Journal of Food Engineering*, **77** (4): 858–863.

Dantigny, P., **A. Guilmart and M. Bensoussan**, 2005. Basis of predictive mycology. *International Journal of Food Microbiology*, **100:** 187–196.

Elustondo, D., A. Mujumdar and M. Urbicain, 2002. Optimum operating conditions in drying foodstuffs with superheated steam. *Drying Technology*, **20** (2): 381–402.

Enitan, A. and J. Aydemo, 2011. Food processing optimization using evolutionary algorithms. *African Journal of Biotechnology*, **10** (72): 16120-16127.

Garcia-Gimeno, R., **C. Hervais-Martinez, R. Rodriguez-Perez and G. Zurera-Cosano,** 2005. Modelling the growth of Leuconostoc mesenteroides by artificial neural networks. *International Journal of Food Microbiology*, **3:** 317–332.

Geeraerd, A., **C. Herremans, C. Cenens and J. Van Impe**, 1998. Application of artificial neural networks as a non-linear modular modelling technique to describe bacterial growth in chilled food products. *International Journal of Food Microbiology*, **44:** 49–68.

Goni, S., **S. Oddone, J. Segura, R. Mascheroni and V. Salvadori,** 2008. Prediction of foods freezing and thawing times: Artificial neural networks and genetic algorithm approach. *Journal of Food Engineering*, **84:** 164–178.

Hajmeer, M., I. Basheer and Y. Najjar, 1997. Computational neural networks for predictive microbiology II. Application to microbial growth. *International Journal of Food Microbiology*, **34:** 51–66.

Ham, F. and I. Kostanic, 2001. Principles of Neurocomputing for Science and Engineering. New York: *McGraw Hill*.

Hernnndez-Perez, J., **M. Garcнa-Alvarado, G. Trystram and B. Heyd,** 2004. Neural networks for the heat and mass transfer prediction during drying of cassava and mango. *Innovative Food Science and Emerging Technologies*, **5:** 56–64.

Islam, M., **S. Sablani and A. Mujumdar**, 2003. An artificial neural network model for prediction of drying rates. *Drying Technology*, **21** (9): 1867–1884.

Jeyamkondan, S., **D. Jayas and R. Holley,** 2001. Microbial growth modelling with artificial neural networks. *International Journal* *of Food Microbiology*, **64:** 343–354.

Kupongsak, S., **I. Hatem, W. Lu, B. Guthrie and M. Tanoff,** 2004. Set point determination from sensory evaluations for food process control. *J. Food Process. Eng.*, **27:** 87–102.

Lertworasirikul, S. and Y. Tipsuwan, 2008. Moisture content and water activity prediction of semi-finished cassava crackers from drying process with artificial neural network. *Journal of Food Engineering*, **84:** 65–74.

Liu, F., **X. Ye, Y. He and L. Wang,** 2009. *Journal of Food Engineering*, **93:** 127–133.

Lou, W. and S. Nakai, 2001a. Artificial neural network-based predictive model for bacterial growth in a simulated medium of modified atmosphere packed cooked meat products. *Journal of Agricultural and Food Chemistry*, **49:** 1799–1804.

Lou, W. and S. Nakai, 2001b. Artificial neural network-based predictive model for bacterial growth in a simulated medium of modified atmosphere packed cooked meat products. *Journal of Agricultural and Food Chemistry*, **49:** 1799–1804.

Marini, F., **R. Bucci and A. Magri,** 2008. *Microchemical Journal*, **88:** 178–185.

Marini, F., **A. Magri and R. Bucci,** 2007. *Chemometrics and Intelligent Laboratory Systems*, **87:** 43–49.

Mentzer, J. and C. Bienstock, 1998. Sales forecasting management: understanding the techniques, systems and management of the sales forecasting process. *Thousand Oaks, CA: Sage publications*.

Murphy, P., **S. Hendrich, C. Landgren and C. Bryant**, 2006. Food mycotoxins: An update. *Journal of Food Science*, **71:** 51–65.

Oonsiviali, A. and R. Oonsiviali, 2009. A genetic algorithms programming application in natural cheese products. *WSEAS Transactions on Systems*, **8** (1): 44-54.

Patriarca, A., **G. Vaamond, V. Fernandez-Pinto and R. Comerio**, 2001. Influence of water activity and temperature on the growth of Wallemiasebi: Application of a predictive model. *International Journal of Food Microbiology*, **68:** 61–67.

Parra, R. and N. Magan, 2004. Modelling the effect of temperature and water activity on growth of Aspergillus niger strains and applications for food spoilage moulds. *Journal of Applied Microbiology*, **97:** 429–438.

Perrot, N., **G. Trystram, F. Guely, F. Chevrie, N. Schoesetters and E. Dugre,** 2000. Feedback quality control in the baking industrial using fuzzy sets. *J. Food Process. Eng.*, **23:** 249–279.

Qiao, J., **M. Ngadi, N. Wang, C. Gariepy and S. Prasher**, 2007. Pork quality and marbling level assessment using a hyperspectral imaging system. *J. of Food Engineering*, **83:** 10–16.

Ross, T. and T. A. McMeekin, 1994. Predictive microbiology. *International Journal of Food Microbiology*, **23:** 241–264.

Stock, J. and M. Watson, 1999. A comparison of linear and nonlinear university models for forecasting economic time series. *In R. F. Engle & H. White (Eds.), Cointegration, causality*, pp. 1–44. Oxford: *Oxford University Press.*

Tan, J., **X. Gao and D. Gerrard**, 1999. Application of fuzzy sets and neural networks in sensory analysis, *J. Sensory Studies*, **14** (2): 119–138.

Van der Vorst, J., **J. Beulens, A. De Wit and P.Van Beek,** 1998. Supply chain management in food chains: Improving performance by reducing uncertainty. *International Transactions in Operational Research*, **5** (6): 487–499.

Westenberg, L., **S. De Jone, D.Van Meel, J. Quadt, E. Backer and R. Duin**, 1989. Fuzzy set theory applied to product classification by a sensory panel. *J. Sensory Studies,* **4** (1): 55–72.

Xueqiang, L. and C. Xiaoguang, 2007. A neural network next term for predicting moisture content of grain drying process using genetic algorithm. *Food Control*, **18:** 928–933.

Zadeh, L., 1965. Fuzzy Sets. *Inform. Control*, **8:** 338–353.

Zogzas, N. and Z. Maroulis, 1996. Effective moisture diffusivity estimation from drying data. A comparison between various methods of analysis. *Drying Technology*, **14:**1543–1573.

Zhang, G., B. Patuwo and M. Hu, 1998. Forecasting with artificial neural networks: The state of the art. *International Journal of Forecasting*, **14** (1): 35–62.

Zhang, G., 2003. Time series forecasting using a hybrid ARIMA and neural network model. *Journal of Neurocomputing*, **50:** 159–175.

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