

ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM AND ARTIFICIAL NEURAL NETWORK ESTIMATION OF APPARENT VISCOSITY OF ICE-CREAM MIXES STABILIZED WITH DIFFERENT CONCENTRATIONS OF XANTHAN GUM

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ABSTRACT:

An adaptive neuro-fuzzy inference system (ANFIS) was used to accurately model the effect of gum concentration (GC) and shear rate (SR) on the apparent viscosity (η) of the ice-cream mixes stabilized with different concentrations of xanthan gum. ANFIS with different types of input membership functions (MFs) was developed. Membership function "the gauss2" generally gave the most desired results with respect to MAE, RMSE and R^2 statistical performance testing tools. The ANFIS model was compared with artificial neural network (ANN) and multiple linear regression (MLR) models. The estimation by ANFIS was superior to those obtained by ANN and MLR models. The ANFIS and ANN model resulted in a good fit with the observed data, indicating that the apparent viscosity values of the ice-cream can be estimated using the ANFIS and ANN models. Comparison of the constructed models indicated that the ANFIS model exhibited better performance with high accuracy for the prediction of unmeasured values of apparent viscosity η parameter as compared to ANN although the performance of ANFIS and ANN were similar to each other. Comparison of the constructed models indicated that the ANFIS model exhibited better performance with high accuracy for the prediction of unmeasured values of apparent viscosity η parameter as compared to ANN although the performance of ANFIS and ANN were similar to each other.

ZUSAMMENFASSUNG:

Ein adaptives, sogenanntes Neuro-Fuzzy-Inferenzsystem (ANFIS) wurde angewandt, um den Einfluss der Gummiharz-Konzentration (GC) und der Schergeschwindigkeit (SR) auf die scheinbare Viskosität (η) von Eiscrème-Mischungen zu untersuchen, die mit unterschiedlichen Konzentrationen von Xanthan stabilisiert wurden. ANFIS mit unterschiedlichen Typen von Eingabefunktionen (MFs) wurden entwickelt. Die Eingabefunktion „the gauss2“ führte generell zu den besten Resultaten hinsichtlich der statistischen Auswertetools MAE, RMSE und R^2 . Das ANFIS-Modell wurde mit künstlichen neuronalen Netzwerken (ANN) und multiplen linearen Regressions (MLR)-Modellen verglichen. Die Abschätzung durch das ANFIS-Modell war besser als die durch die ANN und MLR-Modelle erhaltenen Abschätzungen. Das ANFIS und das ANN-Modell resultierten in einen guten Fit der Messdaten. Dies zeigt, dass die scheinbare Viskosität der Eiscrème durch das ANFIS und das ANN-Modell abgeschätzt werden können. Der Vergleich der entwickelten Modelle zeigte, dass das ANFIS-Modell eine bessere Darstellung mit höherer Genauigkeit für die Vorhersage nicht gemessener Werte der scheinbaren Viskosität η im Vergleich zum ANN-Modell aufwies, obgleich das ANFIS- und das ANN-Modell eine ähnliche Darstellung aufwiesen.

RÉSUMÉ:

Un système adaptif "neuro-fuzzy inference" (ANFIS) a été utilisé pour modéliser précisément l'effet de la concentration en gomme (GC) et de la vitesse de cisaillement (SR) sur la viscosité apparente (η) de mélanges de crèmes glacées stabilisées avec des concentrations différentes de gomme de xanthan. Des ANSIS avec des types différents de fonctions de données membres (MFs) ont été développés. La fonction « le gauss2 » a donné les résultats les plus adéquats relativement aux outils de tests de performance statistique MAE, RMSE et R^2 . Le modèle ANFIS a été comparé avec le réseau neural artificiel (ANN) et les modèles de régression linéaire multiples (MLR). L'estimation par ANFIS est supérieure à celles obtenues avec ANN et MLR. Les modèles ANFIS et ANN ont produit de bons ajustements avec les données observées, ce qui indique que les valeurs de la vis-

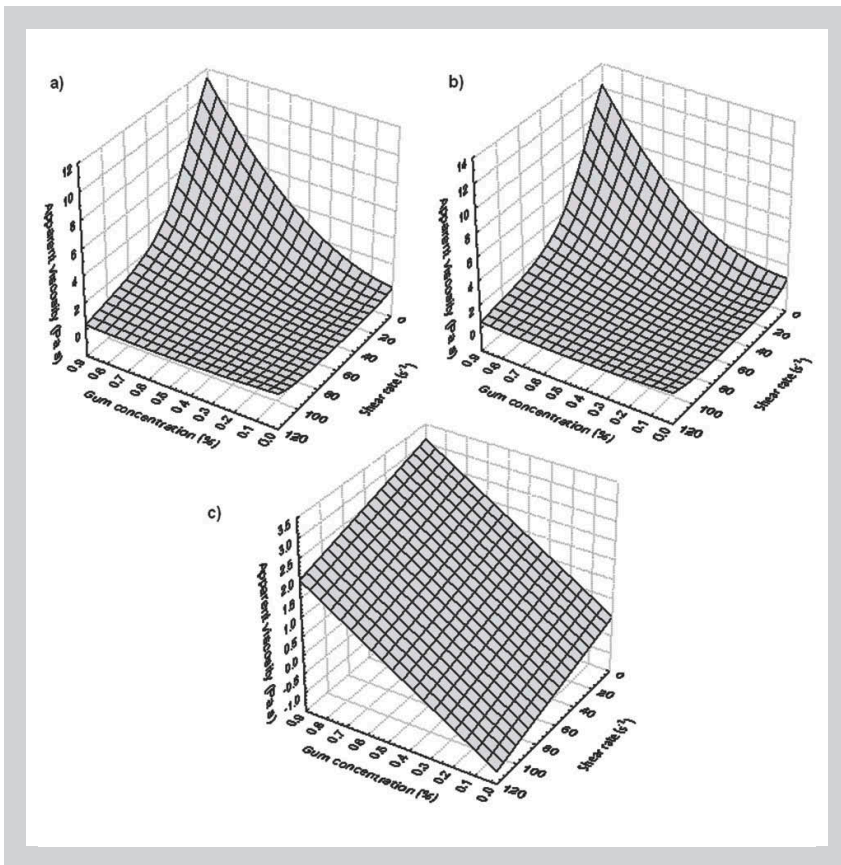


Figure 8: Comparison of three-dimensional plots generated using the apparent viscosity η values of ice cream samples estimated by (a) ANFIS, (b) ANN and (c) MLR models in checking (validation) period. ANFIS, adaptive neuro-fuzzy inference system; ANN, artificial neural network; MLR, multiple linear regression.

4 CONCLUSIONS

Comparison of the constructed models indicated that the ANFIS model exhibited better performance with high accuracy for the prediction of unmeasured values of apparent viscosity parameter as compared to ANN although the performance of ANFIS and ANN was similar to each other. However, MLR model was found to be inadequate for estimating the η values. These results might be useful for ice-cream industry aiming to control the rheological properties of their products added with different concentrations of xanthan gum because it may enable the ice-cream industry to previously estimate how the product viscosity would be before a large scale of production. Early prediction would also pave the way for the industry to save time and cost if it aims to produce a product with acceptable rheological properties. As a conclusion, ANFIS could be proposed to be the best model in order to estimate unmeasured or untested interval values of rheological properties of the ice-cream mixes added with different levels of xanthan gum.

REFERENCES

[1] Garcia-Ochoa F, Santos V, Casas J, Gomez E: Xanthan gum: production, recovery, and properties, *Biotechnol. Adv.* 18 (2000) 549–579.
 [2] Kalogiannis S, Iakovidou G, Liakopoulou-Kyriakides M, Kyriakidis DA, Skaracis GN: Optimization of xanthan gum production by *Xantho-*

monas campestris grown in molasses, *Process Biochem.* 39 (2003) 249–256.

[3] Silva MF, Fornari RCG, Mazutti MA, de Oliveira D, Padilha FF, Cichoski AJ, Cansian RL, Di Luccio M, Treichel H: Production and characterization of xanthan gum by *Xanthomonas campestris* using cheese whey as sole carbon source, *J. Food Eng.* 90 (2009) 119–123.
 [4] Hsu CH, Lo YM: Characterization of xanthan gum biosynthesis in a centrifugal, packed-bed reactor using metabolic flux analysis. *Process Biochem.* 38 (2003) 1617–1625.
 [5] Arbuckle WS, Frandsen JH: *Ice cream*, Avi Pub. Co. (1966).
 [6] Dogan M, Kayacier A: The effect of ageing at a low temperature on the rheological properties of Kahramanmaras-type ice cream mix, *Int. J. Food Prop.* 10 (2007) 19–24.
 [7] Caillet A, Cogné C, Andrieu J, Laurent P, Rivoire A: Characterization of ice cream structure by direct optical microscopy. Influence of freezing parameters, *LWT-Food Sci. Technol.* 36 (2003) 743–749.
 [8] Chan HWS: *Biophysical methods in food research*, Wiley-Blackwell (1984).
 [9] Chang Y, Hartel R: Development of air cells in a batch ice cream freezer, *J Food Eng.* 55 (2002) 71–78.
 [10] Goff HD: Formation and stabilisation of structure in ice-cream and related products, *Curr. Opin. Colloid Interface Sci.* 7 (2002) 432–437.
 [11] Innocente N, Comparin D, Corradini C: Proteoseptone whey fraction as emulsifier in ice-cream preparation, *Int. Dairy J.* 12 (2002) 69–74.
 [12] Martinou Voulasiki IS, Zerfiridis GK: Effect of some stabilizers on textural and sensory characteristics of yogurt ice cream from sheep's milk, *J. Food Sci.* 55 (1990) 703–707.
 [13] Cottrell JIL, Pass G, Phillips GO: The effect of stabilisers on the viscosity of an ice cream mix, *J. Sci. Food Agric.* 31 (1980) 1066–1070.
 [14] Ibanoglu S, Ibanoglu E: Rheological characterization of some traditional Turkish soups, *J Food Eng.* 35 (1998) 251–256.
 [15] Kilimann K, Hartmann C, Delgado A, Vogel R, Ganzle M: A fuzzy logic-based model for the multi-stage high-pressure inactivation of *Lactococcus lactis* ssp. *cremoris* MG1363, *Int. J. Food Microbiol.* 98 (2005) 89–105.
 [16] Madadlou A, Emam-Djomeh Z, Mousavi ME, Javanmardi M: A network-based fuzzy inference system for sonodisruption process of re-assembled casein micelles, *J. Food Eng.* 98 (2010) 224–229.
 [17] Yilmaz, MT: Comparison of effectiveness of adaptive neuro-fuzzy inference system and artificial neural networks for estimation of linear creep and recovery properties of model meat emulsions, *J. Texture Stud.* 43 (2012) 384–399.

- [18] Abu Ghoush M, Samhoury M, Al-Holy M, Herald T: Formulation and fuzzy modeling of emulsion stability and viscosity of a gum-protein emulsifier in a model mayonnaise system, *J. Food Eng.* 84 (2008) 348–357
- [19] Karaman S, Ozturk I, Yalcin H, Kayacier A, Sagdic O: Comparison of adaptive neuro-fuzzy inference system and artificial neural networks for estimation of oxidation parameters of sunflower oil added with some natural byproduct extracts, *J. Sci. Food Agric.* 92 (2012) 49–58.
- [20] Jeyamkondan S, Jayas D, Holley R: Microbial growth modelling with artificial neural networks, *Int. J. Food Microbiol.* 64 (2001) 343–354
- [21] Ramadan MF: Artificial neural networks: A novel tool for detecting GMO, *J. Verbrauch Lebensm.* 6 (2001) 13–23.
- [22] Cabrera AC, Prieto JM: Application of artificial neural networks to the predictions of the antioxidant activity of essential oils in two experimental in vitro models, *Food Chem.* 118 (2010) 141–146.
- [23] Abughoush M, Al-Mahasneh M, Samhoury M, Al-Holy M, Herald T: Formulation and fuzzy modeling of viscosity of an orange-flavored carboxymethylcellulose-whey protein isolate beverage, *Int. J. Food Eng.* 4 (2008) 1–13.
- [24] Krasnov A, Krasulya O, Krasnikov S, Kuznetsova YG, Nikolaeva S: Fuzzy logic as a base for modeling of formulations for meat products, *Myasn. Ind.* 3 (2005) 45–47.
- [25] Mohebbi M, Barouei J, Akbarzadeh-T M, Rowhanimanesh A, Habibi-Najafi M, Yavarmanesh M: Modeling and optimization of viscosity in enzyme-modified cheese by fuzzy logic and genetic algorithm, *Comput. Electron. Agric.* 62 (2008) 260–265.
- [26] Reshetnikova V, Filatova E, Kuznetsov V: Identification of raw materials for the production of vodkas based on the results of gas-liquid chromatographic analysis with the use of fuzzy logic, *J. Anal. Chem.* 62 (2007) 1013–1016.
- [27] Dogan M, Kayacier A, Toker ÖS, Yilmaz MT, Karaman S: Steady, dynamic, creep, and recovery analysis of ice cream mixes added with different concentrations of xanthan gum, *Food Bioprocess Technol.* DOI: 10.1007/s11947-012-0872-z
- [28] Ibarz A, Vicente M, Graell J: Rheological behaviour of apple juice and pear juice and their concentrates, *J. Food Eng.* 6 (1987) 257–267.
- [29] Rao M, Cooley H, Vitali A: Flow properties of concentrated juices at low temperatures, *Food Technol.* 38 (1984) 113–119.
- [30] Takagi T, Sugeno M: Fuzzy identification of system and its applications to modelling and control, *IEEE Trans. Syst. Man Cybern.* 15 (1985) 116–132.
- [31] Cobaner M, Unal B, Kisi O: Suspended sediment concentration estimation by an adaptive neuro-fuzzy and neural network approaches using hydro-meteorological data, *J. Hydrol.* 367 (2009) 52–61.
- [32] Jang JSR, Sun CT, Mizutani E: Neuro-fuzzy and soft computing—A computational approach to learning and machine intelligence, *IEEE Trans. Automatic Control* 42 (1997) 1482–1484.
- [33] Jang JSR: ANFIS: Adaptive-network-based fuzzy inference system, *IEEE Trans. Syst. Man. Cybern.* 23 (1993) 665–685.
- [34] Partal T, Kisi Ö: Wavelet and neuro-fuzzy conjunction model for precipitation forecasting, *J. Hydrol.* 342 (2007) 199–212.
- [35] Drake JT: Communications Phase Synchronization using the Adaptive Network Fuzzy Inference System, New Mexico State University, Las Cruces, USA (2000).
- [36] Altun F, Kişi, Ö, Aydın K: Predicting the compressive strength of steel fiber added lightweight concrete using neural network, *Comput. Material. Sci.* 42 (2008) 259–265.
- [37] Jang JSR, Sun CT: Neuro-fuzzy modeling and control, *Proc. IEEE* 83 (1995) 378–406.
- [38] Han M, Sun Y, Fan Y: An improved fuzzy neural network based on TS model, *Expert. Syst. Appl.* 34 (2008) 2905–2920
- [39] Togrul H, Arslan N: Mathematical model for prediction of apparent viscosity of molasses, *J. Food Eng.* 62 (2004) 281–289.
- [40] Hagan MT, Menhaj MB: Training feedforward networks with the Marquardt algorithm, *IEEE Trans. Neural. Netw.* 5 (1994) 989–993.
- [41] Kisi Ö: Streamflow forecasting using different artificial neural network algorithms, *J. Hydrol. Eng.* 12 (2007). 532.
- [42] Pearson K, Lee A: On the generalised probable error in separate normal correlation, *Biometrika* 6 (1908) 59–68.

