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Statistical and Artificial Neural Network for the Determination of Thermo-Physical Properties of Fomoditine Drug Using Mixed Hydrotropy

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Abstract

The experimental determination of thermo-physical properties of fomoditine drug–mixed hydrotrope concentration mixture is very time consuming as well as tedious process. Any tool helpful in estimation of these properties without experimentation can be of immense utility. In present work, other tools of determination of properties of fomoditine drug–mixed hydrotrope concentration blends were tried. A traditional statistical technique of linear regression (principle of least squares) was used to estimate the specific gravity, viscosity, surface tension and specific conductance of fomoditine drug–mixed hydrotrope concentration mixtures. A set of seven neural network architectures, three training algorithms along with ten different sets of concentration were examined to choose best Artificial Neural Network (ANN) to predict the above-mentioned properties of fomoditine drug–hydrotrope concentration mixtures. The performance of both of the traditional linear regression and ANN techniques were then compared to check their validity to predict the properties of various mixtures concentration of fomoditine drug–mixed hydrotrope concentration.

Keywords: artificial neural network, fomoditine drug, neurons (nodes), network training, perceptron

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INTRODUCTION

Hydrotropy is a unique solubilization technique wherein chemical components called hydrotropes can be used to cause several-fold increase in the solubility of sparingly soluble solutes under normal conditions.[1–3] Among various chemical components, urea, citric acid, sodium benzoate, sodium salicylate, aromatic sulfonic acids and their sodium salts are the commonly used hydrotopes (Neuberg, 1916). Chemical structure of the conventional Neuberg's hydrotropic salts (prototype, sodium salicylate) basically consists of 2 critical parts viz., an anionic group and a hydrophobic aromatic ring/ring system.[4–7] The anionic group plays important role in bringing about high aqueous solubility which is a pre-requisite for a hydrotropic substance. The type of anion or metal ion involved has a minor effect on the phenomenon. On the contrary, planarity of the hydrophobic part is believed to participate in the mechanism of hydrotropic solubilization. However, the molecular mechanism of hydrotropic solubilization has not yet been understood completely. Easy recovery of the dissolved solute and the possible reuse of hydrotropic solutions, make this as the most effective method particularly for pharmaceutical industries.[8–10]

Besides the advantage of certain properties such as high selectivity, inflammability, absence of emulsification, inexpensive aqueous base make this technique superior to other solubilization methods. All hydrotropes are non-reactive and non-toxic without inducing any temperature effect when dissolved in water. Easy availability and cost-effectiveness are other factors that should be considered while selecting hydrotropes.[11,12]

In many real world applications, computers need to perform complex recognition problems. Generally, the conventional computers are not suited to this type of field; therefore features from the physiology are borrowed such as Artificial Neural Systems (ANS) Technology or Neural Networks. Artificial neural network is a branch of artificial intelligence (AI) that attempts to achieve human brain like capability. Traditional approaches for solving problems related to chemical engineering have their own limitations, as for example in the modeling of highly complex and nonlinear systems.[13–15] Artificial neural networks (ANN) have proved to solve complex tasks in several practical applications. The utility of ANN models lie in the fact that they can be used to infer a function from observations. This is typically useful in applications where the complexity of the data/task makes the design of such a function by hand impractical. As ANNs are nets of basis functions, they can provide good empirical models of complex nonlinear processes useful for a wide variety of purposes. Applications of ANNs include detection of medical phenomena, prediction of stock market, credit assignment, monitoring the condition of machinery and engine management.[16,17] It is believed that so far there has been no attempt to truly predict the thermo-physical properties of fomoditine drug across their system temperature using ANNs. The present paper presents the findings of a programme of work devoted to the application of ANNs to the thermo-physical properties of fomoditine drug. The thermo-physical properties of fomoditine drug–mixed hydrotrope concentration are found by experimental work done by us. A predictive method based on ANN has been developed for specific gravity, density, viscosity, surface tension, specific conductance for fomoditine drug at system temperature. The study of thermo-physical properties like for specific gravity, viscosity, surface tension and specific conductance for different systems are very important to understand the molecular interaction and solubility of compounds. Using these data we found out the predicted data for intermediate hydrotrope concentration of different systems without conducting experiments.[18,19]

Scope of Present Work

In the present study the fomoditine drug–mixed hydrotrope concentration was prepared in the laboratory and the properties of its blends were experimentally measured. A linear regression analysis of the obtained data was made to estimate the properties of fomoditine drug–mixed hydrotrope concentration. A set of seven ANNs with different training algorithms and concentrations were examined to select the ANN to give the best estimation of the properties of fomoditine drug–mixed hydrotrope concentration blends. The performance of the best neural network was then compared with the traditional least squares method.

EXPERIMENTAL

Different blends were made from the fomoditine drug–mixed hydrotrope concentration with varying composition. Specific gravity, viscosity, surface tension, and specific conductance were measured as described. Specific gravity was measured using specific gravity bottle. The viscosity was measured using Ostwald viscometer and surface tension was

measured using capillary tube method. Specific conductance was measured by conductivity meter. The values of different thermo-physical properties for various blends are shown in Table 1.

Table 1. *Experimental Values of Properties of Various Blends of Sodium Acetate and Sodium Benzoate.*

Sl. no	Mixture concentration (mol/L)		Specific gravity	Viscosity,(cP)	Surface tension,(kg/s^2)	Specific conductance,(Mho/cm)
	Sodium acetate	Sodium benzoate				
1	0	1	1.003	1.080	41.35	1.35
2	0.1	0.9	1.006	1.120	38.42	1.39
3	0.2	0.8	1.025	1.148	36.29	1.63
4	0.3	0.7	1.028	1.159	34.25	1.78
5	0.4	0.6	1.037	1.163	30.48	1.83
6	0.5	0.5	1.043	1.178	27.39	1.94
7	0.6	0.4	1.049	1.183	24.45	2.23
8	0.7	0.3	1.054	1.196	21.59	2.45
9	0.8	0.2	1.057	1.213	19.73	2.61
10	0.9	0.1	1.066	1.218	16.48	2.68
11	1	0	1.069	1.224	14.89	2.79

The data available in Table 1 was used to draw a scatter gram between hydrotrope concentrations and corresponding specific gravity, viscosity, surface tension, and specific conductance, respectively. A linear relation was observed in each case. The equation of line which best fits was found using principle of least squares in each case. The linear equations obtained were then used to predict the thermo-physical properties of fomoditine drug–mixed hydrotrope concentration mixtures.

Neural Networks: Formulation and Selection

Eight numbers of neural networks having different architecture as shown in Table 2 were used. They were trained using three training algorithms *i.e.*, batch gradient descent with momentum, Levenberg–Marquardt and Scaled Conjugate Gradient.

The each algorithm with ten different sets of concentrations and biases was used to train each neural network for 1200 epochs using experimental values of properties as training data. The goal (mean square error) was used to evaluate the performance of each neural network.

The combination of neural network architectures, training algorithms, concentrations and biases with minimum goal was selected as the desired neural network. In order to check its validity the blend properties of fresh samples were predicted using selected neural network and compared with the experimental measurements. The selected neural network was further generalized using early stopping technique to enhance its performance and was further used to predict the thermo-physical properties of fomoditine drug–mixed hydrotrope concentration mixtures.

Table 2. *Different Neural Network Used.*

Sl. no	Neural network	Architecture
1	NN1	2-1-4
2	NN2	2-2-4
3	NN3	2-3-4
4	NN4	2-4-4
5	NN5	2-5-4
6	NN6	2-6-4
7	NN7	2-7-4
8	NN8	2-8-4

RESULTS AND DISCUSSION

Table 3 summarizes the comparison between the experimental (actual) values of the properties and values of properties predicted using method of least squares. It

was found during the study of performance of seven neural networks that the best combination of architecture and training algorithm for the present problem is NN8 (2-8-4) and Levenberg–Marquardt, respectively. Table 4 indicates comparison between the values predicted by best neural network (*i.e.*, NN8 having best combination of neural network architecture, training algorithm, concentrations, and biases) and the actual values obtained by laboratory experiments for different mixtures. The selected ANN was generalized with early stopping technique to avoid over-fitting for improved performance.

Table 3. *Comparison Between Actual Properties Found by Experimentation and Properties Predicted Using Principle of Least Squares.*

Sl. no	Mixture		Specific gravity		Viscosity		Surface tension		Specific conductance	
	Sodium acetate	Sodium benzoate	Actual	Predicted	Actual	Predicted	Actual	Predicted	Actual	Predicted
1	0.25	0.75	1.023	1.024	1.092	1.095	33.45	33.52	1.27	1.29
2	0.35	0.65	1.029	1.029	1.124	1.128	29.68	29.75	1.36	1.23
3	0.45	0.55	1.031	1.035	1.135	1.133	26.56	26.24	1.47	1.49
4	0.55	0.45	1.042	1.046	1.148	1.152	25.37	25.28	1.59	1.67

Table 4. *Comparison Between Actual Properties and Properties Predicted Using ANN.*

Sl. no	Mixture		Specific gravity		Viscosity		Surface tension		Specific conductance	
	Sodium acetate	Sodium benzoate	Actual	Predicted	Actual	Predicted	Actual	Predicted	Actual	Predicted
1	0.25	0.75	1.023	1.022	1.092	1.093	33.45	31.70	1.27	1.27
2	0.35	0.65	1.029	1.027	1.124	1.126	29.68	27.50	1.36	1.22
3	0.45	0.55	1.031	1.034	1.135	1.134	26.56	24.10	1.47	1.48
4	0.55	0.45	1.042	1.045	1.148	1.146	25.37	23.20	1.59	1.65

Table 5. *Mean Square Error After Generalization.*

Sl. no	Property	Mean square error	
		Least-squares	ANN
1	Specific gravity	4.8E-05	2.6E-05
2	Viscosity	5.7E-05	4.5E-05
3	Surface tension	0.120	0.148
4	Specific conductance	0.029	0.027

Table 5 provides the information about mean square error in prediction of individual properties using principle of least square and generalized neural network.

It is clear that individual mean square error is comparatively much less in case of neural network than principle of least squares.

Figures 1–4 shows the comparison between the experimental values and predicted values of specific gravity, viscosity, surface tension and specific conductance respectively in case of ANN as well as principle of least squares.

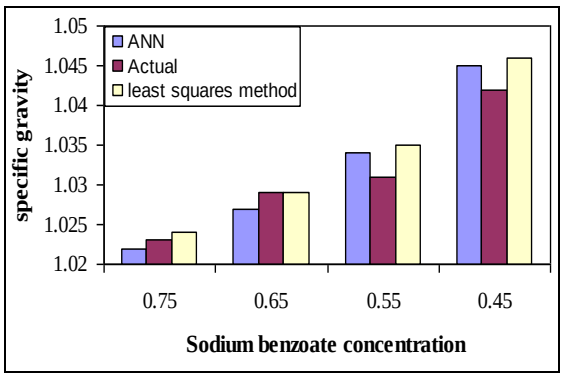

Fig. 1. *Parity Plot for Specific Gravity.*

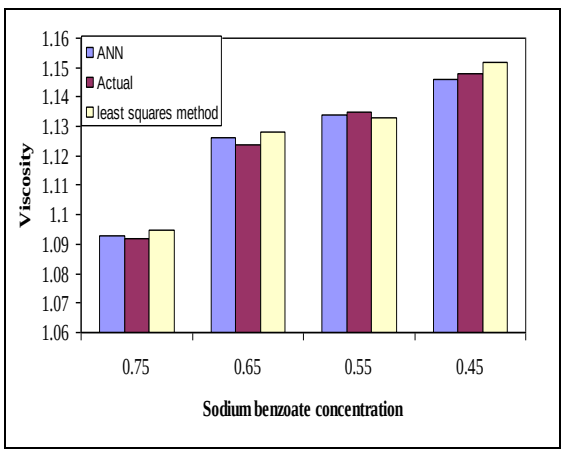

Fig. 2. *Parity Plot for Viscosity.*

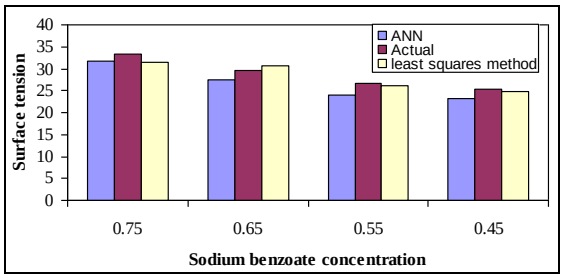

Fig. 3. *Parity Plot for Surface Tension.*

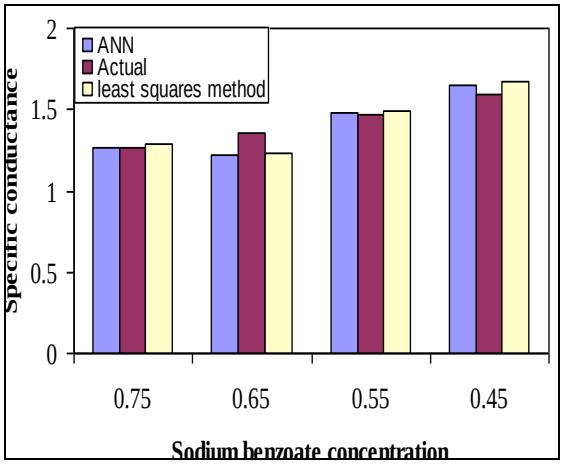

Fig. 4. *Parity Plot for Specific Conductance.*

CONCLUSIONS

The results show that the ANN is a better choice for this particular system. It is clear from Figures 1–4 that the predicted and experimental values of the properties have negligibly small error in case of artificial neural network and it gives a better estimation of said properties than statistical technique of cure fitting (principle of least squares).

It can be inferred that the neural network NN8 (2-8-4) along with Levernberg–Marquardt algorithm can be a better choice over principle of least squares to predict the above-said thermo-physical properties of various mixtures of fomoditine drug–mixed hydrotrope concentration. The performance of neural network may further be improved by adjusting the other training parameters like goal, epochs, learning rate, magnitude of the gradient, etc.

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