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Thin-layer drying of tea leaves: Mass transfer modeling using semi-empirical and intelligent models

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Abstract

Moisture content is a critical factor in quality and shelf-life of foods and agricultural products. This research dealt with prediction of moisture ratio of tea leaves using intelligent genetic algorithm-artificial neural networks (multilayer perceptron, MLP; and radial basis function, RBF) and semi-empirical models during different thin-layer drying processes (i.e. sun, air, hot air, and microwave drying). Effective diffusivities were found in the range of 7.5×10^{-7} to $9457.2\times10^{-7} m^2/h$, which the highest D_{eff} value was achieved for microwave drying. Moisture ratio data were modeled using fourteen semi-empirical equations among which Henderson and Pabis, Henderson and Pabis- modified, two-term-modified and Wang and Singh models received highest correlation coefficients. However, the prediction efficiencies of MLP (MSE, NMSE and MAE of 0.0084, 0.0597 and 0.0722, respectively) and RBF (MSE, NMSE and MAE of 0.0043, 0.0973 and 0.0564, respectively) networks were found to be more competent than semi-empirical models and therefore could be applied successfully for predicting moisture ratio of tea leaves during different drying processes.

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Introduction

Due to its sensory properties, stimulating effects and potential health benefits, tea (*Camellia sinensis* L.) is considered as the most popular beverages after water all over the world (Weisburger, 1997; Yang and Landau 2000). The annual global production of tea was reported to be about 4.51 million tons in 2010 (FAOSTAT, 2010). Tea is used in different types, e.g. green, black, and oolong tea. However, the most significant positive effects on human health have been observed by consumption of green tea (Jain *et al*., 2013).

Possessing critical effects on physical, structural, chemical and nutritional features of the product, makes drying as one of the main operations in tea processing. Different drying methods have been applied for tea; traditionally it is dried using sun or air drying approaches. In spite of widespread usage and low initial operation cost, the quality of tea undergoes significant deterioration (Chan *et al*., 2009). Oven and microwave were also used for drying of tea (Dong *et al*., 2011a; Hatibaruah *et al*., 2012). Oven drying has some disadvantages such as low energy efficiency and long drying time. Compared to oven drying, microwave can significantly reduce drying time of biological materials with minimum quality degradation. Therefore, microwave drying has now gained popularity as an alternative drying method for a variety of food products (Sellami *et al*., 2011; Zielinska *et al*., 2013; Rahimmalek and Goli 2013).

Moisture content significantly influences the quality and shelf life of dried tea. During drying moisture ratio can be estimated applying semi-empirical models (Costa and Pereira, 2013). Although these models give a reasonable fitting of the experimental data, their application is limited due to their semi-empirical nature and therefore, they are only capable of estimating data within the processing conditions in which they were developed or they depend on a large number of physical properties of product (Fathi *et al*., 2011a).

Artificial neural networks (ANN) are intelligent modeling systems based on relationship between dependent and independent variables. This methodology could be used for modeling linear and nonlinear phenomena and does not need the explicit knowledge of the physical meaning of the system or process under investigation (Fathi *et al*., 2011b). ANN have been recently used for prediction of green tea polyphenols content (Xi *et al*., 2013), kiwifruit shrinkage (Fathi *et al*., 2011c) and extraction efficiency of manganese (Khajeh and Barkhordar, 2013). The main drawback of ANN

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is that their parameters such as number of hidden neurons, learning rate and momentum are chosen by trial and error. Genetic algorithm (GA) as an optimization technique can be used for overcoming this limitation of neural network. GA is inspired by the natural selection principles and Darwin's species evolution theory. GA offers several advantages over the conventional optimization method such as less susceptibility to be stuck at local minima, requiring little knowledge of the process being optimized and capability to find the optimum conditions when the search space is very large (Fathi *et al.*, 2011b).

Dong *et al.* (2011b) compared chemical features of Eucommia ulmoides flower tea during microwave and hot air drying and reported that microwave drying method could maximally maintain the functional constituents. Effects of different drying methods (i.e. microwave, oven, sun, air, and freeze-drying) on antioxidant properties of tea were investigated. All three thermal drying methods led to decline in total phenolic content, ascorbic acid equivalent antioxidant capacity, and ferric-reducing power with minimal effects on ferrous ion-chelating ability and lipid peroxidation inhibition activity. High amount of losses were observed for air dried leaves. While, freeze-drying did not resulted in significant decrease in total phenolic content, ascorbic acid equivalent antioxidant capacity, and ferric-reducing power. Panchariya *et al*. (2002) applied different semi-empirical models to predict moisture content during drying of black tea at 80-120ºC and concluded that Lewis model gave better predictions. Effective diffusivity varied from 1.14×10^{-11} to 2.98×10^{-11} m^2/s over the temperature range.

In spite of numerous works conducted on the effect of drying methods on chemical compositions of tea leaves, there was not much attention on modeling of mass transfer during drying. Therefore the objective of this research was to model moisture ratio by semi-empirical and intelligent models during different drying processes (i.e. sun, air, hot air, and microwave drying) of tea leaves.

Materials and Methods

Sample collection and thin-layer drying

Whole tea leaves (Chinese hybrid variety) obtained from a tea farm in Lahijan city in the Northern regions of Iran in the fall growing season. In order to inhibit enzymatic browning, the leaves were immediately blanched using steam at 90ºC for one minute. The leaves were then thin-layer dried using following methods: (i) sun drying at about 35ºC; (ii) air drying in shade at about 25ºC; (iii) hot air drying at 60ºC; (iv) hot air drying at 80ºC; (v) hot air drying at 100ºC; and (vi) microwave drying at 800 W.

For sun drying leaves were exposed to direct sunlight in trays at about 35ºC for 7.5 h in November in Isfahan, Iran. Air drying was carried out under natural air flow in shade for 36 h. Oven drying was conducted in a ventilated oven (Osk, Japan) for 7.5, 5.25 and 4.5 h at 60ºC, 80ºC and 100ºC, respectively. Microwave drying was performed in a domestic digital microwave oven (Nikai, NMO-518N, Japan) with technical features of 230 V, 800 W. The samples were dried for 240 seconds. The thickness of samples for all thin-layer drying methods was kept constant in 5 mm. Moisture contents of samples were determined using moisture meter (Ohaus MB45; Massachusetts, USA) during drying at appropriate time intervals.

Semi-empirical models

The drying curves were represented in moisture ratio *(MR)* (Eq. 1) versus time (*t*, in h).

$$MR = \frac{MC_t - MC_e}{MC_0 - MC_e} \quad (1)$$

MC_0, MC_t and MC_e are initial moisture content, moisture content at time t and equivalent moisture content.

Moisture ratio values were then fitted using fourteen semi-empirical models listed in Table 1 applying SlideWrite plus software. In these equations a, b, c, k, k_1, k_2, k_3 and n model constants.

Artificial neural network

In current research, feedforward network was used for modeling of moisture ratio of tea leaves. Two commonly applied feedforward ANN architectures are multilayer perceptron (MPL) and radial basis function (RBF) networks. MLP consists of (i) an input layer with neurons representing independent variables, (ii) an output layer with neuron(s) representing the dependent variable(s), and (iii) one or more hidden layers containing neuron(s) help to capture the nonlinearity of the system. The processing in hidden layers consists of collecting the data from previous layer, multiplying them by their corresponding weights, summing the values, putting the results in a nonlinear or linear activation function (f) and finally adding a constant value called bias, mathematically:

$$y_j = \sum_{i=1}^{n} f(w_{ij} x_i) + \text{bias}_j \quad (16)$$

where w, x and y are weight, input and output of i (sending) and j (receiving) neurons. RBF network, which consists single radial hidden layer, uses

Table 1. Semi-empirical mathematical models

Model name	Mathematical model	Equation No.
Diffusion approach	$MR = a\exp(-kt) + (1-a)\exp(-kbt)$	(2
Henderson and Pabis	$MR = a\exp(-kt)$	(3
Henderson and Pabis- modified	$MR = a\exp(-k_1 t) + b\exp(-k_2 t) + c\exp(-k_3 t)$	(4
Logarithmic	$MR = a\exp(-kt) + c$	(5
Midilli	$MR = a\exp(-kt^n) + bt$	(6
Newton	$MR = \exp(-kt)$	(7
Page	$MR = \exp(-kt^n)$	(8
Page- modified	$MR = \exp\left[-(kt)^n\right]$	(9
Two-term	$MR = a\exp(-k_1 t) + b\exp(-k_2 t)$	(10
Two-term-exponential	$MR = a\exp(-kt) + (1-a)\exp(-kat)$	(11
Two-term- modified	$MR = a\exp(-k_1 t) + b\exp(-k_2 t) + c$	(12
Verma	$MR = a\exp(-k_1 t) + (1-a)\exp(-k_2 t)$	(13
Wang and Singh	$MR = 1 + at + bt^2$	(14
Weibull	$MR = \exp\left[-\left(\frac{t}{b}\right)^a\right]$	(15

Gaussian transfer function. The radial basis neurons are special neurons which have a centroid (u) and a spreading vector (σ). The output of the RBF layer is determined based on distance between the input vector and its centroid vector (Eq. 17). Training algorithm for hidden neurons is generally accomplished by an unsupervised fashion. While supervised algorithm is used for output layer. This configuration tends to learn much faster than MLP.

$$y_j = \sum_{i=1}^{n}\left[w_{ij}\exp\left(\frac{-|x_i - u_i|}{2\sigma^2}\right) + bias_j\right] \qquad (17)$$

In this study, drying method and drying time were used as input neurons to predict moisture content of tea leaves as the output of network. A hyperbolic tangent activation function was used in hidden layer, while a linear function was applied for the output layer. The number of hidden neurons varied from 1 to 10. For modeling data were first randomized and then divided into three partitions of training (40%), validation (30%) and testing (30%). To avoid over-fitting of the network the training process was carried on for 1000 epochs or until the cross-validation data's mean-squared error (MSE) did not improve for 100 epochs. Testing was carried out with the best weights stored during the training step. Calculation of the performance of the trained network was based on the accuracy of the network in the test partition. Therefore mean-squared error (MSE), normalized mean-squared error (NMSE), mean absolute error (MAE) and correlation coefficient (R) for each output were calculated based on testing data (Fathi *et al*., 2011a).

Genetic algorithm

Genetic algorithm, which inspires the principle of a Darwinian-type survival of the fittest in natural evolution, is essentially an iterative, population based, parallel global search algorithm that has a high ability to find optimal value of a complex objective function, without falling into local optima. The best chromosomes mate with other chromosomes of population and survive for the next generation and the most excellent chromosome, which is the most evolved one, is the optimal value. GA optimization technique consists of three principle processes (i.e. selection, crossover and mutation). The initial population of chromosomes is randomly generated. Selection of individuals to produce successive generations plays an important role in a GA. In this step, each chromosome is evaluated by the fitness function. According to the value of the fitness function, the chromosomes associated with the fittest individuals will be selected more often than those associated with unfit ones. In crossover step, two individuals reproduced into a new individual. The mutation operation randomly alters the value of each element of the chromosome according to the mutation probability. It provides the means for introducing new information into the population and therefore avoids sticking in local minima. This cycle is repeated until desired convergence on optimal or near-optimal of

Table 2. Semi-empirical model parameters and their corresponding performance efficiencies

Model: Diffusion approach

Drying method	a	b	k	R	MSE	NMSE	MAE
Sun drying	0.131352	0.987793	0.362828	0.947	0.0121	0.0860	0.0851
Air drying	1.00218	1.00023	0.081795	0.988	0.0025	0.0212	0.0433
Hot air drying (60 °C)	-11.723687	0.892032	0.553854	0.962	0.0095	0.0768	0.0854
Hot air drying (80 °C)	-78.788631	0.981994	0.846615	0.984	0.0039	0.0282	0.0525
Hot air drying (100 °C)	0.999806	1.005751	0.528175	0.881	0.0285	0.2244	0.1478
Microwave drying	1.000325	1.000315	1.044647	0.682	0.6993	3.2589	0.7803

Model: Henderson and Pabis

Drying method	a	k	R	MSE	NMSE	MAE
Sun drying	1.077	0.38034	0.959	0.0109	0.0720	0.3759
Air drying	1.02	0.090223	0.991	0.0020	0.0161	0.0410
Hot air drying (60 °C)	1.165	0.230545	0.904	0.0223	0.1933	0.1375
Hot air drying (80 °C)	1.143	0.363292	0.927	0.0167	0.1305	0.1148
Hot air drying (100 °C)	1.114	0.437956	0.927	0.0170	0.1296	0.1184
Microwave drying	1.008	109.93567	0.998	0.0004	0.0042	0.0132

Model: Henderson and Pabis- modified

Drying method	a	b	c	k_1	k_2	k_3	R	MSE	NMSE	MAE
Sun drying	0.3592	0.359	0.359	0.38167	0.3816	0.3781	0.958	0.010	0.0719	0.0906
Air drying	0.3401	0.340	0.34	0.09033	0.0899	0.0903	0.991	0.002	0.0164	0.0430
Hot air drying (60 °C)	0.3886	0.388	0.388	0.23054	0.2305	0.2307	0.904	0.022	0.1934	0.1377
Hot air drying (80 °C)	0.3811	0.381	0.381	0.36331	0.3633	0.3629	0.927	0.016	0.1305	0.1147
Hot air drying (100 °C)	0.3713	0.371	0.371	0.43789	0.4378	0.4379	0.926	0.016	0.1296	0.1184
Microwave drying	0.3361	0.336	0.335	109.617	109.61	110.53	0.997	0.000	0.0042	0.0132

Model: Logarithmic

Drying method	a	c	k	R	MSE	NMSE	MAE
Sun drying	1.38615	-0.3332	0.21959	0.981	0.0057	0.0346	0.0661
Air drying	1.09081	-0.08506	0.07363	0.995	0.0013	0.0101	0.0287
Hot air drying (60 °C)	9.33059	-8.21338	0.01688	0.979	72.6829	4.1685	8.9412
Hot air drying (80 °C)	7.49974	-6.41392	0.03081	0.989	35.1051	3.1689	5.5421
Hot air drying (100 °C)	7.26386	-6.20654	0.0367	0.987	37.4761	3.6608	6.1215
Microwave drying	1.00983	-0.0019	109.288	0.998	0.0073	0.0681	0.0831

Model: Midilli

Drying method	a	b	K	N	R	MSE	NMSE	MAE
Sun drying	0.010008	0.010	0.009526	0.000195	0.527	0.2810	2.4756	0.3773
Air drying	1.00144	-0.0011	0.064101	1.095752	0.994	0.0010	0.0098	0.0256
Hot air drying (60 °C)	0.010003	0.010	0.009742	0.000012	0.623	0.4400	3.2758	0.5851
Hot air drying (80 °C)	0.010004	0.010	0.009685	0.000255	0.612	0.3770	2.8148	0.4968
Hot air drying (100 °C)	0.010005	0.010	0.009626	0.000402	0.606	0.3610	2.7386	0.4881
Microwave drying	0.556702	-11.13306	-0.477356	20.497929	0.755	0.0430	0.5153	0.1637

Model: Newton

Drying method	k	R	MSE	NMSE	MAE
Sun drying	0.359003	0.947	0.0121	0.0860	0.0851
Air drying	0.08865	0.990	1.4373	3.4788	1.0376
Hot air drying (60 °C)	0.19418	0.835	0.0279	0.2841	0.1537
Hot air drying (80 °C)	0.31716	0.879	0.0207	0.1866	0.1200
Hot air drying (100 °C)	0.394411	0.893	0.0196	0.1679	0.1173
Microwave drying	109.26852	0.998	0.0005	0.0043	0.0125

Model: Page

Drying method	k	n	R	MSE	NMSE	MAE
Sun drying	0.051195	50.881073	0.766	0.1284	0.7485	0.2093
Air drying	0.269248	16.29711	0.808	0.2268	1.3078	0.3315
Hot air drying (60 °C)	1.915299	16.052815	0.726	0.2805	1.5558	0.4086
Hot air drying (80 °C)	0.399231	41.376999	0.780	0.1647	0.8580	0.2766
Hot air drying (100 °C)	0.893527	41.862887	0.814	0.1257	0.6396	0.2359
Microwave drying	0.010373	1.58E-06	0.682	0.7468	3.3227	0.8051

Model: Page- modified

Drying method	k	n	R	MSE	NMSE	MAE
Sun drying	0.336073	2.13909	1.000	0.00	0.00	0.0022
Air drying	0.085529	1.19172	0.994	0.0014	0.0110	0.0265
Hot air drying (60 °C)	0.204724	2.62258	0.989	0.3124	1.9727	0.4686
Hot air drying (80 °C)	0.321442	2.39034	0.997	0.2329	1.4105	0.3625
Hot air drying (100 °C)	0.386271	2.25149	0.989	0.0030	0.0203	0.0457
Microwave drying	103.45485	1.26794	0.999	0.6900	3.2458	0.7752

Model: Two-term

Drying method	a	b	k_1	k_2	R	MSE	NMSE	MAE
Sun drying	0.538	0.382	0.53882	0.38026	0.959	0.3803	1.1201	0.2068
Air drying	0.51	0.09	0.51016	0.08999	0.991	0.0020	0.0161	0.0410
Hot air drying (60 °C)	0.557	0.437	0.5574	0.43789	0.904	0.0223	0.1933	0.1375
Hot air drying (80 °C)	0.571	0.363	0.57181	0.36337	0.927	0.0167	0.1305	0.1148
Hot air drying (100	0.557	0.437	0.5574	0.43789	0.927	0.0170	0.1296	0.1184
Microwave drying	0.504	109.9	0.50405	109.937	0.998	0.0004	0.0042	0.0132

Model: Two-term-exponential

Drying method	a	K	R	MSE	NMSE	MAE
Sun drying	2.541062	0.677693	0.998	0.0006	0.0035	0.0198
Air drying	0.985728	0.088728	0.990	0.0020	0.0171	0.0394
Hot air drying (60 °C)	0.998333	0.189893	0.832	0.0280	0.2865	0.1515
Hot air drying (80 °C)	2.31888	0.591571	0.980	0.0049	0.0355	0.0580
Hot air drying (100	2.255242	0.702977	0.972	0.0070	0.0504	0.0700
Microwave drying	0.999036	0.806906	0.682	0.7134	3.2777	0.7879

Model: Two-term-modified

Drying method	a	b	c	k_1	k_2	R	MSE	NMSE	MAE
Sun drying	0.693	0.219	0.69308	0.21948	-0.333215	0.981	0.0057	0.0346	0.0661
Air drying	0.545	0.073	0.54541	0.73637	-0.085068	0.994	0.0312	0.2385	0.1310
Hot air drying (60 °C)	3.759	0.021	3.75959	0.02059	-6.400024	0.978	0.0060	0.0456	0.0693
Hot air drying (80 °C)	3.18	0.035	3.18011	0.03797	-5.272352	0.988	0.0032	0.0218	0.0458
Hot air drying (100 °C)	3.127	0.042	3.12797	0.04398	-5.196719	0.986	0.0036	0.0244	0.0519
Microwave drying	0.504	109.2	0.50491	109.288	-0.001971	0.997	0.0004	0.0042	0.0136

Model: Verma

Drying method	a	k_1	k_2	R	MSE	NMSE	MAE
Sun drying	-0.012	0.303027	0.33017	0.933	0.0147	0.1080	0.1042
Air drying	0.2226	0.1	0.10	0.986	0.3948	2.6310	0.5530
Hot air drying (60 °C)	0.1605	0.1	0.10	0.664	0.0723	0.8169	0.1936
Hot air drying (80 °C)	0.1405	0.1	0.10	0.639	0.1297	1.2695	0.2720
Hot air drying (100 °C)	0.2116	0.1	0.10	0.640	0.1652	1.5022	0.3159
Microwave drying	0.005	0.01	0.010	0.682	0.7593	3.3340	0.8122

Model: Wang and Singh

Drying method	a	b	R	MSE	NMSE	MAE
Sun drying	-0.257426	0.015927	0.983	0.0047	0.0301	0.0476
Air drying	-0.062444	0.000928	0.993	0.0030	0.0223	0.0449
Hot air drying (60 °C)	-0.063047	-0.01101	0.989	0.0029	0.0221	0.0446
Hot air drying (80 °C)	-0.150137	-0.010465	0.987	0.0032	0.0230	0.0471
Hot air drying (100 °C)	-0.202238	-0.008239	0.986	0.0036	0.0248	0.0425
Microwave drying	-49.416663	545.86149	0.947	0.0149	0.1228	0.1017

Model: Weibull

Drying method	a	b	R	MSE	NMSE	MAE
Sun drying	2.975544	2.139093	1.00	0.0171	0.0981	0.0807
Air drying	11.691839	1.191714	0.994	0.0014	0.0110	0.0265
Hot air drying (60 °C)	4.884371	2.622632	0.986	0.3581	2.1842	0.4967
Hot air drying (80 °C)	3.110908	2.390327	0.997	0.2319	1.3983	0.3616
Hot air drying (100 °C)	2.588726	2.251383	0.989	0.1818	1.0951	0.3117
Microwave drying	0.009666	1.26777	0.999	0.7632	3.3384	0.8142

the solutions are achieved (Yang and Landau, 2000). In current work, number of hidden neurons and training parameters (learning rate and momentum) were represented by haploid chromosomes consisting of three genes of binary numbers. The first gene corresponds to the number of neurons in single hidden layer and second and third genes represent the learning rate and momentum of network, respectively. An initial population of 60 chromosomes was randomly generated and the termination criterion of 60 was chosen for generation. The roulette wheel selection based on ranking algorithm was applied for the

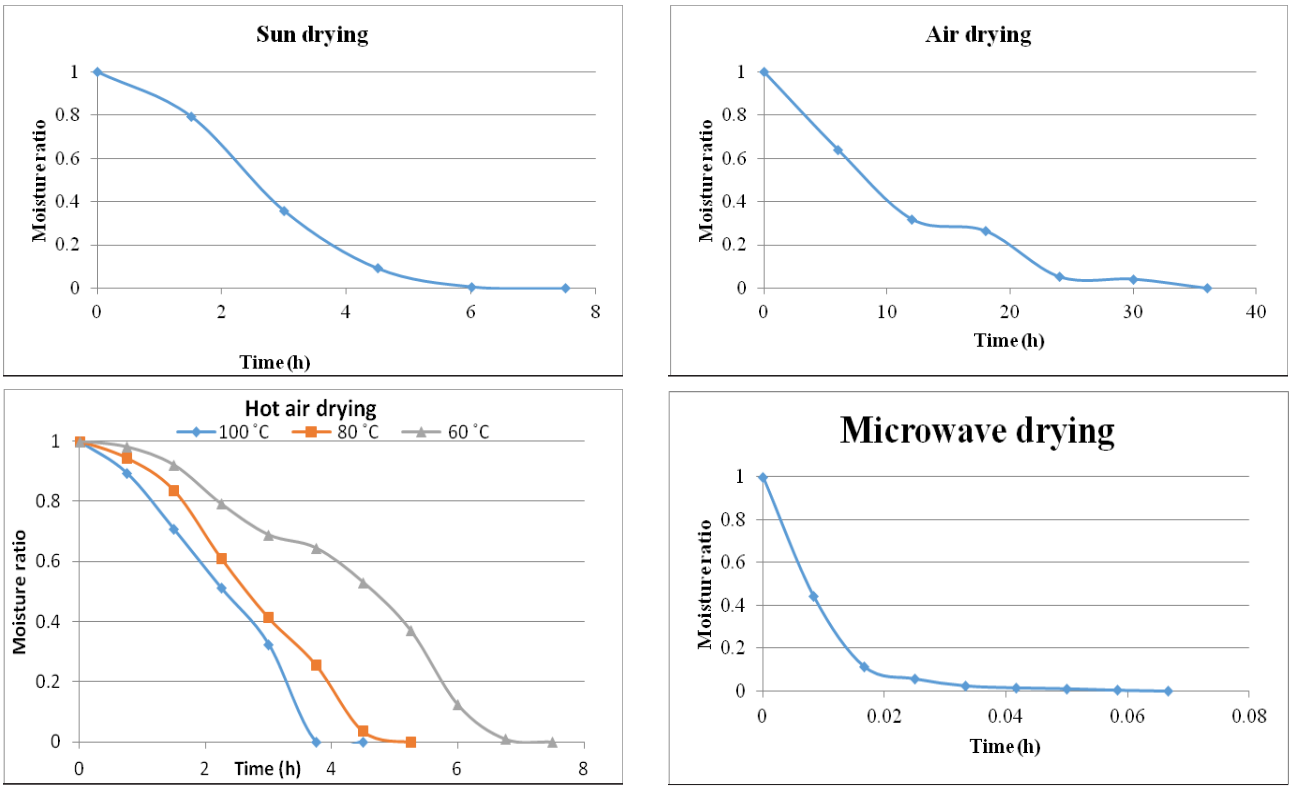


Figure 1. Moisture ratio of tea leaves dried using different drying methods versus time (h)

selection operator. Uniform crossover and mutation operators with mixing ratio of 0.5 were used and the probabilities of the crossover and mutation operators were adjusted at 0.9 and 0.01, respectively. In this study, the ANN modeling and GA optimization were performed by Neurosolution release 5.0, produced by NeuroDimension, Inc.

Statistical analysis

The experiments were conducted in two replications. Analysis of variance (ANOVA) of data was performed using a computerized statistical program called 'MSTAT', version C.

Results and Discussion

In this study tea leaves were dried using different methods and moisture ratio was predicted applying semi-empirical and intelligent models.

Semi-empirical models

Initial moisture content of tea leaves was 77.1±1.8% which indicated their susceptibility and necessity of drying process. Fig. 2 depicts the drying curves (moisture ratio versus time) for different drying methods. The experimental results indicated the absence of constant drying period and therefore drying took place only in the falling rate period. This illustrates that diffusion was the most likely physical mechanism governing moisture removal in the tea leaves. Hence, Fick's second low could be used to determine effective diffusivity. General series solution of Fick's second law for slabs is given in Eq. 18. Constant diffusivity, uniform moisture distribution and Thickness (L) of 0.005 m were assumed for tea leaves.

$$MR = \frac{8}{\pi^2}\sum_{n=0}^{\infty}\frac{1}{(2n+1)^2}\exp\left(-\frac{(2n+1)^2\pi^2 D_{eff}}{4L^2}t\right) \quad (18)$$

Simplifying above equation by considering the first term of series gives:

$$MR = \frac{8}{\pi^2}\exp\left(-\frac{\pi^2 D_{eff}}{4L^2}t\right) \quad (19)$$

Values of D_{eff} for sun drying, air drying 25ºC, hot air drying at 60ºC, 80ºC, 100ºC and microwave drying were 30.9×10^{-7}, 7.5×10^{-7}, 15.2×10^{-7}, 25.7×10^{-7}, 32.4×10^{-7} and 9457.2×10^{-7} m^2/h, respectively. The correlation coefficients for these values were found to be 0.848, 0.935, 0.654, 0.715, 0.744 and 0.964, respectively. It can be seen that D_{eff} values increased with increasing temperature during hot air drying. Microwave drying showed the highest D_{eff} value about three orders of magnitude higher than other drying methods. Effective diffusivities of 3146.04×10^{-7} m^2/h for red bell-pepper (Yang and Landau, 2000) and $1443.24\times10^{-7} m^2/h$ for onion slices (Weisburger, 1997) were reported during microwave drying. The higher obtained D_{eff} value of microwave drying in

Table 3. Model parameter and performance of developed GA-ANN model

ANN configuration	Optimized GA-ANN configuration					GA-ANN performance		
	Number of hidden neurons	Learning rate of hidden layer	Momentum of hidden layer	Learning rate of output layer	Momentum of output layer	MSE	NMSE	MAE
Multilayer perceptron	7	0.5895	0.0617	0.5443	0.6836	0.0084	0.0597	0.0722
Radial basis function	6	0.8372	0.8396	0.7531	0.1224	0.0110	0.0879	0.0783

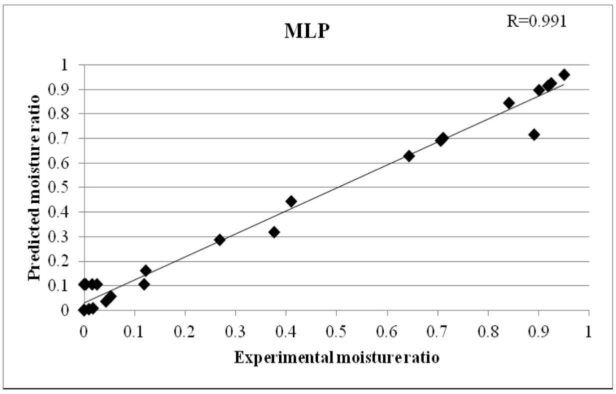
this work could be attributed to the thickness of thin layer sample.

Drying data were fitted to the semi-empirical models. Model parameters and performances of prediction were tabulated in Table 2. The ANOVA test on determined coefficients for logarithmic, Midilli, Page, Page- modified, Verma, and Weibull, were not significant at 95% confidence level and therefore could not be used for moisture ratio prediction. Their high values of MSE, NMSE and MAE also confirm incapability of these models. Apart from above mentioned models, other mathematical equations are fairly good, while did not receive acceptable performance against statistical parameters of MSE (min acceptable value of 0.01), NMSE (min acceptable value of 0.05) and MAE (min acceptable value of 0.05) for all drying methods. Panchariya *et al.* (2002) studied mathematical modeling of MR during thin-layer drying of black tea and reported that Lewis gave better predication ability.

GA-ANN

MLP and RBF neural networks with one hidden layer, 1 to 10 neurons and learning rate and momentum values ranging from 0 to 1 were trained using GA to achieve the optimal network configuration and learning parameters. Optimized MLP and RBF networks had 7 and 6 neurons in hidden layer, respectively. Model parameters and prediction errors of developed GA-ANN are showed in Table 3. Prediction error values indicated much better estimation capability of MLP as well as RBF in comparison to semi-empirical models. The matrices of weights (F matrix of 2×7 between input and hidden layer, G matrix of 1×7 between hidden layer and output layer) and bias values (BHidden matrix of 1×7 for first hidden layer and BOut matrix of 1×1 for output layer) of optimized MLP network are:

$$F = \begin{bmatrix} -2.48437 & -6.4250\times10^{-1} & 5.17409 & 7.7121\times10^{-1} & 3.5690 & 1.84446 & -2.11832 \\ 3.72654 & 4.15236 & -2.4767\times10^{-1} & 7.6905\times10^{-1} & 1.07524 & -1.68915 & 5.25898 \end{bmatrix}$$



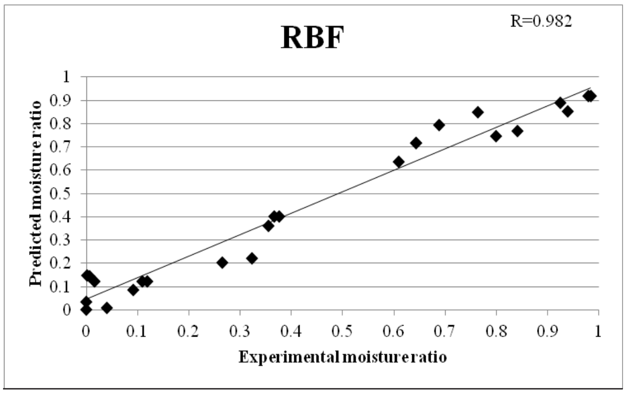


Figure 2. Experimental versus GA-ANN predicted MR values of dried tea leaves for MLP and RBF networks

$$G = \begin{bmatrix} -2.07564 & 9.6676\times10^{-1} & -2.19641 & -1.818\times10^{-2} & -2.03872 & 1.09929 & -1.95867 \end{bmatrix}$$

$$B_{Hidden} = \begin{bmatrix} 1.4998\times10^{-4} & 6.281\times10^{-5} & -2.3834\times10^{-4} & 1.414\times10^{-4} & -1.3593\times10^{-4} & 3.306\times10^{-5} & -2.7040\times10^{-4} \end{bmatrix}$$

$$B_{Out} = \begin{bmatrix} -3.082\times10^{-5} \end{bmatrix}$$

where the values in the first and second rows of matrix of *F* representing the weights of the connections between hidden neurons and drying method and drying time neurons in input layer, respectively.

Weight *(W)* and bias *(B)* values for RBF network between hidden and output layers presented in the following matrices:

$$W = \begin{bmatrix} 1.15403 & 4.4166\times10^{-1} & -7.470\times10^{-2} & 1.15679 & -9.4790\times10^{-1} & 4.2932\times10^{-1} \end{bmatrix}$$

$$B = \begin{bmatrix} -7.6175\times10^{-5} \end{bmatrix}$$

The performance of optimized GA-ANN models of MLP and RBF configurations for estimation of moisture ratio of tea leaves based on test data which never were seen by networks during training were studied and the results were plotted in Fig. 2. This figure shows that the GA-ANN estimated values of moisture ratio closely fitted with the experimental data. However, MLP performed better prediction in comparison than RBF (correlation coefficients values 0.991 and 0.982 for MLP and RBF, respectively) and could be suggested for prediction of moisture ratio during drying of tea leaves.

Conclusion

Tea leaves were dried using different methods and their moisture ratio values were predicted by semi-empirical and GA-ANN. Effective diffusivity were found to be in the range of 7.5×10^{-7} to 9457.2×10^{-7} m^2/h . Semi-empirical models were not fully able to predict moisture ratio of tea leaves. The best model for estimation of MR was found to be MLP genetic algorithm-artificial neural network with 7 hidden neurons and R, MSE, NMSE, and MAE values of 0.991, 0.0084, 0.0597 and 0.0722, respectively. The optimized network could be strongly suggested for prediction of moisture ratio of tea leaves during different drying processes.

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