ARTIFICIAL NEURAL NETWORK MODELLING OF GREEN SYNTHESIS OF SILVER NANOPARTICLES BY HONEY

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Abstract: Nanomaterials draw attention because of their unique physical, chemical and biological properties in areas such as catalysis, electronic, optics, medicine, solar energy conversion and water treatment. Green synthesis of silver nanoparticles has many superiorities compared to physical and chemical methods such as low cost, nontoxicity, eco-sensitive. In this paper, experimental conditions related to green synthesis of silver nanoparticles by honey were modelled using artificial neural network (ANN). While agitation time, agitation rate, pH, temperature, honey concentration, $AgNO_3$ concentration were selected as input parameters, production of silver nanoparticles was used as an output parameter. According to the results, optimum hidden neuron number was found as 40 with Levenberg–Marquardt backpropagation algorithm. In this conditions, the percentages of training, validation and testing were 75, 20 and 5, respectively. After creating neural network separated input data set was applied and then experimental and ANN predicted data were compared. In conclusion, ANN can be an alternative modelling and robust approach that could help researchers in this field to estimate production of silver nanoparticles.

Key words: *artificial neural network, silver nanoparticles, green synthesis, nanobiotechnology, honey*

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1. Introduction

Nanotechnology is a scientific field of characterization, production and application of nanoscale particles sized 1–100 nm [1,2]. Because of their large surface area and small sizes, nanoparticles have different properties such as mechanical, electrical, magnetic, and chemical properties compared to bulk materials [3,4]. Nanoparticles are utilized in areas like electronic, energy, medicine, textile, environmental remediation, space, etc. Metal nanoparticles have a lot of unique properties because of their high chemical activity, high surface area and magnetism. Silver nanoparticles

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draw attention due to their physicochemical properties. There are many application areas of silver nanoparticles such as mechanics, optics, sensors, drug delivery, DNA sequencing, cosmetic, water treatment and biomedical applications [4,5]. Silver nanoparticles are synthesized by physical and chemical methods like chemical reduction, electrochemical methods, sonodecomposition and microwave, laser ablation, lithography [6]. Nonetheless, there are problems with chemical and physical methods like toxicity, time-consuming, high cost and these methods may need a considerable pressure, temperature, energy [7]. The methods of green synthesis use plants, fungi, microorganisms, sugars, vitamins for production of nanoparticle [8]. Green methods have advantages over traditional methods such as simplicity, cost-effective, eco-friendly [8]. Overall, these materials which used in green methods decrease the needs to harmful and toxic chemicals. Green synthesis of silver nanoparticles using honey have been reported in the scientific literature [9–11]. Honey is a natural food which contains water, sugars, proteins, organic acids, vitamins, minerals, phenolic compounds and its characteristics can vary according to the origin [10,12]. The sugars present in honey are about 75 % monosaccharides (fructose and glucose), besides about 10–15 % disaccharides and other sugars [4]. Honey has important bioactivities such as antimicrobial, anti-inflammatory, analgesic and antioxidant properties beside nourishment [10,11]. In addition to before mentioned reducing agents that used in the green synthesis, honey can be used. It is reported that honey acted as a stabilizing agent besides reducing agent [9]. Even if the content which responsible for the reduction of silver cation in honey is unknown it is thought that glucose and proteins, and other natural reducing agents could be responsible for this [10,11].

Artificial intelligence (AI) has been developed since decades and it has been an important part of our daily life nowadays. AI applications are commonly used in information technologies including mobile phones and also their apps. One of the AI applications is artificial neural network (ANN). ANN has many superiorities on the traditional modelling methods. On the other hand, ANN provides important contribution to the understanding of complex situation including non-linear systems. ANN has so far been used in estimation of retention time in HPLC [13], development and validation of anti-cancer drugs [14], drug discovery [15], diagnosis tool for tuberculosis [16], diagnosis of osteoporosis [17]. ANN has been attracted by a wide of scientists from different fields. ANN can solve the problems based on unknown relationships among the data. Based on training, validation and testing steps, ANN develops a learning process and then it generalizes the knowledge for prediction of the response [14].

The aim of this work is to synthesize silver nanoparticles by using honey and to model raw experimental data by ANN.

2. Experimental

Honey was purchased from a local bazaar (blossom honey) in İzmir, Turkey. $AgNO_3$ was purchased from Macron Fine Chemicals. The honey solution was prepared by dissolving 5 g of honey in 20 ml deionized water and 15 ml of stock honey solution added to 20 ml aqueous solution of $AgNO_3$ (10^{-3} M). For optimization of silver nanoparticle synthesis, the experiments were performed at different temperatures (25–85 °C), pH values (3–9), agitation times (0–360 min), agitation rates (0–400 rpm), honey concentrations (0.1–0.75 g/ml) and different $AgNO_3$ concentrations (0.001–0.1 M). The data statistics was given in Tab. I.

Parameters	Data Statistics Range	Mean ± S.D.
Agitation Time (min)	0–360	213 ± 70
Agitation Rate (rpm)	0–400	240 ± 94
Temperature (°C)	25–85	38 ± 15
pH	3–9	6.4 ± 1.0
$AgNO_3$ Concentration (M)	0.001–0.1	0.007 ± 0.02
Honey Concentration ($g.mL^{-1}$)	0.1–0.75	0.29 ± 0.11

Tab. I *The data statistics of model variables.*

The solution colour changed from open yellow to intense brown colour dependent on $AgNO_3$ concentration. The synthesized silver nanoparticles were separated by centrifugation at 12,000 rpm for 1 hour and the precipitate was dried.

3. Artificial neural networks study

Usually ANN techniques describes human brain functioning. In order to solve non-linear and complex problems that require high computational cost ANN supply correct results [18, 19]. Error toleration, intrinsic contextual data processing, fast computation capacity, learning and generalization ability of info can count as principal advantages of ANN [20]. There are neurons (hidden units) in ANN architecture like synapse of biological counterparts. Activation functions that control the propagation of neuron signal to next layer, form hidden unity. The hidden unit is constituted by regression equation that processes the input data into nonlinear output data. Nonlinear correlations can be treated hence more than one neuron is required for constitute an ANN. Threshold function, sigmoid (e.g. hyperbolic tangent), radial basis function (e.g. gaussian) and linear function can be counted as a typical activation functions to form an ANN. ANN techniques can categorize to architecture and neuron connection pattern so these are feedforward networks and feedback networks [20].

In this study, ANN structure includes three-layer feed-forward networks with sigmoid and linear functions (Fig. 1).

The data related to the synthesis of silver nanoparticles was modelled by using neural networks toolbox of MATLAB (R2016b). The input parameters in this networks were agitation time, agitation rate, temperature, pH, $AgNO_3$ concentration and honey concentration. The output data was absorbance value. Before creating network hidden neuron number was optimized under default settings of MATLAB. The MSE and R^2 values in the ANN calculated by following equations;

$$\mathrm{MSE} = \frac{1}{n\sum_{i=1}^{n}(a_i - b_i)^2}, \tag{1}$$

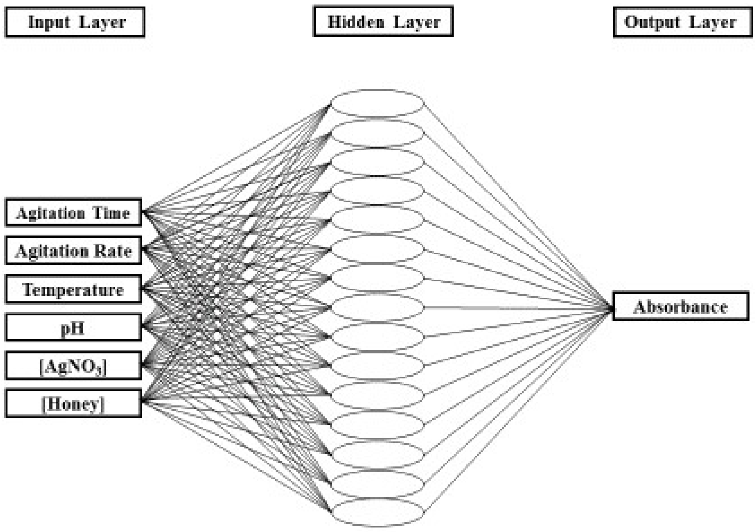


Fig. 1 *Architecture of ANN created in the study.*

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(a_i - b_i)^2}{\sum_{i=1}^{n}(a_i - b_m)^2}, \tag{2}$$

where a_i is the target value, b_i is the output value, b_m is the average of the target values and n is the total number of training patterns. Backpropagation algorithms used in this study was given in Tab. II.

Backpropagation Algorithms	Function
BFGS quasi-Newton backpropagation	*trainbfg*
Powell–Beale conjugate gradient backpropagation	*traincgb*
Fletcher–Reeves conjugate gradient backpropagation	*traincgf*
Polak–Ribiére conjugate gradient backpropagation	*traincgp*
Batch gradient descent	*traingd*
Batch gradient descent with momentum	*traingdm*
Variable learning rate backpropagation	*traingdx*
Levenberg–Marquardt backpropagation	*trainlm*
One step secant backpropagation	*trainoss*
Resilient backpropagation (Rprop)	*trainrp*
Scaled conjugate gradient backpropagation	*Trainscg*

Tab. II *The backpropagation algorithms used in the study.*

In our network creation training, validation and testing data were selected randomly by MATLAB. The total numbers of data were 129. 114 of the data were used for training, testing and validation in ANN modelling. Furthermore, training, validation and test percentages were studied and the percentage which had the highest R^2 and the lowest MSE values were selected for ANN design. The 75 %, 20 % and 5 % of datasets were used for training, validation and testing. 15 of the total data were randomly chosen to compare the experimental and predicted values for testing the efficiency of the developed ANN model. In order to find best performance parameters, 11 different backpropagation algorithms were tested (Tab. II).

4. Results and discussion

4.1 Artificial neural network

Green synthesis of silver nanoparticle was carried by using honey solution. During the optimization process, the experimental data related to agitation time, agitation rate, temperature, pH, honey and $AgNO_3$ concentration were collected. This data was used to create an artificial neural network by MATLAB. According to the results, the optimum hidden neuron number was found as 40 when default settings (the percentages of training, validation and testing are 70, 15 and 15 %, respectively, Levenberg–Marquardt backpropagation algorithm) were applied. The R^2 values of training, validation and testing are 0.9967, 0.9887 and 0.9792, respectively, when hidden neuron number was 40 (Tab. III). In the present study, the effects of data percentages were also studied. The highest R^2 values were found for 75, 20 and 5 % for training, validation and testing, respectively (Tab. IV). After creating the network, we also studied the performances of the 11 different backpropagation algorithms. Levenberg–Marquardt backpropagation algorithm gave best results (Tab. V and VI).

	R^2				MSE			
Hidden neuron number	Training	Validation	Testing	All	Training	Validation	Testing	Iteration number
1	0.7001	0.9572	0.6382	0.6863	0.0628	0.0107	0.1403	10
2	0.5142	0.2584	0.4152	0.4644	0.0886	0.0392	0.1668	8
3	0.9906	0.9950	0.9845	0.9103	0.0020	0.0019	0.0018	79
4	0.9954	0.9949	0.9982	0.9948	0.0008	0.0046	0.0016	196
5	0.9746	0.9948	0.9843	0.9980	0.0054	0.0031	0.0019	23
6	0.9943	0.9853	0.9897	0.9927	0.0016	0.0028	0.0010	53
7	0.9950	0.9927	0.9971	0.9953	0.0012	0.0006	0.0011	61
8	0.9351	0.9372	0.9680	0.9431	0.0142	0.0042	0.0184	15
9	0.9905	0.9986	0.9755	0.9914	0.0022	0.0006	0.0025	33
10	0.9947	0.9792	0.9788	0.9894	0.0014	0.0083	0.0018	42
11	0.9968	0.9965	0.7557	0.8567	0.0007	0.0017	0.3432	160
12	0.9202	0.7487	0.3525	0.7756	0.0149	0.1731	0.1835	9
13	0.9946	0.9950	0.4180	0.7227	0.0010	0.0042	0.7191	42
14	0.9873	0.9813	0.9885	0.9859	0.0020	0.0082	0.0045	21
15	0.9678	0.9837	0.9694	0.9681	0.0071	0.0022	0.0133	17
16	0.9937	0.9851	0.9953	0.9931	0.0013	0.0019	0.0038	31

17	0.9125	0.9646	0.9232	0.9279	0.0153	0.0012	0.0305	11
18	0.9810	0.9763	0.9690	0.9795	0.0057	0.0021	0.0035	14
19	0.8109	0.02491	0.4159	0.6260	0.0680	0.4164	0.0479	8
20	0.9978	0.9896	0.9142	0.9748	0.0005	0.0047	0.0325	52
21	0.9917	0.9916	0.9979	0.9931	0.0013	0.0007	0.0059	37
22	0.9070	0.2592	0.8016	0.7839	0.0272	0.2396	0.0143	8
23	0.9962	0.9972	0.9934	0.9953	0.0006	0.0053	0.0009	70
24	0.9964	0.9971	0.8188	0.9080	0.0008	0.0029	0.1659	95
25	0.7828	0.8169	0.7679	0.7432	0.0349	0.0230	0.1998	8
26	0.9622	0.9956	0.9553	0.9747	0.0060	0.0028	0.0078	13
27	0.9695	0.8872	0.9862	0.9649	0.0087	0.0109	0.0018	11
28	0.9977	0.9872	0.9958	0.9956	0.0004	0.0025	0.0028	78
29	0.9492	0.9713	0.9893	0.9596	0.0115	0.0033	0.0040	9
30	0.9910	0.7925	0.8275	0.9632	0.0026	0.0211	0.0262	16
31	0.9795	0.9796	0.9901	0.9810	0.0050	0.0026	0.0035	11
32	0.9687	0.9894	0.9810	0.9724	0.0072	0.0055	0.0033	10
33	0.9534	0.9732	0.9651	0.9537	0.0114	0.0137	0.0060	10
34	0.9941	0.9936	0.2965	0.9477	0.0009	0.0024	0.0751	41
35	0.9930	0.9758	0.8909	0.9835	0.0016	0.0090	0.0092	36
36	0.9966	0.9811	0.9816	0.9944	0.0009	0.0006	0.0037	84
37	0.9952	0.9980	0.9951	0.9947	0.0008	0.0015	0.0043	34
38	0.9914	0.9033	0.7595	0.9731	0.0024	0.0152	0.0154	14
39	0.9514	0.9341	0.3596	0.6179	0.0120	0.0016	1.0186	9
40	0.9967	0.9887	0.9792	0.9945	0.0009	0.0007	0.0037	41

Tab. III *Effects of hidden neuron number on the ANN performance.*

		R^2				MSE			
#	Training, validation and testing percentages	Training	Validation	Testing	All	Training	Validation	Testing	Epoch #
1	90-5-5	0.9929	0.9799	0.9237	0.9928	0.0018	0.0004	0.0009	34
2	85-5-10	0.9886	0.9991	0.9968	0.9907	0.0022	0.0054	0.0003	21
3	80-5-15	0.9865	0.9806	0.9859	0.9862	0.0027	0.0002	0.0076	13
4	75-5-20	0.9332	0.9973	0.9862	0.9566	0.0126	0.0026	0.0040	9
5	70-5-25	0.9914	0.9796	0.9825	0.9875	0.0018	0.0021	0.0063	15
6	65-5-30	0.4885	0.6464	0.5712	0.5256	0.3768	0.4053	0.1419	8
7	60-5-35	0.9897	0.9982	0.4769	0.8220	0.0025	0.0014	0.1449	19
8	85-10-5	0.9710	0.9812	0.9130	0.9697	0.0073	0.0012	0.0116	14
9	80-10-10	0.9927	0.9963	0.9525	0.9923	0.0020	0.0005	0.0019	45
10	75-10-15	0.9964	0.9881	0.9991	0.9949	0.0005	0.0064	0.0107	57
11	70-10-20	0.5703	0.4884	0.4819	0.5281	0.1312	0.4300	0.2730	7
12	65-10-25	0.9737	0.9858	0.9879	0.9808	0.0043	0.0101	0.0034	15
13	60-10-30	0.9913	0.9925	0.9949	0.9932	0.0015	0.0006	0.0020	29
14	55-10-35	0.9818	0.9997	0.4230	0.6662	0.0035	0.0027	0.3594	15
15	80-15-5	0.9808	0.8709	0.9327	0.9611	0.0048	0.0314	0.0155	10
16	75-15-10	0.9881	0.9662	0.9918	0.9854	0.0023	0.0067	0.0064	19
17	70-15-15	0.9911	0.9374	0.9686	0.9876	0.0025	0.0032	0.0042	18
18	65-15-20	0.9812	0.9959	0.7678	0.9131	0.0045	0.0042	0.0909	15
19	60-15-25	0.9930	0.8301	0.7088	0.9034	0.0016	0.0717	0.0458	13
20	55-15-30	0.7167	0.3326	0.5943	0.6129	0.1195	0.1641	0.1589	7
21	50-15-35	0.9757	0.7711	0.8000	0.9203	0.0084	0.0380	0.0240	10

22	75-20-5	0.9960	0.9955	0.9118	0.9957	0.0011	0.0007	0.0009	85
23	70-20-10	0.9857	0.9967	0.7974	0.9883	0.0034	0.0009	0.0010	21
24	65-20-15	0.9977	0.9880	0.9848	0.9956	0.0007	0.0020	0.0012	68
25	60-20-20	0.9568	0.6350	0.2588	0.5979	0.0014	0.1077	0.8010	8
26	55-20-25	0.9973	0.9979	0.4563	0.7454	0.0004	0.0047	0.3313	32
27	50-20-30	0.9631	0.7595	0.9248	0.9390	0.0162	0.0230	0.0087	10
28	45-20-35	0.9962	0.9906	0.9764	0.9909	0.0011	0.0033	0.0029	7
29	70-25-5	0.7357	0.5595	0.8783	0.6597	0.0500	0.1979	0.0344	7
30	65-25-10	0.9880	0.9434	0.9136	0.9786	0.0036	0.0060	0.0109	18
31	60-25-15	0.9973	0.9822	0.9960	0.9928	0.0003	0.0036	0.0072	78
32	55-25-20	0.9662	0.3428	0.3066	0.6242	0.0111	0.2891	0.3534	8
33	50-25-25	0.9895	0.9918	0.9872	0.9887	0.0020	0.0036	0.0037	27
34	45-25-30	0.9685	0.9008	0.3190	0.4897	0.0036	0.0279	0.5218	20
35	40-25-35	0.9955	0.7600	0.6169	0.8325	0.0014	0.0749	0.0749	11
36	65-30-5	0.8346	0.2532	0.9506	0.6266	0.1055	0.5586	0.1048	7
37	60-30-10	0.9662	0.7982	0.9830	0.9562	0.0069	0.0142	0.0160	10
38	55-30-15	0.9804	0.2578	0.2350	0.4995	0.0067	0.4798	0.9202	9
39	50-30-20	0.8891	0.6451	0.7520	0.7402	0.0020	0.2131	0.6681	7
40	45-30-25	0.9833	0.9910	0.9587	0.9814	0.0041	0.0054	0.0042	11
41	40-30-30	0.9504	0.8585	0.3213	0.6506	0.0229	0.0339	0.2501	8
42	35-30-35	0.9799	0.2391	0.1247	0.2576	0.0022	0.3115	0.4572	19
43	60-35-5	0.9158	0.6529	0.4388	0.7563	0.0043	0.1807	0.5919	8
44	55-35-10	0.9921	0.7094	0.9324	0.8122	0.0014	0.1371	0.0440	23
45	50-35-15	0.9845	0.5447	0.6716	0.6879	0.0016	0.1254	0.1201	12
46	45-35-20	0.9414	0.4985	0.5728	0.6213	0.0132	0.1450	0.2221	8
47	40-35-25	0.9858	0.3318	0.5545	0.6680	0.0076	0.1451	0.1795	10
48	35-35-30	0.9346	0.7885	0.8220	0.8349	0.0216	0.0600	0.0617	8
49	30-35-35	0.9984	0.2397	0.4753	0.4189	0.0001	0.2600	0.1506	24

Tab. IV *Effects of data percentage on the performance of ANN modelling.*

		ANN Algorithms						
#	Experimental	*Trainbfg*	*Trainbr*	*Traincgb*	*Traincgf*	*Traincgp*	*Traingd*	*Traingdm*
1	0.273	0.195	0.3533	0.4451	0.4725	0.2268	0.3089	0.2089
2	0.395	0.195	0.3808	0.3460	0.4612	0.2201	0.3578	0.2076
3	0.400	0.195	0.5658	0.2103	0.4696	0.2315	0.5435	0.3123
4	0.321	0.195	0.5325	0.2502	0.4215	0.2156	0.3501	0.2759
5	0.385	0.195	0.4176	0.2084	0.5664	0.2120	0.4080	0.2125
6	0.238	0.195	0.3351	0.1957	0.3616	0.2100	0.2898	0.2200
7	0.262	0.195	0.4052	0.2023	0.3345	0.2175	0.3004	0.2107
8	0.255	0.195	0.4272	0.2071	0.3271	0.2242	0.3141	0.2092
9	1.171	0.195	0.4117	0.2002	0.4248	0.2007	0.6497	0.3722
10	0.859	0.195	0.6019	0.1951	0.2879	0.2187	0.4753	1.2689
11	0.744	0.195	0.9565	0.1950	0.2408	0.5499	0.7138	1.9070
12	0.278	0.195	0.3909	0.2045	0.4423	0.2007	0.6376	0.3294
13	0.432	0.195	0.6219	0.7090	0.3752	0.3269	0.5134	1.4435
14	0.356	0.195	0.7322	0.9139	0.3947	0.2077	0.7425	0.2674
15	0.402	0.195	1.0063	1.8914	0.3177	0.5944	0.5984	0.2116

Tab. V *Performances of different backpropagation algorithms on the prediction of experimental values.*

In order to compare the experimental and ANN predicted values, Fig. 2 was drawn. This figure showed that the created ANN model can estimate the experi-

		ANN Algorithms						
#	Experimental	*Traingda*	*Traingdx*	*Trainlm*	*Trainoss*	*Trainr*	*Trainrp*	*Trainscg*
1	0.273	0.6553	0.6568	0.3077	0.195	0.3561	0.2200	0.3128
2	0.395	0.4593	0.6192	0.3340	0.195	0.3971	0.2328	0.3194
3	0.400	0.4507	0.6990	0.3643	0.195	0.4192	0.4876	0.5095
4	0.321	0.5238	0.7751	0.3650	0.195	0.4642	0.3424	0.3925
5	0.385	0.4268	0.4227	0.3825	0.195	0.4278	0.2981	0.3836
6	0.238	0.2942	0.2536	0.2507	0.195	0.2876	0.2864	0.3386
7	0.262	0.2471	0.2473	0.2395	0.195	0.2197	0.2363	0.3396
8	0.255	0.2460	0.2434	0.2531	0.195	0.2143	0.2426	0.3517
9	1.171	0.4101	0.4047	1.0570	0.195	0.7840	0.6360	0.7179
10	0.859	0.6938	0.6064	0.9065	0.195	0.9979	0.8997	0.9158
11	0.744	1.0076	0.9875	0.7212	0.195	0.7489	1.2140	1.0530
12	0.278	0.3847	0.3889	0.2821	0.195	0.7145	0.5119	0.6736
13	0.432	0.8647	0.7203	0.4365	0.195	0.4350	0.4443	0.4345
14	0.356	0.5188	0.5126	0.3637	0.195	0.7524	0.5309	0.6317
15	0.402	0.7718	1.5783	0.3988	2.145	1.9402	0.6834	2.1131

Tab. VI *Performances of different backpropagation algorithms on the prediction of experimental values.*

mental values precisely. On the other hand, other backpropagation algorithms did not give promising results.

Shabanzadeh et al (2013) studied neural network modelling for the prediction of the size of silver nanoparticle prepared by the green method. They synthesized silver nanoparticles using soluble starch. Their input parameters were volume of NaOH, temperature, starch and $AgNO_3$ concentration and output parameter was size of nanoparticles. For training, validation and testing steps they used 20, 5, 5 sample respectively. They found number of a hidden neuron as 10. R^2 values of their best predictive model for training, validation and testing were 0.9839, 0.9778 and 0.9787, respectively [21].

Shabanzadeh et al. (2014) also worked neural network modelling for in their paper named Neural Network Modelling for silver nanoparticles in montmorillonite/starch synthesis by chemical reduction method. Their input parameters were $AgNO_3$ and $NaBH_4$ concentration, temperature, weight percentage of starch and output parameter was the size of silver nanoparticle in their ANN model. Their percentage of datasets for training, validation and testing were 70 %, 15 % and 15 %, respectively. They found number of a hidden neuron as 10. R^2 values that their found for training, validation and testing were 0.9979, 0.9952 and 0.9984 [22].

4.2 pH

The effects of pH were carried out in the range of 3–9. Fig. 3a reveals that absorbance value at pH 3 was found as 0.302 and then a decline was observed. After that pH values showed fluctuations and the absorbance value at pH 9 was found as 0.249. However, when temperature and agitation time changed, a different profile was obtain as it is shown in Fig. 3b.

Haiza et al. (2013) carried out their experiment in the pH range 7–8.5. They

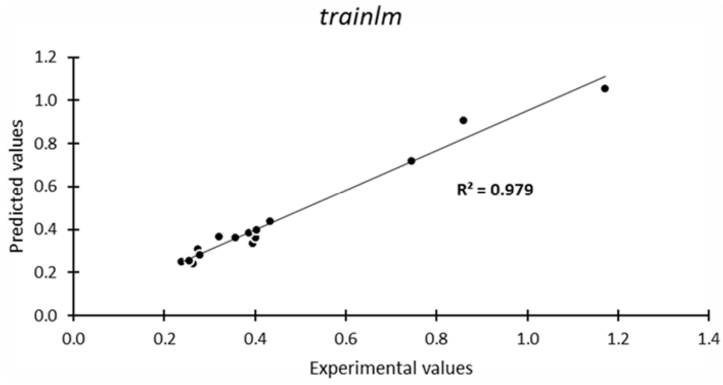
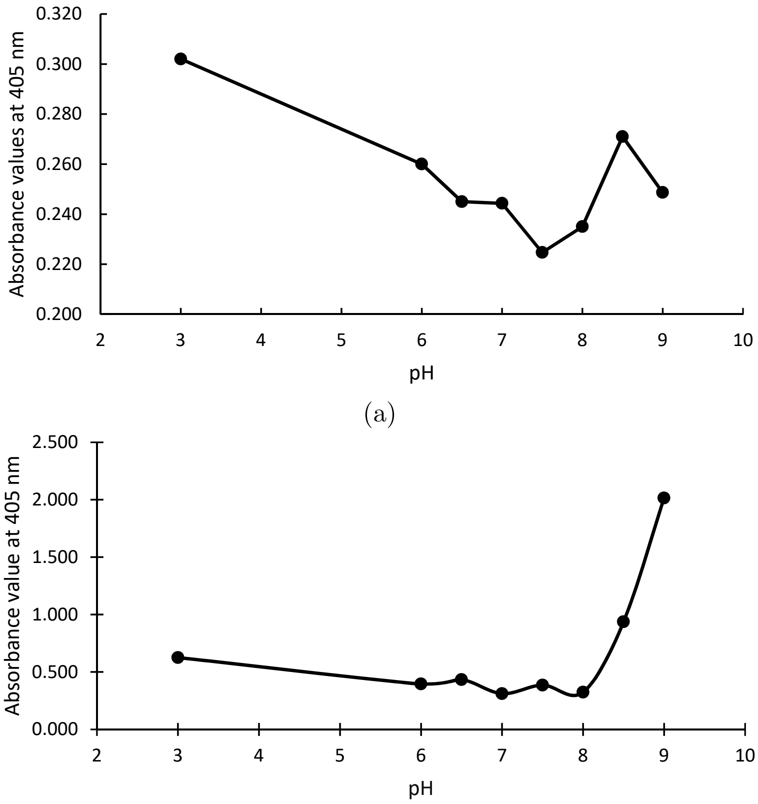


Fig. 2 *Comparison of experimental values with ANN predicted values (Trainlm: Levenberg–Marquardt backpropagation).*



(a)

(b)

Fig. 3 *Effect of pH on the AgNPs synthesis. The conditions for (a) temperature = 25°C, honey concentration = 0.25 g/mL, $AgNO_3$ concentration= 0.001 M, agitation rate = 400 rpm, agitation time = 240 min and, (b) temperature = 50°C, honey concentration = 0.25 g/mL, $AgNO_3$ concentration= 0.001 M, agitation rate = 0 rpm and agitation time = 240 min.*

found that decreased absorbance with increased pH values in their study. This decline was associated with increased size of silver nanoparticles [10].

Philip (2010) found that as the pH increased absorbance value increased and at pH 8.5 absorbance value was highest. Owing to lack of adequate gluconic acid molecules at lower pH values growth is preferred. As pH is increased, more gluconic acid is generated from glucose and reduction of Ag ions is accelerate [11].

González Fá et al. (2016) found that absorbance value of pH 10 at 411 nm was higher than pH 5 [9].

4.3 Temperature

We performed our experiments in the temperature range 25–85 °C. Absorbance value at 25 °C was found as 0.332 after that was observed increment at 65 °C as 0.562 and then absorbance value was decreased to 0.4 at 85 °C (Fig. 4).

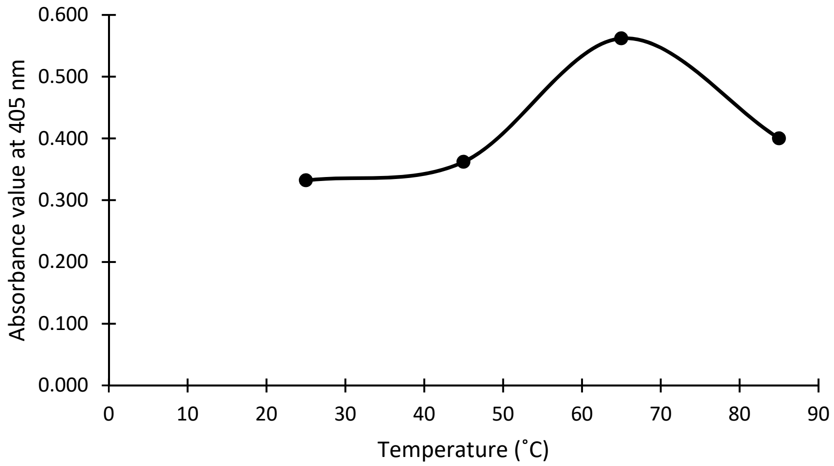


Fig. 4 *Effect of temperature on the AgNPs synthesis (pH = 6.0, honey concentration = 0.5 g/ml, $AgNO_3$ concentration = 0.001 M, agitation time = 240 min, agitation rate = 200 rpm).*

Philip (2010), Haiza et al. (2013) and González Fá et al. (2016) did not mention about the temperature values in their papers [9–11].

4.4 Agitation rate

Agitation rate was studied in the range of 0–400 rpm. This experiment was carried out at different temperatures 25 °C and we observed that there was a linear increase and absorbance value at 400 rpm was found as 0.437 at 25 °C (Fig. 5).

4.5 Agitation time

The experiment was carried out during 390 minute and absorbance values were recorded. There were fluctuations in the diagram but absorbance value of silver

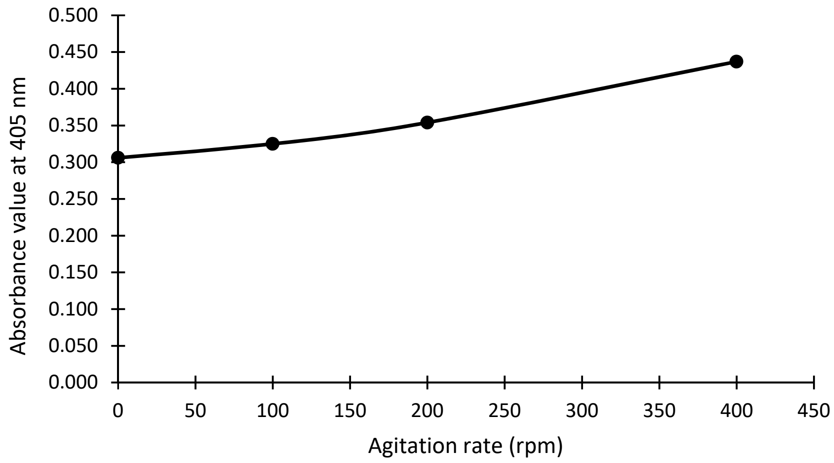


Fig. 5 *Effect of agitation rate on the AgNPs synthesis (pH = 6.0, temperature = 25° C, honey concentration = 0.25 g/ml,* $AgNO_3$ *concentration = 0.001 M).*

nanoparticles in different minutes was not divergent. The optimum agitation time was determined as 240 min. In addition, this experiment was studied in different wavelengths (405 nm, 450 nm, 490 nm, 590 nm, 630 nm) with BioTek^{TM} ELx800^{TM} Absorbance Microplate Reader and highest absorbance values were obtained at 405 nm wavelength (Fig. 6).

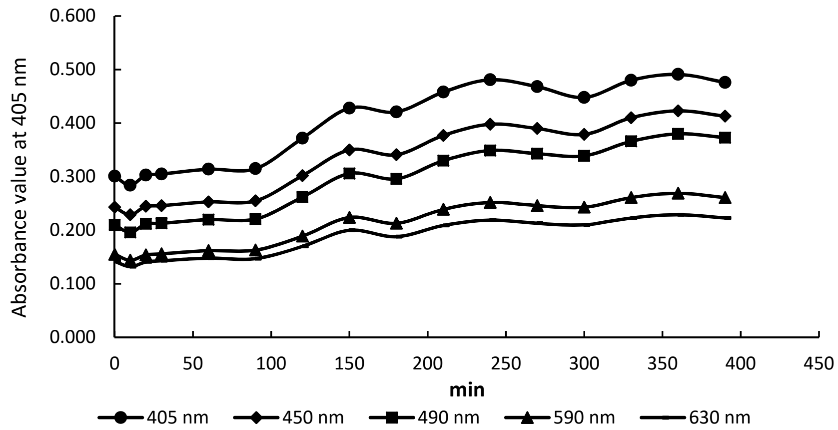


Fig. 6 *Effect of agitation time on the AgNPs synthesis (pH = 6.0, temperature = 50° C, honey concentration = 0.25 g/ml,* $AgNO_3$ *concentration = 0.001 M, agitation rate = 200 rpm).*

In other scientific publications cited in this paper related to the green synthesis of silver nanoparticle, the effects of agitation rate and time were not clearly mentioned. However, it was generally selected as 1 minute [9–11].

4.6 Honey concentration

Honey concentration was worked at a range of 0.1–0.75 g/ml. According to Fig. 7, there was linear increase and absorbance value was 0.435 at 0.75 g/ml honey concentration.

Haiza et al. (2013) reported that honey concentrations had an impact on the particle size of silver nanoparticles produced and Ag ions size were shrink due to an increase in honey concentration. Furthermore, honey ingredients might have played roles of reducing and capping agents [10].

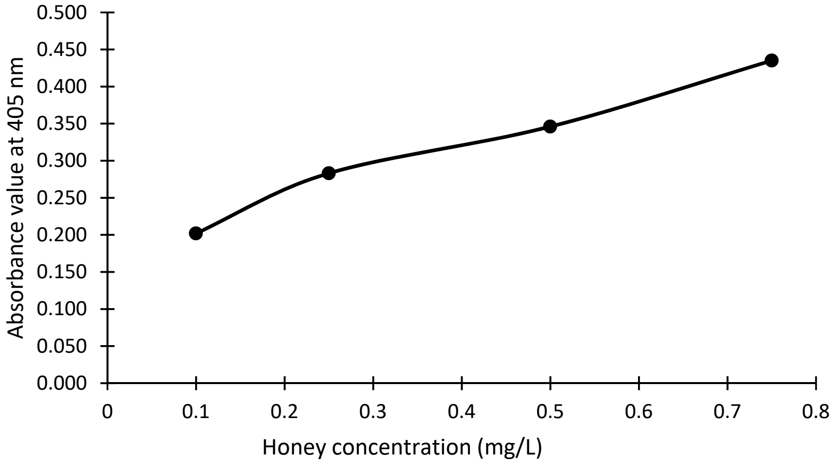


Fig. 7 *Effect of honey concentration on the AgNPs synthesis (pH = 6.0, temperature = 25 °C, $AgNO_3$ concentration = 0.001 M, agitation rate = 200 rpm).*

According to Philip (2010), probable reducing agent was glucose and capping agents which were responsible for stabilization could be proteins in honey [11].

4.7 $AgNO_3$ concentration

The effects of $AgNO_3$ concentration were studied in this work. According to Fig. 8, there was a sharp increase from the concentration of 0.001 M to 0.0075 M. After this point, there was a smooth decline and then showed fluctuations. The decrease in the synthesized silver nanoparticle concentration can be explained with decrease of reducing agent concentration in honey.

5. Conclusion

Number of nano-products in our daily is in increasing trends. The research and development studies on nanotechnologies will provide many different nano-functional

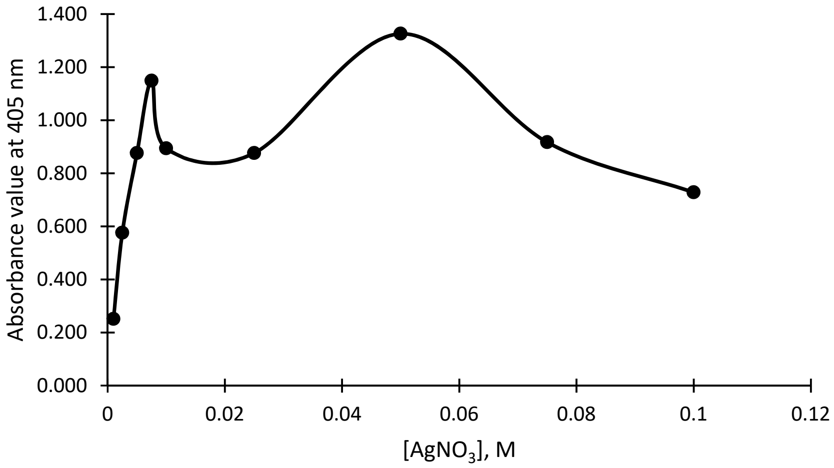


Fig. 8 *Effect of $AgNO_3$ concentration on the AgNPs synthesis (pH = 6.0, temperature = 25°C, honey concentration = 0.25 g/ml, agitation rate = 200 rpm).*

agents in near future. On the other hand, chemical synthesis methods for nanomaterials have some disadvantages due to their dangerous intermediates. Green synthesis methods by using natural biomasses as we mentioned in this paper reveal many advantages compared to traditional methods. In this paper, green synthesis of AgNPs was carried out by a natural product, honey. The data related to optimisation stage of green synthesis of AgNPs was modelled by using a robust and non-linear method, ANN. The results showed that the ANN model created in the present study can efficiently estimate the experimental values. However, ANN modelling parameters should be studied carefully otherwise the model may cause bias. In conclusion, ANN modelling might open a new gate to research and development studies on the green synthesis to estimate the experimental conditions.

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