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Automation in colouration technology to predict dyeing parameters for desired shade and fastness

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In this study, dyeing parameters, such as dye conc., sodium sulphide conc., salt conc., and time, have been statistically framed through full-factorial design software to generate sets of experimental variables. Cotton has been dyed using all these sets of variables separately, and then evaluated for respective surface colour strength (*K*/*S*), and colour fastness properties, such as fastness to light, washing and rubbing. The outputs thus generated are then analyzed using ANN to generate a big data, by which dyer can predict any shade. This will help in eliminating the rigorous laboratory trials and forecasting colour strength & quality of dyeing well before the dyeing process is materialized. The whole data sets are then uploaded in cloud computing to enable to acquire the data. It is observed that by assigning diffent values of *K*/*S* on cloud, the dyeing parameters can be obtained to achieve desired output in further application.

Keywords: Artificial neural network, Cloud computing, Cotton, Full factorial design, Sulphur dye

1 Introduction

Sulphur dyes consist of disulfide (S-S) or oligo sulphide [(S-S)n] bonds and are popular to produce only deep shades on cotton at cheaper cost with good colorfastness, except in case of chlorine[1]. Dyes are reduced and solubilised at boil with sodium sulphide to develop affinity for cotton; after dyeing oxidation reverts the dye structure to its parent insoluble form[2]. Sodium sulphide used in the process is inconsistent in composition, highly toxic and not ecofriendly[3,4].

Dyeing parameters, viz. dye concentration, sodium sulphide and electrolyte (NaCl) concentrations, time and dyeing temperature, require right adjustment to achieve best results in terms of optimum dye strength and levelness of shade, which is difficult to handle through manual adjustment. To accomplish this, full-factorial design can be used to generate sets of variables and to develop so called ‘big data’ against specific colour strength.

Nowadays, organizations and individuals generate large amounts of data (big data) at a very high rate against a specific work. With an impressing volume of data arriving at an exabyte scale, new insights can be obtained from their contents. It helps to gain richer insights, reduce cost and improve their competitiveness[5]. One of the ways to analyze this big data is by using artificial neural networks (ANN) which can predict the output, once the past data is fed into it. This, in quality coloration, automates the process effectively. The ANN models can be applied as alternative mathematical methods to solve a variety of problems in the fields of system identification, prediction, pattern recognition, classification, process control and many others. It has been widely used in various research areas to obtain experimental information to design the water treatment model[6].

Though there has been no direct evidence on use of ANN in colouration of textiles, few studies have been carried out in related areas with greater accuracy, such as (i) removal of basic colour from effluent to predict decolorization efficiency[7-9], (ii) decolorization of C.I. Basic Yellow 2 using peroxi-coagulation process[7,10], (iii) biological decolorization of triphenylmethane based basic dye, e.g. Malachite Green by three microalgae (the Chlorella, Cosmarium and Euglena species)[7,11], (iv) to study the adsorption process of Basic Blue 41 and Reactive Black 5 in glass columns using tree barks[7,12], and (v) optimization of different processes in chemical engineering[13-18]. Optimization of processes using ANN with combination of other methods have been described elsewhere[13,19,20]. Several researchers also described development of operating parameter optimization model

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of crude oil distillation process using back-propagation (BP) neural network[13, 21, 22].

Cloud computing can store the previously generated data obtained through experimental set up for their effective use as per dyers' requirement and hasn't been used until now in the area of quality coloration. Till date different textile mills have their own past data stored only in illogical manner which are difficult to manipulate for a given output. Storage of experimental data in cloud computing can thus help instant access through the use of self-manageable services that are delivered over the web in a pay-as-you-go manner and predict the output against given colouration parameters[23-25].

In the present study, pretreated cotton was dyed with Sulphur Blue dye. Dyeing parameters (inputs) were statistically framed through full-factorial design software to generate sets of experimental variables. Dyed cotton was evaluated for respective surface colour strength (K/S) and colour fastness properties such as fastness to light, wash and rubbing (outputs). The combinations of input parameters, once collected from laboratory trial and research output, generate the input as big data. This big data is then analyzed using ANN so as to learn the input to provide output. The big sets of laboratory data were then uploaded, along with the application of the trained neural network in cloud computing, to enable to acquire the data for subsequent application by which dyer can predict any shade with this dye as per requirement. This helps in eliminating the rigorous laboratory trials and forecasting colour strength as well as colour fastness properties well before the dyeing process is materialized. Sulphur dye was selected, as this dye is often applied on individual basis rather than in combination, thus enabling to develop a simple mechanism for better understanding.

2 Materials and Methods

2.1 Materials and Apparatus

Desized, scoured, bleached and mercerized cotton fabric was used. Dye Sulphur Blue FBL (Sulfast, Mumbai, C I Sulphur Blue 10, C I 53470, λ_{max}: 590 nm) and reducing agent sodium sulphide (SDFCL, Mumbai) were used in this study. Equipments, such as water bath, computer color matching (Datacolor Check, US) to evaluate surface colour strength (*K*/*S*), and reduction potential cum *p*H meter (Century Industries Ltd, Chandigarh) were used to assess reduction potential and *p*H of reduction baths. Light, wash and rub fastness properties were evaluated using light fastness tester (Paresh Engg Works, Ahmedabad, India), wash fastness tester (R B Electronics, Mumbai) and digital crockmeter (Prolific Engg, Noida, India) respectively,

2.2 Dyeing of Cotton

Sulphur dyeing of cotton was carried out using parameters shown in Table 1. In dyeing of cotton, liquor ratio (1:30) and dyeing temperature (95°C) were kept unchanged, while concentrations of dye, reducing agent and salt as well as dyeing time were varied. Full factorial design was prepared with these four variables as summarized in Table 1, generating 81 sets of data to perform dyeing of 81 samples (Table 2). NaOH was not added to dyebaths as sulphide itself produces NaOH in bath, as shown below:

$$Na_2S + H_2O \rightarrow NaHS + NaOH$$

Dye baths were prepared separately with dye and sodium sulphide at boil. In case of dyeing time of 30 min, dyeing was carried out first for 15 min, after which salt was added and dyeing was further continued for 15 min. To dye for 60 and 90 min, salt was added after 30 min of starting of dyeing followed by further dyeing for 30 and 60 min respectively. Dyed cotton was washed thoroughly and oxidized with potassium dichromate and acetic acid (1%, 1 g/L) for 30 min at 50-60°C succeeded by soaping, washing and drying. Dyed cotton was then evaluated for surface colour strength (*K*/*S*). During dyeing, dyebath pH and redox potential were assessed using digital *p*H- cum- oxidation reduction potentiometer (ORP) at the start and end of dyeing to ensure adequate *p*H and reduction potential availability in bath for smooth dyeing.

2.3 Methodology for Working with ANN and Cloud Computing (Learned Colouring Framework)

A system was formulated to list the output variables for the input parameters defined. This was

Table 1 — Various ranges of input values [Liquor ratio 1:30 and Temp. 95°C]

Factor	Level		
	Low (-1)	Centre (0)	High (+1)
Dye conc. (A), %	1	3	5
Reducing agent (B)	1*x**	1.5*x**	2*x**
Dyeing time (C),	30	60	90
Salt (D), g/L	0	15	30

**x*–Dye concentration.

Table 2 — Experimental and ANN generated outputs on *K/S* and colourfastness

Expt No.	Dye conc., %	Reducing agent	Time min	Salt g/L	*K/S*		LF		WF		Dry RF		Wet RF	
					Exp	ANN	Exp	ANN	Exp	ANN	Exp	ANN	Exp	ANN
1	1	1*x*	30	0	0.20	0.21	6	6	4	5	4	4	3	3
2	1	1*x*	30	15	0.21	0.20	6	6	4	5	4	4	3	3
3	1	1*x*	30	30	0.24	0.23	6	6	5	5	4	4	3-4	3
4	1	1*x*	60	0	0.24	0.22	6	6	4	5	4	4	3	3
5	1	1*x*	60	15	0.23	0.22	6	6	4-5	5	4	4	3	3
6	1	1*x*	60	30	0.25	0.26	6	6	5	5	4	4	3	3
7	1	1*x*	90	0	0.29	0.27	6	6	4-5	5	4	4	3	3
8	1	1*x*	90	15	0.26	0.28	6	6	5	5	4	4	3	3
9	1	1*x*	90	30	0.30	0.32	6	6	4	5	4	4	3	3
10	1	1.5*x*	30	0	0.19	0.22	6	6	4-5	5	4	4	3	3
11	1	1.5*x*	30	15	0.22	0.22	6	6	5	5	4-5	4	3	3
12	1	1.5*x*	30	30	0.28	0.25	6	6	5	5	4	4	3	3
13	1	1.5*x*	60	0	0.22	0.24	6	6	5	5	4	4	3	3
14	1	1.5*x*	60	15	0.30	0.26	6	6	5	5	4	4	3-4	3
15	1	1.5*x*	60	30	0.28	0.30	6	6	5	5	4	4	3	3
16	1	1.5*x*	90	0	0.26	0.30	6	6	5	5	4	4	3	3
17	1	1.5*x*	90	15	0.36	0.32	6	6	5	5	4	4	3	3
18	1	1.5*x*	90	30	0.30	0.36	6	6	5	5	4-5	4	3	3
19	1	2*x*	30	0	0.30	0.27	6	6	5	5	4	4	3	3
20	1	2*x*	30	15	0.27	0.27	6	6	5	5	4	4	3	3
21	1	2*x*	30	30	0.30	0.30	6	6	5	5	4-5	4	3-4	3
22	1	2*x*	60	0	0.27	0.30	6	6	5	5	4	4	3	3
23	1	2*x*	60	15	0.34	0.32	6	6	5	5	4	4	3	3
24	1	2*x*	60	30	0.37	0.35	6	6	5	5	4-5	4	3	3
25	1	2*x*	90	0	0.32	0.35	6	6	5	5	4	4	3	3
26	1	2*x*	90	15	0.38	0.38	6	6	5	5	4	4	3	3
27	1	2*x*	90	30	0.37	0.41	6	6	5	4	4	4	3-4	3
28	3	1*x*	30	0	1.23	1.20	6	6	4	5	4	4	3	3
29	3	1*x*	30	15	1.48	1.54	6	6	4-5	5	4	4	3	3
30	3	1*x*	30	30	1.47	1.60	6	6	5	4	4	4	3	3
31	3	1*x*	60	0	1.5	1.43	6	6	4	5	4	4	3	3
32	3	1*x*	60	15	1.82	1.86	6	6	4-5	5	4	4	3	3
33	3	1*x*	60	30	1.98	1.93	6	6	5	5	4-5	4	3-4	3
34	3	1*x*	90	0	1.25	1.40	6	6	4-5	5	4	4	3	3
35	3	1*x*	90	15	1.88	1.80	6	6	5	5	4	4	3-4	3
36	3	1*x*	90	30	1.70	1.87	6	6	5	5	4-5	4	4	3
37	3	1.5*x*	30	0	1.40	1.53	6	6	5	5	4	4	3	3
38	3	1.5*x*	30	15	1.92	1.97	6	6	5	5	4	4	3	3
39	3	1.5*x*	30	30	1.8	2.02	6	6	5	5	4	4	3	3
40	3	1.5*x*	60	0	2.0	1.85	6	6	5	5	4	4	3	3
41	3	1.5*x*	60	15	2.6	2.39	6	6	5	5	4	4	3	3
42	3	1.5*x*	60	30	2.49	2.46	6	6	5	5	4	4	3	3
43	3	1.5*x*	90	0	1.82	1.79	6	6	5	5	4-5	4	3	3
44	3	1.5*x*	90	15	1.79	1.79	6	6	5	5	4	4	3	3
45	3	1.5*x*	90	30	2.62	2.37	6	6	5	5	4	4	3	3
46	3	2*x*	30	0	1.55	1.58	6	6	5	5	4	4	3	3

(*contd.*)

Table 2 — Experimental and ANN generated outputs on *K/S* and colourfastness (*contd.*)

Expt No.	Dye conc. %	Reducing agent	Time min	Salt g/L	*K/S*		LF		WF		Dry RF		Wet RF	
					Exp	ANN	Exp	ANN	Exp	ANN	Exp	ANN	Exp	ANN
47	3	2*x*	30	15	2.04	2.01	6	6	5	5	4	4	3	3
57	5	1*x*	30	30	3.58	3.52	7	6	5	4	4-5	4	4	3
58	5	1*x*	60	0	3.22	3.21	7	6	5	5	4	4	3	3
59	5	1*x*	60	15	4.49	4.12	7	6	5	5	4	4	3	3
60	5	1*x*	60	30	4.20	4.17	7	6	5	5	4-5	4	3-4	3
61	5	1*x*	90	0	3.43	3.02	7	6	5	5	4	4	3	3
62	5	1*x*	90	15	3.68	3.86	7	6	5	5	4	4	3-4	3
63	5	1*x*	90	30	4.01	3.91	7	6	5	5	4	4	3	3
64	5	1.5*x*	30	0	3.56	3.43	7	6	5	5	4	4	4	3
65	5	1.5*x*	30	15	4.40	4.37	7	6	5	5	4	4	3	3
66	5	1.5*x*	30	30	4.36	4.40	7	6	5	5	4.5	4	3-4	4
67	5	1.5*x*	60	0	3.98	4.06	7	6	5	5	4-5	4	3-4	3
68	5	1.5*x*	60	15	4.98	5.20	7	6	5	5	4-5	4	3	3
69	5	1.5*x*	60	30	4.80	5.23	7	6	5	5	4	4	3	3
70	5	1.5*x*	90	0	3.89	3.80	7	6	5	5	4	4	3	3
71	5	1.5*x*	90	15	4.85	4.86	7	6	5	5	4-5	4	3-4	3
72	5	1.5*x*	90	30	4.72	4.89	7	6	5	5	4	4	3	3
73	5	2*x*	30	0	3.45	3.41	7	6	5	5	4	4	3	3
74	5	2*x*	30	15	4.05	4.33	7	6	5	5	4-5	4	3	3
75	5	2*x*	30	30	4.38	4.34	7	6	5	5	4-5	4	4	3
76	5	2*x*	60	0	4.15	4.04	7	6	5	5	4-5	4	4	3
77	5	2*x*	60	15	5.11	5.14	7	6	5	5	5	4	4	3
78	5	2*x*	60	30	5.03	5.15	7	6	5	5	5	4	4	3
79	5	2*x*	90	0	3.92	3.78	7	6	5	5	5	4	4	3
80	5	2*x*	90	15	4.95	4.81	7	6	5	5	5	4	4	3
81	5	2*x*	90	30	4.77	4.82	7	6	5	5	5	4	4	3

x–Dye concentration, K/S– Colour strength, LF–Light fastness, WF–Wash fastness and RB–Rub fastness.

achieved by feeding the laboratory data in the artificial neural network, i.e. uploading this data and designing ANN to cloud. The framework of the system for learning is divided into four parts, viz. initialization, data acquisition, processing and output. In initialization, the possible and required range of input variables was decided. In data acquisition, the input ranges were fed to statistica software, which, in turn, generated various combinations of parameters. For this framework, full factorial design was utilized under statistica, generating 81 combinations of 4 input parameters. Processing included the data from previous step conducted in laboratory to generate outputs for five parameters, viz *K/S*, light fastness, wash fastness, dry rub fastness and wet rub fastness. The outputs were enlisted against the input combinations and then fed to ANN, which, in turn, learned the pattern and generated a program in C language. The compiled program was run on remote system to check for errors. At the end, the C program which is capable of generating outputs against inputs defined, is deployed on cloud alone with the database of 81 combinations. The flowsheet of the mechanism is depicted in Fig. 1.

Architecture of the system for learning comprises four entities, viz user system (textile mills, researchers or single system users), textile tool (Statistica), artificial neural network, and cloud repository. Artificial neural network was designed using statistica itself. Amazon Web Services has been used to deploy the python application which reads inputs from the webpage and then feeds it to the program deployed on cloud generating the output for the user. The ANN design consists of input layer, a hidden layer and an outer layer. The inputs, namely dye (%), Na_2S concentration, dyeing time and salt concentration are fed to the ANN (Fig. 2). The operations are performed on the input data as they reach the hidden layer and then the data is forwarded to the output layer. The bias is used for variating the outputs as desired so as to teach the ANN, to what weights it should change for the desired output without the manual labor each time.

2.4 Evaluation Matrices

Standard deviation, standard error and mean square error were used for evaluation of matrices to judge authenticity of data. The standard deviation (S) was evaluated by the following formula:

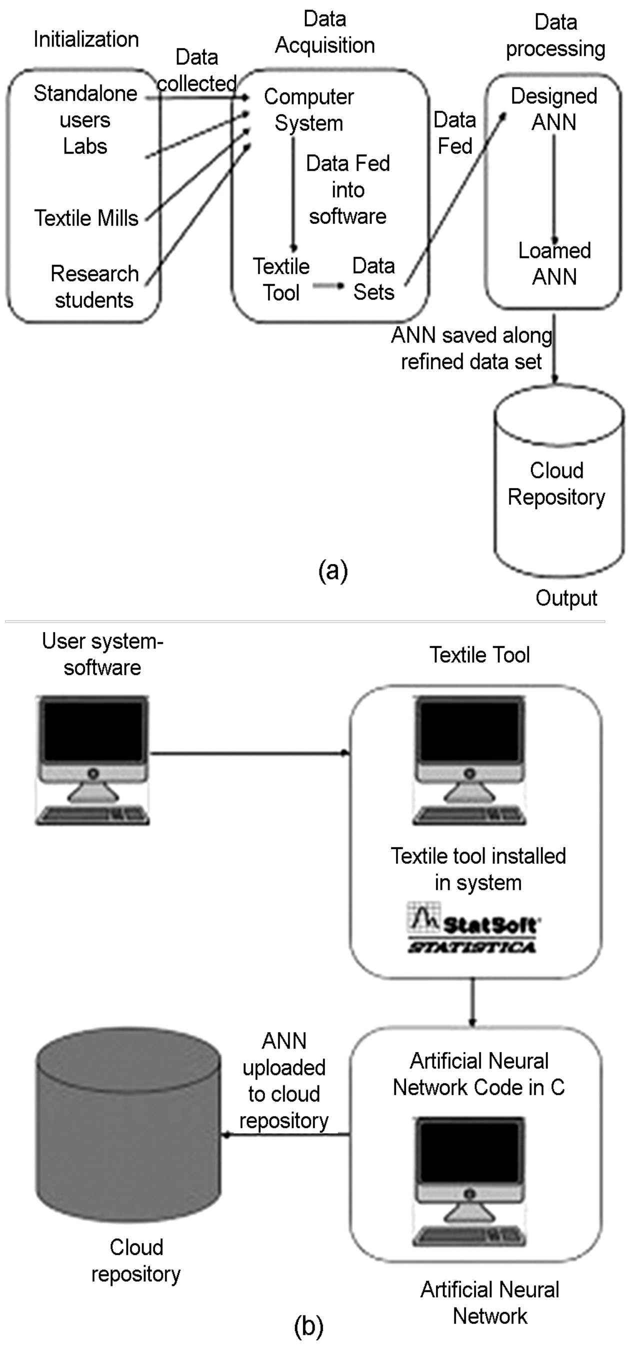

Fig. 1 — Flowsheet of framework for using ANN and cloud (a) system for learning, and (b) architecture of learning system

$$S = \sqrt{\sum(v-u)^2/n}$$

where *v*, *u* and *n* represent values of the observation, mean value of data and number of observations respectively.

Standard error (SE) was evaluated by the following formula:

$$SE= S \div \sqrt{n}$$

where SE, *S* and *n* represent standard error, standard deviation of the mean and number of observations respectively.

Mean square error (MSE) was calculated by the following formula:

$$MSE= \left\{\sum_{k=1}^{k=n}(m-p)^2\right\} \div n$$

where SE, *S*, *n*, *m* and *p* stand for standard error, standard deviation of mean, number of observations, value of observation and predicted value respectively.

2.5 Methodology Adopted to Analyze Results

The range of inputs was used to generate the combinations of the inputs using full factorial design. The generated combinations were then used in laboratory to dye cotton followed by its evaluation for different outputs, such as surface colour strength of cotton (*K*/*S*), and light fastness, wash fastness, dry and wet rub fastness. The output values were then fed into statistica for ANN to learn. The ANN then becomes capable of generating results approximately same as obtained from laboratory. Once trained, the ANN combinations of input, not yet obtained from laboratory, can also be used to calculate output. After the C program for the ANN is generated, it is

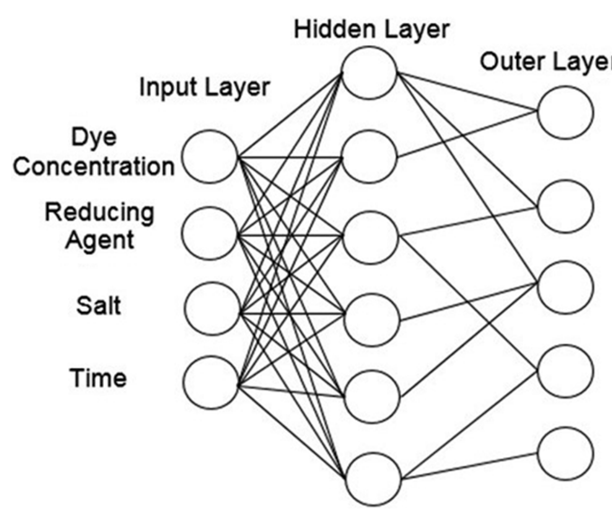

Fig. 2 — Flow of artificial neural network

deployed on cloud using a python application to intercept the user request and feed it to the C program. Amazon Web Services was utilized by anyone across the globe to access the data on demand, without the resources required.

3 Results and Discussion

3.1 Experimental Inputs and Outputs

Cotton fabric specimen (81 nos.) dyed with 81 sets of parameters were evaluated for respective surface colour strength (*K*/*S*) and colour fastness properties (Table 2). It is observed that the surface colour strength increases with increase in concentration of salt, sodium sulphide as well as time of dyeing. Decrease in any of these parameters decreases the *K*/*S* even at higher concentration of dye. The colour fastness of dyeing follows the standard pattern, i.e. light and wash fastness ratings remain in the range of 6-7 and 4-5 respectively, whereas dry and wet rub fastness values are found to be in the range of 4-5 and 3-4 respectively, which are in line with expected results. All the values in the lower range are found to be against lesser dye concentration, which keep on increasing with increase in latter.

Keeping in view all these outputs, ANN has been employed on these 81 sets of data to see if the ANN generated outputs would show almost same or a nearly match with these experimental outputs. The ANN generated outputs obtained are also shown in Table 2 against each experimental value. The deviations or increase in ANN generated data against experimental one are minimal in some of the samples, whereas most of the samples show close / complete match.

Table 2 shows that as far as fastness is concerned, colour fastness of any dyeing depends upon specific dye-fibre system provided dyeing is carried out under optimal conditions. Obviously, fastness data for sulphur dyed textile follow a specific pattern and do not typically depend upon dyeing parameters, provided dyeing is carried out at boil using adequate sulphide; variation in salt and time only limit dye uptake and levelness of shade respectively. This is because, though the ANN generated colourfastness data show little variation from that of experimental data, these may be considered within prescribed confidence limit.

The experimental as well as ANN generated data are analyzed in terms of SD and SE following the procedure as stated to predict the confidence level of the generated data; the descriptive statistical analysis would come out, as shown in Table 3.

The standard deviation values (≤ 0.1) among each sample in multiple numbers against *K*/*S* are in perfect match and within 95% confidence limit, except for a very few samples. The light fastness shows perfect match at lower concentration of dye but variation with increase in dye concentration. Table 2 shows that the LF data follows the same pattern and obviously the change in SD shows close match. For rest of the fastness properties, respective SD shows very close match. However, standard errors for respective parameters are found to be highly supportive in nature; even the mean square values also show full support to this match.

The said observation opens up possibility of automation in dyeing of cotton with sulphur dyes. If the obtained data are stored in cloud computing it displays the dyeing parameters and concentration of chemicals required to develop that specific shade with given colourfastness, i.e. just the opposite of conventional practice, termed as automation in colouration technology to predict dyeing inputs for any given shade with desired fastness

3.2 Deploying Application on Amazon Web Services

Amazon web services (AWS) has been utilized to deploy this framework. For the job of executing the trained neural network code generated in C, Elastic Beanstalk service (EB) of AWS was used; the latter is an easy-to-use service for deploying and scaling web applications and services, developed with Java, NET, PHP, Node.js, Python, Ruby, Go, and Docker on familiar servers such as Apache, Nginx, Passenger, and IIS. Flask is the framework of python used because of its minimalized, lightweight and modular design. The code uploaded was automatically deployed by the EB, which handles capacity provisioning, load balancing and auto-scaling. Web interface was created for the users to interact with the application easily.

For the purpose of testing the efficiency and effectiveness of the application deployed, a scheme of systems has been created (Fig. 3). In this framework, the one master machine is responsible for providing commands to the respectable slave machines to request data or application as required. The slave machines, in turn, requested the cloud server as required. The execution occurs with the help of Elastic Beanstalk component of AWS. The response time for the application to run, and the database to load, with different amount of requests of different

Table 3 — Descriptive statistics of experimental and ANN generated data

[Mean square error: *K*/*S* 0.26, light fastness 0.33, wash fastness 0.09, dry rub fastness 0.11 and wet rub fastness 0.15]

Parameter	Standard deviation					Standard error				
	K/*S*	Light fastness	Wash fastness	Dry rub fastness	Wet rub fastness	*K*/*S*	Light fastness	Wash fastness	Dry rub fastness	Wet rub fastness
Var1	0.0	0.0	0.4	0.1	0.0	0	0	0.3	0.1	0
Var2	0.0	0.0	0.4	0.0	0.1	0	0	0.3	0	0
Var3	0.1	0.0	0.3	0.0	0.3	0.1	0	0.2	0	0.2
Var4	0.0	0.0	0.4	0.0	0.0	0	0	0.3	0	0
Var5	0.1	0.0	0.1	0.0	0.1	0.1	0	0	0	0
Var6	0.1	0.0	0.3	0.0	0.1	0	0	0.2	0	0
Var7	0.0	0.0	0.0	0.0	0.0	0	0	0	0	0
Var8	0.1	0.0	0.3	0.0	0.0	0	0	0.2	0	0
Var9	0.0	0.0	0.4	0.0	0.0	0	0	0.3	0	0
Var10	0.0	0.0	0.1	0.0	0.1	0	0	0	0	0
Var11	0.0	0.0	0.2	0.3	0.1	0	0	0.2	0.2	0
Var12	0.0	0.0	0.2	0.0	0.1	0	0	0.2	0	0
Var13	0.0	0.0	0.3	0.0	0.1	0	0	0.2	0	0
Var14	0.0	0.0	0.2	0.1	0.3	0	0	0.2	0	0.2
Var15	0.0	0.0	0.2	0.1	0.1	0	0	0.2	0	0
Var16	0.1	0.0	0.3	0.0	0.0	0.1	0	0.2	0	0
Var17	0.0	0.0	0.3	0.0	0.1	0	0	0.2	0	0
Var18	0.0	0.0	0.2	0.3	0.1	0	0	0.2	0.2	0
Var19	0.0	0.0	0.3	0.0	0.0	0	0	0.2	0	0
Var20	0.0	0.0	0.2	0.0	0.1	0	0	0.2	0	0
Var21	0.1	0.0	0.2	0.3	0.3	0	0	0.2	0.2	0.2
Var22	0.0	0.0	0.3	0.0	0.1	0	0	0.2	0	0
Var23	0.0	0.0	0.2	0.0	0.1	0	0	0.2	0	0
Var24	0.1	0.0	0.2	0.3	0.1	0.1	0	0.1	0.2	0
Var25	0.1	0.0	0.3	0.0	0.0	0.1	0	0.2	0	0
Var26	0.0	0.0	0.2	0.0	0.1	0	0	0.2	0	0
Var27	0.1	0.0	0.2	0.0	0.3	0.1	0	0.2	0	0.2
Var28	0.2	0.0	0.4	0.0	0.1	0.4	0	0.3	0	0
Var29	0.2	0.0	0.1	0.1	0.1	0.3	0	0.1	0	0.1
Var30	0.3	0.0	0.2	0.1	0.1	0.2	0	0.1	0.1	0.1
Var31	0.0	0.0	0.4	0.0	0.1	0	0	0.2	0	0
Var32	0.3	0.0	0.1	0.1	0.1	0.4	0	0.1	0.1	0.1
Var33	0.4	0.0	0.2	0.3	0.3	0.5	0	0.1	0.2	0.2
Var34	0.2	0.0	0.0	0.0	0.1	0.2	0	0	0	0
Var35	0.3	0.0	0.3	0.0	0.3	0.5	0	0.2	0	0.2
Var36	0.5	0.0	0.2	0.3	0.6	0.3	0	0.1	0.2	0.4
Var37	0.1	0.0	0.2	0.1	0.1	0.1	0	0.2	0	0.1
Var38	0.0	0.0	0.1	0.1	0.1	0	0	0.1	0.1	0.1
Var39	0.2	0.0	0.1	0.1	0.1	0.1	0	0	0.1	0.1
Var40	0.1	0.0	0.2	0.1	0.1	0.1	0	0.2	0	0.1

(*contd.*)

Table 3 — Descriptive statistics of experimental and ANN generated data (*contd.*)

[Mean square error: *K*/*S* 0.26, light fastness 0.33, wash fastness 0.09, dry rub fastness 0.11 and wet rub fastness 0.15]

Parameter	Standard deviation					Standard error				
	K/*S*	Light fastness	Wash fastness	Dry rub fastness	Wet rub fastness	*K*/*S*	Light fastness	Wash fastness	Dry rub fastness	Wet rub fastness
Var41	0.1	0.0	0.1	0.1	0.1	0.1	0	0.1	0.1	0.1
Var42	0.3	0.0	0.0	0.1	0.1	0.2	0	0	0.1	0.1
Var43	0.3	0.0	0.3	0.3	0.1	0.2	0	0.2	0.2	0.1
Var44	0.4	0.0	0.3	0.0	0.1	0.6	0	0.2	0	0.1
Var45	0.2	0.0	0.1	0.1	0.1	0.1	0	0.1	0.1	0.1
Var46	0.2	0.0	0.2	0.1	0.1	0.1	0	0.1	0	0.1
Var47	0.5	0.0	0.1	0.1	0.1	0.5	0	0	0.1	0.1
Var48	0.0	0.0	0.0	0.1	0.1	0	0	0	0.1	0.1
Var49	0.4	0.0	0.2	0.1	0.1	0.3	0	0.1	0	0.1
Var50	0.4	0.0	0.0	0.1	0.1	0.3	0	0	0.1	0.1
Var51	0.1	0.0	0.0	0.1	0.1	0	0	0	0.1	0.1
Var52	0.5	0.0	0.2	0.0	0.1	0.5	0	0.1	0	0
Var53	0.5	0.0	0.1	0.1	0.1	0.7	0	0.1	0.1	0.1
Var54	0.2	0.0	0.0	0.3	0.6	0.1	0	0	0.2	0.4
Var55	0.2	0.7	0.3	0.0	0.0	0.2	0.1	0.2	0	0
Var56	0.2	0.7	0.2	0.4	0.3	0.1	0.1	0.1	0.3	0.2
Var57	0.0	0.7	0.1	0.4	0.7	0	0.1	0.1	0.3	0.5
Var58	0.0	0.7	0.4	0.0	0.0	0	0.1	0.3	0	0
Var59	0.3	0.7	0.2	0.0	0.0	0.2	0.1	0.1	0	0
Var60	0.0	0.7	0.1	0.4	0.3	0	0.1	0.1	0.3	0.2
Var61	0.3	0.7	0.4	0.1	0.0	0.2	0.2	0.3	0	0
Var62	0.1	0.7	0.3	0.0	0.3	0.1	0.1	0.2	0	0.2
Var63	0.1	0.7	0.2	0.0	0.0	0.1	0.1	0.1	0	0
Var64	0.3	0.7	0.2	0.0	0.7	0.4	0.1	0.1	0	0.5
Var65	0.4	0.7	0.0	0.0	0.1	0.3	0.1	0	0	0
Var66	1.0	0.7	0.0	0.3	0.4	0.7	0.1	0	0.2	0.3
Var67	0.3	0.7	0.2	0.4	0.3	0.2	0.1	0.1	0.3	0.2
Var68	0.3	0.7	0.0	0.3	0.1	0.2	0.1	0	0.2	0
Var69	1.0	0.7	0.1	0.0	0.1	0.7	0.2	0	0	0
Var70	0.1	0.7	0.3	0.0	0.0	0	0.1	0.2	0	0
Var71	0.4	0.7	0.1	0.4	0.3	0.5	0.2	0.1	0.3	0.2
Var72	0.1	0.7	0.0	0.0	0.0	0.1	0.1	0	0	0
Var73	0.3	0.7	0.1	0.0	0.0	0.2	0.1	0.1	0	0
Var74	0.2	0.7	0.0	0.3	0.1	0.1	0.1	0	0.2	0
Var75	0.4	0.7	0.1	0.3	0.7	0.3	0.2	0	0.2	0.5
Var76	0.1	0.7	0.1	0.4	0.7	0.1	0.1	0.1	0.3	0.5
Var77	0.1	0.7	0.1	0.7	0.7	0.5	0.1	0	0.5	0.5
Var78	0.1	0.7	0.1	0.7	0.7	0.1	0.1	0.1	0.5	0.5
Var79	0.1	0.7	0.2	0.7	0.7	0.1	0.1	0.1	0.5	0.5
Var80	0.2	0.7	0.0	0.7	0.7	0.6	0.1	0	0.5	0.5
Var81	0.2	0.7	0.1	0.7	0.7	0.3	0.1	0	0.5	0.5

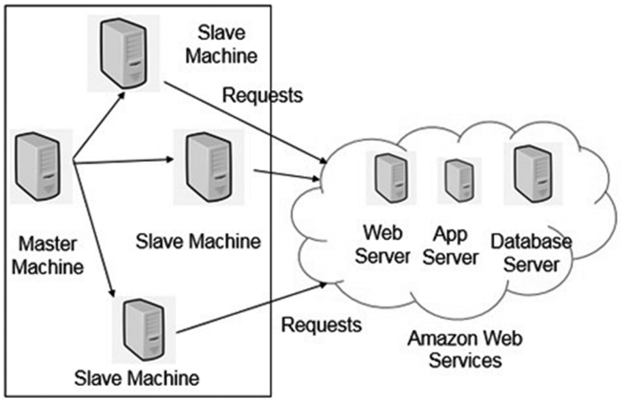

Fig. 3 — Scheme of system to test the efficiency and effectiveness of application

nature was recorded to show the capacity provisioning, load balancing and auto scaling properties of the cloud server.

4 Conclusion

It is learnt that for a set of inputs obtained through laboratory trials, the ANN generated data show close or complete match with outputs, viz. surface colour strength (*K*/*S*), light fastness, wash fastness as well as dry and wet rubbing fastness properties with marginal exceptions. The standard deviation and standard error also show close match with the input-output system keeping within 95% confidence level. Mean square error also show good match with the results. It recognizes that the dyeing output can be forecasted in advance using ANN and cloud computing against given inputs without any further laboratory trial. The accuracy in reproduction from cloud can be further enhanced with more input-output combinations used to train ANN.

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