Article

An ANN Model for Predicting the Compressive Strength of Concrete

Chia-Ju Lin and Nan-Jing Wu *

Department of Civil and Water Resources Engineering, National Chiayi University, Chiayi 600355, Taiwan; s1072800@mail.ncyu.edu.tw

* Correspondence: njwu@mail.ncyu.edu.tw

Abstract: An artificial neural network (ANN) model for predicting the compressive strength of concrete is established in this study. The Back Propagation (BP) network with one hidden layer is chosen as the structure of the ANN. The database of real concrete mix proportioning listed in earlier research by another author is used for training and testing the ANN. The proper number of neurons in the hidden layer is determined by checking the features of over-fitting while the synaptic weights and the thresholds are finalized by checking the features of over-training. After that, we use experimental data from other papers to verify and validate our ANN model. The final result of the synaptic weights and the thresholds in the ANN are all listed. Therefore, with them, and using the formulae expressed in this article, anyone can predict the compressive strength of concrete according to the mix proportioning on his/her own.

Keywords: artificial neural networks; prediction model; compressive strength of concrete; mix proportioning of concrete

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1. Introduction

Due to the high compressive strength and the capability of being casted into any shape and size, concrete is the most used construction material in the world. The compressive strength is related to the proportioning of its ingredients, such as water, cement, coarse aggregates, sand, and other admixtures. How to predict the compressive strength according to the proportioning design is a very practical topic. For example, with a prediction model one can estimate the compressive strengths of dozens of mix designs and just choose those that achieve the required strength for further physical tests. This can reduce the number of trials for a specific compressive strength requirement and can save a lot of money and time. Furthermore, one can determine the most inexpensive choice among those that required compressive strength for economical consideration.

Conventionally, statistics are a useful tool for evaluating the results of strength tests. For instance, one can obtain a regression equation using data of water–cement ratio versus the compressive strengths [1]. However, there are not just one or two factors that affect compressive strength. The predicted results by just using the water–cement ratio could be very poor in many cases.

In recent decades, the artificial neural networks (ANNs) have drawn more and more attention because of the capability of dealing with multivariable analysis. Several authors have used the ANNs to determine the compressive strength of concrete [2–16]. An ANN is like a black box. After training the ANN, one can input several numerical values and the ANN will prompt another numerical value which represents the predicted compressive strength of the concrete. The components for the input can be factors such as the proportioning of water, cement, sand, etc. Recently, more and more new types of ANN structures, such as the Support Vector Machines [17,18], Deep Learning Neural Network [19–23], Radial Basis Function Network [24–29] for various research areas have popped out, as well

as other algorithms like tabu and genetic [15,19,26,28–30] are newly applied for training the ANN.

In [16], data of real concrete mix proportioning listed in [12] were used to establish a database. With that database, the ANN of back-propagation type (BP) with single hidden layer was employed to establish the prediction models of strength and slump of concrete. Cylindrical test samples of 12 additional mix designs were also casted and their compressive strengths were examined in the laboratory to verify the established ANN model. In this study, we use the same database for establishing our new ANN model. However, we think data for establishing a concrete slump prediction model are insufficient due to 39% of slump records being missing from the database. Therefore, we just focus on establishing a prediction model for the compressive strength of concrete in this study.

Typically, the database has to be divided into two parts, one for training and the other for testing. This is for the sake of avoiding over-training and over-fitting. In [16], most of the data were used for training the ANN while only 20 pieces of data were used in the testing process. There are 482 pieces of data in the database, so data for testing were about 4% of the whole. In our opinion, that is inadequate, though the results of verification were still acceptable. Consequently, we contrive an improvement by using fewer data for training and more data for testing, for the reason that the over-fitting can be alleviated.

There are so many choices for establishing the ANN model but for comparison with [16], we still use the BP-ANN with single hidden layer. The final result of the synaptic weights and the thresholds in the ANN are all listed in this paper. Therefore, anyone can use them accompanied with the formulae expressed in the article to predict the concrete compressive strength according to the mix proportioning on his/her own.

Our new ANN model outperforms the ANN model of [16] as we check the result of verification. Further validation is implemented by using the data of [15]. A good agreement is also found. This implies our ANN model really works for practical uses.

2. The Concrete Mix Proportioning

According to [16], the 28-day compressive strength is related to seven factors. They are the mass of water, cement, fine aggregate (or sand), coarse aggregate, blast furnace slag, fly ash, and superplasticizer mixed in 1 m³ concrete. Therefore, the compressive strength of concrete can be expressed as a mathematical function with seven variables:

$$y = f(x) \quad (1)$$

in which;

$$x = [x_1 \ x_2 \ \cdots \ x_7]^T \quad (2)$$

where x_1 to x_7 are those just mentioned proportioning factors while y is the compressive strength of concrete. For the input and output of the ANN, all the data have to be normalized into the range of 0 to 1. The linear transformation is applied. The ranges from x_1 to x_7 are listed in Table 1.

$$\xi_i = \frac{x_i - x_{i,\min}}{x_{i,\max} - x_{i,\min}} \quad (3)$$

$$\eta = \frac{y - y_{\min}}{y_{\max} - y_{\min}} \quad (4)$$

Table 1. The ranges of the inputs and the output in the raw data [12].

	Inputs							Output
	x_1	x_2	x_3	x_4	x_5	x_6	x_7	y
Maximum	255	599	1293	1226	375	330	27.17	95.3
Minimum	116.5	74	30	436	0	0	0	5.66

Printing out all the data might make this paper redundant. Those who need the digital file of the raw data of the database may contact the authors of [16]. Listed data can also be found in the tables of [12] which has been openly published and is downloadable from NCTU library website (<https://ir.nctu.edu.tw/handle/11536/71533> (accessed on 12 March 2021)). For implementing this research, we downloaded [12], and copied the data from the tables in that thesis. The normalized data are listed in Appendix A. One can use them accompanied by those listed in Table 1 to retrieve their original values.

3. The Artificial Neural Network

The artificial neural network used in this study is the Back Propagation (BP) which was proposed in [31]. Following [16], we also use the single hidden layer network. According to the database of the real concrete mix proportioning, we have 7 neurons in the input layer and only 1 neuron in the output layer. The structure of the BP-ANN employed in this study is shown in Figure 1.

Figure 1. The input-output relation for predicting the compressive strength of concrete and the structure of the ANN model.

The formula for the normalized input-output relation can be expressed mathematically:

$$\eta = w_0^{(2)} + \sum_{j=1}^n \left(\frac{w_j^{(2)}}{1 + \exp(-\alpha v_j)} \right) \quad (5)$$

in which;

$$v_j = w_{0,j}^{(1)} + \sum_{i=1}^7 (w_{i,j}^{(1)} \xi_i) \quad (6)$$

where, in Equations (5) and (6), $w_{0,j}^{(1)}$ and $w_0^{(2)}$ are so-called thresholds, $w_{i,j}^{(1)}$ and $w_j^{(2)}$ are the synaptic weights, α is the shape parameter of the activating function, i represents the index of a neuron in the input layer, j represents the index of a neuron in the hidden layer, and n represents the total number of neurons in the hidden layer. The suitable number of neurons in the hidden layer is to be determined.

From the database, N records are randomly chosen for training the ANN. The error residual is defined as:

$$E = \sum_{k=1}^N \left(\eta_k^{(o)} - \eta_k^{(d)} \right)^2 \quad (7)$$

where $\eta_k^{(d)}$ is the desired value which represents the normalized compressive strength in the data, $\eta_k^{(o)}$ is the output of the ANN, and k is the sequential number. We use the underline for k to remind that the samples have been re-numbered because we randomly

picked them up from the database. The training process is to find a set of suitable values for the thresholds and the synaptic weights. In the beginning, all the values of the thresholds and the synaptic weights are set up with small random numbers.

Now the error residual E is a function of the thresholds and the synaptic weights. We can use the steepest descendent method to update their guess values and make them move toward a better solution:

$$w_{ij}^{(1),new} = w_{ij}^{(1),old} - \mu \frac{\partial E}{\partial w_{ij}^{(1)}} \quad (8)$$

$$w_j^{(2),new} = w_j^{(2),old} - \mu \frac{\partial E}{\partial w_j^{(2)}} \quad (9)$$

where μ is the step parameter of the correction. The basic/standard backpropagation algorithm is employed for training. The detailed training procedure can be found in [32] (in Section 3.3 of this book) or traced back in [31]. We coded the programs by ourselves. The computer language is VBA which is embedded in Microsoft Excel®.

In this study, the value of α is chosen as 1. The constant step parameter is employed. The value of μ is chosen as 0.02. It should be kept in mind that in Equations (5) and (6) the beginning numbers of i and j are both 1, but in Equations (8) and (9) the beginning numbers of i and j are both 0. Random numbers in the range of -1 to 1 are chosen as the initial values of the thresholds and the synaptic weights. Accordingly, the results will not be exactly the same in each training process. Even so, the tendency of convergence will be very similar.

4. The Results

There are 482 data in the database. We separate the database into two sets, the training set and the testing set, respectively. The training set includes 85% of the data. Therefore, the training set comprises 410 samples and the testing set comprises 72 samples. Samples included in the testing set are marked in the Appendix A.

Artificial neural networks with 3–12 neurons in the hidden layer are tested. More neurons in the hidden layer mean the ANN is more complicated so it can memorize more detailed features. However, it also means the result of the ANN has a tendency towards over-fitting. Furthermore, too many repetitions of the training iteration will also make the ANN memorize too many detailed features and perform poorly when it is in practical use. A time of iteration indicates all the synaptic weights and the thresholds are updated according to the error residual in the training set.

To help us detect whether over-fitting or over-training happens, both the root-mean-square errors of the training set and the testing are calculated after finishing each iteration. The values of the thresholds and the synaptic weights are also temporarily saved so we can come back to use them when we have selected a suitable ANN structure and have determined the proper iteration times. The root-mean-square error is defined as:

$$E_{r.m.s.} = \sqrt{\overline{(\eta^{(d)} - \eta^{(o)})^2}} \quad (10)$$

where the overbar represents the average in the data set. Note that the numbers of samples in the two data sets are different.

Among all the training results, we chose the results of 3, 7, and 12 neurons in the hidden layer to demonstrate the features of over-fitting and over-training. They are shown in Figure 2. It can be observed that the root-mean-square error of the training set decreases as more iterations are processed, but it does not happen to the testing set. This demonstrates the effect of over-training. One can also find that setting more neurons in the ANN can help reduce the root-mean-square error of the training set. But the root-mean-square error of the testing set seems to not go the same way as more and more neurons in the hidden layer are comprised. This indicates that setting more neurons in the hidden layer tends to

cause over-fitting. With the results shown in Figure 2, we suggest that setting 7 neurons in the hidden layer is sufficient for the ANN in this study. It is worth noting that the ANN in [16] has 14 neurons in the hidden layer.

Figure 2. The result of the training: (a) 3 neurons in the hidden layer, (b) 7 neurons in the hidden layer, (c) 12 neurons in the hidden layer.

The thresholds and the synaptic weights of the 7-hidden-neuron ANN with 12,040 times of training iteration are used for further investigations. This is chosen for the reason that the root-mean-square errors of the training set and the testing set are equivalent to each other. The synaptic weights from the input layer to the hidden layer and the thresholds of the hidden neurons are listed in Table 2. The synaptic weights from the hidden layer to the output neuron and the threshold of the output neuron are shown in Table 3. With these thresholds and synaptic weights, the predicted outputs are calculated and compared with their desired values. The comparison is shown in Figure 3. It can be found that the results of the two data sets have similar divergence. That is because the root-mean-square errors of the two sets are very close. It is also worth noting that in [16] the result of such comparison looks very close to a central inclined line which represents the predicted are exact to their targets.

Table 2. The thresholds of the hidden neurons and the synaptic weights from the input layer to the hidden layer ($w_{i,j}^{(1)}$).

		<i>i</i>							
		0	1	2	3	4	5	6	7
<i>j</i>	1	0.6144	0.8055	0.1110	0.8372	1.7008	−0.3427	0.6209	0.5749
	2	1.3936	1.0523	1.4664	0.1982	−0.4601	−0.5712	0.5264	3.1878
	3	0.5066	−1.7844	0.0736	−1.7298	−1.0940	0.0095	−0.9082	1.1462
	4	−1.3016	0.8221	1.3503	0.2557	0.0471	2.0145	−1.1131	1.5552
	5	−0.4564	0.0257	−1.7657	2.7258	−1.7268	−1.9379	0.2811	1.4361
	6	−0.0404	0.1909	1.1077	2.3484	−0.5073	2.2264	−0.1963	1.4299
	7	0.7199	−0.0957	0.2010	−0.1656	2.5119	−0.2500	0.0705	−0.1386

Table 3. The threshold of the output neuron and the synaptic weights from the hidden layer to the output neuron ($w_j^{(2)}$).

<i>j</i>								
0	1	2	3	4	5	6	7	
−1.0706	−0.2102	2.0741	2.3526	−1.2642	−1.3384	2.2950	−1.5356

Figure 3. The comparison of the outputs of ANN with their target values in which the ANN has seven neurons in the hidden layer and is trained after 12,040 times of iteration.

After the number of neurons in the hidden layer and all the thresholds and synaptic weights are determined, we use our ANN to predict the compressive strengths of the 12 mix designs in [16] and compare the results with the data observed in their laboratory. The results are listed in Table 4. The predicted compressive strengths in [16] are also listed in the same table. The comparisons of the predicted and the actual compressive strengths are plotted in Figure 4. Note that the range shown in this figure is from 0 to 100 due to the range of the compressive strength in the database is from 5.66 to 95.3 MPa. It is found in Figure 4 that the circular dots are more focused to the central inclined line. This implies that our ANN model outperforms the ANN model of [16] in the verification.

Table 4. The predicted and actual compressive strengths of the experimental concrete mixtures in [16].

Ingredients (kg/m ³)							Compressive Strength (MPa)		
Water	Cement	Fine Aggregate	Coarse Aggregate	Blast Furnace Slag	Fly Ash	Super-Plasticizer	Actual	Predicted in Ref. [16]	Predicted by Present Model
194	223	669	1040	76	72	0.74	44.10	34.43	40.20
184	244	649	1104	105	19	0.79	47.99	32.26	42.87
187	194	650	1072	171	22	0.81	49.75	34.85	42.60
189	272	670	1040	121	14	0.70	52.87	35.60	47.14
191	346	549	1136	38	41	0.73	46.70	45.96	43.99
189	261	619	1072	93	57	0.88	47.06	39.04	45.78
204	331	457	1136	99	54	0.77	54.52	54.55	44.53
191	280	555	1104	121	46	0.68	47.61	50.16	46.91
210	300	535	1040	131	51	0.54	46.06	52.05	47.60
207	430	604	960	20	61	0.76	54.30	40.08	52.32
190	329	516	1104	112	52	0.87	54.98	55.07	50.83
208	351	554	960	52	121	0.72	55.13	40.91	52.00

Figure 4. Comparison of predicted compressive strength with the actual strength of the 12 experimental concrete mixtures in [16] (Unit: MPa).

Now the results are no longer in the range of 0 to 1. We use the coefficient of efficiency (C.E.) to evaluate performance:

$$C.E. = 1 - E_{r.r.m.s.}^2 \quad (11)$$

in which

$$E_{r.r.m.s.} = \sqrt{\sum (y^{(p)} - y^{(a)})^2 / \sum (y^{(a)})^2} \quad (12)$$

where $y^{(a)}$ is the actual compressive strength, $y^{(p)}$ is the predicted compressive strength, and $E_{r.r.m.s.}$ is the relative root-mean-square error. The C.E. of the predicted results in [16] is 0.955. The high C.E. means the predicted results in [2] are quite acceptable indeed. However, the C.E. of the results predicted by the present model is 0.991. The improvement is significant for the relative root-mean-square error is reduced by 21.2% to 9.49%.

In [15], the artificial neural network and genetic programming were employed to predict the 28-day, 56-day, and 91-day compressive strengths of concrete admixing with fly ash or without fly ash. The proportions of 76 concrete mixes were listed as well as their compressive strengths. Forty-nine of them are admixed without fly ash while the other 27 are admixed with fly ash. Blast furnace slag and superplasticizer are not admixed in all of them. These data are good for further validation of our prediction model. The predicted results of [15] were not listed in their paper so a further comparison is unavailable.

With our model, the predicted compressive strengths of concrete are calculated and listed in Table 5. The comparisons of the predicted and the actual compressive strengths are plotted in Figure 5. In this figure, it can be found that the predicted compressive strengths of those without fly ash are rather close to the actual values. The C.E. is 0.975. The relative root-mean-square error is 15.8%. Those mixes with fly ash are all slightly overpredicted. The C.E. is 0.940. The relative root-mean-square error is 24.5%. The high C.E. in both sets indicates that our prediction model really works at a good level. The predictions of non-fly ash mixes are more credible. We could expand the database for further improvement in the future.

Table 5. The predicted and actual compressive strengths of the experimental concrete mixtures in [15].

Ingredients (kg/m ³)					Compressive Strength (MPa)		Ingredients (kg/m ³)					Compressive Strength (MPa)	
Water	Cement	Fine Aggregate	Coarse Aggregate	Fly Ash	Actual	Predicted	Water	Cement	Fine Aggregate	Coarse Aggregate	Fly Ash	Actual	Predicted
198.75	375.00	592.50	1143.75	0.00	36.84	37.51	191.25	425.00	463.25	1139.00	0.00	50.35	42.83
200.00	400.00	572.00	1128.00	0.00	43.13	39.88	189.00	450.00	441.00	1102.50	0.00	54.11	47.58
212.00	400.00	616.00	1196.00	0.00	38.58	34.23	198.75	375.00	551.25	903.75	0.00	37.3	50.61
199.75	425.00	544.00	1096.50	0.00	47.16	43.36	200.00	400.00	528.00	884.00	0.00	44.04	54.08
208.25	425.00	590.75	1177.25	0.00	45.05	37.44	212.00	400.00	576.00	944.00	0.00	39.61	45.73
198.00	450.00	513.00	1057.50	0.00	49.63	47.81	199.75	425.00	505.75	862.75	0.00	47.37	58.13
211.50	450.00	562.50	1143.00	0.00	47.42	39.59	208.25	425.00	548.25	926.50	0.00	44.69	50.23
199.50	475.00	498.75	1040.25	0.00	54.01	50.01	198.00	450.00	481.50	837.00	0.00	50.93	63.16
209.00	475.00	565.25	1168.50	0.00	50.05	40.59	211.50	450.00	526.50	900.00	0.00	48.08	52.86
198.75	375.00	592.50	1143.75	0.00	37.81	37.51	199.50	475.00	451.25	798.00	0.00	54.14	68.13
200.00	400.00	572.00	1128.00	0.00	44.11	39.88	209.00	475.00	503.50	874.00	0.00	51.31	57.50
212.00	400.00	616.00	1196.00	0.00	40.9	34.23	180.00	400.00	440.00	1080.00	60.00	39.04	48.88
199.75	425.00	544.00	1096.50	0.00	47.51	43.36	178.50	425.00	416.50	1045.50	63.75	45.09	53.70
208.25	425.00	590.75	1177.25	0.00	45.3	37.44	191.25	425.00	463.25	1139.00	63.75	41.14	44.16
216.75	425.00	641.75	1253.75	0.00	42.54	33.08	199.75	425.00	544.00	1096.50	63.75	38.35	45.00
198.00	450.00	513.00	1057.50	0.00	52.03	47.81	189.00	450.00	441.00	1102.50	67.50	46.13	48.59
211.50	450.00	562.50	1143.00	0.00	48.74	39.59	198.00	450.00	513.00	1057.50	67.50	42.5	49.15
220.50	450.00	616.50	1228.50	0.00	46.59	34.47	211.50	450.00	562.50	1143.00	67.50	39.58	41.91
199.50	475.00	498.75	1040.25	0.00	54.49	50.01	199.50	475.00	498.75	1040.25	71.25	47.34	51.29
209.00	475.00	565.25	1168.50	0.00	53.06	40.59	209.00	475.00	565.25	1168.50	71.25	43.55	43.09
218.50	475.00	584.25	1192.25	0.00	49.18	37.41	191.25	425.00	463.25	1139.00	63.75	42.01	44.16
221.00	425.00	607.75	858.50	0.00	40.02	48.94	199.75	425.00	544.00	1096.50	63.75	38.85	45.00
220.50	450.00	580.50	837.00	0.00	45.25	52.77	189.00	450.00	441.00	1102.50	67.50	47.25	48.59
229.50	450.00	175.95	855.00	0.00	42.68	49.07	198.00	450.00	513.00	1057.50	67.50	43.09	49.15
218.50	475.00	555.75	817.00	0.00	48.67	56.97	211.50	450.00	562.50	1143.00	67.50	40.26	41.91
228.00	475.00	598.50	869.25	0.00	45.52	49.91	220.50	450.00	616.50	1228.50	67.50	37.15	37.48
178.50	350.00	486.50	1141.00	0.00	39.52	40.43	199.50	475.00	498.75	1040.25	71.25	48.41	51.29
189.00	350.00	521.50	1197.00	0.00	31.66	34.46	209.00	475.00	565.25	1168.50	71.25	44.02	43.09
180.00	375.00	468.75	1121.25	0.00	42.73	43.49	218.50	475.00	584.25	1192.25	71.25	40.73	40.26
191.25	375.00	506.25	1196.25	0.00	40.69	35.95	199.75	425.00	505.75	862.75	63.75	38.9	58.24
180.00	400.00	440.00	1080.00	0.00	47.99	48.40	198.00	450.00	481.50	837.00	67.50	43.22	62.94
192.00	400.00	484.00	1168.00	0.00	44.89	39.14	211.50	450.00	526.50	900.00	67.50	39.85	53.71
178.50	425.00	416.50	1049.75	0.00	51.25	53.24	220.50	450.00	580.50	837.00	67.50	36.87	53.69
191.25	425.00	463.25	1139.00	0.00	49.05	42.83	229.50	450.00	625.50	891.00	67.50	35.23	47.81
189.00	450.00	441.00	1102.50	0.00	53.69	47.58	199.50	475.00	451.25	798.00	71.25	47.94	67.52
189.00	350.00	521.50	1197.00	0.00	36.64	34.46	209.00	475.00	503.50	874.00	71.25	43.87	58.03
191.25	375.00	506.25	1196.25	0.00	41.57	35.95	218.50	475.00	555.75	817.00	71.25	40.34	57.64
192.00	400.00	484.00	1168.00	0.00	46.22	39.14	228.00	475.00	598.50	869.25	71.25	37.65	51.32

Figure 5. Comparison of predicted compressive strength with the actual strength of the 76 experimental concrete mixtures in [15] (Unit: MPa).

5. Conclusions

In this study, the database of real concrete mix proportioning listed in [12] is used to establish an ANN prediction model for the concrete compressive strength. The ANN structure chosen in this study is the Back Propagation network with 1 hidden layer. The same database was also used in [16], and the number of hidden layers in the ANN is also the same. The database is divided into two sets, the training set and the testing set, respectively. In comparison with [16], we use fewer data for testing and more data for testing. The testing set comprises 15% of the data while in [16] it was just 4%. Considering the possible effect of over-fitting, the number of neurons in the hidden layer is finally chosen as 7, which is half the number used in [16]. The present ANN model outperforms

the model in [16] in the verification in which we compare the predicted results with the experimental data. For corroborating that our model performs well in further practical use, we use experimental data from [15] for validation. A good agreement has also been found.

The synaptic weights and the thresholds are all listed in this article. With these numbers and using Equations (1)–(6), anyone can predict the compressive strength of concrete according to the concrete mix proportioning on his/her own.

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. The Normalized Data for Training and Testing the ANN. Marked with * at the Serial Numbers Are Those for Testing.

S.N.	ζ_1	ζ_2	ζ_3	ζ_4	ζ_5	ζ_6	ζ_7	η	S.N.	ζ_1	ζ_2	ζ_3	ζ_4	ζ_5	ζ_6	ζ_7	η
1 *	0.119	0.442	0.663	0.544	0.043	0.579	0.758	0.506	242	0.473	0.651	0.625	0.481	0.000	0.315	0.320	0.589
2	0.285	0.577	0.624	0.481	0.053	0.545	0.607	0.550	243	0.473	0.651	0.649	0.465	0.277	0.000	0.276	0.637
3	0.458	0.710	0.584	0.418	0.063	0.512	0.431	0.506	244	0.473	0.453	0.665	0.427	0.555	0.000	0.250	0.671
4 *	0.177	0.413	0.663	0.544	0.041	0.579	0.674	0.439	245	0.355	0.602	0.726	0.469	0.000	0.295	0.180	0.394
5	0.343	0.545	0.624	0.481	0.050	0.545	0.519	0.517	246	0.528	0.508	0.725	0.468	0.000	0.258	0.077	0.305
6	0.523	0.674	0.584	0.418	0.060	0.512	0.346	0.528	247	0.662	0.436	0.725	0.468	0.000	0.229	0.000	0.252
7	0.256	0.253	0.683	0.576	0.029	0.594	0.501	0.249	248	0.757	0.378	0.725	0.468	0.000	0.206	0.000	0.156
8	0.350	0.312	0.663	0.544	0.033	0.579	0.431	0.305	249	0.415	0.427	0.725	0.468	0.530	0.000	0.000	0.521
9 *	0.538	0.432	0.624	0.481	0.042	0.545	0.276	0.327	250	0.568	0.355	0.725	0.468	0.463	0.000	0.000	0.451
10	0.726	0.550	0.584	0.418	0.051	0.512	0.107	0.361	251	0.687	0.299	0.725	0.468	0.410	0.000	0.000	0.312
11	0.158	0.423	0.679	0.543	0.042	0.512	0.568	0.583	252 *	0.781	0.254	0.725	0.468	0.369	0.000	0.000	0.217
12	0.334	0.551	0.639	0.481	0.051	0.483	0.394	0.677	253	0.365	0.517	0.726	0.469	0.276	0.135	0.206	0.461
13	0.476	0.679	0.600	0.419	0.060	0.454	0.392	0.681	254 *	0.540	0.433	0.725	0.468	0.241	0.118	0.088	0.360
14	0.158	0.423	0.679	0.543	0.042	0.512	0.568	0.580	255	0.676	0.368	0.725	0.468	0.214	0.104	0.000	0.279
15	0.334	0.551	0.639	0.481	0.051	0.483	0.394	0.619	256	0.770	0.317	0.725	0.468	0.192	0.094	0.000	0.204
16 *	0.476	0.679	0.600	0.419	0.060	0.454	0.392	0.640	257	0.869	0.979	0.446	0.377	0.000	0.267	0.000	0.606
17	0.158	0.423	0.679	0.543	0.042	0.512	0.568	0.317	258 *	0.826	0.790	0.446	0.377	0.000	0.518	0.000	0.651
18	0.334	0.551	0.639	0.481	0.051	0.483	0.394	0.448	259	0.809	0.717	0.446	0.377	0.000	0.669	0.000	0.584
19	0.476	0.679	0.600	0.419	0.060	0.454	0.392	0.501	260	0.874	0.733	0.550	0.377	0.000	0.209	0.000	0.472
20	0.285	0.623	0.808	0.229	0.056	0.439	0.504	0.638	261	0.837	0.588	0.550	0.377	0.000	0.406	0.000	0.495
21	0.213	0.554	0.834	0.254	0.051	0.455	0.498	0.615	262	0.822	0.532	0.550	0.377	0.000	0.482	0.000	0.405
22	0.047	0.484	0.861	0.278	0.045	0.467	1.000	0.573	263	0.879	0.576	0.616	0.377	0.000	0.174	0.000	0.417
23	0.329	0.349	0.865	0.284	0.037	0.470	0.283	0.441	264 *	0.845	0.458	0.616	0.377	0.000	0.334	0.000	0.394
24	0.264	0.295	0.889	0.305	0.032	0.482	0.267	0.395	265	0.832	0.413	0.616	0.377	0.000	0.396	0.000	0.327
25	0.199	0.242	0.912	0.327	0.029	0.494	0.235	0.299	266 *	0.882	0.467	0.665	0.377	0.000	0.145	0.000	0.294
26	0.422	0.225	0.880	0.296	0.419	0.030	0.195	0.185	267	0.852	0.368	0.665	0.377	0.000	0.289	0.000	0.283
27	0.350	0.183	0.900	0.316	0.429	0.027	0.189	0.172	268	0.840	0.330	0.665	0.377	0.000	0.337	0.000	0.216
28	0.278	0.139	0.922	0.335	0.440	0.024	0.171	0.174	269	0.890	0.825	0.446	0.377	0.473	0.000	0.000	0.684
29	0.523	0.556	0.594	0.505	0.141	0.318	0.287	0.656	270	0.884	0.756	0.446	0.377	0.565	0.000	0.000	0.673
30 *	0.523	0.488	0.631	0.505	0.125	0.285	0.312	0.544	271	0.880	0.696	0.446	0.377	0.645	0.000	0.000	0.562
31 *	0.560	0.446	0.675	0.457	0.117	0.264	0.259	0.489	272	0.892	0.612	0.550	0.377	0.369	0.000	0.000	0.584
32	0.410	0.288	0.689	0.430	0.360	0.273	0.215	0.609	273	0.888	0.558	0.550	0.377	0.441	0.000	0.000	0.573
33	0.410	0.416	0.689	0.465	0.360	0.068	0.215	0.590	274	0.884	0.512	0.550	0.377	0.503	0.000	0.000	0.517
34	0.410	0.159	0.689	0.394	0.360	0.477	0.215	0.575	275 *	0.895	0.476	0.615	0.377	0.302	0.000	0.000	0.472
35 *	0.410	0.459	0.689	0.438	0.120	0.273	0.215	0.605	276	0.891	0.432	0.615	0.377	0.361	0.000	0.000	0.506
36	0.410	0.116	0.689	0.421	0.600	0.273	0.215	0.471	277	0.888	0.394	0.615	0.377	0.412	0.000	0.000	0.450
37	0.329	0.288	0.689	0.467	0.360	0.273	0.215	0.739	278	0.897	0.382	0.661	0.377	0.256	0.000	0.000	0.361
38	0.491	0.288	0.689	0.392	0.360	0.273	0.215	0.490	279	0.893	0.345	0.661	0.377	0.306	0.000	0.000	0.394
39	0.410	0.288	0.689	0.430	0.360	0.273	0.182	0.685	280	0.890	0.313	0.661	0.377	0.349	0.000	0.000	0.294
40	0.410	0.288	0.689	0.430	0.360	0.273	0.248	0.502	281	0.473	0.484	0.652	0.661	0.000	0.112	0.000	0.316
41	0.372	0.240	0.721	0.456	0.320	0.242	0.177	0.542	282	0.473	0.413	0.647	0.652	0.000	0.224	0.000	0.301
42	0.372	0.354	0.721	0.488	0.320	0.061	0.177	0.497	283	0.473	0.347	0.643	0.643	0.000	0.333	0.000	0.287
43	0.372	0.126	0.721	0.424	0.320	0.424	0.177	0.483	284	0.473	0.276	0.638	0.634	0.000	0.442	0.000	0.219
44	0.372	0.392	0.721	0.463	0.107	0.242	0.177	0.533	285	0.675	0.789	0.381	0.729	0.325	0.000	0.114	0.515

Table A1. Cont.

S.N.	ξ_1	ξ_2	ξ_3	ξ_4	ξ_5	ξ_6	ξ_7	η	S.N.	ξ_1	ξ_2	ξ_3	ξ_4	ξ_5	ξ_6	ξ_7	η
45	0.372	0.088	0.721	0.449	0.533	0.242	0.177	0.483	286 *	0.675	0.556	0.374	0.729	0.651	0.000	0.114	0.532
46	0.285	0.240	0.721	0.496	0.320	0.242	0.177	0.639	287	0.675	0.324	0.367	0.729	0.976	0.000	0.114	0.497
47	0.458	0.240	0.721	0.416	0.320	0.242	0.177	0.437	288	0.690	0.581	0.472	0.729	0.253	0.000	0.044	0.403
48	0.372	0.240	0.721	0.456	0.320	0.242	0.147	0.549	289 *	0.690	0.402	0.466	0.729	0.507	0.000	0.044	0.418
49 *	0.372	0.240	0.721	0.456	0.320	0.242	0.206	0.514	290 *	0.690	0.221	0.460	0.729	0.760	0.000	0.044	0.390
50	0.432	0.216	0.721	0.458	0.300	0.227	0.152	0.354	291	0.697	0.450	0.530	0.729	0.208	0.000	0.015	0.315
51	0.432	0.323	0.721	0.489	0.300	0.057	0.152	0.476	292 *	0.697	0.301	0.525	0.729	0.413	0.000	0.015	0.307
52	0.432	0.109	0.721	0.429	0.300	0.398	0.152	0.269	293	0.697	0.154	0.520	0.729	0.621	0.000	0.015	0.284
53	0.432	0.359	0.721	0.466	0.100	0.227	0.152	0.358	294 *	0.314	0.594	0.661	0.475	0.133	0.352	0.221	0.785
54	0.432	0.073	0.721	0.452	0.500	0.227	0.152	0.232	295	0.314	0.486	0.723	0.475	0.112	0.300	0.184	0.662
55	0.350	0.216	0.721	0.496	0.300	0.227	0.152	0.429	296	0.314	0.406	0.768	0.475	0.099	0.261	0.147	0.606
56	0.513	0.216	0.721	0.420	0.300	0.227	0.152	0.289	297	0.314	0.345	0.804	0.475	0.088	0.230	0.147	0.573
57	0.432	0.216	0.721	0.458	0.300	0.227	0.124	0.459	298	0.314	0.594	0.556	0.647	0.133	0.352	0.221	0.796
58	0.432	0.216	0.721	0.458	0.300	0.227	0.180	0.402	299	0.314	0.486	0.617	0.647	0.112	0.300	0.184	0.707
59 *	0.300	0.526	0.625	0.577	0.213	0.212	0.059	0.549	300	0.314	0.406	0.662	0.647	0.099	0.261	0.147	0.640
60	0.477	0.270	0.745	0.541	0.025	0.255	0.103	0.263	301	0.314	0.345	0.698	0.647	0.088	0.230	0.147	0.629
61 *	0.266	0.207	0.716	0.561	0.049	0.498	0.173	0.263	302	0.314	0.594	0.450	0.819	0.133	0.352	0.221	0.818
62	0.365	0.430	0.375	0.947	0.000	0.388	0.110	0.370	303 *	0.314	0.486	0.511	0.819	0.112	0.300	0.184	0.707
63	0.473	0.430	0.496	0.706	0.000	0.388	0.081	0.249	304	0.314	0.406	0.557	0.819	0.099	0.261	0.147	0.651
64 *	0.639	0.430	0.541	0.561	0.000	0.388	0.074	0.249	305 *	0.314	0.345	0.591	0.819	0.088	0.230	0.147	0.584
65	0.466	0.285	0.730	0.562	0.000	0.290	0.147	0.272	306	0.314	0.385	0.533	0.647	0.221	0.585	0.221	0.796
66	0.264	0.335	0.580	0.600	0.525	0.303	0.497	0.630	307	0.314	0.307	0.597	0.647	0.189	0.500	0.184	0.707
67	0.264	0.526	0.409	0.929	0.349	0.200	0.497	0.735	308	0.314	0.250	0.645	0.647	0.165	0.436	0.147	0.673
68	0.538	0.417	0.625	0.438	0.131	0.445	0.252	0.427	309	0.314	0.206	0.683	0.647	0.147	0.385	0.147	0.517
69	0.372	0.354	0.705	0.385	0.533	0.000	0.239	0.545	310	0.350	0.341	0.648	0.542	0.552	0.000	0.220	0.689
70	0.386	0.469	0.568	0.475	0.499	0.288	0.397	0.715	311	0.350	0.362	0.633	0.542	0.576	0.000	0.230	0.783
71	0.567	0.579	0.649	0.447	0.347	0.097	0.313	0.620	312	0.814	0.644	0.643	0.374	0.000	0.139	0.000	0.321
72	0.377	0.240	0.633	0.448	0.293	0.485	0.147	0.327	313	0.814	0.557	0.628	0.374	0.000	0.278	0.000	0.289
73	0.495	0.217	0.656	0.591	0.299	0.227	0.138	0.338	314	0.814	0.470	0.613	0.374	0.000	0.416	0.000	0.255
74	0.422	0.202	0.624	0.677	0.192	0.327	0.132	0.316	315	0.814	0.470	0.625	0.374	0.122	0.278	0.000	0.267
75 *	0.374	0.341	0.608	0.489	0.243	0.491	0.138	0.320	316	0.814	0.470	0.631	0.374	0.183	0.208	0.000	0.278
76 *	0.495	0.579	0.649	0.447	0.347	0.097	0.313	0.594	317	0.814	0.470	0.637	0.374	0.244	0.139	0.000	0.305
77	0.538	0.417	0.625	0.438	0.131	0.445	0.248	0.427	318 *	0.339	0.269	0.709	0.594	0.000	0.652	0.055	0.164
78	0.567	0.417	0.623	0.435	0.104	0.476	0.293	0.396	319	0.325	0.269	0.705	0.594	0.280	0.318	0.048	0.349
79	0.567	0.411	0.671	0.432	0.107	0.364	0.267	0.340	320	0.069	0.630	0.511	0.872	0.000	0.136	0.515	0.893
80	0.495	0.335	0.658	0.522	0.320	0.242	0.184	0.465	321 *	0.069	0.545	0.511	0.872	0.000	0.273	0.515	0.877
81	0.495	0.240	0.770	0.387	0.267	0.303	0.162	0.349	322	0.069	0.459	0.511	0.872	0.000	0.409	0.515	0.853
82	0.372	0.430	0.705	0.397	0.613	0.000	0.234	0.647	323	0.069	0.545	0.511	0.872	0.240	0.000	0.515	1.000
83	0.372	0.430	0.705	0.397	0.491	0.139	0.234	0.578	324	0.069	0.373	0.511	0.872	0.480	0.000	0.515	0.914
84	0.372	0.430	0.705	0.397	0.368	0.279	0.234	0.554	325	0.069	0.202	0.511	0.872	0.720	0.000	0.515	0.904
85	0.372	0.430	0.705	0.397	0.307	0.348	0.234	0.544	326	0.430	0.240	0.737	0.389	0.179	0.476	0.280	0.244
86	0.372	0.430	0.705	0.397	0.245	0.418	0.234	0.478	327	0.408	0.335	0.724	0.373	0.176	0.467	0.313	0.320
87	0.372	0.430	0.705	0.397	0.123	0.558	0.234	0.552	328	0.401	0.430	0.711	0.357	0.168	0.448	0.302	0.396
88 *	0.372	0.430	0.705	0.397	0.000	0.697	0.234	0.422	329	0.386	0.526	0.698	0.342	0.163	0.430	0.324	0.472
89	0.220	0.560	0.686	0.525	0.107	0.285	0.314	0.583	330	0.430	0.697	0.541	0.609	0.000	0.333	0.273	0.716
90	0.220	0.560	0.686	0.525	0.149	0.248	0.317	0.549	331	0.430	0.488	0.530	0.586	0.000	0.667	0.273	0.616
91	0.220	0.560	0.686	0.525	0.187	0.212	0.318	0.526	332	0.430	0.278	0.519	0.563	0.000	1.000	0.245	0.467
92	0.531	0.534	0.638	0.431	0.407	0.116	0.280	0.727	333	0.430	0.697	0.550	0.627	0.293	0.000	0.384	0.775
93	0.567	0.421	0.638	0.431	0.486	0.138	0.346	0.625	334	0.430	0.488	0.548	0.622	0.587	0.000	0.368	0.830
94	0.567	0.421	0.638	0.431	0.486	0.138	0.308	0.513	335	0.430	0.278	0.546	0.618	0.880	0.000	0.327	0.808
95	0.567	0.335	0.653	0.431	0.527	0.150	0.293	0.603	336	0.430	0.697	0.546	0.618	0.147	0.167	0.294	0.796
96	0.552	0.345	0.653	0.431	0.530	0.151	0.296	0.623	337 *	0.430	0.488	0.539	0.604	0.293	0.333	0.276	0.632
97	0.538	0.345	0.653	0.431	0.541	0.154	0.300	0.586	338	0.430	0.278	0.532	0.591	0.440	0.500	0.163	0.711
98	0.567	0.278	0.653	0.431	0.581	0.165	0.290	0.501	339 *	0.588	0.545	0.620	0.531	0.000	0.273	0.118	0.518
99	0.531	0.250	0.653	0.431	0.637	0.181	0.296	0.588	340	0.588	0.373	0.610	0.514	0.000	0.545	0.109	0.436
100	0.567	0.250	0.667	0.431	0.569	0.162	0.278	0.491	341	0.588	0.202	0.600	0.497	0.000	0.818	0.110	0.275
101	0.531	0.240	0.667	0.431	0.606	0.172	0.285	0.560	342	0.588	0.545	0.628	0.544	0.240	0.000	0.136	0.595
102 *	0.531	0.240	0.668	0.450	0.569	0.162	0.275	0.468	343	0.588	0.373	0.626	0.541	0.480	0.000	0.127	0.584
103	0.531	0.240	0.662	0.470	0.552	0.157	0.270	0.470	344	0.588	0.202	0.624	0.537	0.720	0.000	0.103	0.564
104	0.567	0.240	0.662	0.470	0.524	0.149	0.262	0.489	345	0.588	0.545	0.624	0.537	0.120	0.136	0.118	0.633
105	0.567	0.307	0.656	0.490	0.149	0.395	0.248	0.256	346	0.588	0.373	0.618	0.527	0.240	0.273	0.118	0.535
106	0.567	0.297	0.644	0.529	0.140	0.372	0.239	0.228	347	0.588	0.202	0.612	0.517	0.360	0.409	0.103	0.449
107	0.588	0.686	0.668	0.390	0.000	0.145	0.178	0.368	348	0.803	0.745	0.697	0.195	0.000	0.258	0.395	0.329
108	0.552	0.575	0.668	0.390	0.000	0.285	0.173	0.321	349	0.809	0.697	0.697	0.195	0.000	0.333	0.405	0.307
109	0.516	0.470	0.668	0.390	0.000	0.415	0.169	0.290	350	0.843	0.650	0.697	0.195	0.000	0.409	0.365	0.288
110	0.480	0.370	0.668	0.390	0.000	0.542	0.165	0.264	351 *	0.851	0.592	0.697	0.195	0.000	0.500	0.365	0.279
111	0.617	0.705	0.668	0.390	0.131	0.000	0.181	0.381	352	0.903	0.535	0.697	0.195				

Table A1. Cont.

S.N.	ξ_1	ξ_2	ξ_3	ξ_4	ξ_5	ξ_6	ξ_7	η	S.N.	ξ_1	ξ_2	ξ_3	ξ_4	ξ_5	ξ_6	ξ_7	η
126	0.386	0.278	0.735	0.449	0.320	0.242	0.170	0.395	367	0.863	0.392	0.880	0.072	0.000	0.288	0.000	0.341
127	0.422	0.335	0.726	0.449	0.240	0.242	0.170	0.438	368	0.892	0.392	0.858	0.057	0.000	0.364	0.000	0.344
128	0.401	0.240	0.717	0.449	0.533	0.152	0.182	0.449	369	0.928	0.392	0.838	0.043	0.000	0.424	0.000	0.333
129	0.422	0.088	0.705	0.449	0.320	0.242	0.182	0.465	370	0.957	0.392	0.814	0.027	0.000	0.500	0.000	0.312
130	0.386	0.621	0.709	0.449	0.267	0.000	0.184	0.569	371	0.870	0.469	0.894	0.082	0.000	0.152	0.000	0.375
131 *	0.372	0.383	0.707	0.449	0.600	0.000	0.184	0.571	372 *	0.892	0.469	0.865	0.061	0.000	0.242	0.000	0.399
132	0.386	0.383	0.675	0.449	0.333	0.303	0.184	0.440	373	0.913	0.469	0.844	0.047	0.000	0.318	0.000	0.411
133	0.473	0.453	0.586	0.524	0.555	0.000	0.383	0.751	374	0.942	0.469	0.817	0.028	0.000	0.409	0.000	0.413
134 *	0.473	0.453	0.586	0.503	0.416	0.158	0.364	0.718	375	0.971	0.469	0.793	0.013	0.000	0.485	0.000	0.396
135	0.473	0.453	0.586	0.482	0.277	0.315	0.346	0.618	376	1.000	0.469	0.775	0.000	0.000	0.561	0.000	0.378
136	0.473	0.453	0.586	0.461	0.139	0.473	0.346	0.568	377 *	0.242	0.621	0.533	0.900	0.000	0.303	0.276	0.822
137	0.473	0.453	0.586	0.439	0.000	0.630	0.364	0.484	378	0.242	0.621	0.533	0.900	0.267	0.000	0.276	0.828
138	0.336	0.248	0.572	0.735	0.000	0.412	0.063	0.215	379	0.242	0.621	0.533	0.900	0.133	0.152	0.276	0.837
139	0.161	0.217	0.721	0.556	0.000	0.570	0.235	0.242	380	0.314	0.316	0.462	0.997	0.000	0.485	0.092	0.235
140	0.235	0.288	0.657	0.537	0.000	0.682	0.215	0.337	381	0.343	0.278	0.459	1.000	0.000	0.545	0.096	0.212
141	0.372	0.373	0.681	0.500	0.240	0.273	0.141	0.469	382	0.314	0.240	0.464	0.999	0.000	0.606	0.099	0.195
142	0.386	0.339	0.698	0.503	0.224	0.255	0.124	0.421	383 *	0.170	0.430	0.486	0.885	0.000	0.606	0.055	0.664
143	0.314	0.255	0.712	0.497	0.277	0.312	0.140	0.331	384	0.170	0.430	0.489	0.891	0.200	0.379	0.074	0.836
144	0.458	0.446	0.583	0.692	0.192	0.094	0.166	0.357	385	0.170	0.335	0.486	0.885	0.000	0.758	0.055	0.544
145 *	0.372	0.328	0.672	0.489	0.365	0.221	0.201	0.396	386	0.386	0.295	0.502	0.871	0.501	0.000	0.107	0.303
146	0.296	0.288	0.721	0.518	0.000	0.455	0.179	0.435	387	0.386	0.341	0.492	0.839	0.552	0.000	0.119	0.408
147	0.296	0.373	0.689	0.473	0.000	0.545	0.215	0.495	388	0.386	0.621	0.496	0.854	0.267	0.000	0.129	0.427
148	0.166	0.288	0.689	0.499	0.000	0.682	0.248	0.507	389	0.386	0.383	0.481	0.814	0.600	0.000	0.129	0.512
149	0.623	0.872	0.023	0.671	0.000	0.179	0.151	0.625	390 *	0.386	0.097	0.489	0.837	1.000	0.000	0.129	0.375
150 *	0.623	0.760	0.070	0.671	0.000	0.358	0.151	0.565	391	0.386	0.469	0.467	0.776	0.677	0.000	0.148	0.636
151 *	0.623	0.646	0.116	0.671	0.000	0.536	0.151	0.501	392	0.386	0.514	0.458	0.751	0.749	0.000	0.161	0.667
152	0.653	0.568	0.009	0.671	0.000	0.124	0.000	0.367	393	0.502	0.392	0.495	0.923	0.245	0.000	0.000	0.395
153 *	0.653	0.490	0.042	0.671	0.000	0.252	0.000	0.316	394	0.502	0.213	0.495	0.923	0.496	0.000	0.000	0.331
154	0.653	0.221	0.074	0.671	0.000	0.376	0.000	0.266	395 *	0.502	0.392	0.495	0.923	0.000	0.279	0.000	0.288
155	0.653	0.366	0.000	0.671	0.000	0.091	0.000	0.168	396	0.097	0.156	0.515	0.978	0.000	0.655	0.132	0.295
156	0.653	0.310	0.023	0.671	0.000	0.179	0.000	0.128	397	0.841	0.874	0.446	0.376	0.000	0.403	0.000	0.695
157	0.653	0.253	0.047	0.671	0.000	0.270	0.000	0.085	398	0.848	0.653	0.549	0.376	0.000	0.315	0.000	0.532
158	0.653	0.872	0.417	0.671	0.157	0.000	0.000	0.554	399	0.856	0.510	0.615	0.376	0.000	0.258	0.000	0.413
159	0.653	0.760	0.414	0.671	0.315	0.000	0.000	0.614	400	0.863	0.413	0.664	0.376	0.000	0.218	0.000	0.337
160	0.653	0.535	0.406	0.671	0.632	0.000	0.000	0.604	401	0.899	1.000	0.446	0.376	0.237	0.000	0.000	0.652
161	0.653	0.568	0.535	0.671	0.109	0.000	0.000	0.419	402	0.892	0.905	0.446	0.376	0.365	0.000	0.000	0.674
162	0.653	0.490	0.532	0.671	0.221	0.000	0.000	0.442	403	0.899	0.747	0.549	0.376	0.187	0.000	0.000	0.539
163	0.653	0.331	0.527	0.671	0.443	0.000	0.000	0.436	404	0.892	0.674	0.549	0.376	0.285	0.000	0.000	0.533
164	0.653	0.366	0.622	0.671	0.080	0.000	0.000	0.220	405 *	0.899	0.589	0.615	0.376	0.152	0.000	0.000	0.427
165	0.653	0.310	0.619	0.671	0.157	0.000	0.000	0.219	406	0.899	0.526	0.615	0.376	0.232	0.000	0.000	0.457
166	0.653	0.196	0.615	0.671	0.315	0.000	0.000	0.218	407	0.899	0.423	0.660	0.376	0.197	0.000	0.000	0.311
167	0.650	0.760	0.407	0.671	0.157	0.179	0.014	0.549	408	0.260	0.692	0.622	0.532	0.061	0.337	0.276	0.485
168	0.650	0.648	0.393	0.671	0.157	0.358	0.016	0.502	409	0.134	0.550	0.664	0.602	0.051	0.359	0.184	0.300
169	0.649	0.423	0.395	0.671	0.632	0.179	0.017	0.512	410	0.000	0.413	0.705	0.670	0.041	0.380	0.151	0.280
170	0.649	0.310	0.381	0.671	0.632	0.358	0.017	0.463	411	0.295	0.555	0.645	0.569	0.051	0.349	0.099	0.314
171	0.653	0.490	0.530	0.671	0.109	0.124	0.000	0.449	412	0.300	0.365	0.676	0.622	0.037	0.365	0.074	0.243
172	0.653	0.411	0.520	0.671	0.109	0.252	0.000	0.396	413	0.329	0.621	0.645	0.518	0.427	0.000	0.453	0.717
173 *	0.653	0.253	0.522	0.671	0.443	0.124	0.000	0.408	414	0.514	0.530	0.637	0.606	0.626	0.000	0.304	0.642
174 *	0.653	0.175	0.511	0.671	0.443	0.252	0.000	0.354	415	0.514	0.530	0.637	0.606	0.269	0.405	0.387	0.466
175	0.653	0.310	0.649	0.671	0.080	0.091	0.000	0.229	416	0.514	0.530	0.637	0.606	0.000	0.711	0.566	0.404
176	0.653	0.253	0.669	0.671	0.080	0.179	0.000	0.191	417	0.514	0.362	0.641	0.600	0.861	0.000	0.287	0.561
177	0.653	0.141	0.707	0.671	0.315	0.091	0.000	0.207	418 *	0.514	0.362	0.641	0.600	0.370	0.558	0.431	0.462
178	0.653	0.084	0.726	0.671	0.315	0.179	0.000	0.191	419	0.444	0.495	0.657	0.627	0.255	0.384	0.595	0.394
179	0.278	0.556	0.626	0.643	0.000	0.276	0.168	0.452	420	0.444	0.495	0.657	0.627	0.000	0.674	0.198	0.566
180 *	0.278	0.469	0.614	0.643	0.000	0.415	0.168	0.445	421	0.444	0.336	0.657	0.627	0.816	0.000	0.216	0.586
181	0.278	0.381	0.603	0.643	0.000	0.555	0.168	0.432	422	0.444	0.336	0.657	0.627	0.351	0.528	0.275	0.442
182	0.278	0.295	0.591	0.643	0.000	0.694	0.168	0.299	423	0.444	0.336	0.657	0.627	0.000	0.927	0.403	0.359
183 *	0.278	0.208	0.580	0.643	0.000	0.830	0.168	0.235	424	0.375	0.461	0.676	0.646	0.562	0.000	0.516	0.422
184	0.278	0.120	0.568	0.643	0.000	0.970	0.168	0.141	425	0.375	0.461	0.676	0.646	0.258	0.345	0.563	0.350
185	0.314	0.400	0.709	0.643	0.000	0.215	0.000	0.373	426	0.375	0.461	0.676	0.646	0.000	0.638	0.187	0.549
186	0.314	0.333	0.699	0.643	0.000	0.324	0.000	0.329	427	0.375	0.310	0.676	0.646	0.772	0.000	0.205	0.569
187	0.314	0.265	0.690	0.643	0.000	0.430	0.000	0.291	428	0.375	0.310	0.676	0.646	0.355	0.474	0.261	0.344
188	0.314	0.198	0.681	0.643	0.000	0.539	0.000	0.213	429	0.375	0.310	0.676	0.646	0.000	0.878	0.381	0.331
189	0.314	0.130	0.672	0.643	0.000	0.645	0.000	0.154	430	0.516	0.530	0.637	0.606	0.627	0.000	0.259	0.662
190 *	0.314	0.063	0.662	0.643	0.000	0.755	0.000	0.068	431 *	0.254	0.457	0.494	0.831	0.279	0.317	0.328	0.552
191	0.314	0.303	0.755	0.643	0.000	0.176	0.000	0.284	432	0.250	0.458	0.495	0.831	0.280	0.318	0.386	0.572
192	0.314	0.248	0.747	0.643	0.000	0.264	0.000	0									

Table A1. Cont.

S.N.	ξ_1	ξ_2	ξ_3	ξ_4	ξ_5	ξ_6	ξ_7	η	S.N.	ξ_1	ξ_2	ξ_3	ξ_4	ξ_5	ξ_6	ξ_7	η
207	0.422	0.545	0.689	0.461	0.000	0.273	0.182	0.502	448	0.285	0.240	0.721	0.496	0.320	0.242	0.177	0.639
208	0.292	0.373	0.689	0.473	0.000	0.545	0.215	0.495	449	0.458	0.240	0.721	0.416	0.320	0.242	0.177	0.437
209	0.162	0.288	0.689	0.499	0.000	0.682	0.248	0.507	450	0.321	0.398	0.721	0.504	0.192	0.133	0.159	0.608
210	0.069	0.202	0.689	0.524	0.000	0.818	0.298	0.428	451	0.321	0.082	0.721	0.457	0.448	0.352	0.159	0.518
211	0.432	0.430	0.721	0.486	0.000	0.227	0.142	0.373	452	0.422	0.263	0.721	0.418	0.192	0.352	0.159	0.412
212	0.296	0.288	0.721	0.518	0.000	0.455	0.196	0.435	453	0.422	0.217	0.721	0.447	0.448	0.133	0.159	0.528
213	0.161	0.217	0.721	0.556	0.000	0.570	0.208	0.488	454	0.432	0.216	0.721	0.458	0.300	0.227	0.152	0.347
214 *	0.053	0.145	0.721	0.587	0.000	0.682	0.273	0.339	455	0.432	0.323	0.721	0.489	0.300	0.057	0.152	0.391
215	0.426	0.545	0.689	0.461	0.000	0.273	0.158	0.502	456	0.432	0.109	0.721	0.429	0.300	0.398	0.152	0.270
216 *	0.296	0.373	0.689	0.473	0.000	0.545	0.182	0.495	457	0.432	0.359	0.721	0.466	0.100	0.227	0.152	0.358
217	0.166	0.288	0.689	0.499	0.000	0.682	0.238	0.507	458	0.432	0.073	0.721	0.452	0.500	0.227	0.152	0.293
218	0.069	0.202	0.689	0.524	0.000	0.818	0.272	0.428	459 *	0.350	0.216	0.721	0.496	0.300	0.227	0.152	0.452
219	0.856	0.494	0.426	0.770	0.000	0.178	0.000	0.422	460	0.513	0.216	0.721	0.420	0.300	0.227	0.152	0.289
220	0.856	0.382	0.408	0.770	0.000	0.356	0.000	0.321	461	0.383	0.365	0.721	0.503	0.181	0.126	0.169	0.392
221	0.856	0.492	0.440	0.770	0.157	0.000	0.000	0.461	462	0.383	0.067	0.721	0.459	0.419	0.329	0.169	0.253
222	0.856	0.382	0.436	0.770	0.314	0.000	0.000	0.406	463	0.479	0.238	0.721	0.423	0.181	0.329	0.169	0.254
223	0.675	0.905	0.381	0.729	0.000	0.185	0.114	0.417	464	0.479	0.195	0.721	0.449	0.419	0.126	0.135	0.314
224	0.675	0.789	0.373	0.729	0.000	0.370	0.114	0.396	465 *	0.342	0.173	0.690	0.721	0.000	0.435	0.000	0.228
225	0.675	0.672	0.366	0.729	0.000	0.555	0.114	0.392	466	0.423	0.173	0.567	0.721	0.343	0.400	0.297	0.452
226	0.690	0.672	0.472	0.729	0.000	0.142	0.044	0.340	467	0.458	0.198	0.568	0.723	0.346	0.359	0.131	0.372
227 *	0.690	0.581	0.466	0.729	0.000	0.288	0.044	0.334	468	0.426	0.178	0.567	0.722	0.346	0.390	0.287	0.394
228	0.690	0.491	0.461	0.729	0.000	0.430	0.044	0.320	469	0.291	0.187	0.654	0.722	0.036	0.522	0.162	0.311
229	0.697	0.524	0.529	0.729	0.000	0.118	0.015	0.347	470	0.349	0.190	0.605	0.722	0.133	0.526	0.238	0.361
230	0.697	0.450	0.525	0.729	0.000	0.236	0.015	0.382	471	0.343	0.177	0.586	0.723	0.201	0.506	0.291	0.397
231	0.697	0.377	0.520	0.729	0.000	0.352	0.015	0.392	472	0.403	0.190	0.567	0.723	0.249	0.485	0.358	0.357
232 *	0.623	0.872	0.424	0.680	0.158	0.000	0.152	0.614	473	0.362	0.222	0.609	0.814	0.000	0.379	0.364	0.213
233	0.623	0.760	0.420	0.680	0.315	0.000	0.152	0.598	474	0.544	0.335	0.655	0.649	0.000	0.290	0.196	0.239
234	0.623	0.535	0.413	0.680	0.631	0.000	0.152	0.569	475	0.308	0.266	0.587	0.769	0.000	0.528	0.429	0.433
235	0.650	0.568	0.542	0.680	0.110	0.000	0.015	0.419	476	0.388	0.230	0.690	0.711	0.000	0.305	0.275	0.351
236	0.650	0.490	0.540	0.680	0.221	0.000	0.015	0.472	477	0.552	0.338	0.573	0.769	0.000	0.358	0.212	0.306
237	0.650	0.332	0.535	0.680	0.441	0.000	0.015	0.423	478	0.355	0.230	0.694	0.722	0.000	0.305	0.275	0.137
238	0.653	0.366	0.622	0.680	0.079	0.000	0.000	0.210	479	0.519	0.338	0.576	0.750	0.000	0.358	0.234	0.242
239 *	0.653	0.310	0.619	0.680	0.158	0.000	0.000	0.207	480	0.455	0.193	0.567	0.725	0.282	0.428	0.082	0.213
240	0.653	0.197	0.615	0.680	0.315	0.000	0.000	0.228	481	0.581	0.347	0.608	0.717	0.014	0.236	0.262	0.182
241	0.473	0.750	0.625	0.500	0.000	0.158	0.287	0.647	482 *	0.482	0.309	0.616	0.716	0.169	0.215	0.205	0.270

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