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Appendices

Appendix A
Training Investigation Results

Table A.1 MSE results for data set I trained with BP

Hidden	Weight Initialisation						Standard
Nodes	1	2	3	4	5	Average	Deviation
1	***0.453***	***0.453***	***0.453***	***0.453***	***0.453***	0.453	0.000
2	0.448	***0.438***	0.448	0.448	***0.438***	0.444	0.005
3	0.443	***0.434***	0.442	0.440	0.435	0.439	0.004
4	0.427	0.427	0.429	0.433	***0.418***	0.427	0.006
5	***0.417***	0.431	0.421	0.425	0.427	0.424	0.005
6	***0.412***	***0.412***	0.413	0.418	0.416	0.414	0.003
7	0.410	0.412	0.407	***0.398***	0.412	0.408	0.006
8	0.403	0.414	0.406	***0.400***	0.404	0.405	0.005
9	0.393	0.406	***0.377***	0.388	0.406	0.394	0.013
10	0.396	0.388	0.386	***0.374***	0.392	0.387	0.008

Table A.2 MSE results for data set I trained with the GA

Hidden	Weight Initialisation						Standard
Nodes	1	2	3	4	5	Average	Deviation
1	***0.450***	***0.450***	***0.450***	***0.450***	***0.450***	0.450	0.000
2	***0.438***	***0.438***	***0.438***	***0.438***	***0.438***	0.438	0.000
3	0.440	0.442	***0.436***	0.438	0.438	0.439	0.002
4	0.431	0.435	***0.430***	0.434	0.433	0.433	0.002
5	0.431	0.435	***0.427***	0.430	0.442	0.433	0.006
6	0.431	0.430	***0.418***	0.429	0.420	0.425	0.006
7	0.425	***0.408***	0.422	0.423	0.430	0.422	0.008
8	***0.404***	0.414	0.410	0.424	0.411	0.413	0.007
9	0.424	0.419	***0.404***	0.406	0.406	0.412	0.009
10	0.399	0.403	***0.395***	0.405	0.428	0.406	0.013

Table A.3 MSE results for data set I trained with the SCE-UA algorithm

Hidden	Weight Initialisation						Standard
Nodes	1	2	3	4	5	Average	Deviation
1	***0.448***	***0.448***	***0.448***	***0.448***	***0.448***	0.448	0.000
2	***0.438***	***0.438***	***0.438***	***0.438***	***0.438***	0.438	0.000
3	0.434	0.435	0.436	***0.426***	0.436	0.433	0.004
4	***0.422***	0.429	0.431	0.428	0.427	0.427	0.004
5	***0.412***	0.427	0.426	0.419	0.416	0.420	0.006
6	***0.411***	0.419	0.423	0.421	0.415	0.418	0.005
7	0.410	***0.401***	0.416	0.402	0.403	0.407	0.007
8	***0.390***	0.401	0.400	0.400	0.393	0.397	0.005
9	0.400	0.395	***0.391***	0.396	0.395	0.396	0.003
10	***0.386***	0.405	0.394	0.403	0.396	0.397	0.007

Table A.4 MSE results for data set II trained with BP

Hidden	Weight Initialisation						Standard
Nodes	1	2	3	4	5	Average	Deviation
1	***0.641***	***0.641***	***0.641***	***0.641***	***0.641***	0.641	0.000
2	0.631	***0.558***	0.631	***0.558***	0.631	0.602	0.040
3	0.629	0.606	***0.485***	0.622	0.548	0.578	0.061
4	0.497	0.521	***0.478***	0.589	0.511	0.519	0.042
5	0.471	***0.463***	0.531	0.536	0.492	0.498	0.034
6	***0.458***	0.466	0.515	0.464	0.470	0.475	0.023
7	0.463	0.448	0.468	***0.438***	0.451	0.454	0.012
8	0.448	0.449	***0.433***	0.484	0.435	0.450	0.020
9	0.432	0.434	0.488	0.429	***0.420***	0.441	0.027
10	0.424	0.434	***0.414***	0.446	0.425	0.429	0.012

Table A.5 MSE results for data set II trained with the GA

Hidden	Weight Initialisation						Standard
Nodes	1	2	3	4	5	Average	Deviation
1	0.641	0.641	0.641	0.641	***0.640***	0.641	0.000
2	0.633	0.634	0.633	***0.609***	0.617	0.625	0.011
3	0.527	0.610	0.629	0.537	***0.515***	0.564	0.052
4	0.625	0.538	0.498	0.506	***0.481***	0.529	0.057
5	0.485	0.486	0.479	0.493	***0.474***	0.483	0.007
6	***0.459***	0.526	***0.459***	0.477	0.470	0.478	0.028
7	0.482	0.459	***0.456***	0.463	0.464	0.465	0.010
8	0.487	***0.453***	0.454	0.478	0.471	0.469	0.015
9	0.447	0.475	0.465	0.447	***0.446***	0.456	0.013
10	0.460	0.460	***0.445***	0.447	0.448	0.452	0.007

Table A.6 MSE results for data set II trained with the SCE-UA algorithm

Hidden	Weight Initialisation						Standard
Nodes	1	2	3	4	5	Average	Deviation
1	***0.639***	***0.639***	***0.639***	***0.639***	***0.639***	0.639	0.000
2	***0.629***	0.632	***0.629***	***0.629***	0.632	0.630	0.001
3	0.621	0.620	***0.480***	***0.480***	***0.480***	0.536	0.077
4	***0.471***	0.473	0.473	0.477	0.473	0.473	0.002
5	0.467	***0.465***	0.506	0.468	0.469	0.475	0.018
6	0.460	0.462	0.462	***0.459***	0.463	0.461	0.002
7	0.459	0.453	***0.450***	0.454	0.492	0.462	0.017
8	***0.447***	***0.447***	0.451	0.455	0.450	0.450	0.004
9	0.449	***0.445***	0.446	0.462	0.459	0.452	0.008
10	0.440	0.470	0.446	0.444	***0.433***	0.447	0.014

Table A.7 MSE results for data set III trained with BP

Hidden Nodes	Weight Initialisation 1	2	3	4	5	Average	Standard Deviation
1	***3.543***	***3.543***	***3.543***	***3.543***	***3.543***	3.543	0.000
2	2.592	2.592	***2.403***	***2.403***	3.030	2.604	0.256
3	1.693	$\boxed{\mathbf{\mathit{1.419}}}$	$\boxed{\mathbf{\mathit{1.419}}}$	2.004	1.693	$\boxed{1.646}$	0.243
4	1.652	***0.653***	***0.653***	1.646	***0.653***	1.051	0.546
5	***0.559***	***0.559***	0.635	***0.559***	0.580	0.579	0.033
6	0.558	0.575	0.582	***0.521***	0.536	0.554	0.026
7	***0.516***	0.531	0.553	0.558	0.519	0.535	0.019
8	0.582	0.517	0.518	$\boxed{\mathbf{\mathit{0.509}}}$	0.522	0.530	0.030
9	0.523	0.512	0.513	$\boxed{\mathbf{\mathit{0.502}}}$	0.518	$\boxed{0.514}$	0.008
10	$\boxed{\mathbf{\mathit{0.489}}}$	0.506	0.497	0.497	0.501	$\boxed{0.498}$	0.006

Table A.8 MSE results for data set III trained with the GA

Hidden Nodes	Weight Initialisation 1	2	3	4	5	Average	Standard Deviation
1	***3.540***	3.541	***3.540***	***3.540***	***3.541***	3.541	0.000
2	2.551	2.554	2.417	2.544	***2.414***	2.496	0.074
3	2.524	***1.449***	1.730	2.480	1.732	1.983	0.488
4	1.858	0.756	0.942	0.752	***0.737***	$\boxed{1.009}$	0.482
5	0.644	0.639	0.738	***0.603***	0.643	0.653	0.050
6	0.693	***0.536***	0.601	0.611	0.625	0.613	0.056
7	0.605	0.560	***0.549***	0.639	0.637	0.598	0.042
8	0.631	0.571	0.605	0.561	***0.540***	0.582	0.036
9	0.572	***0.539***	0.546	0.556	0.558	0.554	0.013
10	***0.531***	0.544	***0.531***	0.541	0.557	0.541	0.011

Table A.9 MSE results for data set III trained with the SCE-UA algorithm

Hidden Nodes	Weight Initialisation 1	2	3	4	5	Average	Standard Deviation
1	$\boxed{\mathbf{\mathit{3.538}}}$	$\boxed{\mathbf{\mathit{3.538}}}$	$\boxed{\mathbf{\mathit{3.538}}}$	$\boxed{\mathbf{\mathit{3.538}}}$	$\boxed{\mathbf{\mathit{3.538}}}$	$\boxed{3.538}$	0.000
2	$\boxed{\mathbf{\mathit{2.356}}}$	$\boxed{\mathbf{\mathit{2.356}}}$	$\boxed{\mathbf{\mathit{2.356}}}$	$\boxed{\mathbf{\mathit{2.356}}}$	$\boxed{\mathbf{\mathit{2.356}}}$	$\boxed{2.356}$	0.000
3	***1.656***	***1.656***	***1.656***	***1.656***	***1.656***	1.656	0.000
4	1.620	$\boxed{\mathbf{\mathit{0.600}}}$	1.627	1.640	$\boxed{\mathbf{\mathit{0.600}}}$	1.218	0.563
5	0.566	0.529	0.545	0.527	$\boxed{\mathbf{\mathit{0.526}}}$	$\boxed{0.539}$	0.017
6	$\boxed{\mathbf{\mathit{0.518}}}$	0.520	0.567	0.519	0.528	$\boxed{0.530}$	0.021
7	0.513	0.517	$\boxed{\mathbf{\mathit{0.511}}}$	$\boxed{\mathbf{\mathit{0.511}}}$	0.512	$\boxed{0.513}$	0.003
8	***0.511***	0.514	0.537	***0.511***	0.513	$\boxed{0.517}$	0.011
9	0.524	***0.516***	0.520	0.519	***0.516***	0.519	0.004
10	0.526	0.549	0.538	0.550	***0.520***	0.537	0.013

Appendix B
Results of Assessment of Input Importance Measures

In the tables presented in this appendix, the methods used for assessing relative input importance are numbered as follows:

(1) Connection Weight Approach

(2) Garson's Method

(3) Modified Connection Weight Approach

(4) Modified Garson's Method

Table B.1 RI results for data set I trained by BP.

Hidden	(1)			(2)			(3)			(4)		
Nodes	y_{t-1}	y_{t-4}	y_{t-9}	y_{t-1}	y_{t-4}	y_{t-9}	y_{t-1}	y_{t-4}	y_{t-9}	y_{t-1}	y_{t-4}	y_{t-9}
1	20.71	41.59	37.70	20.71	41.59	37.70	21.24	41.15	37.61	20.71	41.59	37.70
2	27.43	59.21	13.36	20.66	39.36	39.98	24.27	41.03	34.70	21.11	40.21	38.68
3	11.76	37.15	51.09	16.35	29.73	53.92	15.58	45.73	38.70	14.11	37.24	48.65
4	22.55	42.59	34.86	20.93	38.33	40.75	21.96	39.60	38.45	21.09	40.04	38.87
5	50.30	14.64	35.06	31.46	31.73	36.81	22.98	37.19	39.83	18.57	48.60	32.83
6	34.09	44.65	21.26	30.93	36.22	32.86	29.46	62.92	7.62	69.83	27.19	2.98
7	42.87	50.53	6.60	21.29	47.64	31.08	33.48	48.58	17.93	32.92	48.91	18.17
8	26.69	57.77	15.53	27.04	39.24	33.72	31.97	51.58	16.45	27.09	50.87	22.04
9	31.12	31.29	37.60	35.77	31.22	33.01	21.69	44.55	33.75	19.39	49.97	30.64
10	1.62	33.52	64.87	18.89	38.80	42.31	8.48	37.44	54.09	4.75	32.39	62.85
Mean	26.91	41.29	31.79	24.40	37.38	38.21	23.11	44.98	31.91	24.96	41.70	33.34
St. Dev.	14.14	13.25	17.97	6.44	5.41	6.68	7.49	7.86	13.79	17.41	7.99	16.57

Table B.2 RI results for data set I trained by GA.

Hidden	(1)			(2)			(3)			(4)		
Nodes	y_{t-1}	y_{t-4}	y_{t-9}	y_{t-1}	y_{t-4}	y_{t-9}	y_{t-1}	y_{t-4}	y_{t-9}	y_{t-1}	y_{t-4}	y_{t-9}
1	20.76	41.85	37.39	20.76	41.85	37.39	21.27	41.40	37.33	20.76	41.85	37.39
2	17.69	43.74	38.57	24.46	39.82	35.73	18.33	42.89	38.78	20.46	41.92	37.62
3	20.14	42.90	36.96	28.40	38.30	33.30	19.02	42.78	38.20	17.28	44.24	38.48
4	24.07	44.24	31.69	25.28	42.26	32.46	19.54	44.64	35.82	19.38	45.50	35.12
5	19.72	43.61	36.67	19.05	52.58	28.37	20.96	40.02	39.01	16.22	47.95	35.83
6	19.69	38.99	41.32	38.74	33.57	27.68	22.12	40.78	37.10	24.81	42.85	32.35
7	22.18	38.70	39.12	32.38	41.31	26.30	22.36	38.47	39.17	22.40	42.27	35.32
8	25.99	42.61	31.40	28.04	37.44	34.52	28.08	42.18	29.75	27.74	44.42	27.84
9	20.09	37.40	42.51	33.73	27.02	39.25	19.49	42.59	37.92	21.04	35.66	43.30
10	28.08	38.35	33.57	19.54	50.55	29.91	30.50	36.06	33.44	40.41	26.63	32.96
Mean	21.84	41.24	36.92	27.04	40.47	32.49	22.17	41.18	36.65	23.05	41.33	35.62
St. Dev.	3.24	2.59	3.76	6.52	7.43	4.34	4.02	2.48	2.98	6.96	6.07	4.12

Table B.3 RI results for data set I trained by SCE-UA.

Hidden	(1)			(2)			(3)			(4)		
Nodes	y_{t-1}	y_{t-4}	y_{t-9}	y_{t-1}	y_{t-4}	y_{t-9}	y_{t-1}	y_{t-4}	y_{t-9}	y_{t-1}	y_{t-4}	y_{t-9}
1	20.75	41.81	37.45	20.75	41.81	37.45	21.21	41.40	37.39	20.75	41.81	37.45
2	19.29	43.12	37.59	19.09	43.27	37.65	21.09	41.31	37.60	19.09	43.27	37.65
3	20.32	41.99	37.68	21.15	41.80	37.05	20.94	41.11	37.95	16.92	44.04	39.03
4	20.44	42.67	36.90	19.90	42.75	37.36	21.01	41.89	37.10	19.90	42.75	37.36
5	19.71	43.27	37.02	19.63	42.09	38.28	19.84	42.26	37.89	18.39	42.74	38.87
6	19.74	44.26	36.00	16.87	47.99	35.14	20.87	43.81	35.32	18.35	50.89	30.76
7	19.22	43.10	37.68	21.02	40.40	38.59	19.45	42.59	37.96	19.23	41.02	39.75
8	23.28	41.48	35.25	23.83	42.19	33.99	23.25	41.30	35.45	20.41	44.08	35.51
9	19.53	44.03	36.44	17.06	49.35	33.60	19.31	44.20	36.49	11.93	55.21	32.85
10	22.01	41.67	36.31	31.96	36.17	31.87	21.61	42.04	36.35	21.36	45.80	32.84
Mean	20.43	42.74	36.83	21.13	42.78	36.10	20.86	42.19	36.95	18.63	45.16	36.21
St. Dev.	1.30	0.98	0.82	4.31	3.69	2.29	1.15	1.07	1.00	2.69	4.48	3.08

Table B.4 RI results for data set II trained by BP.

Hidden	(1)				(2)				(3)				(4)			
Nodes	y_{t-1}	y_{t-4}	y_{t-9}	x_t	y_{t-1}	y_{t-4}	y_{t-9}	x_t	y_{t-1}	y_{t-4}	y_{t-9}	x_t	y_{t-1}	y_{t-4}	y_{t-9}	x_t
3	8.51	13.26	10.51	67.73	10.18	18.56	19.02	52.23	26.04	40.04	31.52	2.40	20.98	38.24	37.94	2.84
4	11.94	19.96	18.14	49.95	8.47	15.38	15.76	60.39	21.81	34.37	30.42	13.40	19.25	34.96	34.26	11.52
5	17.75	31.67	28.11	22.46	8.19	15.00	14.16	62.65	23.04	35.69	32.43	8.85	18.18	33.28	31.43	17.11
6	8.38	26.03	18.07	47.52	10.31	13.87	15.62	60.20	21.15	36.98	32.17	9.70	18.85	32.58	32.49	16.07
7	15.25	36.28	17.86	30.61	9.22	16.77	18.21	55.81	23.03	45.07	28.21	3.68	14.29	38.18	22.53	25.00
8	15.17	21.98	15.70	47.15	7.59	12.45	12.42	67.55	20.93	37.06	27.63	14.38	13.70	26.35	23.17	36.78
9	12.49	34.91	21.91	30.69	10.57	14.71	14.98	59.74	11.33	49.34	34.57	4.75	6.34	35.59	28.94	29.14
10	12.40	22.43	19.98	45.19	11.28	22.62	14.54	51.56	21.96	38.67	29.25	10.13	17.59	32.27	30.07	20.08
Mean	12.74	25.82	18.78	42.66	9.48	16.17	15.59	58.76	21.16	39.65	30.78	8.41	16.15	33.93	30.10	19.82
St. Dev.	3.28	7.97	5.04	14.28	1.31	3.18	2.15	5.36	4.28	5.10	2.35	4.43	4.66	3.83	5.25	10.55

Table B.5 RI results for data set II trained by GA.

Hidden	(1)				(2)				(3)				(4)			
Nodes	y_{t-1}	y_{t-4}	y_{t-9}	x_t	y_{t-1}	y_{t-4}	y_{t-9}	x_t	y_{t-1}	y_{t-4}	y_{t-9}	x_t	y_{t-1}	y_{t-4}	y_{t-9}	x_t
3	9.35	17.14	19.23	54.28	7.46	15.79	14.56	62.18	19.36	34.64	37.93	8.08	17.70	34.72	33.52	14.07
4	8.83	13.82	11.16	66.19	7.60	14.98	14.52	62.90	26.50	41.02	31.51	0.96	19.54	38.50	33.59	8.38
5	11.84	20.13	17.54	50.49	7.78	15.01	13.18	64.02	23.56	36.38	27.31	12.75	18.91	35.11	30.22	15.76
6	16.99	34.08	30.19	18.74	6.92	15.39	11.98	65.71	20.63	37.06	32.77	9.54	18.43	32.14	31.06	18.38
7	11.63	18.04	17.89	52.44	9.79	16.48	16.75	56.98	22.96	32.10	29.52	15.42	18.05	35.05	32.90	14.00
8	6.70	14.15	10.21	68.95	8.48	12.54	18.87	60.11	19.09	37.80	36.02	7.09	15.84	29.52	19.66	34.97
9	24.81	56.87	18.10	0.22	8.25	18.11	14.04	59.60	24.24	43.09	16.76	15.90	29.86	42.63	23.13	4.38
10	16.52	27.46	22.92	33.09	11.61	17.36	13.38	57.65	23.87	38.36	26.72	11.05	18.72	32.40	34.43	14.45
Mean	13.33	25.21	18.40	43.05	8.49	15.71	14.66	61.15	22.53	37.56	29.82	10.10	19.63	35.01	29.81	15.55
St. Dev.	5.86	14.54	6.33	23.91	1.52	1.70	2.19	3.08	2.60	3.45	6.57	4.88	4.28	4.06	5.46	9.00

Table B.6 RI results for data set II trained by SCE-UA.

Hidden	(1)				(2)				(3)				(4)			
Nodes	y_{t-1}	y_{t-4}	y_{t-9}	x_t	y_{t-1}	y_{t-4}	y_{t-9}	x_t	y_{t-1}	y_{t-4}	y_{t-9}	x_t	y_{t-1}	y_{t-4}	y_{t-9}	x_t
3	9.49	13.08	11.30	66.13	10.07	18.85	19.14	51.94	27.31	37.86	32.74	2.09	17.42	32.59	33.09	16.91
4	11.26	17.54	14.62	56.58	10.52	19.22	19.89	50.37	24.84	36.68	30.44	8.04	21.17	38.68	39.36	0.79
5	10.96	19.25	16.76	53.03	8.92	15.97	16.98	58.13	23.01	37.03	31.41	8.56	18.30	32.94	32.10	16.66
6	15.29	38.03	5.66	41.02	7.55	15.73	17.68	59.04	23.39	39.17	22.90	14.55	20.18	42.04	28.91	8.87
7	15.83	13.67	0.43	70.07	18.39	31.04	18.08	32.50	38.83	29.46	20.28	11.42	30.92	34.27	21.49	13.32
8	12.98	21.57	21.08	44.37	8.36	17.03	12.11	62.50	20.83	33.50	32.87	12.80	16.31	33.80	28.86	21.03
9	16.78	27.79	24.91	30.53	8.73	13.13	15.13	63.01	24.79	36.46	31.83	6.93	17.27	31.51	30.02	21.21
10	13.86	26.19	17.92	42.04	8.81	20.18	18.16	52.85	25.44	36.72	27.78	10.06	17.74	34.20	33.30	14.76
Mean	13.31	22.14	14.09	50.47	10.17	18.89	17.15	53.79	26.05	35.86	28.78	9.31	19.91	35.01	30.89	14.19
St. Dev.	2.59	8.32	8.05	13.46	3.45	5.40	2.48	9.83	5.50	3.04	4.77	3.87	4.73	3.55	5.09	6.75

Table B.7 RI results for data set III trained by BP.

Hidden	(1)					(2)					(3)					(4)				
Nodes	x_1	x_2	x_3	x_4	x_5	x_1	x_2	x_3	x_4	x_5	x_1	x_2	x_3	x_4	x_5	x_1	x_2	x_3	x_4	x_5
5	12.75	10.82	19.59	37.25	19.58	30.80	32.26	26.08	6.96	3.89	13.55	17.67	7.36	40.23	21.20	11.29	5.90	14.35	44.13	24.33
6	12.54	31.84	2.54	35.82	17.27	33.39	26.68	25.78	8.91	5.25	13.89	30.73	0.63	36.82	17.93	1.43	27.44	7.79	40.62	22.72
7	6.74	6.75	4.92	54.42	27.18	37.90	26.57	20.19	10.00	5.34	6.42	16.10	1.30	50.63	25.55	18.60	8.10	5.82	44.71	22.78
8	26.19	31.25	2.09	28.28	12.19	31.67	30.98	25.62	7.35	4.38	19.59	17.11	2.28	41.85	19.16	16.35	9.93	21.56	33.38	18.78
9	24.31	28.32	1.57	34.35	11.45	33.14	33.55	20.67	8.12	4.52	14.62	24.61	6.63	35.29	18.85	18.37	24.94	6.83	31.55	18.31
10	42.55	12.76	2.17	30.39	12.13	36.45	28.05	19.33	10.01	6.16	20.58	16.44	1.49	42.56	18.93	25.96	0.75	7.48	43.21	22.60
Mean	20.85	20.29	5.48	36.75	16.63	33.89	29.68	22.95	8.56	4.92	14.78	20.44	3.28	41.23	20.27	15.33	12.84	10.64	39.60	21.59
St. Dev.	13.00	11.38	7.01	9.29	6.12	2.75	2.99	3.19	1.30	0.81	5.08	5.95	2.93	5.41	2.80	8.29	10.81	6.15	5.73	2.44

Table B.8 RI results for data set III trained by GA.

Hidden	(1)					(2)					(3)					(4)				
Nodes	x_1	x_2	x_3	x_4	x_5	x_1	x_2	x_3	x_4	x_5	x_1	x_2	x_3	x_4	x_5	x_1	x_2	x_3	x_4	x_5
5	21.65	35.24	13.87	18.77	10.48	31.13	28.90	25.74	9.31	4.92	25.19	22.30	3.94	31.09	17.49	6.71	2.98	24.51	42.49	23.31
6	0.12	3.41	1.34	63.33	31.79	27.50	25.41	28.69	11.98	6.42	16.74	5.40	4.53	48.57	24.76	11.22	1.44	11.66	49.27	26.41
7	49.66	2.32	2.23	30.54	15.25	35.32	26.96	20.92	10.53	6.26	34.22	4.31	3.37	38.19	19.90	22.62	5.97	6.53	41.48	23.40
8	32.07	26.48	0.05	26.48	14.92	29.30	33.02	21.11	11.48	5.09	15.97	8.14	2.56	46.36	26.98	6.97	28.24	3.19	40.78	20.82
9	11.15	8.42	5.87	45.92	28.64	32.48	25.40	23.15	13.40	5.57	4.16	5.78	10.26	49.46	30.34	7.76	6.79	3.83	57.33	24.30
10	16.18	6.43	6.10	46.65	24.64	27.70	30.30	26.53	10.13	5.34	6.78	4.58	7.96	52.37	28.31	1.25	16.11	11.99	44.88	25.78
Mean	21.81	13.72	4.91	38.62	20.95	30.57	28.33	24.36	11.14	5.60	17.18	8.42	5.44	44.34	24.63	9.42	10.25	10.29	46.04	24.00
St. Dev.	17.30	13.74	5.02	16.34	8.59	3.03	3.01	3.14	1.46	0.62	11.26	6.93	3.01	8.07	5.00	7.21	10.19	7.91	6.33	2.00

Table B.9 *RI* results for data set III trained by SCE-UA.

Hidden	(1)					(2)					(3)					(4)				
Nodes	x_1	x_2	x_3	x_4	x_5	x_1	x_2	x_3	x_4	x_5	x_1	x_2	x_3	x_4	x_5	x_1	x_2	x_3	x_4	x_5
5	11.05	7.95	36.10	29.33	15.57	34.12	35.65	22.61	4.80	2.82	12.25	13.27	23.98	32.97	17.53	9.23	5.40	4.46	52.28	28.63
6	20.06	35.22	2.05	27.53	15.14	33.26	36.58	22.61	4.58	2.96	23.81	19.93	0.09	36.20	19.98	15.97	25.25	21.59	23.08	14.11
7	31.72	36.70	4.84	15.92	10.82	41.63	39.02	10.77	6.29	2.28	27.65	32.28	5.79	20.22	14.07	36.39	30.05	3.93	19.35	10.27
8	18.53	35.00	6.40	26.77	13.30	32.62	29.05	26.59	7.10	4.64	9.42	21.71	5.45	41.82	21.60	24.63	10.02	8.06	36.26	21.03
9	19.07	31.20	6.78	27.01	15.94	29.04	40.36	19.62	7.28	3.70	17.05	13.05	16.48	34.84	18.59	13.98	41.18	11.11	22.36	11.37
10	22.31	4.83	1.26	47.65	23.95	36.17	27.20	22.51	9.23	4.90	8.46	14.34	3.02	49.67	24.50	20.32	2.77	12.45	43.98	20.48
Mean	20.46	25.15	9.57	29.03	15.79	34.47	34.64	20.79	6.55	3.55	16.44	19.09	9.13	35.95	19.38	20.08	19.11	10.27	32.89	17.65
St. Dev.	6.70	14.68	13.19	10.30	4.43	4.21	5.36	5.38	1.73	1.05	7.88	7.41	9.15	9.80	3.57	9.58	15.38	6.52	13.42	7.02