

Design and Analysis of Evolutionary and Swarm Intelligence Techniques for Topology Design of Distributed Local Area Networks

by

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Abstract

Topology design of distributed local area networks (DLANs) can be classified as an NP-hard problem. Intelligent algorithms, such as evolutionary and swarm intelligence techniques, are candidate approaches to address this problem and to produce desirable solutions. DLAN topology design consists of several conflicting objectives such as minimization of cost, minimization of network delay, minimization of the number of hops between two nodes, and maximization of reliability. It is possible to combine these objectives in a single-objective function, provided that the tradeoffs among these objectives are adhered to. This thesis proposes a strategy and a new aggregation operator based on fuzzy logic to combine the four objectives in a single-objective function. The thesis also investigates the use of a number of evolutionary algorithms such as stochastic evolution, simulated evolution, and simulated annealing. A number of hybrid variants of the above algorithms are also proposed. Furthermore, the applicability of swarm intelligence techniques such as ant colony optimization and particle swarm optimization to topology design has been investigated. All proposed techniques have been evaluated empirically with respect to their algorithm parameters. Results suggest that simulated annealing produced the best results among all proposed algorithms. In addition, the hybrid variants of simulated annealing, simulated evolution, and stochastic evolution generated better results than their respective basic algorithms. Moreover, a comparison of ant colony optimization and particle swarm optimization shows that the latter generated better



results than the former.

Keywords: Optimization, Local area networks, Fuzzy logic, Simulated annealing, Simulated evolution, Stochastic evolution, Swarm intelligence, Ant colony optimization, Particle swarm optimization, Unified And-Or operator.

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Dedicated to my beloved parents



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Contents

	List	of Ta	bles xv
	List	of Fig	gures xvi
1	Intr	oducti	on 1
	1.1	Motiva	ation
	1.2	Object	tives
	1.3	Metho	$dology \dots \dots$
	1.4		butions
	1.5	Organ	ization of Thesis
2	Opt	imizat	ion and Optimization Approaches 11
	2.1	Optim	ization
	2.2	Const	rained Multi-objective Optimization
		2.2.1	Weighted Sum Method
		2.2.2	ε -Constraint Method
		2.2.3	Lexicographic Ordering
		2.2.4	Goal Programming
		2.2.5	Goal Attainment
		2.2.6	Other Approaches
	2.3		Logic and Multi-objective Optimization
		2.3.1	Fuzzy Set Theory
		2.3.2	Fuzzy Reasoning
		2.3.3	Linguistic Variables
		2.3.4	Fuzzy Rules
		2.3.5	Fuzzy Logic System
		2.3.6	Common Fuzzy Operators
		2.3.7	Role of Preferences in Multi-objective Optimization 41
	2.4	Optim	ization Algorithms
		2.4.1	Genetic Algorithm
		2.4.2	Simulated Evolution
		2.4.3	Stochastic Evolution
		2.4.4	Simulated Annealing
		245	Tahu Search 63



		2.4.6 Ant Colony Optimization	. 67
		2.4.7 Particle Swarm Optimization	. 77
	2.5	Conclusion	. 85
3	Top	ology Design of Distributed Local Area Networks	86
	3.1	Background	. 86
	3.2	Assumptions and Problem Statement	. 90
		3.2.1 Assumptions	. 90
		3.2.2 Problem Statement	. 91
	3.3	Design Objectives and Constraints	. 92
		3.3.1 Design objectives	. 92
		3.3.2 Constraints	. 95
	3.4	Fuzzy Logic Approach to the DLAN Topology Design Problem	. 96
	3.5	Characteristics of Test Cases	. 100
		3.5.1 Upper and Lower Bounds for Objective Values	. 101
	3.6	Conclusion	
4	The	Unified AND-OR Fuzzy Operator	104
	4.1	Definition of the Unified AND-OR Operator	. 104
	4.2	Mathematical Properties	
	4.3	Fuzzy Rules for Topology Design	
		4.3.1 Case 1: Simultaneous Optimization of All Four Objectives .	
		4.3.2 Case 2: Simultaneous Optimization of Three Objectives	
		4.3.3 Case 3: Simultaneous Optimization of Two Objectives	
		4.3.4 Case 4: Optimization of Any One Objective	
	4.4	Preferences and UAO	
		4.4.1 Preference rules involving all four objectives:	
		4.4.2 Preference rules involving three objectives:	
		4.4.3 Preference rules involving two objectives:	
		4.4.4 Combining the main rules with preference rules	
	4.5	Application of UAO to Topology Design	
	4.6	Empirical Results and Discussion	
		4.6.1 Application of UAO and OWA to Ex1	
		4.6.2 Application of UAO and OWA to Ex2	
	4.7	Conclusions	
5	Fuzz	zy Stochastic Evolution Algorithm for DLAN Topology Desig	n 130
-	5.1	Fuzzy Stochastic Evolution	
	5.2	Tabu Stochastic Evolution	
	5.3	Experimental Results	
		5.3.1 Effect of Tabu List Size	
		5.3.2 Comparison of FStocE and TFStocE	
	5.4	Dynamic Value of R_c	
		Comparison of OWA and UAO Operators	



	5.6	Conclusions	153
6	Fuz	zy Simulated Evolution for DLAN Topology Design	155
	6.1	Fuzzy Simulated Evolution Algorithm	
		6.1.1 Initialization	156
		6.1.2 Fuzzy Evaluation	156
		6.1.3 Fuzzy Allocation	160
	6.2	Tabu Simulated Evolution	
	6.3	Experimental Results	
		6.3.1 Effect of Tabu List Size	
		6.3.2 Comparison of FSimE and TFSimE	164
	6.4	Dynamic Bias	171
	6.5	Comparison of OWA and UAO Operators	176
	6.6	Conclusions	178
7	Fuz	zy Simulated Annealing for DLAN Topology Design	180
	7.1	5 J 1	
		7.1.1 Initialization	181
		7.1.2 Metropolis Algorithm	182
		7.1.3 Evaluation of a solution	183
		7.1.4 Stopping Criterion	183
	7.2	Hybrid Simulated Annealing Algorithms	
		7.2.1 Tabu Fuzzy Simulated Annealing	184
		7.2.2 Evolutionary Tabu Fuzzy Simulated Annealing	184
	7.3	Results and Discussion	186
		7.3.1 Effect of Tabu List size	187
		7.3.2 Comparison of FSA, TFSA, and TEFSA	
	7.4	Dynamic Markov chain size	201
		7.4.1 Comparison of OWA and UAO	205
	7.5	Conclusion	211
8	Fuz	zy Ant Colony Optimization Algorithm for DLAN Topolo	ogy
	Des	sign	212
	8.1	Fuzzy Ant Colony Optimization Algorithm	213
		8.1.1 Initialization (Generation of Ants)	213
		8.1.2 Ants Activity	213
		8.1.3 Fuzzy Heuristic Value	215
	8.2	Results and Discussion	215
		8.2.1 Effect of Pheromone Deposit and Evaporation	216
		8.2.2 Effect of Number of Ants	219
		8.2.3 Comparison of OWA and UAO	227
	8.3	Conclusions	229

9	Fuzz	zy Par	ticle Swarm Optimization for DLAN	Topology	Design	231
	9.1	Fuzzy	Particle Swarm Optimization Algorithm .			. 231
		9.1.1	Particle Position and Velocity Representa	tion		. 232
		9.1.2	Velocity Update			. 233
		9.1.3	Particle Position Update			. 237
		9.1.4	Fitness Evaluation			. 237
		9.1.5	Initialization			. 238
		9.1.6	Particle Activity			. 238
	9.2	Result	s and Discussion			. 239
		9.2.1	Effect of Swarm size			. 240
		9.2.2	Effect of Acceleration Coefficients			. 246
		9.2.3	Effect of Inertia Weight			. 248
		9.2.4	Effect of Velocity Clamping			. 250
	9.3	Comp	arison of OWA and UAO			. 252
	9.4	Concl	usions			. 254
10	Con	nparis	on of Techniques			255
	10.1	Comp	arison of Single Solution Algorithms			. 255
	10.2	Comp	arison of Population Based Algorithms			. 258
			ll Comparison of OWA and UAO			
	10.4	Overa	ll Best Algorithm			. 262
	10.5	Concl	usion			. 263
11	Con	clusio	n			264
	11.1	Summ	nary			. 265
	11.2	Future	e Research			. 268
	App	endix	A - Nomenclature			308
	App	endix	B - Linear Regression Analysis			311
	App	endix	C - Derived Publications			313



List of Tables

3.1 3.2	Network characteristics assumed for experiments	
4.1	Results for UAO for Ex1. N= number of local sites in the network, B=Bias, C=Cost, D=Delay, H=Hops, R=Reliability, Avg= Average percentage improvement of the five test cases. Statistically significant improvements are in italics.	125
4.2	improvements are in italics	123
4.3	improvements are in italics	126
4.4	improvements are in italics	128
5.1 5.2	Parameter settings for fuzzy StocE used in the experiments Effect of tabu list size on the quality of overall goodness for TFStocE using OWA. Run time is in seconds. Statistically significant improvement is in italics. NA = Not Applicable (since size 7 was used as the	135
5.3	reference for comparison)	
5.4	reference for comparison)	140
	ment. Statistically significant percentage improvements are in italics.	144



5.5	Comparison of FStocE and TFStocE for UAO. TL = Tabu List Size,
	Time = Run time (in seconds), and % imp = percentage improvement. Statistically significant percentage improvements are in italics. 144
5.6	Ratio of tabu moves for TFStocE using UAO
5.7	Effect of different R_c values on overall goodness of solutions with
• • •	$p_0 = 0.1$ and $p_{incr} = 0.05$ for OWA and UAO. Statistically significant
	difference is in italics
5.8	Comparison of FStocE and DTFStocE for OWA. Time = Run time (in seconds), and % imp = percentage improvement. % improvement is for DTFStocE compared to FStocE. Statistically significant improvement is in italics
5.9	Comparison of FStocE and DTFStocE for UAO. Time = Run time (in seconds), and % imp = percentage improvement. % improvement is for DTFStocE compared to FStocE. Statistically significant improvement is in italics
5.10	Comparison of OWA and UAO for TFStocE
6.1	Effect of tabu list size on the quality of overall goodness for TFSimE using OWA. Run time is in seconds. Statistically significant improvement is in italics. NA = Not Applicable (since size 7 was used as the
6.2	reference for comparison)
6.3	reference for comparison)
6.4	ment. Statistically significant percentage improvements are in italics. 170 Comparison of FSimE and TFSimE for UAO. TL = Tabu List Size, Time = Run time (in seconds), and % imp = percentage improvement. Statistically significant percentage improvements are in italics. 170
6.5	Comparison of FSimE and DTFSimE for OWA. Time = Run time (in seconds). % improvement is for DTFSimE compared to FSimE.
6.6	Statistically significant improvement is in italics
6.7	Comparison of OWA and UAO for DTFSimE
7.1	Summary of best overall goodness with Markov chain size $M=10$ and $M=30$ using the OWA operator for FSA. % improvement shows improvement achieved by $M=10$ with reference to $M=30$. Statistically significant improvement is in italics
	viceni, viening improvement to in rounce



7.2	Summary of best overall goodness with Markov chain size $M = 10$
	and M = 30 using the UAO operator for FSA. % improvement shows
	improvement achieved by $M = 10$ with reference to $M = 30$. Statis-
7.9	tically significant improvement is in italics
7.3	Effect of tabu list size on the quality of overall goodness for TFSA
	using OWA. Run time is in seconds. Statistically significant improve-
	ment is in italics. NA = Not Applicable (since size 7 was used as the
	reference for comparison)
7.4	Effect of tabu list size on the quality of overall goodness for TFSA
	using UAO. Statistically significant improvement is in italics. NA =
	Not Applicable (since size 7 was used as the reference for comparison).191
7.5	Summary of overall goodness and percentage improvement with OWA
	for FSA, TFSA, and TEFSA. TL = Tabu list size, imp = percentage
	improvement. Statistically significant improvement is in italics 194
7.6	Average run time (in seconds) of algorithms in Table 7.5 194
7.7	Summary of overall goodness and percentage improvement with UAO
	for FSA, TFSA, and TEFSA. TL = Tabu list size, imp = percentage
	improvement. Statistically significant improvement is in italics 195
7.8	Average run time (in seconds) of algorithms in Table 7.7 195
7.9	Average goodness of links for FSA, TFSA, and TEFSA using the
	OWA operator. AGL represents the average goodness of links. Sta-
	tistically significant percentage difference is given in italics 200 $$
7.10	Comparison of FSA and DTEFSA for OWA. Time = Run time (in sec-
	onds). % imp shows percentage improvement achieved by DTEFSA
	compared to FSA. Statistically significant results are in italics 205
7.11	Comparison of FSA and DTEFSA for UAO. Time = Run time (in sec-
	onds). % imp shows percentage improvement achieved by DTEFSA
	compared to FSA. Statistically significant results are in italics 206
7.12	Comparison of OWA and UAO for monetary cost of best solutions of
	30 runs for FSA. % imp = percentage improvement achieved by UAO
	compared to OWA. Statistically significant results are in italics. $$ 207
7.13	Comparison of OWA and UAO for monetary cost of best solutions
	of 30 runs for TFSA. % imp = percentage improvement achieved by
	UAO compared to OWA. Statistically significant results are in italics. 207
7.14	Comparison of OWA and UAO for monetary cost of best solutions of
	30 runs for TEFSA. % imp = percentage improvement achieved by
	UAO compared to OWA. Statistically significant results are in italics. 207
7.15	Comparison of OWA and UAO for delay of best solutions of 30 runs
	for FSA. % imp = percentage improvement achieved by UAO com-
	pared to OWA. Statistically significant results are in italics 208
7.16	Comparison of OWA and UAO for delay of best solutions of 30 runs
	for TFSA. % imp = percentage improvement achieved by UAO com-
	pared to OWA. Statistically significant results are in italics 208



7.17	Comparison of OWA and UAO for delay of best solutions of 30 runs	
	for TEFSA. % imp = percentage improvement achieved by UAO com-	
	pared to OWA. Statistically significant results are in italics	208
7.18	Comparison of OWA and UAO for number of hops of best solutions	
	of 30 runs for FSA. % imp = percentage improvement achieved by	
	UAO compared to OWA. Statistically significant results are in italics.	209
7.19	Comparison of OWA and UAO for number of hops of best solutions	
	of 30 runs for TFSA. % imp = percentage improvement achieved by	
	UAO compared to OWA. Statistically significant results are in italics.	209
7.20	Comparison of OWA and UAO for number of hops of best solutions	
	of 30 runs for TEFSA. % imp = percentage improvement achieved by	
	UAO compared to OWA. Statistically significant results are in italics.	209
7.21	Comparison of OWA and UAO for reliability of best solutions of 30	
	runs for FSA. % imp = percentage improvement achieved by UAO	
	compared to OWA. Statistically significant results are in italics	210
7.22	Comparison of OWA and UAO for reliability of best solutions of 30	
	runs for TFSA. % imp = percentage improvement achieved by UAO	
	compared to OWA. Statistically significant results are in italics	210
7.23	Comparison of OWA and UAO for reliability of best solutions of 30	
	runs for TEFSA. % imp = percentage improvement achieved by UAO	
	compared to OWA. Statistically significant results are in italics	210
0.1	Description of the ACO and the DED 116	
8.1	Parameter settings for fuzzy ACO used in experiments. DEP = dif-	216
8.2	ference between pheromone deposit and evaporation rates Results for best and worst average overall goodness and their respec-	210
0.2	tive pheromone deposit and evaporation rate setup using OWA. Time	
	= Run time (in seconds), % imp = percentage improvement. Statis-	
	tically significant improvement is in italics	217
8.3	Results for best and worst average overall goodness and their respec-	411
0.0	tive pheromone deposit and evaporation rate setup using UAO. Time	
	= Run time (in seconds), % imp = percentage improvement. Statis-	
	tically significant improvement is in italics	218
8.4	Results for n50 with OWA for different population size, pheromone	210
0.1	deposit rate, and evaporation rate. OG = average overall goodness	
	with standard deviation	222
8.5	Results for n40 with OWA for different population size, pheromone	
	deposit rate, and evaporation rate. Goodness = average overall good-	
	ness with standard deviation.	222
8.6	Results for n33 with OWA for different population size, pheromone	
	deposit rate, and evaporation rate. Goodness = average overall good-	
	ness with standard deviation	223
8.7	Results for n25 with OWA for different population size, pheromone	
	deposit rate, and evaporation rate. Goodness = average overall good-	
	ness with standard deviation	223



8.8	Results for n15 with OWA for different population size, pheromone deposit rate, and evaporation rate. Goodness = average overall good-	22.4
8.9	ness with standard deviation	. 224
	with standard deviation	. 224
8.10	Results for n40 with UAO for different population size, pheromone deposit rate, and evaporation rate. $OG = average$ overall goodness	
0 11	with standard deviation	. 225
8.11	Results for n33 with UAO for different population size, pheromone deposit rate, and evaporation rate. Goodness = average overall good-	225
8.12	ness with standard deviation	. 225
Q 19		. 226
0.10	deposit rate, and evaporation rate. Goodness = average overall goodness with standard deviation.	. 226
8.14	Improvement with respect to increase in number of ants for different DEP rates using OWA. Statistically significant improvements are in	. 220
8.15	italics	. 227
	DEP rates using UAO. Statistically significant improvements are in italics	. 227
8.16	Comparison of OWA and UAO for ACO	
9.1 9.2	Parameter settings for fuzzy PSO used in experiments Effect of swarm size on overall goodness for $n50$ with OWA and UAO.	. 240
9.3	Effect of swarm size on overall goodness for $n40$ with OWA and UAO.	. 241
	Time = Run time (in seconds), % Diff = % Difference. Statistically significant difference is in italics	242
9.4	Effect of swarm size on overall goodness for $n33$ with OWA and UAO. Time = Run time (in seconds), % Diff = % Difference. Statistically	. 242
9.5	significant difference is in italics	. 242
J.U	Time = Run time (in seconds), % Diff = % Difference. Statistically significant difference is in italics	949
9.6	Effect of swarm size on overall goodness for $n15$ with OWA and UAO. Time = Run time (in seconds), % Diff = % Difference. Statistically	. 444
	significant difference is in italics	. 243



9.7	Results for best and worst average overall goodness and their respec- tive number of particles for OWA. Statistically significant improve-	
	ment is in italics	. 244
9.8	Results for best and worst average overall goodness and their respec-	. - 11
	tive number of particles for UAO. Statistically significant improve-	
9.9	ment is in italics	. 244
0.0	= average overall goodness, Time = Run time (in seconds). % imp	
	shows the improvement achieved by one set of values of c_1 and c_2	
	over the other set of values. Statistically significant improvement is	
	in italics	. 246
9.10	Effect of acceleration coefficients on the test cases, for UAO. Good	
	= average overall goodness, Time = Run time (in seconds). $\%$ imp	
	shows the improvement achieved by one set of values of c_1 and c_2	
	over the other set of values. Statistically significant improvement is	0.45
0.11	in italics	. 247
9.11	Effect of inertia weight on the test cases, for OWA. Good = average overall goodness, Time = Run time (in seconds). % imp shows	
	the improvement achieved by one value of w over the other value.	
	Statistically significant improvement is in italics	. 248
9.12	Effect of inertia weight on the test cases, for UAO. Good = aver-	. = 10
	age overall goodness, Time = Run time (in seconds). % imp shows	
	the improvement achieved by one value of w over the other value.	
	Statistically significant improvement is in italics	. 249
9.13	Effect of velocity clamping on the test cases, for OWA. % imp shows	
	the improvement achieved by one value of V_{max} compared to the other	
0.14	value. NA = Not Applicable	. 250
9.14	Average algorithm run time (in seconds) for different values of V_{max} given in Table 9.13	. 251
0.15	given in Table 9.13	. 231
9.10	the improvement achieved by one value of V_{max} compared to the other	
	value. NA = Not Applicable	. 251
9.16	Average algorithm run time (in seconds) for different values of V_{max}	
	given in Table 9.15	. 252
9.17	Comparison of OWA and UAO for FPSO	. 253
10 1	Comparison of TFStocE, DTFSimE, and TEFSA using OWA. % imp	
10.1	denote percentage improvements. Statistically significant improve-	
	ment is in italics	. 256
10.2	Average run time (in seconds) of algorithms in Table 10.1	
	Comparison of TFStocE, DTFSimE, and TEFSA using UAO. % imp	
	denote percentage improvements. Statistically significant improve-	
	ment is in italics	
10.4	Average run time (in seconds) of algorithms in Table 10.3	. 258



10.5	Comparison of FACO and FPSO for OWA. dep = pheromone deposit	
	rate, evap = pheromone evaporation rate, % imp = percentage im-	
	provement achieved by FACO. OG = overall goodness. Statistically	
	significant improvement is in italics	. 259
10.6	Average run time (in seconds) of algorithms in Table 10.5	. 259
10.7	Comparison of FACO and FPSO for UAO. dep = pheromone deposit	
	rate, evap = pheromone evaporation rate, % imp = percentage im-	
	provement achieved by FACO. OG = overall goodness. Statistically	
	significant improvement is in italics	. 260
10.8	Average run time (in seconds) of algorithms in Table 10.7	. 261
10.9	Comparison of FACO and TEFSA for OWA. dep = pheromone de-	
	posit rate, evap = pheromone evaporation rate, Time = run time	
	(in seconds), % imp = percentage improvement achieved by TEFSA.	
	Statistically significant improvement is in italics	. 262
10.10	OComparison of FACO and TEFSA for UAO. dep = pheromone de-	
	posit rate, evap = pheromone evaporation rate, Time = run time	
	(in seconds), % imp = percentage improvement achieved by TEFSA.	
	Statistically significant improvement is in italics	. 263



List of Figures

2.1	Example of global maximum \mathbf{x}^* and local maximum $\mathbf{x_b}$		14
2.2	Membership function for a fuzzy set A		30
2.3	Fuzzy logic system		35
2.4	Effect of β on OWA-AND function		39
2.5	Effect of β on OWA-OR function		40
2.6	Structure of the simulated evolution algorithm		50
2.7	The stochastic evolution algorithm		53
2.8	The Perturb function		55
2.9	The update procedure for stochastic evolution algorithm		57
2.10	Structure of the simulated annealing algorithm		58
2.11	Algorithmic description of tabu search		64
2.12	Pseudo-code of the ant colony optimization meta-heuristic		75
2.13	Pseudo-code of the basic particle swarm optimization algorithm		79
3.1	A typical distributed local area network (WS represents a workgroup		
	switch)		88
3.2	Basic components of a good topology		97
3.3	Membership function of the objective to be optimized		97
4.1	Effect of ν on Unified AND-OR operator	. 1	06
5.1	Two disjoint trees containing nodes P and Q \dots	. 1	32
5.2	Candidate moves (illustrated with dotted lines) that can replace the		
	removed link between P and Q		
5.3	The fuzzy stochastic evolution algorithm for DLAN topology design	. 1	34
5.4	Plots of average overall goodness versus tabu list size for FStocE using		
	the OWA operator for (a) n50 (b) n40 (c) n33 (d) n25 (e) n15 \dots	. 1	41
5.5	Plots average overall goodness versus tabu list size for FStocE using		
	the UAO operator for (a) n50 (b) n40 (c) n33 (d) n25 (e) n15	. 1	42
5.6	Plots of average overall goodness versus tabu list size for FStocE using		
	the OWA operator for (a) n50 (b) n40 (c) n33 (d) n25 (e) n15	. 1	49
6.1	Depths of links with respect to the root node R	. 1	57
6.2	Plots of average overall goodness versus tabu list size for FSimE using		
	the OWA operator for (a) n50 (b) n40 (c) n33 (d) n25 (e) n15	. 1	67



6.3	Plots average overall goodness versus tabu list size for FSimE using the UAO operator for (a) n50 (b) n40 (c) n33 (d) n25 (e) n15 168
6.4	Plots of average goodness of links versus iterations for n40 using OWA
6.5	obtained with (a) FSimE (with bias = 0.0) (b) DTFSimE 174 Plots of variation in bias versus iterations for n40 using OWA obtained with DTFSimE
7.1	Plots of maximum, minimum, and average values of membership func-
	tion "Good topology" versus tabu list size using the OWA operator for (a) n50 (b) n40 (c) n33 (d) n25 (e) n15
7.2	Plots of maximum, minimum, and average values of membership function "Good topology" versus tabu list size using the UAO operator
7.3	for (a) n50 (b) n40 (c) n33 (d) n25 (e) n15
	"Good topology" using the OWA operator for FSA, TFSA, and TEFSA for (a) n50 (b) n40 (c) n33 (d) n25 (e) n15
7.4	Frequency of solution in different membership ranges for function "Good topology" using the UAO operator for FSA, TFSA, and TEFSA
7.5	for (a) n50 (b) n40 (c) n33 (d) n25 (e) n15
	execution time using the OWA operator for FSA, TFSA, and TEFSA for (a) n50 (b) n40 (c) n33 (d) n25 (e) n15
7.6	Plots of best value of membership function "Good topology" versus execution time using the UAO operator for FSA, TFSA, and TEFSA
	for (a) n50 (b) n40 (c) n33 (d) n25 (e) n15
8.1	Plot for overall goodness for test case $n50$ using FACO with DEP = 0.2 and DEP = 0.5
8.2	Percentage improvement with increase in number of ants for different parameter setup using (a) OWA (b) UAO
9.1 9.2	Network topology for PSO example
J. <u>-</u>	(d) n25 (e) n15



"For	the t	thin as	we	have	to	learn	before	we	can	do	them.	we	learn	bu	doina	them.	"
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Aristotle

"I learned this, at least, by my experiment; that if one advances confidently in the direction of his dreams, and endeavors to live the life which he has imagined, he will meet with a success unexpected in common hours."

Henry David Thoreau