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고정비용 수송문제에 적용된 적응형 진화 알고리즘

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An Adaptive Evolutionary Algorithm Applied to the Fixed Charge Transportation Problem

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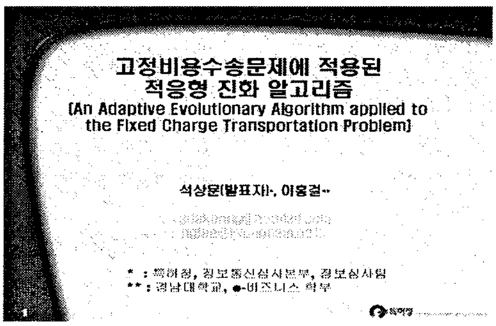
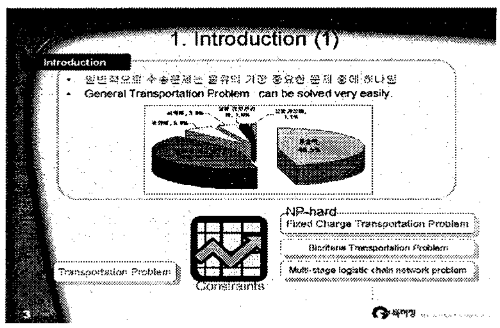
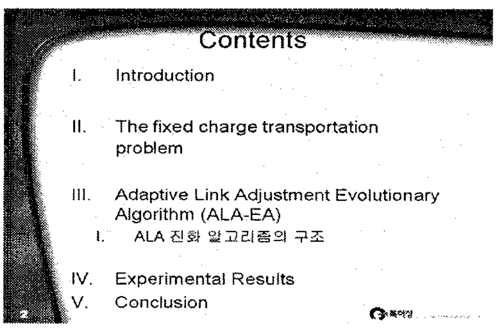
요 약 : 본 논문에서는 고정비용수송문제와 같은 다양한 네트워크 최적화 문제들에 적용될 수 있는 새로운 진화 알고리즘을 소개한다. 제안하는 알고리즘은 기존의 진화 알고리즘과 비교에서 두가지 다른 특징을 지닌다. 첫째, 해 표현법이 다르다. 초기에, 모든 유전인자 값이 '0'으로 설정된다. 둘째, 각 해들은 일치하는 적합도 값에 따라 일종의 라마크식(Lamarckian) 적응 과정을 수행한다.

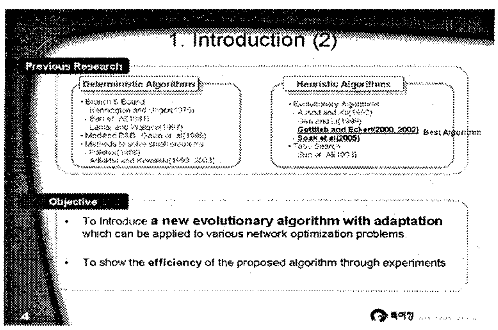
제안하는 적응적 진화 알고리즘의 성능을 측정하기 위해 고정비용수송문제에 적용하였으며 또한 동시에 제안하는 알고리즘을 최적화하기 위해 다양한 실험을 수행하였다. 결론적으로, 제안하는 알고리즘은 기존에 고정비용수송문제를 위해 제안된 가장 우수한 알고리즘보다 더 우수한 성능을 보여주었다.

핵심용어 : 진화 알고리즘, 고정비용수송문제, 최적화 문제, 수송문제, 라마크식 적응형 학습









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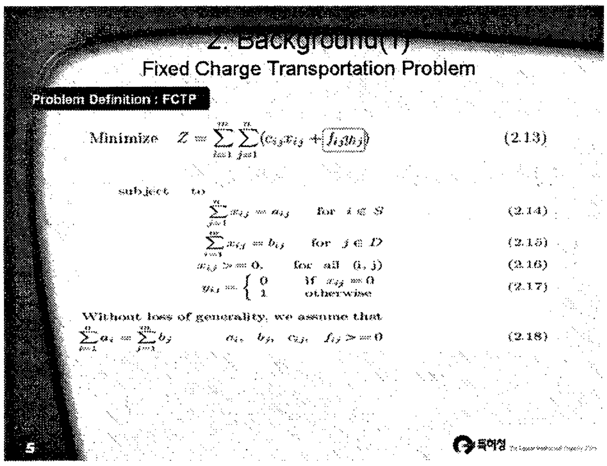
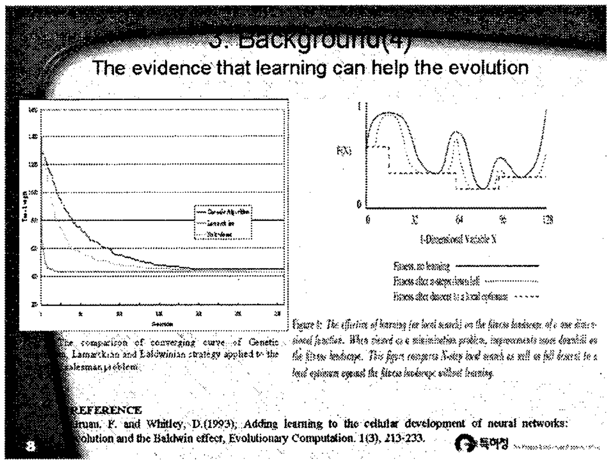
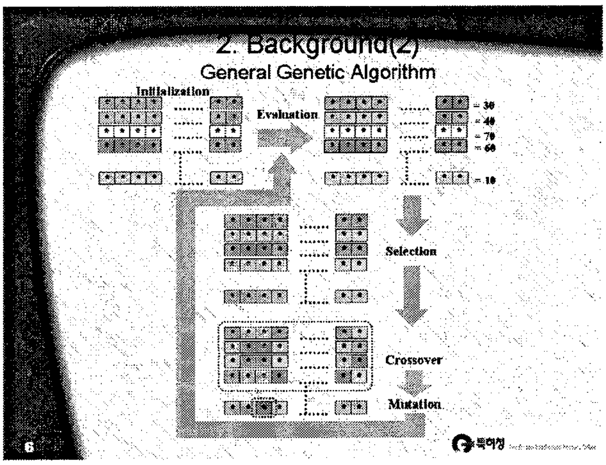
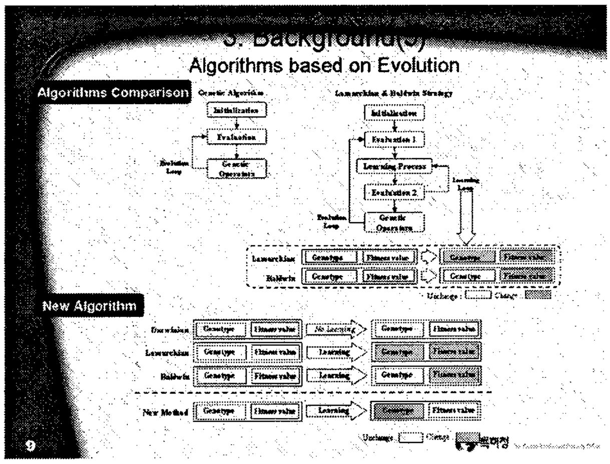
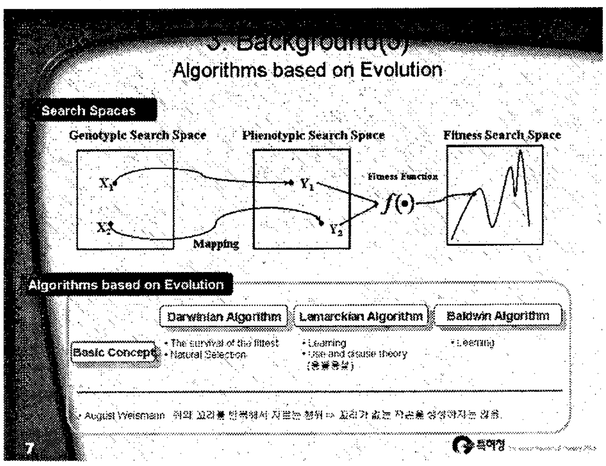

2. Background(1)
Fixed Charge Transportation Problem
Problem Definition : FCTP
Minimize $Z = \sum_{i=1}^{m}\sum_{j=1}^{n}(c_{ij}x_{ij} + f_{ij}y_{ij})$ (2.13)
subject to
$\sum_{j=1}^{n} x_{ij} = a_{ij}$ for $i \in S$ (2.14)
$\sum_{i=1}^{m} x_{ij} = b_{ij}$ for $j \in D$ (2.15)
$x_{ij} >= 0,$ for all (i, j) (2.16)
$y_{ij} = \begin{cases} 0 & \text{if } x_{ij} = 0 \\ 1 & \text{otherwise} \end{cases}$ (2.17)
Without loss of generality, we assume that
$\sum_{i=1}^{n} a_i = \sum_{j=1}^{m} b_j$ $a_i, b_j, c_{ij}, f_{ij} >= 0$ (2.18)
5


3. Background(4)
The evidence that learning can help the evolution
1-Dimensional Variable X
The comparison of converging curve of Genetic, Lamarckian and Baldwinian strategy applied to the salesman problem
REFERENCE
Gruau, F. and Whitley, D.(1993), Adding learning to the cellular development of neural networks: Evolution and the Baldwin effect, Evolutionary Computation. 1(3), 213-233.
8


2. Background(2)
General Genetic Algorithm
Initialization
Evaluation
Selection
Crossover
Mutation
6


3. Background(5)
Algorithms based on Evolution
Algorithms Comparison
New Algorithm
Lamarckian
Baldwin
Darwinian
New Method
9


3. Background(3)
Algorithms based on Evolution
Search Spaces
Genotypic Search Space
Phenotypic Search Space
Fitness Search Space
Fitness Function
Mapping
Algorithms based on Evolution
Darwinian Algorithm
Lamarckian Algorithm
Baldwin Algorithm
Basic Concept
• The survival of the fittest
• Natural Selection
• Learning
• Use and disuse theory
• Learning
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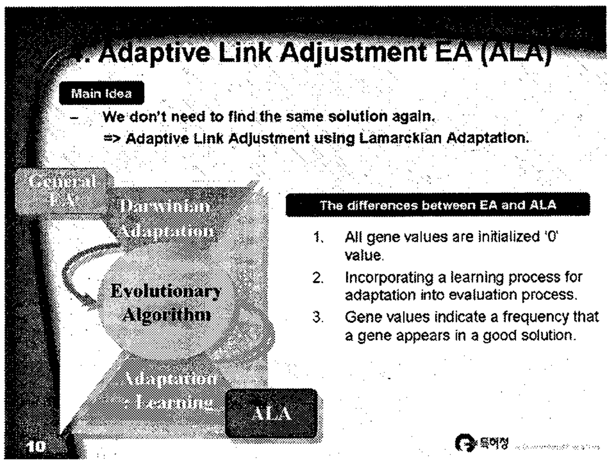
4. Adaptive Link Adjustment EA (ALA)
Main Idea
– We don't need to find the same solution again.
=> Adaptive Link Adjustment using Lamarckian Adaptation.
General EA
Darwinian Adaptation
Evolutionary Algorithm
Adaptation : Learning
ALA
The differences between EA and ALA
1. All gene values are initialized '0' value.
2. Incorporating a learning process for adaptation into evaluation process.
3. Gene values indicate a frequency that a gene appears in a good solution.
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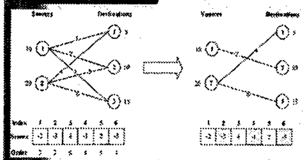
4. Encoding Method for FCTP

Encoding Method



1. 초기화 단계 [illegible]
2. [illegible]
   for [illegible] to pop_size do
   2.1 [illegible]
   2.2 [illegible]
3. 선택과정 (Selection)
4. 교차연산자 (Crossover operator)
5. 변이연산자 (Mutation operator)

pop_size : [illegible]

Figure 2. Pseudo code of ALA applied to FCTP

5. Experimental Results

Table 9.2: Experimental Results on FCTP Instances

Gap(%)		Prüfer	Permutation			Matrix			Direct			RK			ALA		
Instances	Opt.	Avg.	Min.	Avg.	Max.	Min.	Avg.	Max.	EICR	NLO1	NLO2	Min.	Avg.	Max.	Min.	Avg.	Max.
bal8x12	471.55	0.00	-	-	-	-	-	-	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00
ran10x10a	1499	-	0.00	0.59	4.74	0.00	0.00	0.00	-	-	-	0.00	1.24	2.06	0.00	0.18	2.06
ran10x10b	3073	-	0.00	0.29	4.07	0.00	0.54	4.07	-	-	-	0.00	0.00	0.00	0.00	0.00	0.00
ran10x10c	13007	-	0.00	0.19	0.91	0.00	0.28	0.85	-	-	-	0.00	0.01	0.33	0.00	0.03	0.33
ran4x64	9711	21.34	0.58	3.00	5.21	0.00	0.67	1.70	0.29	0.33	0.21	0.00	0.30	1.05	0.00	0.14	0.39
ran6x43	6330	-	0.87	5.30	10.63	0.00	1.28	3.98	-	-	-	0.00	0.51	2.06	0.00	0.36	1.91
ran8x32	5247	-	3.14	6.94	8.61	0.55	3.29	7.62	-	-	-	0.66	1.48	3.33	0.55	0.78	1.31
ran10x26	4270	-	1.55	7.03	11.65	1.85	7.03	11.92	-	-	-	0.00	1.66	3.37	0.00	1.35	2.71
ran12x21	3664	-	3.87	8.32	12.69	1.26	4.53	8.98	-	-	-	0.39	3.11	5.07	0.00	1.32	2.62
ran14x18	3712	13.44	0.45	5.67	9.35	0.00	5.01	8.80	1.73	2.42	1.72	0.00	2.81	5.81	0.00	2.17	3.87
ran16x16	3823	16.58	2.27	5.89	9.86	0.92	4.76	8.53	1.89	1.22	1.90	0.10	2.53	5.41	0.49	0.81	1.59
ran10x12	2714	-	0.00	2.89	5.64	0.00	0.70	5.64	-	-	-	0.00	0.80	5.12	0.00	0.23	2.35
ran12x12	2291	-	0.00	2.71	6.37	0.00	1.51	8.88	-	-	-	0.00	0.74	3.71	0.00	0.46	2.26
ran13x13	3252	-	0.95	3.26	7.26	0.98	3.06	6.59	-	-	-	0.49	1.23	3.81	0.58	0.87	2.30
ran17x17	1373	-	2.02	8.57	15.85	0.58	5.40	10.27	-	-	-	0.00	2.10	7.13	0.00	0.38	1.96
Total Avg.		11.84	4.25			2.71			1.14	0.99	0.95	1.10				0.62	

EICR: Edge-Insert Cycle-Redistribution Mutation, NLO: Node Local Optimize Mutation

Table 3. Degree of improvement : the optimized ALA vs. the previous algorithms.

Improvement(%)	ALA Results		ALA vs. PN	ALA vs. PE	ALA vs. Matrix	ALA vs. Direct			ALA vs. RK
Instances	Gap(%)	CPU(s)				EICR	NLO1	NLO2	
bal8x12	0.00	9.6	0.000	-	-	0.000	0.010	0.000	0.000
ran10x10a	0.00	13.5	-	0.598	0.000	-	-	-	0.043
ran10x10b	0.00	11.4	-	0.289	0.537	-	-	-	0.517
ran10x10c	0.00	21.9	-	0.100	0.278	-	-	-	0.030
ran4x64	0.05	158.4	17.546	2.894	0.515	0.238	0.079	0.180	0.309
ran6x43	0.00	66.65	-	5.055	1.284	-	-	-	0.406
ran8x32	0.58	187.8	-	5.149	2.824	-	-	-	0.721
ran10x26	1.25	177.7	-	5.418	5.418	-	-	-	0.193
ran12x21	0.79	167.75	-	6.352	3.573	-	-	-	0.720
ran14x18	1.66	178.05	10.208	3.808	3.000	-0.128	0.547	-0.138	1.040
ran16x16	0.87	185.55	8.761	4.741	3.718	0.513	0.346	1.011	0.671
ran10x12	0.12	45.2	-	2.505	0.578	-	-	-	0.871
ran12x12	0.12	83.85	-	2.922	1.068	-	-	-	1.120
ran13x13	0.70	122.05	-	2.479	2.280	-	-	-	1.042
ran17x17	0.10	103.75	-	7.985	5.029	-	-	-	1.660
Total Avg.	0.429		8.134	2.591	2.164	0.156	0.235	0.256	0.872

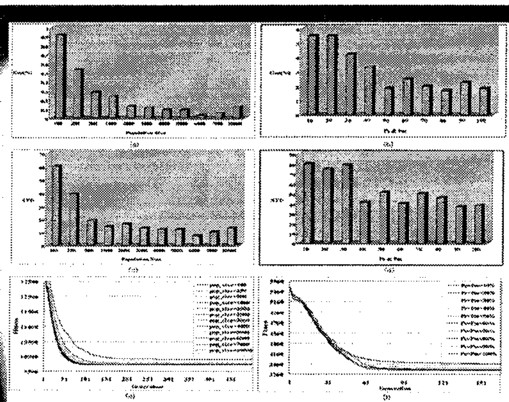


Figure 4. Investigating population size, and crossover and mutation rates: (a), (c) and (e) indicate the Gap measure(%), the standard deviation(STD) of Gap, and the convergence curve for different population sizes on the ran4x64 instances respectively and (b), (d) and (f) indicate the Gap(%), the standard deviation(STD), and convergence curves for different crossover and mutation probabilities, this time on the ran14x18.

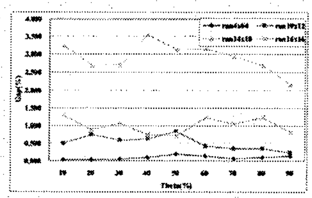


Figure 5. Results tested on various Θ values

Table 4. Experimental results in case using different α and β, and result comparison with the optimized RK(Soak et al. 2005).

Gap (%)		pop_size=3000						pop_size=5000						RK (Soak et al. 2005)		
		α=1, β=1			α=0, β=1			α=1, β=1			α=0, β=1					
Instance	OPT	Min.	Avg.	Max.	Min.	Avg.	Max.	Min.	Avg.	Max.	Min.	Avg.	Max.	Min.	Avg.	Max.
bal8x12	471.55	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
ran10x10a	1499	0.00	0.20	2.06	0.00	0.48	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.21	2.06
ran10x10b	3073	0.00	0.00	0.00	0.00	0.00	2.08	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
ran10x10c	13007	0.00	0.05	0.33	0.00	0.03	0.33	0.00	0.05	0.33	0.00	0.00	0.00	0.00	0.00	0.00
ran4x64	9711	0.00	0.12	0.60	0.00	0.14	0.38	0.00	0.03	0.26	0.00	0.05	0.26	0.00	0.14	0.55
ran6x43	6330	0.00	0.38	1.91	0.00	0.36	1.31	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.08	1.78
ran8x32	5247	0.00	0.79	1.31	0.55	0.76	1.31	0.55	0.61	0.83	0.55	0.68	0.83	0.55	0.64	1.54
ran10x26	4270	0.00	1.84	5.31	0.00	1.35	2.71	0.14	1.36	2.45	0.00	1.23	2.45	0.00	0.95	2.45
ran12x21	3664	0.00	1.17	3.38	0.00	1.32	2.62	0.00	0.97	1.94	0.00	0.79	1.98	0.00	0.81	3.54
ran14x18	3712	0.00	2.34	3.77	0.00	2.17	3.87	0.75	3.09	3.58	0.00	1.88	3.50	2.04	2.61	3.58
ran16x16	3823	0.10	0.98	1.59	0.49	0.81	1.59	0.49	1.01	1.59	0.49	0.87	1.59	0.49	0.93	2.82
ran10x12	2714	0.00	1.84	2.35	0.00	0.23	2.35	0.00	0.88	2.35	0.00	0.12	2.58	0.00	0.07	1.58
ran12x12	2291	0.00	0.43	1.57	0.00	0.48	2.28	0.00	0.25	0.83	0.00	0.12	0.69	0.00	0.53	1.59
ran13x13	3262	0.58	1.08	2.84	0.58	0.87	2.30	0.58	0.68	1.38	0.58	0.79	2.84	0.49	0.83	1.58
ran17x17	1373	0.00	0.50	2.84	0.00	0.36	1.96	0.00	0.02	0.59	0.00	0.10	1.01	0.00	0.36	4.86
Total Avg.		0.737			0.683			0.564			0.428			0.60		

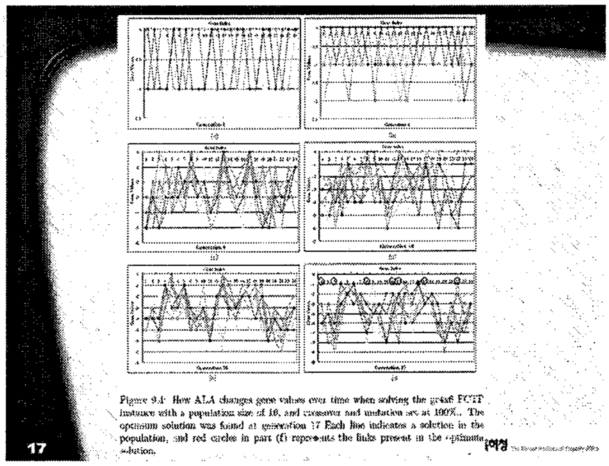


Figure 9.4: How ALA changes gene values over time when solving the gr4x6 FCTP instance with a population size of 10, and crossover and mutation set at 100%.. The optimum solution was found at generation 17 Each line indicates a solution in the population, and red circles in part (f) represents the links present in the optimum solution.
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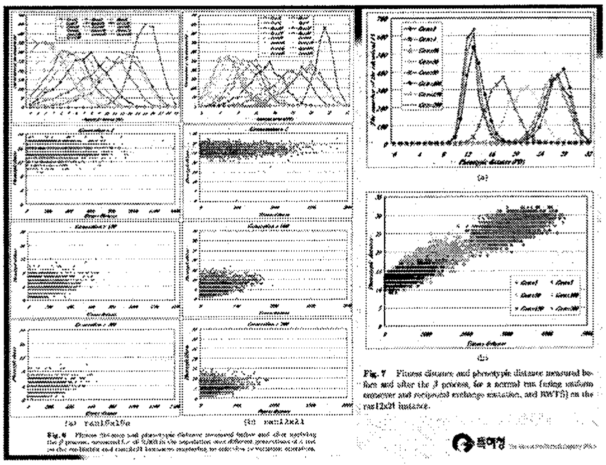
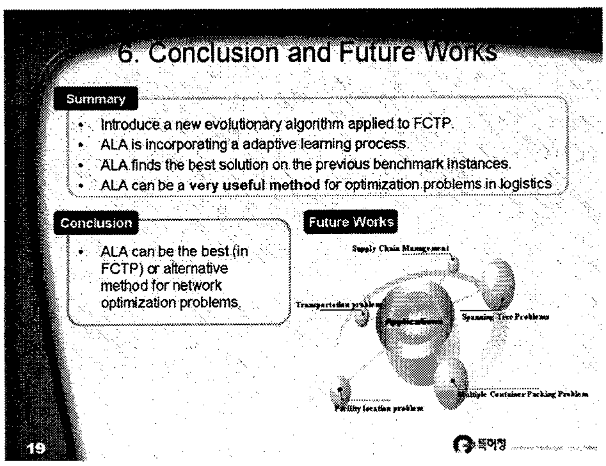

(a) ran10x10a
(b) ran12x21


6. Conclusion and Future Works
Summary
Introduce a new evolutionary algorithm applied to FCTP.
ALA is incorporating a adaptive learning process.
ALA finds the best solution on the previous benchmark instances.
ALA can be a very useful method for optimization problems in logistics
Conclusion
ALA can be the best (in FCTP) or alternative method for network optimization problems.
Future Works
Supply Chain Management
Transportation problem
Applications
Spanning Tree Problems
Multiple Container Packing Problem
Facility location problem
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