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Data Partition and Communication on Parallel Heuristik Model Based on Clonal Selection Algorithm

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Abstract

This research conducted experiments on population-based heuristic parallel algorithms, which are inspired by the clonal selection, called Clonal Selection Algorithm (CSA). Course-grained parallelism model applied to improve execution time. Inter-process communication overhead is addressed by adjusting communication frequencies and size of data communicated. Experiments on six parallel computing models represent all possible partitions and communications and using data of NP-Problem, Traveling Salesman Problem (TSP). The algorithm is implemented using model of message passing libraries MPJExpress and ran in a cluster computation environment. Result shows the best parallelism model is achieved by partitioning initial population data at the beginning of communication and the end of generation. Communication frequency can be up to per 1% of a population size generated. Using four dataset from TSPLib, experiments show the effect of communication frequency that increased best cost, from 44.16% to 87.01% for berlin52.tsp; from 9.61% to 53.43% for kroA100.tsp, and from 12.22% to 17.18% for tsp225.tsp. With eight processors, using communication frequency will be reduced execution time e.g 93.07%, 91.60%, 89.60%, 74.74% for burma14.tsp, berlin52.tsp, kroA100.tsp, and tsp225.tsp respectively. We conclude that frequency of communication greatly affects execution time, and also best cost. It improved execution time and best cost.

Keywords: *clonal selection algorithm, parallel clonal selection algorithm, parallel heuristic model, data partition, coarse-grained communication, traveling salesman problem, message passing interface, MPJExpress*

1. Introduction

CSA (Clonal Selection Algorithm) is one of the population-based heuristic search algorithms. This algorithm has been able to solve combinatorial problems [1],[2], from classical problem the Traveling Salesman Problem (TSP) [2],[3] to particular optimization problems in Iterative Learning Control (ILC) [4]. CSA is part of the Artificial Immune System (AIS), a bio-inspired computing approach to solve complex problems [5],[6]. This approach, like other population approaches, requires significant amount of computation time. Many ideas attempt to address this problem by adopting parallel computation paradigm. As the initiators, Watskin [7] is not specific to the CSA and applied to pattern recognition problems. Hongbing et al. [8] apply the CSA parallelism for protein structure prediction using Open-MPI. Dabrowski and Kobale [9] using the parallel-CSA computation for graph coloring problem.

In this research, parallel computing models will be developed to exploit the available parallelism potential on the clonal selection and CSA. In addition to considering the characteristics possessed by the immune system on the clonal selection events, models built refers to the principles and concepts of parallel computation design, taking into account many aspects: partitioning, communication, agglomerations, and mapping [10]

Based on the principle of communication, there are two groups of models of computation, the master-slave model with a processor acts as a communications controller, and others acting as slave processors are governed by the main processor/master. Other computational model is called multi-communication model or coarse-grained communication, where all processors communicate with each other without any centralized control processor [11],[10].For a population that has been set, the multi-communication model shows better computation speed. However, this has yet to be showed the linkage between computing speed performance and CSA's parameters, i.e. population size, number of the selection, and the amount of data

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communicated between the whole processes. On the other hand, one of the other drawbacks is the need for inter-processor communication. We need to minimize the effect of this communication overhead.

This research will be focused to search for patterns of relations between parameters of CSA and its relations with parallel computation. The parameters investigated are: size of initial population (whether partitioned or not), size of population data that is communicated between processes, and their relations with computational results (best cost and execution time). This study also makes observations on the communication frequencies on multi-communication models. The models are implemented on parallel computing with multicore and cluster environment using MPJExpress (Java Message Passing Model). MPJExpress is a library that implemented with Message Passing Interface (MPI's) specification library [12]. MPI could support parallelizing population based algorithm, such us genetic algorithm [13].

The study focuses on the aspects that must be considered in the library application, the resulting computational models, as well as the results of the computation itself. Systematically, this paper contains: Introduction, The Proposed Method/Algorithm, Research Methods, Results and Discussion, and Conclusion.

2. The Proposed Method/Algorithm

2.1. Parallel Clonal Selection Algorithm

Clonal Selection Algorithm (CSA) is an algorithm that inspired by the immune system, especially on the clonal selection events [9]. Clonal selection is an event in the immune re-sponse, whereby an attack of antigen, B-cells as antibody-producing cells would be multiplied if its receptors match with the antigens' receptor. Cells that do not have matched receptor do not participate in the selection. The match calculation is known as affinity maturation.

CSA is part of Bio-Inspired Algorithm family called Artificial Immune System (AIS) [2],[14],[1]. CSA maps antibodies (an immune component) as a population intended to be a solu-tion, whereas antigen mapped as an issue (problem). In mapping the problem with a solution based on the inspiration of immune system, there is an activity called as immune engineering [6] [3]. In the TSP problem; immune response represents a solution whereas antigen represents the problem; in this case is a collection of node/city where the salesman must visit, the B-cells (antibody) represents a tour that is formed [3]. Details about the CSA can be found in [2] and the principles of this parallel algorithm design can be seen in [10].

Using multicommunication model, which all processes communicate with each other without any master control, we then defined population data partition. Referring to the behavior of the immune system and clonal selection, there are two ideas, e.g. initial population generated by single processor, and each processor independently generating initial population.. Communication between processors is done after clonal selection operation, i.e. selection - cloning - hypermutation - random replacement. The best population in each processor then sent to all processors.

2.2. Parallel Clonal Selection Algorithm for TSP

To apply the clonal selection algorithm into the optimization problem, in this case the TSP problem, we need mapping between problem and a clonal selection algorithm scheme. This mechanism is called immune engineering. In immune engineering, there are two main activities that must be considered, namely representation and affinity maturation. Representation is a problem that mapped into populations in the immune system, which is the expected optimal individual tour TSP. The affinity maturation is cost calculation between the proximity of a tour in each population with the expected best solution. Here's an overview of immune engineering in Table 1.

3. Research Method

This study is experimental, started with the construction of computational models, which are then implemented by utilizing MPJExpress library in parallel computing environments such as multicore and cluster. Research method can be seen in the Figure 1.

Table 1. Immune engineering

Clonal Selection Processes	TSP Problem
Population initialization	Set of randomly generated tour. There are (n-1)! possibilities that the tours may be raised. This population is part of the whole tours. The number of tours is generated by the specified population size.
Affinity evaluation	Evaluation of affinity checks each tour that has raised, find the cost required to form the tour.
Selection: affinity maturation	Affinity is how close the cost of a tour with the optimal/best cost. The closer, the higher affinity and will be selected.
Cloning	Cloning is process to copy selected tour, number of copies are depends on clone factor: □
Hypermutation	Cloned/copied tour will be mutated according to hypermutation probability mutate factor: □
Edit receptor/elisitation	After mutate, we will have the best tours-that will be replacedthe worst tours in the initial population.The number worst tour replaced will be depends on some random size replacement d.
Stop condition	Clonal selection process will be repeated until a stop condition obtained. Stopping criteria could be the number of generations, or numbers of populations (tours) are evaluated, or best cost found.
Processing element communications	Exchange best tours produced by each of the processing elements to other processing elements.

Here the description about research method that used in this research:

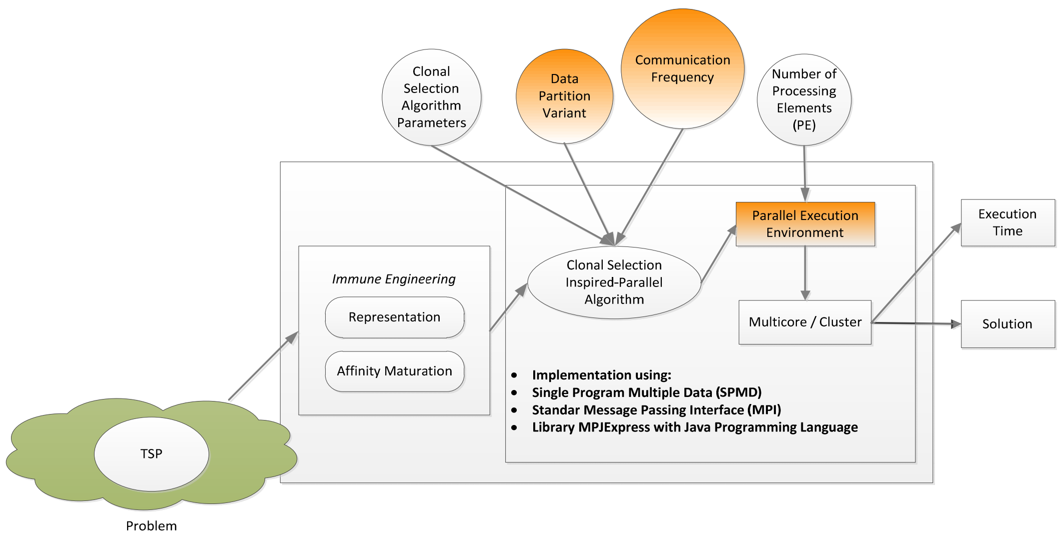

Clonal Selection Algorithm Parameters
Data Partition Variant
Communication Frequency
Number of Processing Elements (PE)
Parallel Execution Environment
Execution Time
Immune Engineering
Representation
Affinity Maturation
Clonal Selection Inspired-Parallel Algorithm
Multicore / Cluster
Solution
Implementation using:
Single Program Multiple Data (SPMD)
Standar Message Passing Interface (MPI)
Library MPJExpress with Java Programming Language
TSP
Problem

Figure 1. Reseach method

The problems are going to have immune engineered; which are representation and affinity maturation.There are parallel clonal selection algorithm called clonal selection inspired parallel algorithm (CSI-PA) that has several parameters that has been set. Parameters of the clonal selection consists of the population size (N), the number of selection (n), the number of generations (g), and the number of nodes (non) from TSP Problem. These algorithms are executed in parallel execution environment, e.g multicore and cluster computer. There are several procesing elements to process.These executions will result solustion, e.g. the best tour with their best cost and time for execution. These algorithms are implemented using single program multiple data model, using message passing interface standard (MPI) and libray named MPJExpres using Java Programming language. The algorithms will be executed using some variant of data partition and communication frequency.

Experiments conducted on multicore and cluster environment with a headnode and 16 compute nodes. Eight compute nodes used in these experiments with their specification: 16 x 2.90GHz CPUs storage of 895.465GB in RAID5 configuration. The head-node is using CPUs 32x2.90GHz, 126.13GB memory, local disk 895.465GB and Linux 2.6.32-279. The compute-nodes are using CPUs 16x2.70GHz, 15.66GB memory, local disk 142.835GB and Linux 2.6.32-279. Software environments are using Java Message Passing Model, MPJExpress that developed using the IDE Netbean 7.2.1 with Java 1.7.0_13 version. Entirely run on Windows 7 Operating System v6.1.

To execute it, compiled simulation execution can be seen in Table 2 as follows:

Table 2. Experiments scenario

Dataset Name		Burma14, Berlin52, KroA100, tsp225
Known Best Cost from TSPLib [***16***]		3.323,7.542,21.282,3.916
Number of Node		14, 52, 100, 225
Number of Generation		100,000
Parameter Value	N, initial population	50
	n, number of selection	10
	Size of population data communicated	Number of partition- N
	Clone factor β	0.1
	Mutate factor δ	2.5
Number of processor		2, 4, 8
Processing Environment		Multicore, Cluster

Some parameter values have been defined, such as the value of the initial population, the number of selection, clone factor, and mutate factor. Initial population partition was done in Figure 2 as follows:

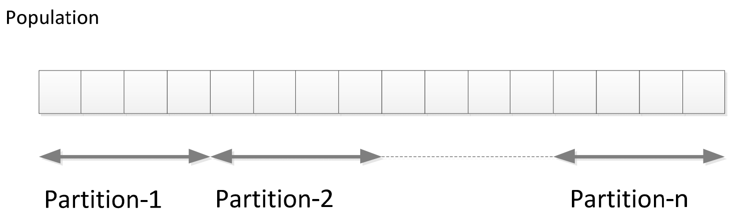


Figure 2. Population partition

Description:

- Number of partition = number of processors (np)
- Population size in 1st, 2nd… (np-1)th Partition (pp) = N/np
- np^{th} Number of Population in Partition (pp) = N – (np*pp)
- Example: N = 50, np = 4. Number of partition = 4, Population size in 1st, 2nd , 3rd partition = 12, population size in 4th partition = 14.

Experiment overview can be resumed in Figure 3. Thus we have six models for experiment. We do several executions for each experiment, and then get the average result from each ex-periment to report in section Result and Discussion. After that, we will check the effect of communication frequency to execution time result and the best cost obtained.

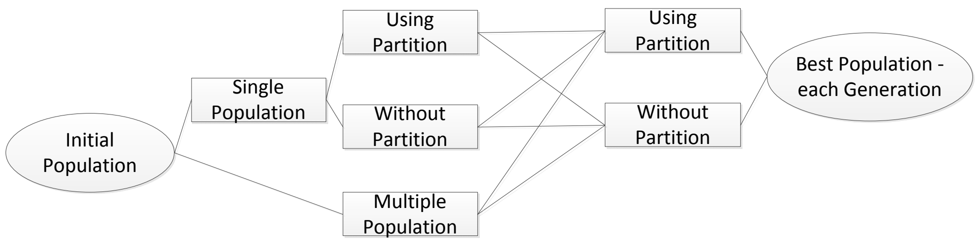


Figure 3. Experiment scenarios

4. Result and Discussion

Based on the above scenario, conducted experiments on cluster environment with four datasets, e.g., burma14.tsp, berlin52.tsp, kroA100.tsp,and tsp225.tsp. Results logged from main processor (process 0). For the six models, we observed effects of the number of generations and the frequency of communication on the best cost and the execution time. We do with 100.000 number of generation. There are two result experiments, first result will show the effect of partition and the second one is the effect of communication frequency to exe-cution time and best cost obtained. Detail of the result will be presented in the following section.

4.1. Result I

The first experiment was to observe the six models in terms of the number of genera-tions, best cost, and execution time. Table 3 below shows the results for the six experiments based on weight and execution time. Experiments about execution time are summarized in Table 4 below.

Table 3. Best cost for all dataset

Number of Node	Number of Process	Best Cost					
		Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
14	2	3.394	3.359	3.323	3.394	3.359	3.323
	4	3.371	3.323	3.323	3.371	3.323	3.323
	8	3.403	3.336	3.336	3.323	3.438	3.413
	Average	3.389	3.339	3.327	3.363	3.373	3.353
52	2	17.079	19.226	17.573	17.079	19.226	17.573
	4	20.028	20.341	20.325	20.028	20.341	20.325
	8	19.353	20.124	19.070	20.856	19.437	19.453
	Average	18.820	19.897	18.989	19.321	19.668	19.117
100	2	109.807	124.267	124.241	110.579	114.163	113.407
	4	108.539	122.320	122.265	116.127	113.717	121.420
	8	127.794	125.157	121.283	119.702	116.325	121.233
	Average	115.380	123.915	122.596	115.469	114.735	118.687
225	2	32.309	34.333	32.283	33.411	33.543	34.193
	4	34.440	32.047	33.814	33.344	33.883	33.913
	8	34.321	33.392	33.823	32.281	34.556	33.731
	Average	33.690	33.257	33.307	33.012	33.994	33.946

Table 4. Execution time for all dataset

Number of Node	Number of Process	Execution Time					
		Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
15	2	71.039	65.484	55.213	64.205	72.257	60.230
	4	105.511	96.915	102.549	93.889	102.149	92.042
	8	186.131	203.690	180.388	186.855	174.511	179.612
	Average	120.894	122.030	112.717	114.983	116.306	110.628
52	2	186.928	156.777	202.463	181.735	168.952	210.396
	4	298.612	340.347	340.399	291.097	316.998	349.252
	8	347.178	456.233	477.473	435.925	464.344	459.695
	Average	277.573	317.786	340.112	302.919	316.765	339.781
100	2	382.329	412.065	395.405	396.022	380.500	378.781
	4	584.470	684.217	664.053	674.349	671.874	667.572
	8	572.945	855.017	845.576	864.971	849.929	872.740
	Average	513.248	650.433	635.011	645.114	634.101	639.698
225	2	1.441.560	1.400.791	1.393.369	1.430.928	1.408.072	1.535.162
	4	1.854.656	1.908.771	1.975.035	1.912.938	1.952.451	1.876.631
	8	1.649.006	2.430.180	2.456.985	2.404.307	2.436.130	2.381.234
	Average	1.648.407	1.913.247	1.941.796	1.916.058	1.932.218	1.931.009

As we can see, each models gain their best cost differently for each dataset and num-ber of processing elements. For dataset burma14 that has number of node = 14, the best cost was obtained by several models, with 2 and 4 number of processing elements. Their best costs are 3323 which is same as best known best cost from TSPLib for burma14.tsp dataset. But increasing number of node made different results, as we can see model number 1 gained better best cost for dataset berlin52, kroA100, and tsp225 with 2 number of processing elements, close to model number 2 with 4 number of processing element. Table above shows that number of processing elements has no direct impact for best cost obtained for all dataset. It because, best costs obtained are more depend on.cloning and hypermutation mechanism that result random tour. Tabel 4 shows experiment results for execution time. If we use more processing element, then we will need more time to execute. There are communication overheads between processing elements. Except model 1, that if we use 8 number of processing elements, we will have better execution time than if we use 4 number of processing elements. Averagely, model number 1 has better execution time than others for all datasets.

4.2. Result II

In this experiment, we carried out some reductions of the frequency of communication between processors. The ultimate goal is to get the execution time as possible, but does not reduce the quality of the final result, i.e. best cost. Table 5 shows summary of the best cost after we controlled the communication frequency.

Table 5. Best cost for all dataset after controlled communication frequency

Number of Node	Number of Process	Execution Time after controlled Comm. Frequency					
		Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
14	2	13.965	13.876	13.101	12.822	13.064	14.593
	4	13.695	13.488	14.166	14.059	15.296	15.936
	8	12.905	16.469	15.904	13.848	17.521	17.213
	Average	13.522	14.611	14.390	13.576	15.294	15.914
52	2	48.347	49.279	48.468	47.233	51.105	47.659
	4	48.690	54.209	52.884	51.390	55.027	52.415
	8	39.501	55.954	53.954	36.604	55.549	53.125
	Average	45.513	53.147	51.769	45.076	53.894	51.066
100	2	118.584	119.178	122.385	116.806	118.913	118.218
	4	116.400	117.955	122.642	123.459	121.134	121.325
	8	90.327	124.685	125.294	89.993	122.733	127.565
	Average	108.437	120.606	123.440	110.086	120.927	122.369
225	2	788.580	786.276	782.141	789.671	793.007	787.424
	4	777.486	798.155	787.218	790.475	794.047	781.497
	8	620.036	794.198	803.693	607.228	797.229	793.964
	Average	728.701	792.876	791.017	729.125	794.761	787.628

Table 6 shows the best execution times after we controlled communication frequency.

Table 6. Execution for all dataset after controlled communication frequency

.	Number of Process	Best Cost after controlled Comm. Frequency					
		Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
14	2	3.371	3.323	3.394	3.359	3.359	3.346
	4	3.323	3.336	3.388	3.323	3.369	3.336
	8	3.323	3.336	3.323	3.323	3.371	3.336
	Average	3.339	3.332	3.368	3.335	3.366	3.339
52	2	13.887	13.938	12.437	12.896	13.026	13.289
	4	9.034	12.988	12.904	8.735	12.888	13.795
	8	9.303	12.399	12.582	8.668	10.997	11.892
	Average	10.741	13.108	12.641	10.100	12.304	12.992
100	2	49.952	55.588	54.893	62.895	58.913	53.916
	4	39.830	47.974	52.386	41.524	44.997	47.142
	8	46.211	43.555	46.905	46.971	51.436	43.100
	Average	45.331	49.039	51.395	50.463	51.782	48.053
225	2	24.384	24.646	25.364	25.231	25.456	25.911
	4	22.793	23.861	24.283	23.146	24.474	24.621
	8	23.811	23.661	23.978	23.856	23.725	23.557
	Average	23.663	24.056	24.542	24.078	24.552	24.696

After we controlled communication fre-quency, we gained execution times 12.822ms (M4; np2), 36.604ms (M4; np2), 89.993ms (M4; np8), and 607.228ms (M4; np8) for burma14.tsp, berlin52.tsp, kroA100.tsp and tsp225.tsp respectively. Compare to Table 4 above, the execution time reductions are 93.07%, 91.60% , 89.60%, 74.74% respectively. The average execution time shows that Model 1 gained the best execution time.
We can see that controlled frequency greatly affects the execution time, and also the best cost. It improved execution time and also best cost.

4.3. Result III

This section shows comparison the result from section 4.2 with another approach from another researcher. Since another researchs using different case and different parallel programming environment, we need to do re-created algorithm and program and apply it to the same case, TSP problem, with some assumption. Since model 1, with single population and partition shows the best result, we choose it and compare to algorithm from [8]. Figure 4 describe parallel computing model from Hongbing, using ring communciation; compare to model 1 from section 4.2, using mesh communication, can be shown in Figure 5 below:

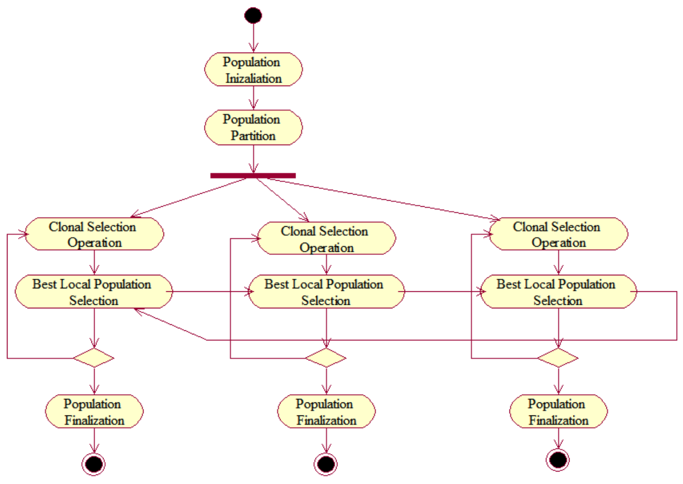


Figure 4. Single-population with ring communication

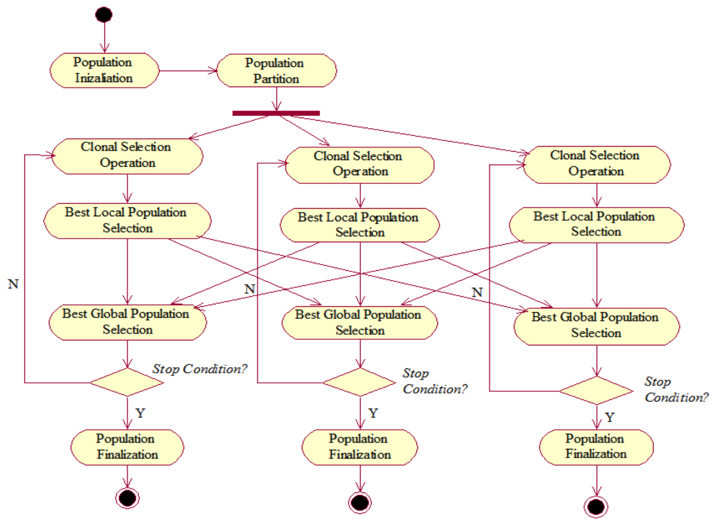
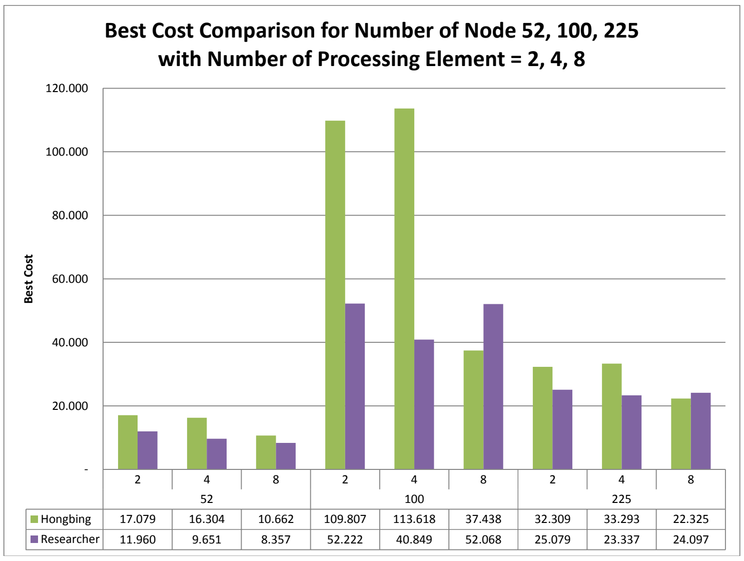

Population Inizaliation
Population Partition
Clonal Selection Operation
Best Local Population Selection
Best Global Population Selection
Stop Condition?
N
Y
Population Finalization

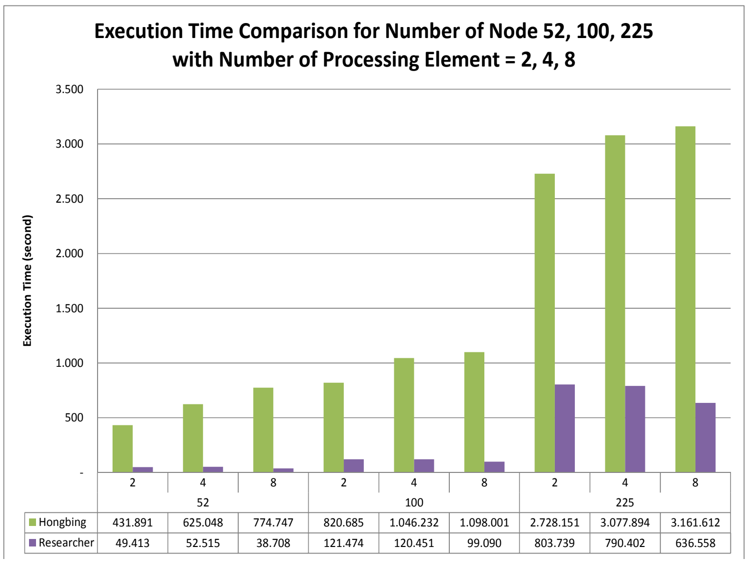
Figure 5. Single-population with mesh communication

Figure 6 shows best cost comparison for all dataset with number of processing element 2, 4, and 8 and Figure 7 show execution time comparison for all dataset with number of processing element 2, 4, and 8. As we can see, from best cost, there are some differences results from each dataset. But over all, result from researcher gain better best cost than other researcher. From execution time point of view, result from researcher gain significant improvement than result from other researcher. We conclude that our approaced lead to better result.



	2	4	8	2	4	8	2	4	8
	52			100			225		
🟩 Hongbing	17.079	16.304	10.662	109.807	113.618	37.438	32.309	33.293	22.325
🟪 Researcher	11.960	9.651	8.357	52.222	40.849	52.068	25.079	23.337	24.097

Figure 6. Best cost comparison for all dataset with several number of processing element



	2	4	8	2	4	8	2	4	8
	52			100			225		
🟩 Hongbing	431.891	625.048	774.747	820.685	1.046.232	1.098.001	2.728.151	3.077.894	3.161.612
🟪 Researcher	49.413	52.515	38.708	121.474	120.451	99.090	803.739	790.402	636.558

Figure 7. Execution time comparison for all dataset with several number of processing element

5. Conclusion

Experiment results showthat all the models, produce best weight relatively close to known-best-cost for burma14 dataset. However, for other dataset need more generation to obtain best know result. Before and after controlled communication frequency, there are some models that obtained 100% known best cost e.g:Model 2 wih np=4 (M2; np4),M4; np8,M5; np4,M6; np2 np4,M1; np4 np8,M2; np2,M3; np8,M4; np4 np8. The execution time significantly differs for each model, increases with the number of gener-ations and the number of processors used. It appears that the amount of processing affects the execution time but does not affect the best cost. Frequency of communication greatly affects the execution time, and also the best cost. It improved execution time and best cost. Communication frequency can be up to per 1% of a population size generated. Using four dataset from TSPLib, experiments show the effect of communication frequency that increased best cost, from 44.16% to 87.01% for berlin52.tsp; from 9.61% to 53.43% for kroA100.tsp, and from 12.22% to 17.18% for tsp225.tsp. With eight processors, using communication frequency will be reduced execution time e.g 93.07%, 91.60%, 89.60%, 74.74% for burma14.tsp, berlin52.tsp, kroA100.tsp, and tsp225.tsp respectively.

We conclude that with six models, to obtain best cost the best model is M1, e.g single population with partition in initial population and its best population; and to obtain best execution time, the best model is M4, e.g single population with partition at the end of generation. For the average execution time we can see Model 1 gained the best cost and the execution time. These conditions are best if the communication frequency is controlled. After compare to another approach from another researcher, from execution time point of view, result from researcher gain significant improve-ment than result from other researcher. We conclude that our approaced lead to better result

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