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Coopetition in Solving Combinatorial Optimization Problem: Application to the Industrial Assembly Line Balancing Problem

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Article Info
Volume 82
Page Number: 11992 - 12000
Publication Issue:
January-February 2020

Article History
Article Received*: 18 May 2019*
Revised*: 14 July 2019*
Accepted*: 22 December 2019*
Publication*: 21 February 2020*

Abstract
Optimization problem, specifically combinatorial optimization problem, has been investigated for decades. While a variety of computational approaches have been introduced, little works had adopted the concept of coopetition in solving the complex combinatorial optimization problem. This paper introduces coopetition strategy, adopted in an approximate approach inspired from biological system to effectively address the underlying problem. Also, problem-specific information was also incorporated to improve the approach quality. The proposed approach was justified by applying to 242 data set instances of assembly line balancing problems. The approach had obtained the optimal results for all data sets instances, with new optimal was found in some data instances. In addition, the approach also obtained statistically significant results in three out of five approaches up to 99.5% confidence interval. This shows that coopetition strategy may be the key to improving the performance of an approximate approach.

Keywords: *Combinatorial optimization, competition, cooperation, coopetition, simple assembly line balancing, artificial immune system.*

I. INTRODUCTION

A combinatorial optimization problem can be defined as discrete optimization problem while either minimizing or maximizing a given objective function under a given set of constraints [1]. Interactions between two or more discrete variables, form the very basis of combinatorial optimization problem. In the case of complex combinatorial problems, approximate approaches have been frequently adopted compared to exact and heuristic approaches due to time and computational limitations [2]. An example of such approach is the multi-agent system where interactions among the agent forms the emergence behavior, which considered to be much more complex than the sum of a single agent, involving global control or structure that could dynamically and autonomously change to obtain a unique goal through a concerted effort [2]. In essence, this can be loosely defined the concept of cooperation.

In contrast, competition has been regarded as the opposite of emergence behavior but with novel benefits [3]. Previous study had justified the beneficial drives either from the perspective of competition or cooperation in the context of organizational performance and firm innovation. However, the study on both concepts called coopetition, had been limited. If certain combination of two or more discrete variables is regarded as an entity, interactions of one or more entity may be investigated in term of the coopetition concept. Such a concept would provide a new perspective in solving the complex combinatorial optimization problem. The goal of this paper is to determine the impact and

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benefits of coopetition within the domain of combinatorial optimization problem.

The assembly line balancing (ALB) problem had been modelled as a discrete and complex combinatorial problem that involves design considerations and the intricacy of multiple components in the assembly line [4]. The problem arises when a firm introduces a new assembly line or redesigns an existing one in order to manufacture high-demand products. A balanced system is expected to save capital expenditure and reduce cycle time less than value that predefined based on the desired production rates [4]. The type E simple assembly line balancing (SALB-E) problem is considered in this paper as the test bed since it had been utilized for decades for testing the performance of different approaches.

In the context of a combinatorial optimization problem, an efficient approximate approach is well-suited for SALB-E problem. Although optimality is not guaranteed, the complexity can be reduced to obtain near-optimal solution. Several well-known methods such as genetic algorithm [5], simulated annealing (MRMOSA) [6], constraint programming (RMCP) [7], to name a few. Since the artificial immune system (AIS) approach is naturally enriched with rapid search, diversity preserving, and elitism [8], AIS had been widely utilized in a variety of domain problems. As such, this paper adopted an enhanced AIS approach in solving the SALB-E problem.

Up to this point, the focus of most previous approaches was either to improve the optimization approach itself or the optimization problem to be solved. While improvement on the optimization approach is crucial for improving the possibility of finding optimal solutions, incorporating a problem-specific information enhances the capabilities of that approach. Therefore, utilizing a problem-specific information can be utilized into the search process of the existing approach, improving the final solution quality. This study is interested in problem-specific information called the shifting bottleneck identification.

Bottleneck identification in the SALB-E context can be defined the process of identifying the manufacturing resources (or machine) which significantly impact the performance of the production system [9]. Bottleneck that occurred at the time of the current operation of an assembly line is known as sole bottleneck, while bottleneck that occurred in the subsequent or future operations is called as shifting bottleneck due to their shifting positions in the production system caused by operator's learning or machine's downtime. Most methodologies focus on sole bottleneck identification which focuses on the present or past state of the system. Additionally, the shifting bottleneck is scarcely studied and identifying it is not a straightforward procedures [9]. While simulation bottleneck can demonstrate the possibility of evaluating the production system realistically prior to realization and investment of capital, it failed to emphasize the possible improvements afterward.

Note that this paper extends the work conducted by [4] in which the major contribution is twofold. Firstly, an enhancement of the AIS approach based on problem-specific information to effectively address the SALB-E problem is introduced. Secondly, this paper realizes the concept of coopetition in the context of the SALB-E problem and determines its impact to the discrete combinatorial optimization in general.

II. PROBLEM BACKGROUND

Manufacturing a product on a simple assembly line requires delegating the total amount of work into a set of elementary operations named tasks (j). Performing a task j consumes a task time (t_j). Due to technological and organizational requirements, the precedence constraints of tasks need to be satisfied. Another restriction involves assigning each task to exactly one station. The S_{jk} set of tasks are assigned to a machine (k), constituting the machine load, where the cumulated task time $t(S_{jk}) = \sum t_j$ is called

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machine time. When a fixed common cycle time C_t is given, a line balance is feasible only if the machine time of any station does not exceed C_t.

A precedence diagram, which represents the assembly network of tasks of a certain product, is best explained by visualization (Fig. 1). It contains a node for each task, node weights for the task times and arcs for the precedence constraints. Figure 1 shows an example of a precedence diagram with J = 11, each having task times between 1 and 7 (time units). The precedence constraints of task 7 refer to its processing requirement where tasks 3, 4 and 5 (direct predecessors) and 1 (indirect predecessor) need to be completed. On the other hand, task 7 must be completed before its (direct and indirect) successors, task 9 and task 11 can be started.

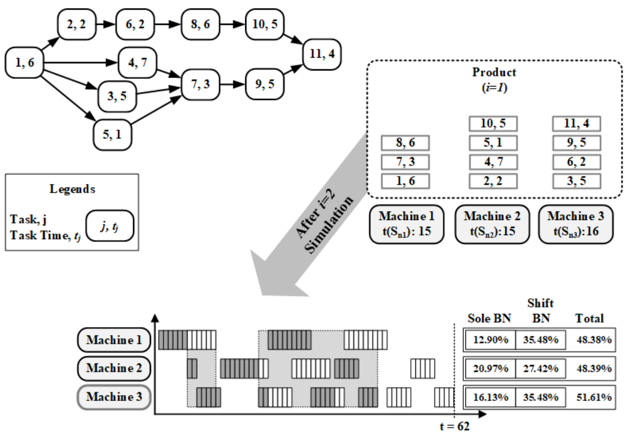

Figure 1: An example of the precedence diagram with 11 tasks and the possible shifting and sole bottleneck (denoted as shift and sole BN) identification. Assuming several products I with three available machines in the assembly line with their respective the task sequence and machine allocation. Based on the maximum t(Sjk), machine 3 is identified as main bottleneck machine that mitigated the long-term performance.

The standard shifting bottleneck identification in the context of the assembly line involves simulating the continuous assignment of a sequence of tasks (S_{jk}) of multiple products on the available machines K, without assuming the violation of the cycle time (C_t). The percentage of sole bottleneck (b^k_{sole}) is computed based on the active period of a machine of assigned tasks to the machine (adapted from [9]). The overlap of the active period of one machine with the previous or the subsequent active period of another machine represents the percentage of shifting bottleneck (b^k_{shift}).

The decision variables x_{jk} possessing a value of 0 and 1 integers where the variable is 1 of task j is assigned to machine k; 0, if otherwise. The objective function in (1) defines the maximization of the assembly line efficiency (E) involving the simultaneous minimization of C and K. The precedence constraints in (2) state that all predecessor of task j must be assigned to a machine, which is in front (l = k - 1) of or the same as the machine that task j is assigned in. Assignment constraint in (3) ensures that task j must be assigned to only one machine. The cycle time constraint in (4) calculates the total machine time $t(S_{jk})$ on machine k and guarantees that the total machine time $t(S_{jk})$ is not greater than the upper bound (C_t). The integrity constraints in (5) enforce the correct binary value of the decision variables.

$$\max E = \left\{ \frac{t_{sum}}{K \times C} \right\} \times 100. \tag{1}$$

$$\sum_{k=1}^{K} x_{jk} \geq \sum_{k=1}^{K} x_{lk}, \forall l \in \mathrm{Pr}e(j) \forall j. \tag{2}$$

$$\sum_{k=1}^{K} x_{jk} = 1, \forall j. \tag{3}$$

$$T_j = \sum_{j=1}^{J} t_j x_{jk} \leq C_t, \forall k. \tag{4}$$

$$x_{jk} \in \{0,1\}, \forall j, k \tag{5}$$

III. THE PROPOSED CONTAGIOUS IMMUNE SYSTEM APPROACH

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The elementary structure of the natural immune system exhibits agent-like behaviours that conduct simple actions but solve complex problem by exploiting diversity, highly distributed and coordinated system [8]. There are three fundamental structure of immune system; affinity maturation, cellular reproduction, and somatic hyper-mutation. The affinity maturation reflects the relation of the affinity proliferation rate to become more capable of recognizing antigens or die. Then, these immune cells undergo cellular reproduction through cloning where the offspring are created by copying their parent cells subject to a certain degree of mutations (somatic hyper-mutation), producing high number of offspring cells with high-affinity (effector cells) and long-lasting high-affinity cells (memory cells) to effectively drive faster response in future encounters. The complex building blocks of the natural immune system act as the source of inspiration for solving the complex combinatorial nature of the SALB-E problem.

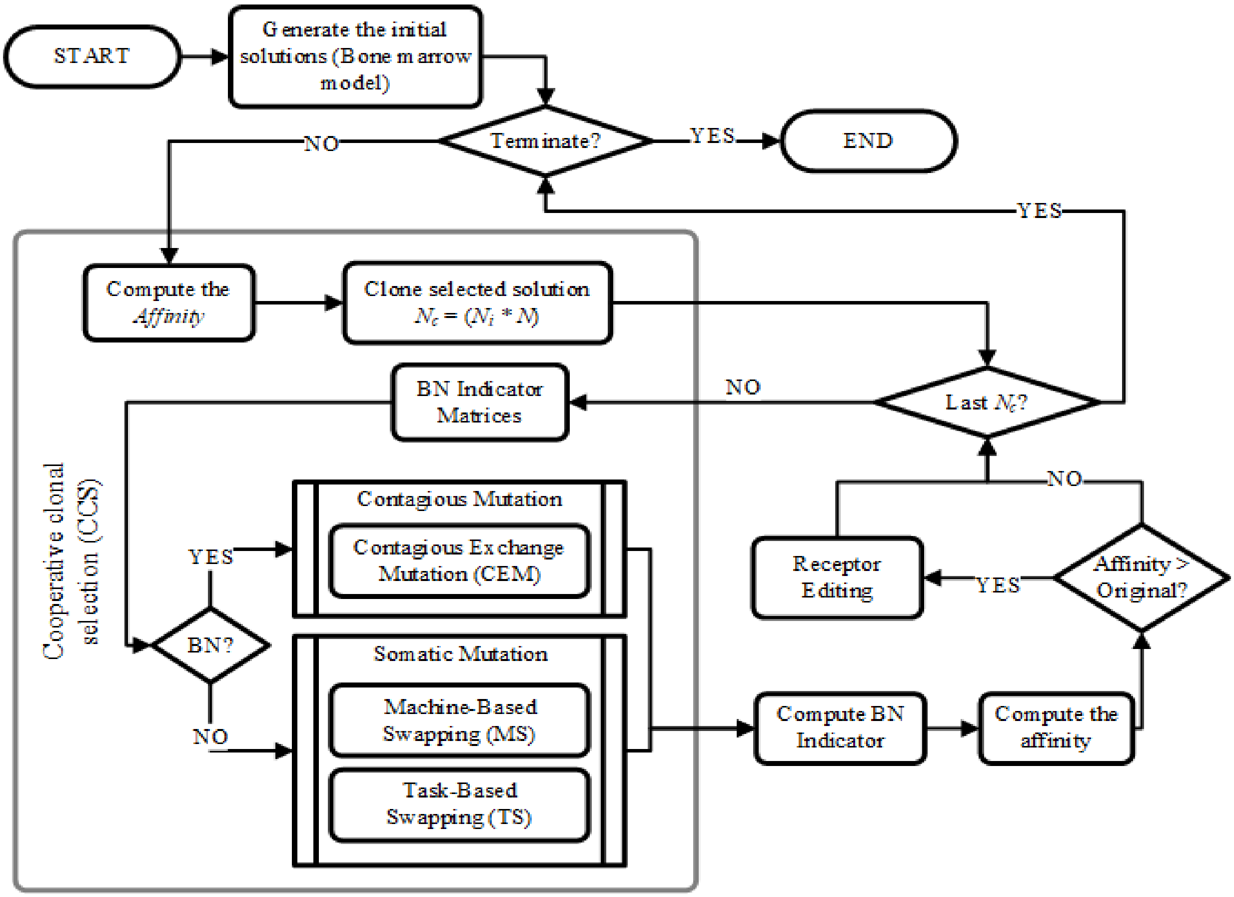

Figure 2: The flowchart of the overall structure of the proposed CIS approach. The *cooperative clonal selection* represents the *cooperative* mechanism and the *contagious mutation* represents the *competitive* mechanisms.

The proposed contagious immune system (CIS) approach was partly inspired by the work in [8]. The notion of "contagious" of the CIS approach is a coopetition element in the population of individuals that "infects" the neighbouring individuals rapidly, projecting a "mass psychogenic illness" phenomenon (illness caused by illness triggers in isolation, but become infectious in term of psychological rather than physical) [10]. The cooperative element is the information interactions that occurred among the population of solutions. Meanwhile, the competitive element is represented by the change of information of a single solution representation of the CIS approach, which involves a rapid combination exchanges of machine and task that occurred along the "hotspot" region of each individual solution to accelerate its solution improvement. The flowchart of the proposed CIS approach is given in Fig. 2.

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A. The Solution Representation

The initial production of solutions (or population) for CIS approach is correspond to the bone marrow model where unique sequences of task and machine are combined by a pool-like manner from pooling the collections of feasible sequences. The number of these unique sequences are based on the number of population (N). The sequence of the unique machine allocation ($1 \leq k \leq K$) is generated based on the length of the task (J). Conversely, the sequence of the unique task assignment is generated with respect to the precedence constraint by employing a directed acyclic graph (DAG) model. The graph is traversed starting from node without predecessor followed into its successor node, where the selection of the node is randomized. If all the predecessor of the selected node is assigned, then the currently selected node is assigned. This process repeats until all nodes were assigned into a unique task sequence. The bone marrow model aid the CIS approach by starting the search procedure within a good search region of the problem search space, especially when dealing with large sized data sets. The initial population are based on N generated feasible solution where the maximum population may be up to N × 10 and the termination criteria (generation size, G) is when the optimal affinity (correspond to E value) was found.

B. The Cooperative Mechanism in CIS Approach

Cooperative clonal selection (CCS) is proposed not only to determine the solution needed to be clone, but also influence the cooperative elements of the CIS approach. In each generation, the population will undergo CCS by randomly selecting a set of solutions, 5/100 × N. This CCS compares their affinities with a calculated threshold ($h = affinity_n \times N/5$). The solutions with affinity less than the h, designated as p_{less}, will be cloned and mutated, designated as $p_{less'}$. Meanwhile, solution with affinity greater than the h, designated as p_{more}, will be cloned and mutated designated as $p_{more'}$.

If $p_{less'} > p_{less}$, then $p_{less} = p_{less'}$; else, $p_{less'}$ is discarded. If $p_{more'} > p_{more}$, then $p_{more} = p_{more'}$; else $p_{more'}$ is discarded. Then, the mutated solution clones will be simultaneously compared with the best solution of the population (p_{best}) by sorting them in decreasing affinity. Then, the best solution will replace the p_{best} whilst the second best will replace the original solution. CCS operator encourage fast convergence of the solutions, which demonstrated by the cooperative reinforcement of performance between the p_{more}, p_{less} and p_{best}. In other word, more than a single solution within the population of CIS will strives to reach better solution by referencing its neighbouring solutions, achieving “concerted” effort in common goal.

C. The Competitive Mechanism in CIS Approach

The competitive mechanism in the CIS approach involves the hyper-mutation operators, which can be divided into two. The first mutation procedure is targeted toward type of information it represents: task-based mutation (TS) and machine-based mutation (MS). The rationale includes introducing an independent solution improvisation, reduction on computational complexity, and the rapid solution exploration of the domain search space. Both MS and TS performed a simple swapping mechanism of machine sequence and task sequence, respectively, which are focused on local exploration or changes of the solution and escaping local optimum by suggesting a different assignment of machine or task.

The second mutation procedure is called contagious exchange mutation (CEM). A repetitive point mutation specifically focused on the identified bottleneck machine is conducted. Thus, the likelihood of trapping in local optima was reduced when the procedures force the solution to rapidly explore more than the immediate neighbourhood of the solution. The CEM procedure is conducted by swapping out the tasks of the bottleneck machine (so called “hotspot”) repeatedly and randomly into another potentially non-bottleneck machine several

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times until the currently found bottleneck indicator of the solution (max b^{k}_{total}) is changed.

The rate (repetition of the mutation process, M) for these mutations is defined as $M = N \times e^{[-\omega \times pn)/100]}$, where pn is the affinity of solution n. This quantifying method was chosen to provide enough maturity to the mutated solution. As such, the lower the affinity, the higher the mutation rate will be.

II. EXPERIMENTAL RESULT AND ANALYSIS

The computational experiment was conducted using benchmark SALB-E data sets consist of 242 test instances of 24 precedence graphs from real industrial assembly line environment. The SALB-E data sets were taken from both open literature [11] and the web (http://assembly-line-balancing.mansci.de/). Each of the SALB-E data instance was composed of a pair of numbers (K_t, C_t), which represent the known minimal number of the machines and cycle time, respectively. Also, the required processing time of each task and the precedence relations between the tasks were given. The experiments were run 20 times, where the initial values were set for the population size (N = J) and the generation number (G = 1). Extensive experimentation had found that the best value for the parameter ω = 0.5. As such, optimal solutions have been successfully achieved for all instances of the SALB-E data sets (Table 1). In addition, CIS approach had also found new optimal for all instances of the Bowman, Lutz1 and Hahn data sets.

Table 1: The average efficiency E against the known optimal obtained by the CIS approach for the 24 data sets with their respective number of instances.

Data	J	Inst.	Average E (%)		Data	J	Inst.	Average E (%)	
			Optimal	CIS				Optimal	CIS
Mertens	7	2	89.762	89.762	Kilbridge	45	4	99.374	99.374
Bowman	8	2	88.761	94.118	Hanh	53	4	96.594	99.397
Jaeschke	9	5	84.438	84.438	Warnecke	58	14	98.589	98.589
Jackson	11	3	94.556	94.556	Tonge	70	11	99.569	99.569
Mansoor	11	2	97.908	97.908	Wee-Mag	75	18	96.919	96.919
Mitchell	21	4	97.743	97.743	Arcus1	83	13	99.334	99.334
Roszieg	25	5	96.602	96.602	Lutz2	89	20	96.985	96.985
Heskiaoff	28	8	99.542	99.542	Lutz3	89	13	99.062	99.062
Buxey	29	7	97.996	97.996	Arcus2	111	16	99.879	99.879
Sawyer	30	8	98.247	98.247	Barthold	148	9	99.941	99.941
Lutz1	32	6	96.781	99.309	Barthol2	148	30	99.687	99.687
Gunther	35	8	96.769	96.769	Scholl	297	30	99.981	99.981

Note: Inst. = Data instances; Optimal = Known optimal of the data instance;

The proposed CIS approach is compared against six approaches identified from the literature, namely as the multi-rule multi-objective simulated annealing (MRMOSA) [6], priority-based genetic algorithm (PriGA) [12], rule-based modeling and constraint programming (RMCP) [7], two-phased genetic algorithm (2P-GA) [13], multiple assignment genetic algorithm (MA-GA) [5]. Task assignment rules and alternative rule-based model were adopted by MRMOSA and RMCP, respectively, while a bidirectional task assignment was adopted by MA-GA. The 2P-GA approach utilizes two-phased generational improvement where the first phase seeded the second phase with best-so-far solutions to lead the overall population into better search regions. The PriGA approach used task priority information of

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its solutions to improve their performance over several iterations.

The results of E value obtained for each approach were collected. However, each approach only applied on a certain portion of the SALB-E data sets, which requires paired comparison with the CIS approach. To standardize the reported results, the average of the percentage E deviation with respect to their adopted instances of SALB-E data sets were determined. Similarly, CIS was also computed for their total average E deviation and compared accordingly. A paired one-tailed Wilcoxon-Mann-Whitney U (WMW) tests are were conducted to determine the significant differences between the proposed approaches against the approaches from the literature. This statistical analysis test was chosen because the adopted samples (or results) of the CIS approaches and the compared approaches were independently obtained (Table 2). The CIS approach has also obtained results that statistically significant compared to MRMOSA, PriGA, and 2P-GA approaches (MRMOSA and PriGA approaches up to 99% confidence interval while 2P-GA approach up to 99.5% confidence interval), while not statistically significant compared to RMCP and MA-GA approaches even though better overall result was obtained.

Table 2: The total average efficiency E deviation (\%) of the CIS approach against the compared approaches and their statistical significant

Total % E Deviation				WMW U Test		
Approach	Data (Inst.)	Result	CIS	z-value	p-value	Significance?
MRMOSA	10 (27)	5.47	2.81E-09	2.4826	0.0066	Yes**
PriGA	7 (15)	6.02	-2.04E-04	2.6753	0.0037	Yes**
RMCP	5 (18)	-1.14	-8.05E-02	-0.8384	0.2005	No
2P-GA	18 (134)	1.35	-2.08E-01	4.0083	< 0.0001	Yes***
MA-GA [5]	7 (5)	1.17	-4.58E-04	1.4725	0.0708	No

Inst.= instances; **significant at $\alpha < .05$ & $\alpha < .01$; ***significant at all α values;

The finding so far implied that introducing the coopetition strategy improves the performance of the proposed approach where competition and cooperation were embedded in the individual and among the population level, respectively. In addition, incorporating problem-specific information such as the shifting bottleneck may also narrow down the feasible region of the search space. As such, combinations of these two factors have been demonstrated to lead the search result in a better search region that had not been encountered in the previous research. Nevertheless, larger and complex data sets still pose as a challenge, which may be a good direction for future endeavors.

IV. CONCLUSION

This study considered a discrete combinatorial optimization problem where encoding the problem is not straightforward and overcoming the inherent problem and its constraint is challenging. A new perspective of problem solving through the cooperation and competition strategy was introduced where combining them (called coopetition) can result in better approximate search strategy. The SALB-E problem with shifting bottleneck identification was adopted as the test bed to evaluate this concept by proposing the contagious immune system (CIS) approach. The CIS approach had excelled in solving all the data set instances of the SALB-E problem while able to discover new optimal solution in some of the data set instances. This shows that coopetition strategy may be the key in approximating search approach for solving much more complex problems in the future.

ACKNOWLEDGMENTS

The authors wish to thank Japan Advanced Institute of Science and Technology (JAIST), in collaboration with Universiti Sains Malaysia (USM), for the support it has extended in the completion of the present research through the Research University Initiative Grant (RUI) (1001/PKOMP/8014084).

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