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A METAHEURISTIC APPROACH FOR STATIC SCHEDULING BASED ON CHEMICAL REACTION OPTIMIZER

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ABSTRACT

Over the past several decades, scheduling has emerged as an area of critical research, thereby constituting a requisite process for myriad applications in real life. In this regard, many researchers have experimented and utilized various optimization algorithms to obtain optimized schedules. It is also noteworthy that the concepts of some optimization algorithms are essentially derived from nature. This paper aims to augment a compiler using a chemical reaction optimizer in order to identify an optimized instructions static schedule capable of being used within both single and multicore computer systems. This scheduling algorithm, which is denoted as SS-CRO (static scheduling using chemical reaction optimizer), is unique in that it provides alternative schedules involving different costs. Subsequently, SS-CRO tests the schedules in accordance with different types of instructions dependencies before making an appropriate selection. SS-CRO demonstrates that it can not only provide different schedule orders, but also make a competent selection of accepted solutions, whilst dismissing the inappropriate ones in a reasonable span of time. So, this paper presents SS-CRO algorithm that is used to obtain an optimized static scheduling, where SS-CRO has been implemented and evaluated analytically and experimentally. As analytical results, the number of steps for the SS-CRO approximately is O(*Num_iteration*×CROFun), where CROFun is the number of steps of the selected function. In the experiments results, SS-CRO achieved better execution time and higher accepted solutions in comparison with other optimization algorithms such as; SS-DA (static scheduling using duelist algorithm) and SS-GA (static scheduling using genetic algorithm). Furthermore, SS-CRO achieved the maximum percentage of number of solutions with respect to the execution time of all experiments for all proposed input cases, which is ranged as (10%-30%).

Keywords: *Chemical Reaction Optimizer, Compiler, Instruction Set, Metaheuristic Approach, Static Scheduling*

1. INTRODUCTION

In recent times, the concept of optimized scheduling gained prominence across a plethora of applications. Within this overarching theme, the computer architecture finds inclusion among such applications wherein a number of approaches have been adopted with a view to fulfil the onerous task of enhancing the performance of computations. Notably, the trend to improve the performance of computer applications has it genesis in two distinct avenues. First, the efficacy of dynamic scheduling in augmenting the speed as well as capacity of the hardware has been recognized. Second, static scheduling is known to improve the quality of software that exerts control over the hardware. In fact, the primary application has been observed to focus on software improvement issues, which then leads to a reduction in the amount of time necessary to run the application on the device. By functioning intelligently and via an improvement in any of its stages, a compiler can accelerate the pace of computation. To illustrate, the generic parser was proposed by authors of [1], whereas (a predictive bottom-up parser was postulated by authors of [2]. Similarly, the authors of [3] put forward the notion of compiler support pertaining to automatic parallelization on multicore systems. Meanwhile, the authors of [4] presented a scalable parser framework for massive text-based file using graphic processing units. While the dynamic scheduling has been known to be used more frequently, the element of exorbitant cost has been a matter of disappointment. It is for this reason that static scheduling is utilized as a complementary approach to dynamic scheduling. However, the majority of existing static scheduling techniques is premised on classical dependency analysis and is characterized on the basis of its stymied capabilities. Against this backdrop, this study is aimed at meeting the need for a refreshing approach to resolve this problem. Correspondingly, chemical reaction optimizer has demonstrated its efficaciousness in several fields and hence, can be used to make improvements in a program's static scheduling at different levels, including tasks and instruction. This, in turn, is justified by the following facts:

- A program denotes a set of instructions that are executed based on their inter-dependencies. The compiler can be used to generate an optimized static schedule of these instructions [3]. Actually, the optimized schedule is intended to feed the pipeline whilst to simultaneously executing the instructions. Thus, bridging the gap in pipeline stages, as demonstrated by the authors of [5]. In pipelining, the main predicament is to maintain all the stages in their entirety with a view to reduce latency to the maximum extent possible using an intelligent compiler. According to [6], this can be accomplished by instruction reordering/serialization, and multiple instruction issues.
- The chemical reaction is a natural process that causes some substances from an unstable state to become stable through a number of iterations [7]. Concurrently, this process necessitates energy preservation in accordance with the conservation of energy law whilst transferring it from one entity or form to another. As a result, it becomes possible to replicate these laws to resolve problems in different regions; authors of [8] termed this process as a nature-inspired computing. Correspondingly, the authors of [7] presented chemical reaction as a metaheuristic for optimization. The chemical reaction optimizer (from now CRO) algorithm begins with a set of input values as an input vector, Subsequently, the vector will be manipulated by four types of operations (on-wall ineffective collision; decomposition; inter-molecular ineffective collision; and synthesis) to obtain an optimized solution whilst maintaining a set of constraints.

To reiterate, static scheduling and CRO algorithm performs operations with similar effects. Hence, a correspondence can be established between their respective operations. Therefore, we will incorporate chemical reaction optimizer as a tool for a static scheduling in the proposed algorithm static scheduling using chemical reaction optimizer (from now SS-CRO), in this paper. Notably, once we establish a correspondence between molecules and program segments the four types of chemical reactions are considered to be ways of optimization. Subject to constraints (instruction dependencies), such optimization is reduced to instruction reordering/serialization and decomposition into multiple issues (segments).

Meanwhile, three cases of a program dependency graph (*PDG*) of a program segment were proposed to test SS-CRO, which are varies in the dependencies between their nodes (i.e. program segment instructions). The less dependency a *PDG* has, the more solutions achieved by SS-CRO. SS-CRO is been compared with two distinct optimization algorithms such as static scheduling using duelist algorithm (from now SS-DA) and static scheduling using genetic algorithm (from now SS-GA). SS-CRO achieved the lowest execution time for all proposed input cases, and for all iteration numbers. On the other hand, SS-CRO achieved the maximum percentage of accepted solutions (from now PerSol) with respect to execution time, which was ranged as (10%-30%), while PerSol of the SS-DA achieved the moderate range as (0%-21%), and the minimum values of PerSol was for the SS-GA, which was ranged as (0%-1%).
The main objectives of this paper are: define the static scheduling of instructions, formalize the program instructions dependencies, decompose the program into basic blocks and reflect the program dependencies using CRO, present and apply the Chemical Reaction Optimizer to obtain an optimized static scheduling, implement static scheduling using CRO, evaluate analytically and experimentally the SS-CRO algorithm.

Furthermore, SS-CRO can be used in many modern devices to enhance their compilers; such as, personnel computers and laptops, embedded systems in smart devices, smart phones, super computers, and special purpose computer in critical systems.

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The remaining portion of this paper is organized in the following manner: Section 2 undertakes a description of literature review, while Section 3 presents a brief background of CRO, GA and DA. Meanwhile, section 4 demonstrates Instruction Static Scheduling and CRO. On the other hand, Section 5 elucidates the proposed algorithm SS-CRO pertaining to instructions static scheduling in compilers. Section 6 outlines the results of the experiment, whereas Section 7 summarizes the conclusions.

2. LITERATURE REVIEW

In an extensive body of extant study, researchers have proposed a number of evolutionary algorithms in order to solve complex problems. These algorithms demonstrated their ability to solve range of problems. One of the areas that evidence the usage of evolutionary algorithms is optimizing task schedules of various types of problems. Most of the researchers have looked toward nature to identify possible solutions. For example, authors of [9] came up with the particle swarm optimization (PSO), while the author of [10] and the authors of [11] put forward the memetic algorithm (MA). Similarly, differential evolution (DE) was presented by authors of [12], ant colony optimization (ACO) was the brainchild of the work in [13], harmony search (HS) was postulated by authors of [14], Sea Lion optimization algorithm presented by authors of [15].

In the past, researchers have also used evolutionary algorithms such as genetic algorithms to optimize task scheduling as well as to solve the problem of traveling salesman problem (TSP); for this purpose, authors have adopted interesting approaches to arrive at a feasible solution [16, 17]. In particular, authors of [16] used genetic algorithms to provide optimal or near optimal solutions for scheduling various tasks on several processors. This evolutionary algorithm can be helpful in augmenting the efficiency of executing programs on multiprocessor scheduling problem in parallel. They also extended their solution by assigning the problem to appropriate processors and focusing on the reduction of execution time of the entire system. In addition to creating some genes to present the tasks that can be configured in a directed graph to underpin. the inter-dependencies of tasks, author of [16] used three main operators in order to manipulate their presented algorithm, including selection, crossover, and mutation. Finally, they implemented the entire genetic algorithm scheduling precedence on constrained task graphs.

In particular, many heuristic algorithms were employed in different fields to solve range of problems, such as; solving the travelling salesman problem [18, 19]. Meanwhile, authors presented performance evaluation for different parallel heuristic algorithms as shown in [20-22]. Moreover, many metaheuristic algorithms were proposed to solve range of problems such as; task scheduling in cloud computing using vocalization of humpback whale optimization algorithm [23]; test Jordan University Hospital Databases (JUH DBs) exceptions by applying genetic algorithm [24]; using genetic algorithm as a test data generator [25]; using multiple-population genetic algorithm for branch coverage test data generation [26]; a solution for traveling salesman problem using grey wolf optimizer algorithm [27].

Meanwhile, the authors of [28] presented a common model to schedule tasks with advance reservation requests as well as computational batch tasks. In addition, they lowered the effect of advance reservations on a schedule quality by putting forward unambiguous on-line scheduling policies and generic advices.

Correspondingly, authors of [29] formulated the (primal) problem as a nonlinear integer programming model. In addition, they demonstrated their ability to solve this problem by resolving a corresponding dual problem using a nonlinear relaxation. More specifically, they utilized genetic algorithm since both primal and dual problems are NP-hard. They observed that the genetic algorithm consistently outperformed a standard mathematical programming package with regard to computation time and solution quality.

Analogously, authors of [30] put forth a three-stage algorithm for resource-aware scheduling of computational jobs within a large-scale heterogeneous data center. Their algorithm aimed at allocating job classes to machine configurations in order to obtain an efficient mapping between capacity profiles concerning machine resources and request profiles relating to job resources. Meanwhile, authors of [31] presented a task scheduling framework considering both thermal issues in 3D integration technology and power supply noise interactions on different cores.

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Similarly, authors of [32] presented an algorithm named as clusters dimension exchange method (CDEM) in order to augment both the load balancing technique and job scheduling within the OTIS (Optical Transpose Interconnection System)-hypercube interconnection network.

In [33], authors leveraged the efficacy of the chemical reaction optimization algorithm for the purpose of multi-objective optimization. By premising their work on non-dominated sorting, they were able to propose a new quasi-linear with average time complexity concerning the quick non-dominated sorting algorithm. Additionally, the authors compared their findings with several multi-objective algorithms on a gamut of benchmarks problems, thus highlighting the efficiency and effectiveness of their proposed algorithm.

Meanwhile authors of [34] utilized CRO to resolve the printed circuit board drilling problem (PCBDP), which is the primary component of computers and electronic equipment (PCB). The authors focused their attention to solving the problem of controlling the drilling machine within the drill holes in PCB. More specifically, they aligned it as a TSP. Finally, they used CRO to solve the problem, which was subsequently implemented as an illustration of TSP.

In [1], authors presented a twofold generic parser that simulated the behavior of multiple parsing automata. This proposed parser, which was an extended version of Position Parsing Automation (PPA), accepted the strings drawn from regular tree grammar, context-free grammar, or both of them. Importantly, this parsing enhancement can help compilers perform their jobs efficiently.

Correspondingly, authors of [35] presented a hybrid load balancing algorithm that chained cubic tree interconnection network. This algorithm combines two common load balancing strategies: dynamic load balancing and parallel scheduling. In the study, the performance was measured using several metrics. In addition, the presented algorithm underpinned the importance of parallel scheduling with dynamic load balancing.

Meanwhile, authors of [36] presented a system that identifies transformation algorithms for an input program where programs' specific features is been considered.

Finally, authors of [2] proposed the implementation of a predictive bottom-up parser in two versions. Both versions were used as components of the proposed algorithm that simulates the operation of a shift–reduce automaton, which is defined and constructed by integrating its parsing actions with conflict resolution, reduction prediction, and error recovery.

3. BACKGROUND

This section introduces a brief background of three optimization algorithms; namely, chemical reaction optimizer (CRO), genetic algorithm (GA) and duelist algorithm (DA).

First, the chemical reaction optimizer that is presented by authors of [7], and it is inspired from the chemical reaction between unstable molecules. The molecular go through four different reactions defined by the authors of [7], which are on-wall ineffective collision; decomposition; inter-molecular ineffective collision; and synthesis. Subsequently, the unstable molecules are converted to stable one. Importantly, this algorithm extracted it's constrains from the low energy that is used in the natural chemical reaction, which is based on energy preservation where this energy should be reserved before and after any reaction. Actually, authors used CRO to solve several problems, and the results achieved by CRO were competitive. For more details in regards of CRO can be found in [37-40].

Second, genetic algorithm (GA) is a well-known metaheuristic algorithm presented by authors of [41]. Basically, GA is been inspired from the natural selection and used for solving constrained and unconstrained optimization problems. Mainly, GA modifies a population of individual solutions periodically. In every iteration, GA selects randomly two distinct individuals from the available solutions in the current population. Moreover, GA has three main steps: selection step, crossover step and mutation step. In particular, in the selection step, two distinct individuals denoted as parents and will be used in next step. In the crossover step, GA combines the parents from the previous step to generate offspring for the new population. In the mutation step, GA randomly applies some changes for the parents to generate new offspring. Furthermore, many researchers used GA to solve optimization problems and their experimental results showed that GA can achieve optimal solutions. Thus, more details of GA can be found in [16, 17, 24-26, 41-43].

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Third, duelist algorithm (DA) is a recent optimization algorithm, which inspired by how the duelist improve their skills in a duel [44], which is considered as a pure random algorithm. Actually, DA is based on human fight and how they improve their capabilities from each duelist, where it starts with a duelist population and chooses randomly two duelists to fight. Thus, in every duel there is a winner and a loser, where a loser learns from the winner. On the other hand, the winner uses new skills to improve its fighting capabilities, where the duelist with highest capabilities will be noted as champions. Subsequently, champions are responsible to train new duelists and duelists with worst capabilities will be eliminated. Thus, for more details in regards of DA can be found in [44-46]

4. INSTRUCTIONS STATIC SCHEDULING AND CRO

In static scheduling, the compiler can potentially reorder the program instructions in varying orders to reduce the latency whilst concurrently saving the inter-dependencies between the instructions. Notably, these interdependencies imply that the program yields the same results, at a reduced cost (CPU time) [5]. Furthermore, it is possible to perform static scheduling by decomposing program segment into multiple ones, with a proper serialization to maintain interdependencies between instructions. The multiple segments constitute code parallelization. Such segments are appropriate for multicore and multiple issue processors.

On the other hand, the primary objective of CRO is to present an optimized solution for a problem. This process is underscored by the contours of different types of chemical reactions such as: on-wall ineffective collision, decomposition, inter-molecular ineffective collision, and synthesis[7] . Each type entails its own properties. However, these operations mimic the static scheduling in terms of reordering/serialization and generation of multiple schedules.

The static scheduling and its reflection by CRO are formalized as follows:

Let $<I_1,\ldots, I_n>$ be a sequence of instructions constituting a program *P.*

Let $C = \{c_i,\ldots, c_i\}$ be a set estimated execution costs of the individual instructions.

Let D= $\{D_{12},\ldots, D_{ij}\}$ be a set of instruction dependencies as described in Section 3.1. D_{ij} represents the dependency between I_i and I_j.

Let a program dependency graph (*PDG*) be defined as $PDG = (N, E, C)$, where:

- $N= \{np_1, np_2, np_3,\ldots,np_n\}$ is a set of nodes such that np_i represents I_i . In [47], authors pretended that there are two distinct kinds of nodes in a *PDG* such as:
    - o Regular node that has a regular statement such as; assignment statement
    - o Control node that has a control statement such as; a condition in a loop or an if statement.
- $E = \{e_{11}, e_{12}, e_3, \ldots, e_{ij}\}$ is a set of edges such that e_{ij} represents D_{ij} between the nodes np_i and np_j and labeled by the cost c_j. In [47], authors pretended that there are two distinct kinds of edges in a *PDG* such as:
    - o Solid edge that presents data a dependency or a name dependency
    - o Dashed edge that represents a control dependency

Let an optimized static schedule *S* respective to *P* be defined as *PDG* decomposition maintaining the constraints implied by *D*. Such decomposition constitutes specific order O(*PDG*) of the *PDG* nodes. It is obtained through iterative application of the following operations:

- Reordering/Serialization operation SRO $(PDG) \rightarrow S=O<np_1, np_2, np_3,\ldots,np_n>$ is a sequence of nodes in a specific order with minimal cost and satisfying *D*.
- Multiple scheduling operation MS(*PDG*) $\rightarrow S$, where $S=S_1, \ldots, S_n$ is a decomposition of *PDG* into multiple schedules $S_1= O<np_1,np_2, np_3,\ldots,np_m>,\ldots, S_n=O< np_{l+1}, np_{l+2}, np_{l+3} \ldots, np_n>$ with minimal cost and satisfying *D*.

The reflection of static Scheduling is achieved by establishing a correspondence between its four reactions and the operations SRO (reordering/serialization) and MS (multiple scheduling). Reflected static scheduling is then defined by the composite function FCRO(*PDG*)=OC◦DC◦IC◦SN(*PDG*)$\rightarrow S$, where OC, DC, IC and SN are correspondent functions to the CRO reactions: on wall ineffective collision; decomposition, inter-molecular ineffective collision; and synthesis, respectively. The definitions of these functions with the illustrative examples are given in Section 4.2, while the

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implementation of FCRO is given in Section 5. In subsequent section we use words instruction and node interchangeably. This is justified by the definition of *PDG*.

4.1 Dependencies in Instructions Static Scheduling

This section includes the definition of the primary types of dependencies, as defined by authors of [5]. Instructions static scheduling comprises of three types of dependencies: data dependency, name dependency, and control dependency. Dependencies manifest in a schedule between two instructions I_i and I_j under specific conditions, as enlisted below for each type of dependencies. Once we define the sets D=$\{D_{12},\ldots,D_{ij}\}$and $CONT=\{ContI_i,\ldots,ContI_m\}$ respective to data (name) and control dependencies a *PDG* respective to an input program *P* can be constructed as given by the formal definition. In addition, they will be used as the objective function (from now OF) in the SS-CRO, which will be used further to evaluate the effectiveness and the acceptability of the solution. The construction of D and CONT proceeds as given below.

Let $P=<I_1, \ldots,I_n>$ denotes a sequential schedule of *n* instructions of a program segment *P* we define:

- PRO(I_i) as the set of data operands that hold the results from I_i, and
- USE(I_i) as the set of data operands used in the instruction I_i. Let us assume that USE(I_i), and PRO(I_i), $\neq \emptyset$, $\forall i$. Subsequently, an edge e_{ij} between np_i and np_j in *PDG* will be exists if and only if there is any kind of dependencies such as $d_{ij}\in$D or $ContI_i \in$ CONT. In addition, the cost of e_{ij} is defined as c_{ij}, where $c_{ij}\in C$.

In congruence with the observation by authors of [5], we will define the instruction dependencies set D= $\{D_{12},\ldots,D_{ij}\}$in terms of

- $D_{ij} = USE(I_i) \in PRO(I_i)$ (1)
- $D_{ij}=USE(I_k)\in PRO(I_i) \neq \emptyset$, and $USE(I_j)\in PRO(I_k) \neq \emptyset, \exists I_k$ (2)

Where dependencies defined in Equation 1 and 2 are used to represent data dependency (also referred to as true data dependency), wherein, I_j signifies the data dependent on I_i if any of the following conditions holds:

- Instruction I_j uses a result produced by instruction I_i, as illustrated in Equation 1, i.e. in the *PDG* there is an edge e_{ij} between np_i and np_j.
- Instruction I_j data meanwhile is predicated on instruction I_k, while I_k data is dependent on instruction I_i, as depicted in Equation 2, i.e. in the *PDG* there are two edges e_{ik} between np_i and np_k and e_{kj} between np_k and np_j.

  - $D_{ij}= r_i\in PRO(I_i)$ and $r_i\in USE(I_j)$,where $\exists r_i$ (3)
  - $D_{ij}=(r_i\in PRO(I_i)\cap USE(I_i\ \ ))$and $r_i\in (USE(I_j)\cap PRO(I_j))$,where $\exists r_i$ (4)

Meanwhile, dependencies defined in Equation 3 and 4 are used to represent name dependency occurs in case there is an absence of data flow between two instructions, but they make use of the same registers or memory locations. Authors of [5] presented the following two types of name dependency:

- An anti-dependence between instruction I_i and I_j takes place when I_i writes an operand r_i that is read by I_j. Therefore, the original order needs to be preserved in order to ensure that every instruction involves the correct value, as illustrated in Equation 3, i.e. in the *PDG* there is an edge e_{ij} between np_i and np_j.
- An output dependence occurs when two instructions I_i and I_j are writing on the same operand r_i, which is why we should maintain the order of the instructions in order to make sure that the last value is written within the register, as evidenced in Equation 4, i.e. in the *PDG* there is an edge e_{ij} between np_i and np_j.

Control dependency takes place when an instruction execution gets controlled by such a branch. We define the set *CONT* as follows. Let us assume that I_i in a program *P* features a control instruction and subsequently dominant to the sequence of dependent instructions$<I_{j+1},I_{j+2}, \ldots,I_m>$. Then we define a control dependency *CONT* such that $ContI_i = <ConI_{j+1}, \ldots,ConI_m> \in CONT$ in schedule *S*. Assume $\forall I_i \in S, \exists!O(I_i)$ where O(I_i)is the order of I_i in *P* (where I_i refers to an instruction or a nested of instructions such as nested loop or nested if statements in *P*). In a *PDG* the nested nodes will get two distinct kinds of edges such as; the first edge is a regular solid edge which connects two dependent instructions according to the dependent operands and the second edge is a

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control dashed edge that controls the order of the instruction according to the control node which reflects a condition statement in the loop/if statement. Analogously, the two constraints pertaining to control dependency are as follows:

- An instruction controlled by a branch cannot move before, which will prevent the branch from controlling it, as illustrated in Equation 5. In a *PDG,* a control node should be connected with all of its successors by dashed edge.

$$ContI_i = O(I_{ik}) > O(I_i), \forall I_{ik} \in ContI_i \quad (5)$$

- An instruction out of the branch cannot be made after the branch, which, in turn, will control its execution, as depicted in Equation 6. In a *PDG,* a dependent node should be connected with its predecessors by a dashed edge.

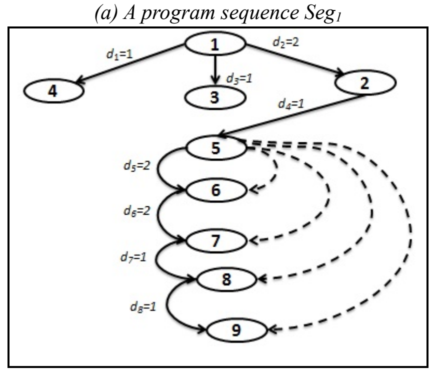
$$ContI_i = O(I_{ik}) > O(I_{im+1}), \forall I_{ik} \in ContI_i \quad (6)$$

4.2 Definitions and Examples of Instructions Static Scheduling Using CRO Reactions

This section defines chemical reaction in accordance with the instructions of the static scheduling problem. Four distinct reactions are observed in the iterations made in CRO: (i) on wall ineffective collision (OC); (ii) decomposition (DC); (iii) inter-molecular ineffective collision (IC); and (iv) synthesis (SN). Each of these reactions has its own properties, such as the number of actual inputs and the number of outputs needed. The following subsections depict an example for each type of reaction using two program sub-segments Seg_1 and Seg_2. These sub-segments and their respective *PDG*s, are shown in Figure 1 and Figure 2, respectively. Notice that both sub-segments are extracted from the same program segment *P*, for illustrative purpose. One more, instruction number 10 is excluded from the *PDG* because its job is been demonstrated in the *PDG* implicitly

Instructions		Cost(*c*)
1:	DIV.D F1,F2,F3;	0
2:	ADD.D F2,F4,F1;	2
3:	SUB.D F5,F1,F6;	1
4:	MUL.D F7,F1,F8;	1
5:	LOOP: L.D F0, 0(R1);	0
6:	ADD.D F4,F0,F2;	2
7:	S.D F4, 0(R1);	2
8:	DADDUI R1,#-8;	1
9:	BNE R1,	1
10:	LOOPEND;	
	Total	10

(a) A program sequence Seg_1

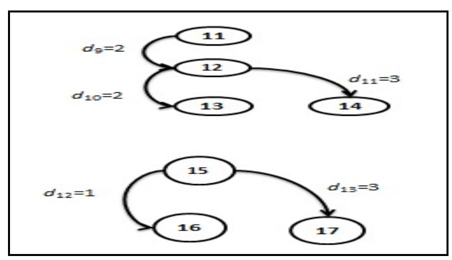


(b) PDG_1 of Seg_1

Figure 1: S_1 and its respective PDG_1

Instructions		Cost(*c*)
11:	DIV.D F9,F10,F11;	0
12:	ADD.D F12,F9,F10;	2
13:	SUB.D F13,F12,F11;	2
14:	MUL.D F13,F12,F11;	3
15:	MUL.D F14,F15,F16	0
16:	ADD.D F15, #8	1
17:	MULD. F14,F15,F16	3
Total		11

(a) A program sequence Seg_2



(b) PDG_2 of Seg_2

Figure 2: Seg_2 and its respectiveDPG$_2$

4.2.1 On wall ineffective collision

According to our purpose, we interpret the on wall ineffective collision (OC) as a molecular *S* (old schedule) hits an outer object. Subsequently, a reordering of the instructions will be resulted. The reflection of static scheduling by OC will be reduced to altering the order of the instructions in

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schedule S and providing a new schedule S' (new molecular). Where S' has a new PDG' that has the same nodes of PDG, but reordered. Formally, we define OC as a reordering operation SRO over a given flow-graph, as given by Equation 7.

$$OC = SRO(PDG) \rightarrow PDG': S \rightarrow S' \quad (7)$$

Where S refers to a schedule of n instructions $S = O<I_1,\ldots,I_n>$, such that each I_i has a specific order, and the initial PDG of S has the dependency set D and estimated cost c. The on wall ineffective collision is then defined as a reordering process to produce $S'=O<I_1, \ldots,I_n>$, where $\exists I_k \in S$ and $\exists I_k \in S'$ are two distinct instructions have the same order k in both schedules S and S', but they are not equal to each other. Moreover, S' preserves the data dependency exists in S. On the other hand, PDG' is the flow-graph of S' after applying OC on S. PDG' has the same nodes of PDG, but in a different order, where PDG' preserves data dependency set D of S. On the other hand, the estimated cost of PDG' is c', where $c' \leq c$.

Finally, if $c' > c$ or D is not preserved then PDG' will be dismissed. This, in turn, necessitates its exclusion from the solution area. To illustrate, the reaction moves one instruction like instruction 6 (node np_6) from the LOOP command and extricates it from the LOOP boundaries (it may be noted that LOOP and BNE are used to signify the beginning and ending boundaries of the instructions inside the loop statement). Hence, if any instruction is moved out of these boundaries, the solution needs to be summarily dismissed, as illustrated in Figure 3, wherein OC function has been applied on S_1. In this example, in the PDG' a dashed edge is been broken as a result a control node np_5 lost one of its' successors, which it is np_6 and np_6 lost its' control predecessor np_5. i.e. PDG' does not preserve the dependency set D, so it will be dismissed.

This can be accomplished by ascertaining the inter-dependencies between instructions in the schedule prior to and after the reaction, that is, the total new energy resulted by PDG' such as the sum of PE' and KE' should be less than or equal to the total energy of the original PDG such as the sum of PE and KE, as depicted in Equation 8.

$$PE' + KE' \leq PE + KE \quad (8)$$

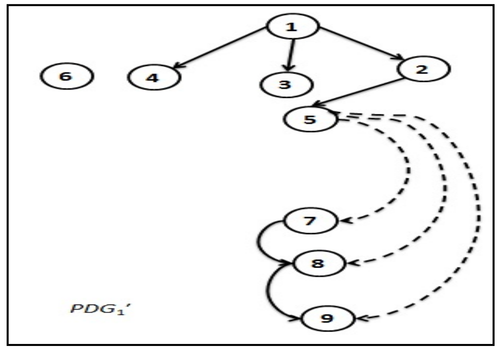

Figure 3: PDG_1 after on wall ineffective collision

4.2.2 Decomposition

In this paper, the decomposition (DC) occurs when a molecular S (old schedule) collides with the wall and yields two new molecules such as $S'_1$and S'_2.The reflection of static scheduling by DC is shown as the old schedule will be divided to create new schedules. In the realm of static scheduling, this can be considered as a multiple issue scheduling, where a program segment can be split into multiple pieces (sub-program segments) before being distributed across more than one processor. Formally, we define DC as a multiple scheduling process MS of a given flow-graph, as given by Equation 9.

$$DC= MS(PDG) \rightarrow (PDG'_1, PDG'_2): S\rightarrow(S'_1,S'_2) \quad (8)$$

Notably, S denotes a schedule of n instructions $S = O<I_1, \ldots,I_n>$ that has an initial flow-graph such as PDG. Importantly, the decomposition reaction signifies a multiple issue scheduling process carried out by dividing S into two sub-schedules such as S'_1 of k instructions $S'_1 =O<I_1, \ldots,I_k>$ as well as S'_2 of m instructions $S'_2 = O<I_1, \ldots,I_m>$, where $m+k = n$ and S'_1 and S'_2 preserve the data dependencies existing in S. Moreover, PDG'_1 and PDG'_2 are the flow-graphs of S'_1 and S'_2 respectively. PDG'_1 and PDG'_2 should preserve the data dependency set of PDG, unless they will be dismissed.

In the case of instructions static scheduling, we will compute the total energy for the new schedules and ascertain whether the dependencies between the instructions and the total energy have been reserved, as shown in Equation 10. If that is not the case, we will not only obtain a higher cost, but also risk computing wrong schedules. Therefore, we will dismiss the new incorrect schedules from the solution set, indicating that we will lose some data dependency between the instructions.

Consequently, energy conservation is not satisfied in this analysis, which builds the case for excluding the new particles. This will manifest in the division and be determined based on whether it occurs in the middle of a loop instruction or separates two dependent instructions.

$$PE'_1 + KE'_1 + PE'_2 + KE'_2 \le PE_S + KE_S \quad (9)$$

An example of an unacceptable decomposition becomes apparent when new schedules are shown to hold the dependent components presented by two or more instructions and the reaction split them, as illustrated in Figure 4, where it becomes evident that decomposition reaction is been applied on S_1. In this example, the new flow graphs PDG'_1 and PDG'_2 did not preserve the dependency D of PDG_1, where node np_5 lost its dependent edge from node np_2, so the new flow-graphs will be dismissed.

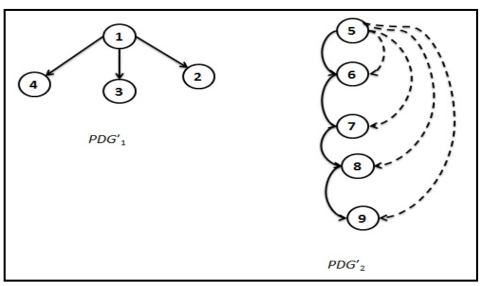

Figure 4: PDG1 after decomposition

4.2.3 Inter-molecular ineffective collision

According to our approach, the inter-molecular ineffective collision (IC) occurs when two distinct schedules hit each other, resulting in two new schedules. In this instance, the reflection of static scheduling by IC on S_1 and S_2 will interchange the instructions between them to provide two new schedules S'_1 and S'_2. This reaction is unique in that it will definitely find acceptance if the new schedules save dependency sets and do not cost more than their predecessors. Formally, we define IC as two successive operations of multiple scheduling MS and reordering SRO of given two flow-graphs, as illustrated in Equation 11. On the other hand, the data dependency and total energy should be saved after this reaction, as shown in Equation 12.

$$IC = MS(SRO(PDG_1,PDG_2)) \rightarrow (PDG'_1,PDG'_2): (S_1,S_2) \rightarrow (S'_1,S'_2) \quad (10)$$

$$PE'_1 + KE'_1 + PE'_2 + KE'_2 \le PE_1 + KE_1 + PE_2 + KE_2 \quad (11)$$

Clearly, S_1 signifies a schedule of k instructions S_1=O<I_1, …,I_k> and S_2 refers to a schedule of m instructions S_2 = O<I_1, …,I_m>, where $m+k = n$. The respective flow-graphs of S_1 and S_2 are PDG_1 and PDG_2, respectively. The reflection of static scheduling by IC is essentially a combination of reordering SRO and multiple scheduling MS operations by combining both schedules, reordering them, and finally re-dividing them into two new schedules S'_1 of g instructions S'_1 = O<I_1, …,I_g> in addition to S'_2 of h instructions S'_2=O<I_1, …,I_h>, where $g+h=n$, and S'_1 and S'_2 will save the data dependences existing in S_1 and S_2.

In this reaction, a scenario may arise wherein two independent schedules impart two new independent schedules after they hit each other (before the reaction). Consequently, such a solution should be aborted if the execution costs would be higher or data dependency set is not saved, as illustrated in Figure 5, where IC has been applied on S_1 and S_2. In this reaction, both operations SRO and MS will be used to get $PDG'_1$and PDG'_2, those have same nodes of $PDG_1$and PDG_2, and preserve dependency. In this Example, the dependency between np_2 and np_5 was lost, while two new wrong dependencies were been added between np_2 and np_{15}, and between np_8 and np_{11}. Also one wrong control dependency has been added between np_5 and np_{11}, i.e. a foreign instruction entered the loop statement. This implies that $PDG'_1$and PDG'_2 should be dismissed.

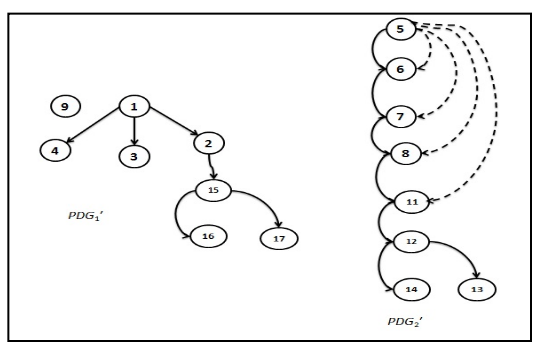

Figure 5: PDG1 and PDG2 after IC

4.2.4 Synthesis

Synthesis (SN) reaction is the opposite of decomposition reaction and refers to a scenario where two schedules S_1 and S_2 hit each other to yield a single schedule S'. In this instance, reordering operation SRO will indeed reflect the

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issue in static scheduling. This solution can be deemed safe if it does contribute towards energy conservation, as shown above and illustrated in Equation 14. Formally, we define *SN* as a reordering SRO process of given two flow-graphs, as shown above as illustrated in Equation 13.

$$SN=SRO(PDG_1,PDG_2) \rightarrow PDG': (S_1,S_2) \rightarrow (S') \quad (12)$$

$$PE' + KE' \leq PE_1 + KE_1 + PE_2 + KE_2 \quad (13)$$

Clearly, S_1 denotes a schedule of *m* instructions $S_1 = O<I_1, \ldots,I_m>$ and S_2 be a schedule of *k* instructions $S_2 = O<I_1, \ldots,I_k>$. Synthesis reaction is a reordering process that combines both schedules S_1 and S_2 into a single schedule S', such as $S'= <I_1, \ldots,I_n>$, where $n= m+k$ and S' preserves the data dependences existing in S_1 and S_2.

Figure 6 illustrates an example of rejected solution resulted by synthesis between two independent schedules and affect each other's results when they hit each other. Therefore, it is necessary to ignore this particular solution. The result of SRO operation over PDG_1 and PDG_2 in this example is a new flow graph *PDG'*. In *PDG'*, a new wrong control edge is been added between np_5 and np_{11}, which violates the existing dependency set, and so *PDG'* should be dismissed.

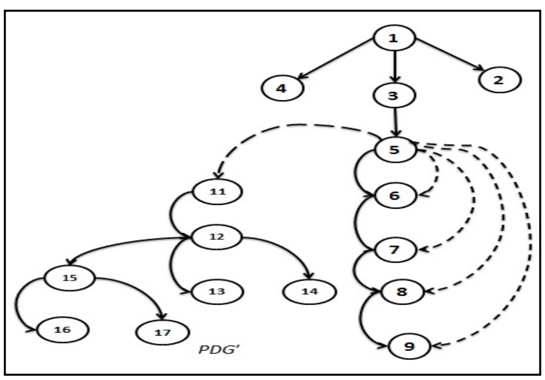

Figure 6: PDG_1 and PDG_2 after Synthesis

4.3 CRO Meanings and Attributes in SS-CRO

Given a *PDG* respective to program *P*, the implementation of static scheduling for *P* by CRO is reduced to applying the composite function FCRO(*PDG*), as depicted by Figure 7. FCRO is implemented by the proposed algorithm SS-CRO as illustrated in Algorithm 1, which is been inspired from the CRO algorithm that posited by the authors of [7]. SS-CRO has a *PDG* of a program segment as its input. *PDG* is then manipulated by the four different functions respective to CRO reactions as depicted in Section 5.2, which will yield a distinct set (solution set) of candidate solutions. Subsequently, this algorithm will ascertain all types of dependencies *D* to verify whether the solution is correct or if it needs to be dismissed.

Table 1: Chemical meaning as used in SS-CRO algorithm

Chemical Meaning	SS-CRO
Molecular structure	Candidate solution – *PDG*
Potential energy	Value of dependency preserved of a *PDG* for such candidate solution (which preserved all kinds of dependencies)
Kinetic energy	Measure of tolerance of having worse *PDG*
Minimum structure	Current optimal *PDG*

Based on CRO algorithm presented by the author of [7], Table 1 enlists the meanings of chemical reactions that will be used within the SS-CRO algorithm, and Table 2 enlists the interpretation of CRO attributes in SS-CRO. Finally, the execution time complexity analysis will be explained in section 5.3.

Table 2: CRO attributes in SS-CRO

Attribute name	Attributes in SS-CRO
Molecular structure (ω)	Denotes the solution to our problem - *PDG*
Potential energy (*PE*)	Refers to the objective function that provides feedback on the accuracy of the solution (ω) (ascertains whether it is correct one). In our situation, it constitutes the constraints achievements, including instruction dependencies.
Kinetic energy (*KE*)	Signifies a type of tolerance measurement that prevents the algorithm from devising an inferior solution
Minimum structure (*Min-Sch*)	Refers to a schedule with minimum *PE* that

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	represents the current optimal solution
Minimum PE (*MinPE*)	Is used when a molecular attains its *Min-Sch* state; for this reason, its *PE* features the minimum current value such as *MinPE*
Minimum hit number (*MinHit*)	Denotes the number of hits that is necessary to reach the *Min-Sch* of a molecular

5. SS-CRO ALGORITHM

In this subsection, the implementation of SS-CRO will be presented. As shown in Algorithm 1, SS-CRO algorithm has three phases that operates in the following order: initialization phase; iteration phase; and solution confirmation phase. The workflow of the algorithm is shown in Figure 7. The following paragraphs will explain the SS-CRO algorithm phases in details.

In the initialization phase, the algorithm generates threshold values of some variables, which includes *PDG*_size that equals the number of nodes of the initial *DPG*, the number of iterations required in the iteration phase. Initially, *Min-Sch* is assigned to be the initial *PDG* that (PDG_1) as the best solution, and the solution set holds only PDG_1. The first seven lines in the algorithm make the entire process evident. In particular, the step of calling the objective function OF will ascertain the dependency for each node and its' corresponding edge in its' *PDG* (see Section 4.1), before returning the nodes dependency state and its *PE* and *KE* values. Thus, *MinPE* will get its initial value as the *PE* of PDG_1, and the *MinHit* equals to zero. Furthermore, the algorithm checks if the initial PDG_1 has less than two nodes it will be terminated, because it will be unable to apply any of its functions.

In the iteration phase, the algorithm commences with the consideration of the PDG_1 as the most optimal solution, as shown in SS-CRO algorithm. Thereafter, this algorithm will select the type of requisite collision by verifying *molecule* (the available number of *PDG* in the solution set). The algorithm forces *PDG* to be decomposed by calling DC, when the *molecule* equals one and the existing *PDG* is dividable. Subsequently, the algorithm applies the SRO operations on one particular *PDG* such as; calling OC or DC functions. Since it will only feature one *PDG* in the first instance with at least two nodes. Thus, the algorithm selects the DC function in the event the splitting option can be implemented. Importantly, this new solution will ensconce two valid PDG'_1 and PDG'_2 that will be checked and evaluated to determine their accept ability. Alternatively, the OC function will be chosen if the splitting cannot be accomplished, which may give one valid *PDG'*. Clearly, the entry of any *PDG'* resulted from either OC or DC will be added into the solution set that is predicted to be in the selection made by the algorithm in next iterations. Once, the proposed algorithm has two valid *PDG* in the solution set it will be possible to apply both kinds of operations: the SRO; and the MS operations. As an implication, the algorithm makes a random selection between SRO and MS operations. With regard to the SRO operations, it undertakes an evaluation to determine whether the PDG'_j can be reordered or divided into more than one *PDG*. With regard to the MS operations - the process of selecting the reaction is predicated on the ability to merge the two available graphs such as PDG'_j and PDG'_h. Correspondingly, the algorithm will select SN function if the merging ability is found to exist. However, if that is not the case, the algorithm will select the IC function.

Further iterations are performed to obtain an optimal solution. However, the iteration phase will commence if the number of iterations are ended or it is unable to identify a better solution.

In the solution confirmation phase, the algorithm evaluates the identified *PDG* in order to project the ideal *PDG* on the basis of the functions carried out in each run to finalize the SS-CRO.

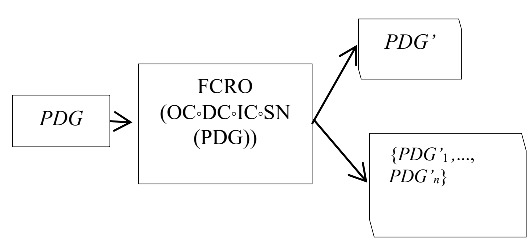

Figure 7: Workflow of the SS-CRO

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Algorithm 1. SS-CRO Algorithm (Main)

```
Input: PDG_int
Output: {PDG_int}/{PDG'_1} / {PDG'_1,… , PDG'_n},
MinPE, MinHit
    /* initialization phase */
    int Max_sch
    Global Solution_set ={PDG_int}
    Global Min_Struct = PDG_int, MinPE = PE,
    MinHit = 0
    Max_sch = PDG_size(PDG_1)/2
     /* PDG_size is the number of node in a PDG
       Max_sch is used to be sure that a PDG is
    dividable or not, but each PDG in the
    Solution_set has at least two nodes*/
    {Min_Struct, PE, KE}= OF(PDG_1)
    Generate molecule = 1
    If (PDG_size(PDG_1)< 2)
      exit;
    /* Iteration phase */
    for (int i=0;(i < Num_iteration) &&
    (PDG_size(PDG_i)> 1))
        Generate b ∈ [0, Max_sch]
    If (molecule == 1) || (molecule <= b) then
    {
      Randomly select PDG_j from Solution_set
      /* SRO operation */
      If PDG_size(PDG_j) ≥ 2 then
         if (divide (PDG_j)) then
      /* PDG_j can be divided */
            Solution_set = DC(PDG_j, PE, KE)
         else
            Solution_set = OC(PDG_j, PE, KE)
      end if
    }
     else
    {
      Randomly select PDG_j and PDG_h from
    Solution_set
     /* MS operation*/
       if (merge (PDG_1 and PDG_2)) then
         Solution_set = SN(PDG_j, PE_j, KE_j, PDG_h,
    PE_h, KE_h)
       else
         Solution_set = IC(PDG_j, PE_j, KE_j, PDG_h,
    PE_h, KE_h)
      end if
     end if
    /* Solution confirmation phase */
     Check for any new solution
     end for-loop
    /* Final phase */
    return Solution_set Min_Struct, MinPE, MinHit
```

5.1 Functions of SS-CRO

In this subsection we present Functions 1-5 that are used in SS-CRO algorithm. As shown in Function 1, the OC function receives the *PDG* as an input and makes an attempt to reorder its' nodes. When the new order is ready, the function sends it to OF in order to validate the new order of these nodes. Additionally, if the total energy of the new order is found to be smaller than its older counterpart, the latter is obliterated and the former is returned to the solution set. Otherwise, the *PDG'* created by the function gets destroyed and consequently, status quo is maintained.

Function 1. OC() // On wall ineffective collision function

```
Input: PDG, PE, KE
Output: Solution_set
     PDG'_j =generate new PDG randomly
     Call Objective function for the PDG'_j
     {Min_struct, var PE'_j, KE'_j} =
     OF(PDG'_j)
     /*confirm the PDG'_j or dismiss it*/
     If (PE'_j+KE'_j ≤ PE +KE) then
     {
       Solution_set = Solution_set – {PDG}
       Solution_set = Solution_set ∪
     {PDG'_j}
     }
     else
       dismiss PDG'_j
     end if
```

In Function 2, the IC function depicts the reaction between two varying graphs such as PDG_j and PDG_h. Thus, IC function will merge PDG_j and PDG_h and randomly split them into PDG'_j and PDG'_h. Subsequently, IC function will go through each of PDG'_j and PDG'_h and try to reorder their nodes and test if they are valid *PDG* or not. Upon receiving PDG'_j, it reorders its nodes, and subsequently calculates its PE'_j and KE'_j through the use of OF. Upon receiving PDG'_h, the same process gets repeated for PDG'_h that IC reorders its nodes and calculates its PE'_h and KE'_h through the use of OF. Subsequently, the function gets the total sum of the resultant values PE'_j, PE'_h, KE'_j and KE'_h and compare it with the total sum of PE_j, PE_h, KE_j and KE_h, if the new sum has smaller value then PDG'_j and PDG'_h will be confirmed; otherwise, they will be destroyed. Under this scenario, this

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function either adds two new flow-graphs to the solution set and removes the original ones, or retains the original ones in the event that the splitting and the reordering do not preserve the energy for both original flow-graphs.

Function 2. IC() // Inter-molecular ineffective collision function

```
Input: PDGj, PDGh, PEj, PEh, KEj, KEh// two molecules
Output: Solution_set
Merge both PDGj, PDGh then spilt them
    randomly into PDG'j, PDG'h
PDG'j= randomly reorder PDG'j
{Min_struct, PE'j, KE'j } = OF(PDG'j)
PDG'h= randomly reorder PDG'h
{Min_struct, PE'h, KE'h} = OF(PDG'h)
If (PE'j+PE'h+KE'j+KE'h ≤
    PEj+PEh+KEj+KEh) then /*new solutions
    confirmed*/
    {
      Solution_Set = Solution_Set – {PDGj,
      PDGh}
      Solution_Set = Solution_set ∪ {PDG'j,
      PDG'h}
    }
else
  dismiss PDG'j,PDG'h
end if
```

In Function 3, the DC function receives one PDG_j and divides it into two sub-graphs such as PDG'_j and PDG'_h. At the beginning, DC checks the ability of decomposing the PDG_j, where if a PDG_j has less than two nodes the decomposition process will be rejected. Subsequently, if a PDG_j has more than two nodes DC will randomly split the PDG_j into two new sub-graphs. Then it dispatches the new sub-graphs PDG'_j and PDG'_h to the objective function to obtain their PE'_j, PE'_h, KE_j and KE'_h values, respectively. If the total sum of the resultant values PE'_j, PE'_h, KE_j and KE'_h is found to be smaller than the original total energy, the used portions of the original *PDG* gets accepted and a PDG'_j and PDG'_h will be added to the solution set, and the original one will be removed from the solution set, as illustrated in lines 4 up to11.

Moreover, the *molecule* will be incremented by one, i.e. the available number of *PDG* in the solution set is increased by one. Briefly, this reaction takes a *PDG* and then divides it into two sub-graphs (PDG'_j and PDG'_h) with smaller total energy value.

Function 3. DC() // Decomposition Function

```
Input: PDGj, PEj, KEj
Output: Solution_set

        If PDG_size >2
2:        Randomly split PDG into PDG'j,
          PDG'h
3:      else
          return Decomposition fail
4:      {Min_struct, PE'j, KE'j } = OF(PDG'j)
5:      {Min_struct, PE'h, KE'h} = OF(PDG'h)
6:      If (PE'j+PE'h + KE'j+ KE'h ≤PEj +
        KEj) then // PDG'j and PDG'h
        confirmed
        {
7:         Solution_set = Solution_Set –
        {PDGj}
8:         Molecule ++
9:         Solution_set = Solution_set ∪
        {PDG'j, PDG'h}
        }
10:     else
11:       destroy PDG'j, PDG'h
12:     end if
```

As shown in Function 4, the SN function is a very easy reaction. In particular, it takes two distinct graphs such as PDG_j and PDG_h and merges them in a new graph; such as PDG'_j. Thus, SN calls the objective function for PDG'_j to get its respective PE'_j and KE'_j. Subsequently, if the resultant total energy of PE'_j and KE'_j is smaller than the total of original energy PE_j, PE_h, KE_j and KE_h, then SN adds PDG'_j to solution set and removes original ones; otherwise, the merger will not occur. Moreover, the molecule will be decremented by one, i.e. the number of available *PDG* in the solution list is decreased by one.

As shown in Function 5, the objective function OF is the most important function used in the algorithm. This function has two phases the dependency check phase and the cost evaluation phase. In the dependency check phase, OF receives the *PDG* and evaluates all types of dependencies, including data dependency, name dependency, and control dependency. Subsequently, it assigns a value to the dependency status of the *PDG* such as *PE* and computes the *KE*. The node or the edge violation of any given dependency concept returns a null value to suggest that the *PDG* should be

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dismissed. In the cost check phase, OF calculates the cost of the *PDG* and compare it with the current best solution (*Min-Sch*) which has the current lowest cost. Therefore, if *PDG* has a lower cost than the current best solution, then *Min-Sch* will be replaced by the current *PDG*; otherwise *Min-Sch* will not be changed.

```
Function 4. SN() // Synthesis Function
Input: PDGj, PDGh, PEj, PEh, KEj, KEh
Output: PDG'j, PE'j
Merge PDGj, PDGh as PDG'j
{Min_struct, PE'j, KE'j } = OF(PDG'j)
If PEj+PEh+KEj+KEh<PE'j+KE'j then
  destroy PDG'j
/*invalid solution PDG'*/
else
   {
    Solution_set = Solution_set - { PDG1 ,PDG2};
    Solution_set = Solution_set ∪ {PDG'};
    Molecule --;
   }
```

```
Function 5. OF() // Objective Function
Input: PDG
Output: PE, KE
Int rand(b) ϵ [0, 1]
/* Dependency phase*/
D=Check_Data_Depedency() + Check_Name_Dependency()
CONT =Check_Control_Dependency()
PE = D& CONT
KE =(PDG_size/1.5)*b
/* Cost Check phase */
Get cost(PDG)
If cost(PDG) < cost(Min_Struct) then
   {
    Min_Struct = PDG
    MinPE = PE
    Minhit++
   }
```

5.2 Time Complexity of SS-CRO Algorithm

In this section, we present the number of steps for SS-CRO algorithm, which depends mainly on the number of iterations (see *Num_iteration* in line 7 of the SS-CRO algorithm), and the random selection of the four functions. The number of steps for the SS-CRO approximately is O(*Num_iteration*×CROFun), where CROFun is the number of steps of the selected function. Table 3 entails the number of steps for each function, where *c* is a constant number, *nd* is the number of nodes and *ed* is the number of edges. The execution time complexity for any of the four functions approximately is O(*ed*). On the other hand, the worst case of the execution time complexity of SS-CRO is when it has a solution in every iteration and at each iteration it should check-out all kinds of dependencies that each edge node should be checked, which leads to O(*Num_iteration*×*ed*×*nd*).

Table 3: Number of steps for SS-CRO and its functions

Function name	Number of steps
OC	$c+ nd+ed+1$
IC	$2c+ nd+ed+1$
DC	$c+ nd+ed+1$
SN	$c+ nd+ed+1$
OF	$nd+ed$
SS-CRO	$(Num\_iteration)\times(2c+ed+nd+1)$

6. EXPERIMENTAL RESULTS

This section presents the experimental results of the proposed algorithm. The experiments will be done using the following three distinct cases of the *PDG* of the program segment *P*, see section 4.2.

- First case: each node in a PDG implements an instruction from the program segment.
- Second case: in the PDG, each control statement such as the loop and the if statements will be clustered into one unbreakable node, and the rest will be the same as the first case.
- Third case: each group of dependent instructions will be clustered together into one independent unbreakable node.

These three cases will be entered to the three distinct algorithms SS-CRO algorithm, SS-GA (static scheduling using genetic algorithm) algorithm and SS-DA algorithm (static scheduling using duelist algorithm). Finally, the results will be shown and compared.

In the first case, program segment *P* illustrates the initial state wherein it is the input program segment that holds both segments in Seg_1 *and* Seg_2 and their *PDG*'s with their associated costs, see Figure1 and Figure 2. Program segment *P* will be entered into the main algorithm SS-CRO in order to identify distinct valid schedules. In SS-CRO, when the input *PDG* is presented as one molecular then it will be forced to enter either decomposition function (DC) or on-wall effective collision function (OC), until it has at least two sub graphs

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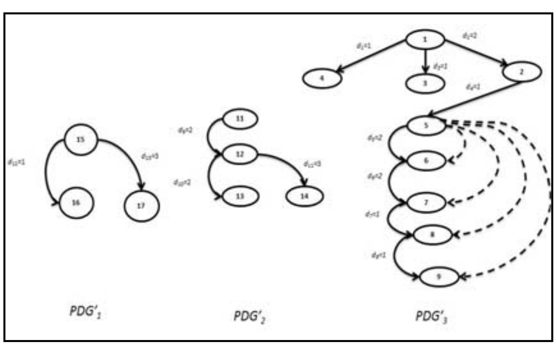
such as *PDG′*$_1$ and *PDG′*$_2$ to enter the synthesis (SN) and the intermolecular functions (IC).

For example, Figure 8 reveals a result of a valid solution found, where the first case is used. The result shows the multiple schedule of the program segment *P*. The new multiple schedules have three new schedules *P′*$_1$, *P′*$_2$ and P′$_3$ with total cost as 4, 7 and 10, respectively. Every schedule has a specific cost. The minimum cost reached for the multiple schedules is 4 for *P′*$_1$, while the maximum cost was 7 for *P′*$_3$. This can lead us that SS-CRO can divide a program segment into optimized independent counter parts.

P′$_1$		
Instructions		Cost(*d*)
15:	MUL.D F14,F15,F16	0
16:	ADD.D F15, #8	1
17:	MULD. F14,F15,F16	3
	Total	4
P′$_2$		
Instructions		Cost(*d*)
11:	DIV.D F9,F10,F11;	0
12:	ADD.D F12,F9,F10;	2
13:	SUB.D F13,F12,F11;	2
14:	MUL.D F13,F12,F11;	3
	Total	7
	P′$_3$	
Instructions		Cost(*d*)
1:	DIV.D F1,F2,F3;	0
2:	ADD.D F2,F4,F1;	2
3:	SUB.D F5,F1,F6;	1
4:	MUL.D F7,F1,F8;	1
5:	LOOP: L.D F0, 0(R1);	0
6:	ADD.D F4,F0,F2;	2
7:	S.D F4, 0(R1);	2
8:	DADDUI R1,#-8;	1
9:	BNE R1,	1
10:	LOOPEND;	0
	Total	10



(a) P′$_1$*, P′*$_2$ *and P′*$_3$ *program segments*

(b) PDG of P′$_1$ *,P′*$_2$ *and P′*$_3$

Figure 8: A valid solution based on multiple schedule approach

Furthermore, Figure 9 depicts another valid solution that illustrates the serialization/reordering approach, which reordered the original schedule and gives a new schedule with the same cost as 20, but in different instructions' order.

In the second case, the PDG of a program segment is been improved by clustering the control statements such as loop statements into one unbreakable node, which maximizes the chance of finding new acceptable solutions. In this case, the *PDG* of a program *P* will be recreated as shown in Figure 10. Notice that the SS-CRO algorithm will not be allowed to break up the loop statement. In other words, control dependency will be excluded from the *PDG*, which will increase the chance of finding more accepted solutions.

In the third case, the *PDG* is been improved more than the second case, where dependent nodes have been clustered in one unbreakable independent component. In Figure 18, nodes 1-4 and the loop node have been clustered in Comp$_1$, nodes 11-14 have been clustered in Comp$_2$, and nodes 15-17 have been clustered in Comp$_3$.
In this improvement, all kinds of dependencies have been excluded from the *PDG*, which increases the chance of finding more acceptable solutions, because of the reduction of *PDG*'s restrictions, i.e. instructions' dependencies.

Furthermore, the SS-CRO algorithm is compared with two distinct optimization algorithms, which is static scheduling based on genetic algorithm is denoted as SS-GA, where it is implemented based on the well-known genetic algorithm presented by authors of [41]. Moreover, static scheduling based on duelist algorithm and denoted as SS-DA, which is implemented based on the recent known algorithm duelist presented by authors of [44]. The input of the three algorithms will be the same, which it is the *PDG* of a program segment in its three cases as shown above.

In SS-GA algorithm, the scenario of the algorithm is inspired from the well-known genetic algorithm posited in [41], which will be explained as follows. First, SS-GA takes the *PDG* and generates random population of chromosomes (a chromosome is a binary vector that reflects the dependencies between the *PDG* nodes) by reordering the *PDG* nodes, let *Pop* be the size of population. Second, SS-GA uses a probability of crossover randomly choses two parents from the population to be the parents of the new offspring,

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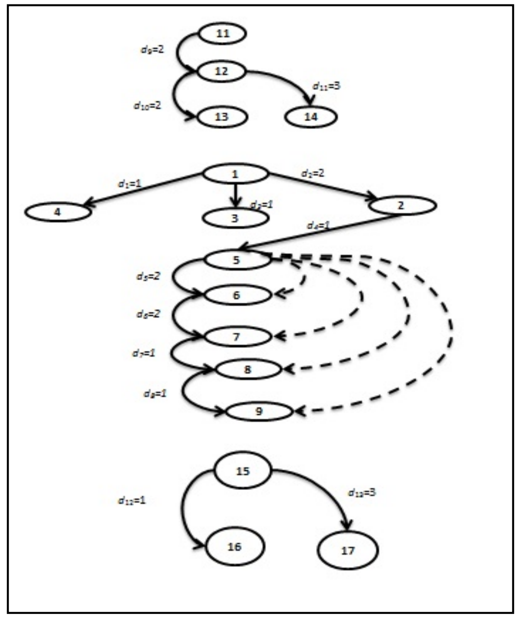
then it applies the crossover function over them to get the new offspring. Third, SS-GA calls the fitness function for each chromosome (the fitness function here checks all nodes dependencies in the chromosome relates to their *PDG*). Forth, SS-GA uses a probability of mutation to mutate the nodes of the new offspring. Fifth, SS-GA places the new offspring in the population, after it is been accepted (i.e. preserves the nodes dependencies). This process will be repeated until the algorithm is been terminated according to the number of iterations.

In SS-DA algorithm, the scenario of the algorithm is inspired by the duelist algorithm posited in [44], as follows. First, SS-DA generates a random population by reordering the PDG nodes the same way as SS-GA, see the above paragraph. Second, SS-DA choses two duelist then it computes the luck variable, which is done using the dependency between the nodes some random numbers for each duelist. The luck of each duelist will be compared and the winner will have the better luck. Third, SS-DA treats the winner and a new solution will be added to the solution list, and then SS-DA returns the looser back to the population to give it a chance to reenter the competition. SS-DA will repeat the process according to its number of iterations

P'_1		
	Instructions	Cost(d)
11:	DIV.D F9,F10,F11;	0
12:	ADD.D F12,F9,F10;	2
13:	SUB.D F13,F12,F11;	2
14:	MUL.D F13,F12,F11;	3
1:	DIV.D F1,F2,F3;	0
2:	ADD.D F2,F4,F1;	2
3:	SUB.D F5,F1,F6;	1
4:	MUL.D F7,F1,F8;	1
5:	LOOP: L.D F0, 0(R1);	0
6:	ADD.D F4,F0,F2;	2
7:	S.D F4, 0(R1);	2
8:	DADDUI R1,#-8;	1
9:	BNE R1,	1
10:	LOOPEND;	0
15:	MUL.D F14,F15,F16	0
16:	ADD.D F15, #8	1
17:	MULD. F14,F15,F16	3
Total		20

(a) P'_1 program segments



(b) PDG of P'_1

Figure 9: A valid solution based on reordering approach

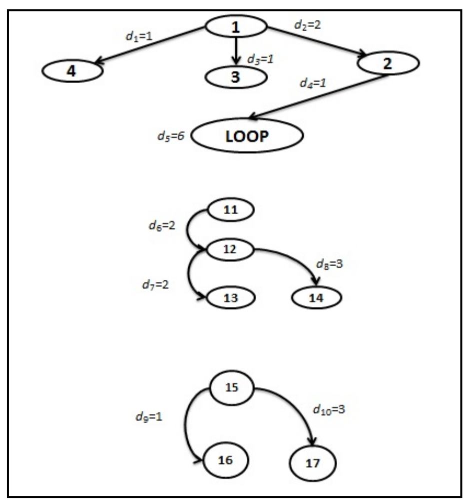


Figure 10: PDG in the second case

In the following figures, the experimental results of the three algorithms will be shown. The experiments were done using the three cases of the PDG of the program segment that shown above. Different numbers of iterations have been used for each experiment such as; 50; 100; 150; 200; 300; 400; 500; 700; 1000; 2000; 3000 and 5000. The number of population used in SS-GA and SS-DA algorithms is 1000. The figures can be categories as follows; Fig 11-13 illustrate the comparison according to the number of solutions achieved (notice that solution duplication is allowed), while Figures 14-16 illustrate the comparison according to the execution time between the three algorithms, and Figure 17 illustrates the percentage of accepted solutions with respect to the execution time.

Meanwhile, Figures 11 and 12 illustrate the comparison of how many accepted solutions does each algorithm achieved. Clearly, SS-CRO has the highest number of solutions in Figures 11 and 12, because SS-CRO has the ability to give multiple schedules using MS operation and reordering using SRO operation, but neither SS-GA nor SS-DA can give multiple schedules. Thus, SS-CRO has the chance to achieve a higher number of solutions than the other algorithms in these the proposed input case such as; the first case and the second case.

In Figure 13, SS-DA has the highest number of correct solutions because in every iteration there is a winner, where all chromosomes in the population are equally likely and are correct because they always have no dependency restrictions, but they may are different in their luck, which is the only factor that determines the winner, so every iteration there is a winner. On the other hand, SS-CRO has the opportunity to lose a solution in some iterations, when it chooses a *PDG* with one node (see Algorithm 1). In general, the decreasing of program segment dependency in the proposed cases of the *PDG* gives the chance for all algorithms to achieve more correct solutions.

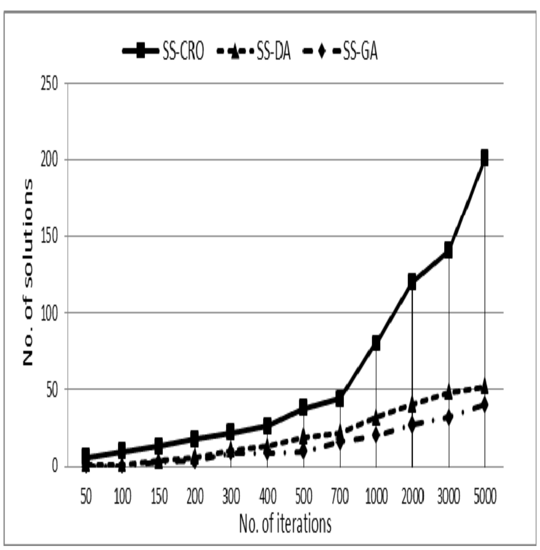


Figure 11: Comparison of three algorithms according to the number of solutions in first case

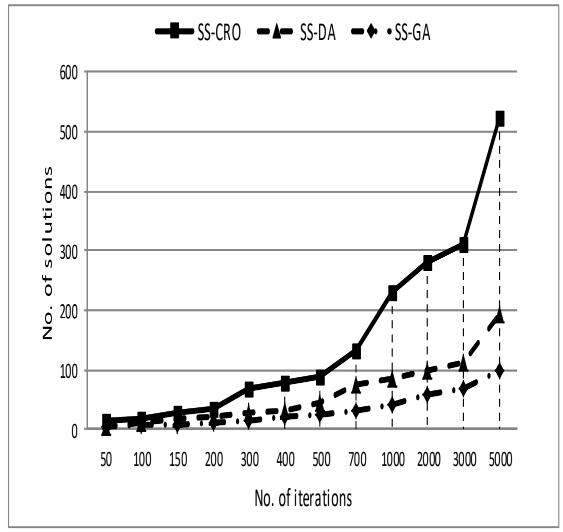


Figure 12: Comparison of three algorithms according to the number of solutions in second case

Meanwhile, figures 14-16 illustrate the time comparison between the three algorithms. Clearly, SS-CRO has the lowest execution time because it has fewer steps than the SS-DA and SS-GA. Both SS-DA and SS-GA should generate a population of solution candidates and a chromosome for every candidate solution in the generated population to start their work. In particularly, both SS-DA and SS-GA should have at least two distinct solutions due to do their job such as; the competition between the duelists in SS-DA and cross-over between parents in SS-GA. Put differently, SS-CRO can do two distinct kinds of reaction even it has only one candidate solution using OC and DC functions, also it has the ability to work with more than one candidate using SN and IC functions. Subsequently, in our work, SS-CRO does not need to generate neither a population of candidate solution to start it job, nor a chromosome for each candidate solution, it start its operation on the *PDG* directly using its four distinct functions however the situation of the number of candidate solutions.

Furthermore, one of the difficulties that were confronted with the use of SS-CRO algorithm was when the input code presented multiple loop statements. In another experiment, two different cases were used such as the first one has two loop statements, while the second portion does not have any loop statement. Additionally, both of them constitute the same number of instructions. During our experimental work, we used a number of varying iterations, commencing from ten iterations reaching all the way up to 1500 iterations for both of the codes portions.

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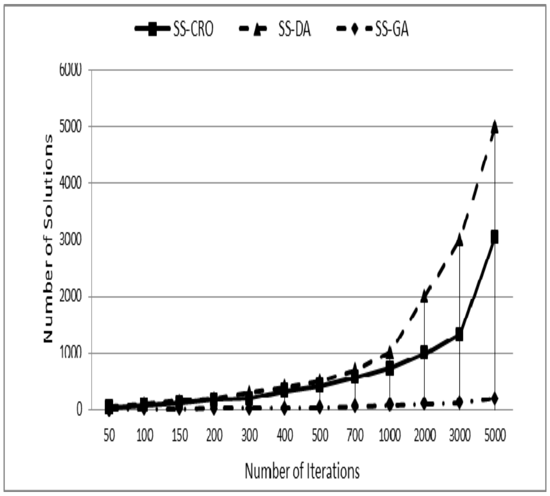


Figure 13: Comparison of three algorithms according to the number of solutions in third case

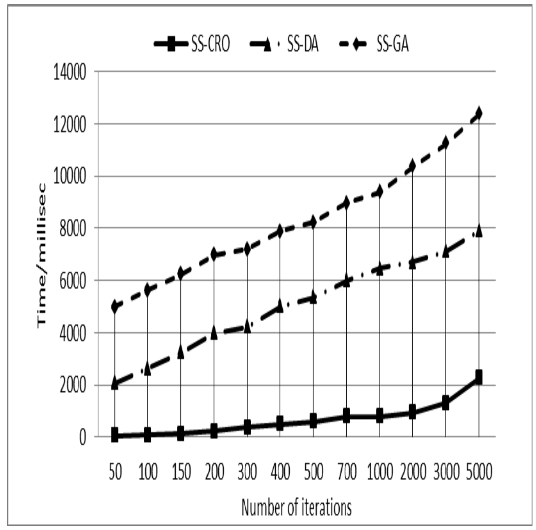


Figure 14: Time comparison between three algorithms using the first case

While the requisite time was too close in both instances, the number of accepted solutions in the code that is bereft of loops is always higher than the number of accepted solutions relating to the code with two loops. Thus, when the code was found to have more than one loop statement, it caused difficulties for SS-CRO algorithm. This particularly occurs with an increase in the number of control dependencies within the loop statements case. Put differently, when an instruction from a particular set of instructions inside of the loop statement is moved outside, the loop statement will trigger a control dependency violation. Inexorably, the resulting solution will be dismissed. Meanwhile when an instruction that does not pertain to the loop statement gets inside loop statement and causes a control violation, the resultant solution will also get dismissed. Therefore, the findings reveal that the number of accepted solutions goes up with an increase in the number of iterations. The scenario paves the way for more new solutions since there are more chances to perform more reactions.

Finally, in Figure 17 illustrates the comparison according to the percentage of the average of number of solutions (from now AvgSol) in each case with respect to the average of the execution time (from now AvgExe). This percentage that denoted as PerSol and calculated by Equation 15, showed that SS-CRO achieved the maximum percentage values of all experiments' for all proposed input cases.

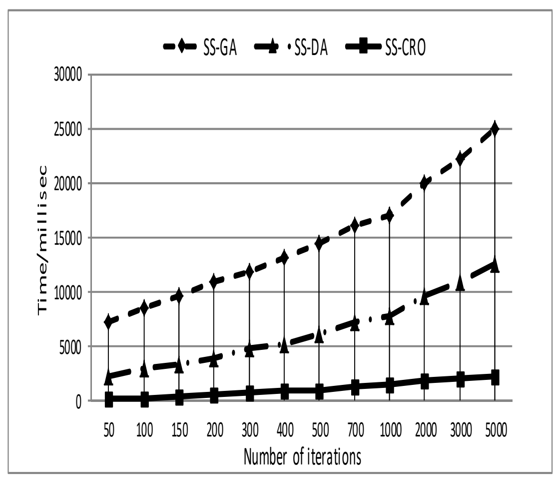


Figure 15: Time comparison between three algorithms using the second case

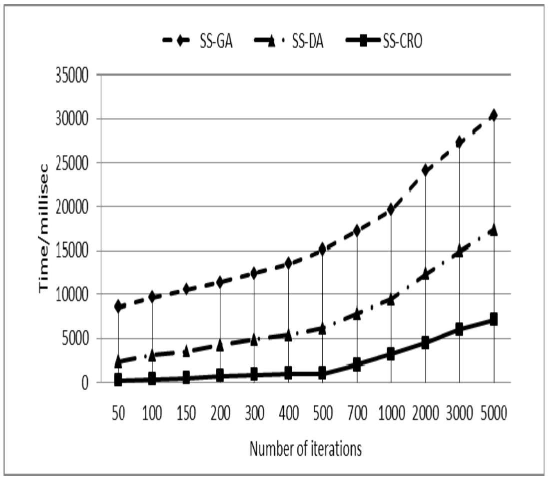


Figure 16: Time comparison between three algorithms using the third case

In particular, the PerSol of the SS-CRO achieved the maximum range as (10%-30%), while the PerSol of the SS-DA achieved the moderate range as (0%-21%), and the percentage of PerSol of the SS-GA has the lowest range as (0%-1%).

$$\text{PerSol} = (\text{AvgSo}/\text{AvgExe})\% \quad (14)$$

The limitations of this research was in the following: the environment used which may be improved; that is more benchmarks can be used to evaluate the SS-CRO algorithm.

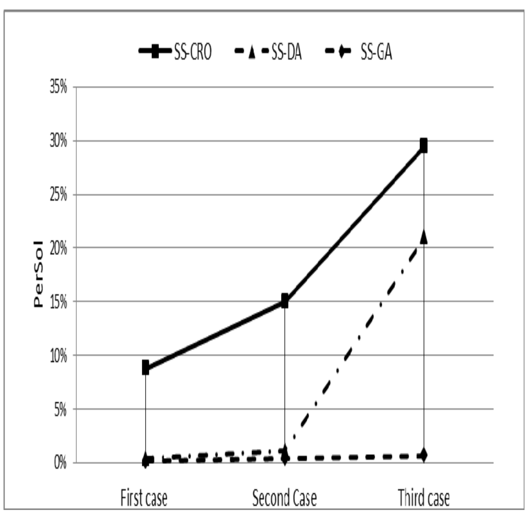


Figure 17: Comparison between the three algorithms according to the percentage of the number of solutions

7. CONCLUSIONS

Here in the current day and age, scheduling can be utilized in several real-life areas, wherein the main endeavor is time reduction. In this paper, we proposed a solution in the form of CRO for instructions static scheduling. In particular, we leveraged the chemical reaction optimizer in order to optimize instructions static scheduling. According to the study's findings, SS-CRO is capable of generating several solutions and determining their validity. These solutions are based on two scheduling operations; multiple scheduling (MS) and serialization (SRO) of instructions. On the other hand, we observed that when the program entails more than one loop statement, the number of accepted solutions decreases. This could possibly be attributed to the fact that the loop statement is unbreakable and therefore, should remain as one block, thereby implying that no new instruction from the program code should get inside or vice versa.

In the experimental results, we compared SS-CRO with two metaheuristic algorithms; SS-DA and SS-GA. Moreover, we proposed in a preprocessing stage of the *PDG* three distinct cases, where each case has fewer dependencies than its predecessor. The *PDG* in its three cases have been applied to the three algorithms. SS-CRO achieved the lowest time in all experiments, and the highest percentage of number of solutions with respect to the execution time, which is ranged as (10%-30%).

REFRENCES:

[1]: Jabri, R. A Generic Parser for Strings and Trees. *Computer Science and Information Systems*, 9(1), 2012, 381-410.

[2]: Jabri, R. A predictive bottom-up parser. *Journal of Computing*, 92(2), 2011, 123–167.

[3]: Andión, M., Manuel, A., Gabriel, & R., Juan, T. A novel compiler support for automatic parallelization on Multicore systems. *In Proc. the Parallel Computing*, 39, 2013, 442-460.

[4]: Jo, S., Jeong, Y., & Lee, S. GPU-Driven Scalable Parser for OBJ Models. *Journal of Computer Science and Technology*, 33(2), 2018, 417-428.

[5]: Hennessy, J., & Patterson, D. *Computer architecture: a quantitative approach*, 2011, Elsevier.

[6]: Chang, P., Chen, W., Mahlke, S., & Hwu, W. Comparing static and dynamic code scheduling for multiple-instruction-issue processors. *In Proc. the 24thannual international symposium on Microarchitecture*, 1991, 25-33, ACM.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

[7]: Lam, A., & Li, V. Chemical reaction optimization: a Tutorial. *Memetic Computing*, 4(1), 2012, 3-17.
[8]: Shadbolt, N. Nature-inspired computing .*IEEE Intell. Syst*., 19(1), 2004, 2–3.
[9]: Kennedy, J., & Eberhart, R. *Swarm*, *Intelligence* 2001, San Francisco: Morgan Kaufmann, ISBN:1-55860-595-9.
[10]: Chen, X., Ong, Y., Lim, M., & Tan, K. A Multi-facet Survey on Memetic Computation. *IEEE Trans Evolutionary Computation*, 15(5), 2011, 591–607.
[11]: Ong, Y., Lim, M., & Chen, X. Research Frontier: Memetic Computation Past, Present and Future. *IEEE Computational Intelligence Magazine*, 5(2), 2010, 24–36.
[12]: Price, K., Storn, R., & Lampinen, J. *DifferentialEvolution: A Practical Approach to Global Optimization*, 2005, Berlin: Springer.
[13]: Dorigo, M., & Stutzle, T. *Ant Colony Optimization,* 2004, Cambridge, MA, USA: The MIT Press.
[14]: Geem, Z., Kim, J., & Loganathan, G. A New Heuristic Optimization Algorithm: Harmony Search. *Simulation*, 76.2, 2001, 60-68.
[15]: Masadeh, R., Mahafzah, B., & Sharieh, A. Sea lion optimization algorithm. *International Journal of Advanced Computer Science and Applications*, 10(5), 2019, 388-395.
[16]: Golub, M., & Kasapovic, S. Scheduling multiprocessor tasks with genetic algorithms. *In Proc. of the Applied Informatics-Proceedings*, 2002, 273-278.
[17]: Potvin, J.-Y. Genetic algorithms for the traveling salesman problem. *Annals of Operations Research*, 63, 1996, 339-370.
[18]: Al-Adwan, A., Sharieh, A. & Mahafzah, B. Parallel heuristic local search algorithm on OTIS hyper hexa-cell and OTIS mesh of trees optoelectronic architectures. *Applied Intelligence*, 49(2), 2019, 661-688.
[19]: Al-Adwan, A., Mahafzah, B., & Sharieh A. Solving traveling salesman problem using parallel repetitive nearest neighbor algorithm on OTIS-Hypercube and OTIS-Mesh optoelectronic architectures. *Journal of Supercomputing*, 74(1), 2018, 1-36.
[20]: Mahafzah B. Performance evaluation of parallel multithreaded A* heuristic search algorithm. *Journal of Information Science*, 40(3), 2014, 363-375.
[21]: Mahafzah, B. Parallel multithreaded IDA* heuristic search: Algorithm design and performance evaluation. *International Journal of Parallel, Emergent and Distributed Systems*, 26(1), 2011, 61-82.
[22]: Duwairi, R., Mahafzah, B., & Al-Ayyoub A. A framework for performance assessment of parallel bi-directional heuristic search. *The International Conference on Artificial Intelligence* (IC-AI'02), Las Vegas, USA, June/2002, 24-27.
[23]: Masadeh, R., Sharieh, A., & Mahafzah B. Humpback whale optimization algorithm based on vocal behavior for task scheduling in cloud computing. *International Journal of Advanced Science and Technology*, 13(3), 2019, 121-140.
[24]: Alshraideh, M., Jawabreh, E., Mahafzah, B., & Al Harahsheh, H. Applying genetic algorithms to test JUH DBs exceptions. *International Journal of Advanced Computer Science and Applications*, 4(7), 2013, 8-20.
[25]: Alshraideh, M., Mahafzah, B., Eyal Salman, H., & Salah I. Using genetic algorithm as test data generator for stored PL/SQL program units, *Journal of Software Engineering and Applications*, 6(2), 2013, 65-73.
[26]: Alshraideh, M. , Mahafzah, B., & Al-Sharaeh. S, A multiple-population genetic algorithm for branch coverage test data generation, *Software Quality Journal*, 19(3), 2011, 489-513.
[27]: Shaheen, A., Sleit A., Al-Sharaeh, S. A Solution for Traveling Salesman Problem Using Grey Wolf Optimizer Algorithm. *Journal of Theoretical and Applied Information Technology*, 96(18), 2018.
[28]: Kurowski, K., Oleksiak, A., Piątek, W., & Weglarz, J. Hierarchical scheduling strategies for paralleltasks and advance reservations in grids. *Journal ofScheduling*, 16(4), 2013, 349–368.
[29]: Xu, S., & Bean, J. C. Scheduling parallel-machine batch operations to maximize on-time delivery performance. *Journal of Scheduling*, 19, 2016, 583–600.
[30]: Padmanabhan, M., Li, H., Tran, T., Zhang, P., Down, D., & Beck, J. Multi-stage resource-aware scheduling for data centers with heterogeneous servers. *Journal of Scheduling*, 2017/07.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

[31]: Zhao, Y. L., Yang, J. L., Zhao, W. S., Todri-Sanial, A., & Cheng, Y. Q. Power Supply Noise Aware Task Scheduling on Homogeneous 3D MPSoCs Considering the Thermal Constraint. *Journal of Computer Science and Technology*, 33(5), 2018, 966-983.

[32]: Mahafzah, B., & Jaradat, B. The load balancing problem in OTIS-Hypercube interconnection networks. *Journal of Supercomputing*, 46(3), 2008, 276-297.

[33]: Bechikh, S., Chaabani, A., & Said, L. An efficient chemical reaction optimization algorithm for multi-objective optimization. *IEEE transactions on cybernetics*, 45(10), 2015, 2051-2064.

[34]: Eldos, T., Kanan, A., Nazih, W., & Khatatbih, A. Adapting the Chemical Reaction Optimization Algorithm to the Printed Circuit Board Drilling Problem. *In Proc. of the International Conference on Computer, Computational and Mathematical Sciences*, 2015, Zürich-Switzerland.

[35]: Mahafzah, B., & Jaradat, B. The hybrid dynamic parallel scheduling algorithm for load balancing on chained-cubic tree interconnection networks. *Journal of Supercomputing*, 52(3), 2010, 224-252.

[36]: Filho, J.F., Rodriguez, L.G.A. & da Silva, A.F,Yet. Another Intelligent Code-Generating System: A Flexible and Low-Cost Solution. *J. Comput. Sci. Technol*, 33, 2018, 940–965.

[37]: Alrezaamiri H., Ebrahimnejad A., & Motameni H. Software requirement optimization using a fuzzy artificial chemical reaction optimization algorithm. *Soft Computing*, 2018.

[38]: Dam TL., Li K., & Fournier-Viger P. Chemical reaction optimization with unified tabu search for the vehicle routing problem. *Soft Computing*, 21, 2017, 6421–6433.

[39]: Islam MR., Saifullah CK., Asha ZT., & Ahamed R. Chemical reaction optimization for solving longest common subsequence problem for multiple string. *Soft Computing*, 2018, 1–25.

[40]: Barham, R., Sharieh, A., & Sliet, A. Chemical reaction optimization for max flow problem. *IJACSA International Journal of Advanced Computer Science and Applications*, 7(8), 2016.

[41]: Mitchell M. *An Introduction to Genetic Algorithms*, 1996, Cambridge, MA: MIT Press. ISBN 9780585030944.

[42]: Woo, K. Application of Fitness Switching Genetic Algorithm for Solving 0-1 Knapsack Problem. *Journal of Theoretical and Applied Information Technology*, 96(22), 2018, 7339-7348.

[43]: Fauzi, N., Jaya, A., Jarrah, M., Akbar, H., Yunos, A., Basari, A., Ahmad, N., Daimon, M., Rahman, A., Tahir & L., Madhusudhanarao, C. Thin film roughness optimization in the TiN coatings using genetic algorithms. *Journal of Theoretical and Applied Information Technology*, 95(24), 2017, 6690-6698.

[44]: Biyanto T., Fibrianto H., Nugroho G., Hatta A., Listijorini E., Budiati T., & Huda H. Duelist Algorithm: An Algorithm Inspired by How Duelist Improve Their Capabilities in a Duel. *In preceding of International Conference in Swarm Intelligence*, Bali, Indonesia, 2016.

[45]: Biyanto, T. Optimization of Energy Efficiency and Conservation in Green Building Design Using Duelist, Killer-Whale and Rain-Water Algorithms, 2017. https://doi.org/10.31227/osf.io/x4srd.

[46]: Biyanto T., Sehamat N., Sordi N., & Zabiri H. Optimization of PID controller tuning parameters for multivariable system using Duelist algorithm, *IOP Conference Series: Materials Science and Engineering*, 458, 2018, 012053.

[47]: Kanemitsu, T., Higo, Y., & Kusumoto, S. A visualization method of program dependency graph for identifying extract method opportunity. *In Proceedings of the 4th Workshop on Refactoring Tools*, 2011, 8-14, ACM.

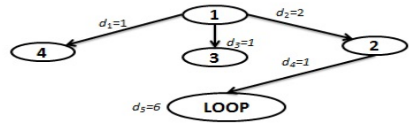
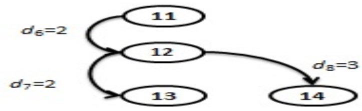
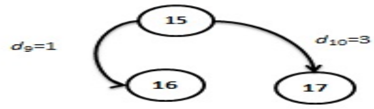
Component	Clustered instrucitons in the component
	
	
	

Figure 18: PDG in the third case