IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received August 8, 2017, accepted September 4, 2017, date of publication September 8, 2017, date of current version October 12, 2017.

Digital Object Identifier 10.1109/ACCESS.2017.2750209

Incorporating the Range-Based Method into GridSim for Modeling Task and Resource Heterogeneity

KAILUN ENG, ABDULLAH MUHAMMED, MOHAMAD AFENDEE MOHAMED, AND SAZLINAH HASAN
University Putra Malaysia, Serdang 43400, Malaysia

Corresponding author: Kailun Eng (marcus2204.upm@gmail.com)

This work was supported by the Malaysian Ministry of Higher Education under Grant FRGS/1/2014/ICT03/UPM/03/1.

ABSTRACT Over the years, many heuristic algorithms have been proposed for solving various Grid scheduling problems. GridSim simulator has become a very popular simulation tool and has been widely used by Grid researchers to test and evaluate the performance of their proposed scheduling algorithms. As heterogeneity is one of the unique characteristics of Grid computing, which induces additional challenges in designing heuristic-based scheduling algorithms, the main concern when performing simulation experiments for evaluating the performance of scheduling algorithms is how to model and simulate different Grid scheduling scenarios or cases that capture the inherent nature of heterogeneity of Grid computing environment. However, most simulation studies that based on GridSim have not considered the nature of heterogeneity. In this paper, we propose a new simulation model that incorporates the range-based method into GridSim for modeling and simulating heterogeneous tasks and resources in order to capture the inherent heterogeneity of Grid environments that later can be used by other researchers to test their algorithms.

INDEX TERMS Simulation, heterogeneity modeling, grid computing, GridSim, scheduling algorithm.

I. INTRODUCTION

Grid computing is a computing environment that enables heterogeneous resources, which are geographically dispersed, to collaborate to each other with the objective of obtaining the capabilities to solve data-intensive or computational-intensive problems [1]. One of the key challenges in Grid computing is designing an efficient resource management system, which is able to efficiently perform the scheduling process that involves the assignment of application tasks to the resources. Scheduling tasks to resources in Grid computing environment is a NP-Complete problem.

Over the years, many studies have been carried out in an attempt to develop an efficient heuristic-based scheduling algorithm for solving the Grid scheduling problem [2]–[13]. In order to examine and evaluate the performance of their proposed scheduling algorithms, researchers need to carry out repeatable, configurable, and controllable experiments, but it is difficult to perform this in the real Grid system due to the unique characteristics of Grid computing environments such as autonomous, dynamic, and heterogeneous [1], [14]. Accordingly, most of the Grid researchers have chosen experimental simulation for their studies as it is easier to perform the evaluation of scheduling algorithms with the help of simulation [15]. Therefore, the need of a simulation that captures the real world Grid system properties such as heterogeneity is necessary.

There are a number of simulators available for modeling and simulating the Grid computing environment [16], and one of the most popular simulators is the GridSim toolkit [17]. It is a Java-based discrete-event simulator, which utilizes object-oriented techniques to model and simulate all the entities that involve in the scheduling event of a real Grid system, such as Grid users, Grid Information Service (GIS), Grid scheduler, and Grid resources. Most importantly, it allows tasks and resources with different characteristics to be modeled and simulated.

When simulating and modeling the Grid computing environment, it is extremely important to accommodate heterogeneity as it is one of the unique characteristics of real Grid system that has a significant impact on the performance of scheduling algorithms. Thus, the main concern when performing simulation experiments for evaluating the performance of scheduling algorithms is how to model and simulate distinct Grid scheduling scenarios or cases that capture the inherent nature of heterogeneity of real world Grid computing environment. In this work, we design a new simulation model, aiming to accommodate the nature of heterogeneity of Grid computing environment when using GridSim.

II. RELATED WORKS

As GridSim simulation is discrete-event driven and objected-oriented, every entity that involves in the scheduling event (Grid user, Grid resources, Grid scheduler, GIS, and user's tasks) has to be modeled with a number of essential attributes or characteristics and behaviors that well reflect the same kind of entities of the real Grid computing environment. In GridSim simulation, the tasks that submitted by Grid users to Grid scheduler for scheduling are modeled as Gridlet objects, which have attributes such as identification number (id), task length in MI (millions of instructions), size of input file and output file in byte, whereas heterogeneous resources are modeled as GridResource objects, which have attributes such as computing power in terms of MIPS (millions of instructions per second), internal allocation policies (time-shared or space-shared), number of machines, and number of processing elements per machine (PE). In brief, modeling and simulating the tasks for Grid computing system in GridSim require four basic attributes to be defined: id, length, input file size, and output file size, whereas resources need five fundamental attributes: name, computing power, number of machine, number of PE, and internal allocation policy (time-shared or space-shared).

Kalantari and Akbari [2] defined the length of gridlets in GridSim randomly based on uniform distribution when modeling and simulating the independent tasks for evaluating their proposed scheduling algorithm. Similarly, Hao *et al.* [4] simulated tasks in GridSim simulation by defining the length of gridlets within a specific range of values. In addition, they simulated 30 resources with same number of machine and PE, in which every PE is between 1 and 5 MIPS or between 1 and 10 MIPS. Prado *et al.* [3] designed and simulated a grid scenario based on GridSim toolkit to evaluate the performance of the proposed fuzzy rule-based meta-scheduler. Their simulation modeled and simulated a number of independent tasks following a Poisson distribution. Besides, resources are simulated with different computational power between 12000 and 18500 MIPS, corresponding to resource heterogeneity. However, task heterogeneity was not taken into account in the study. Lee *et al.* [6] performed different experiments with GridSim by defining different range of task length and resource computing power. In the first experiment, the length of every task is randomly generated between 200,000 and 400,000 MI, whereas the computing power of resource is randomly generated between 500 and 5000 MIPS. In their third experiment, the length of tasks is set to be randomly generated between 300,000 and 500,000 MI, whereas the computing power of each resource is randomly generated between 500 and 5000 MIPS. Although the experiments have considered different range of task length and resource's computing power, the heterogeneity is not specifically considered and covered in their simulation set up. In contrast to Lee *et al.* [6], Aron and Chana [5] has specifically considered heterogeneity in GridSim simulation for analyzing empirically the performance of the proposed bacterial foraging based hyper-heuristic resource scheduling algorithm. He has simulated two different heterogeneous cases (low heterogeneous case and high heterogeneous case) for the performance evaluation. However, instead of concerning the heterogeneity by simulating tasks and resources with different range of task length and computing power respectively, they have only considered the heterogeneity of resource and simulated all the resources to have different number of PEs within a certain range of value. For example, the low heterogeneous case is set up by simulating each resource to have a random number of PEs between 1 and 5, whereas high heterogeneous case is set up by simulating each resource to have a random number of PEs between 7 and 30. Moreover, 5000 gridlets have been simulated with a random number of length between 1000 and 6000 MI. Clearly, only the resource heterogeneity has been taken into account in their simulated heterogeneous cases for evaluating the performance of scheduling algorithms, and the task heterogeneity, which is one of the essential and indispensable characteristics to reflect and represent the true nature of heterogeneity of Grid computing environment, was not taken into consideration.

Overall, from the reviewed scientific literatures, it is observed that the heterogeneity nature is not fully taken into account in evaluating the performance of scheduling algorithms when using GridSim. One question that needs to be asked, however, is whether the simulation that based on GridSim is able to well capture the heterogeneity nature of Grid computing environment. It is important to examine how any proposed scheduling algorithm responds to different heterogeneities of tasks and resources in order to show that it is applicable to real-world scheduling scenarios of Grid computing. Conducting simulation experiments with configurable heterogeneity properties is mandatory to avoid bias. Hence, in this paper, we present a simulation model that allows Grid researchers to be able to consider heterogeneity properties in their simulation studies when using GridSim.

III. HETEROGENEITY MODELING

The concept of computational heterogeneity was first introduced by Armstrong [18]. According to Armstrong, both resources and tasks must be taken into consideration in order to better characterize computational heterogeneity. Correspondingly, four categories of heterogeneity regarding different combinations of task heterogeneity and resource heterogeneity were presented. These four categories can be described as quadrants of heterogeneity and referred as lolo, lohi, hilo, and hihi. For example, lohi refers to low task heterogeneity and high resource heterogeneity.

With the concept of heterogeneity quadrant [18], two methods, namely range-based and CVB (Coefficient of Variation Based), were then developed [19] for generating ETC (expected time to compute) matrices. As the range-based and CVB methods are deliberately developed for the generation of ETC matrices with heterogeneity properties, the definition of task and resource heterogeneity are described in the context of the variation along a row and column of an ETC matrix respectively [19]. Task heterogeneity is described as the degree to which the execution times of each task vary for a given resource, whereas resource heterogeneity is described as the degree to which the execution times of a given task across all the resources.

In the simulation model of Braun *et al.* [20], the range-based and CVB methods have been adopted and modified with different values of the parameters of heterogeneity for generating ETC matrices in order to examine the relative performance of eleven static heuristics for mapping a class of independent tasks onto heterogeneous distributed computing systems. Thenceforth, Ali *et al.*'s and Braun *et al.*'s simulation models have become popular and been widely used for evaluating heuristic-based scheduling algorithms in heterogeneous computing environments such as Grid computing and Cloud computing [7]–[13], [21]–[23]. In spite of that, this concept of heterogeneity quadrant and the methods (range-based and CVB) have never been applied in GridSim simulation as GridSim concerns about modeling and generating Grid computing entities such as tasks and resources, and does not concern about generating ETC matrices. Therefore, in this study, we try to reveal the possibility of incorporating the range-based method into GridSim in order to accommodate the concept of heterogeneity quadrant.

IV. ACCOMMODATING THE CONCEPT OF HETEROGENEITY QUADRANT IN GridSim

The key idea of our simulation model is to accommodate the concept of heterogeneity quadrant in GridSim by incorporating the range-based method into GridSim for modeling and simulation of tasks and resources. In order to put heterogeneity in the context of GridSim simulation, we define task heterogeneity as the variation of the length (millions of instructions) of simulated gridlets, whereas resource heterogeneity is defined as the variation of the computing power (millions of instructions per second) of simulated resources. A Grid system is said to have ''low'' task heterogeneity if the tasks that submitted from users to Grid scheduler have small range of variation in length. Alternatively, a grid system, which comprising tasks of varying length (huge range of variation in length) is said to have ''high'' task heterogeneity. Meanwhile, a Grid system is said to have ''low'' resource heterogeneity if it consists mainly of resources of similar computing power (small range of variation in computing power), whereas a Grid system consists of diversely capable (huge range of computing power) resource is said to have ''high'' resource heterogeneity.

In the range-based method that presented in [19], the task heterogeneity and the resource heterogeneity, which denoted as R_{task} and R_{mach}, respectively, are used independently as the upper boundary of a uniform distribution for generating random numbers. The random number that sampled from the uniform distribution in the interval $[1, R_{task})$ is denoted as $U(1, R_{task})$, whereas $U(1, R_{mach})$ denotes the random number that sampled from the uniform distribution in the interval $[1, R_{mach})$. By multiplying $U(1, R_{task})$ and $U(1, R_{mach})$, the elements of an ETC matrix can then be basically obtained. More specifically, for each row of the ETC matrix, a random number, $U(1, R_{task})$ is generated, and for each column in the row, a random number, $U(1, R_{task})$ is generated and multiplied with the corresponding $U(1, R_{task})$ in order to obtain the value as the element of an ETC matrix. On the other hand, Braun *et al.* [20] used ϕ_b to denote task heterogeneity and ϕ_r for resource heterogeneity. Different values of task heterogeneity and resource heterogeneity were defined to reflect the environment for their research project (MSHN).

In our simulation model, we modified the range-based method by changing the way the task heterogeneity and resource heterogeneity are used. Instead of using the range-based method to generate ETC matrix, we used it in generating the length of gridlets and the computing power of resources for GridSim simulation. Let H_{task} and H_{res} be the parameters that represent task heterogeneity and resource heterogeneity, respectively, in which higher the value of these parameters, higher the heterogeneity. Consider X_{task} as a random number generated from a uniform distribution in the interval $[1, H_{task})$, the length of a gridlet (denoted as L) is defined as

$$L = X_{task} \times H_{res}. \tag{1}$$

Given t (the total number of tasks that need to be simulated), H_{task}, and H_{res}, t tasks can be simulated by using (1) to generate the length of each task. The procedure for simulating t tasks using (1) in GridSim is shown in Fig. 1, where *gridlets* denotes a vector that consists of t simulated tasks.

Require: t, H_{task}, H_{res}
Ensure: $gridlets$

for $0 \le i < t$ **do**
  $X_{task} \leftarrow U(1, H_{task})$
  $L \leftarrow X_{task} \times H_{res}$ ▷ Generate gridlet's length
  $gridlets[i] \leftarrow createGridlet(id, L, ...)$
end for
return $gridlets$

FIGURE 1. Modified Range-based method for simulating tasks in GridSim.

In terms of computing power of resources, it is defined by using the resource heterogeneity, H_{res}, as the upper boundary to generate a random number from a uniform distribution. P denotes the computing power of a resource and X_{res} denotes the random number generated from a uniform distribution in the interval $[1, H_{res})$, P is defined as

$$P = \frac{H_{res}}{X_{res}}. \tag{2}$$

Given r (the total number of resources that need to be simulated) and H_{res}, r resources can be simulated by using (2) to generate the computing power of each resource. The procedure for simulating r resources using (2) in GridSim is shown in Fig. 2, where *resources* denotes a vector that consists of r simulated resources.

```
for 0 ≤ j < r do
    X_res ← U(1, H_res)
    P ← H_res ÷ X_res            ▷ Generate computing power
    resources[j] ← createResource(name, P, ...)
end for
return resources
```

FIGURE 2. **Modified Range-based method for simulating resources in GridSim.**

V. ANALYSIS

To verify that the concept of heterogeneity quadrant is able to be accommodated in GridSim with the proposed simulation model, we generated ETC matrices indirectly from the simulated Grid environment in GridSim. Then we analyzed the properties of the generated ETC matrices. In GridSim, an ETC matrix can be indirectly constructed based on a set of simulated gridlets and resources. Given t (number of gridlets) and r (number of resources), the dimension of the ETC matrix is $t \times r$, and each element of the ETC matrix is obtained from the ratio of the gridlet's length and resource's computing power.

Proposition 1: When task heterogeneity (H_{task}) and resource heterogeneity (H_{res}) parameters are used to simulate gridlets and resources in GridSim as in Fig. 1 and 2, the possible range for any given element of the ETC matrix is $[1, H_{task}H_{res})$.

Proof: Assume that t is the total number of gridlets, and r is the total number of resources, where $t > 0$ and $r > 0$. Let $A(i, j)$ denotes the element of matrix A at row i and column j, where $i \in 0, \ldots, t-1, j \in 0, \ldots, r-1$, the value of $A(i, j)$ is calculated by

$$A(i, j) = \frac{L_{i+1}}{P_{j+1}}, \tag{3}$$

where L_{i+1} represents the length of $(i+1)$th gridlet, and P_{j+1} represents the computing power of $(j+1)$th resource. Note that $A(i, j)$ is minimal if and only if L_{i+1} is the minimal and P_{j+1} is the maximal. Conversely, $A(i, j)$ is maximal if and only if P_{j+1} is maximal and P_{j+1} is minimal. Since $L \in [H_{res}, H_{task} \times H_{res})$ and $P \in [1, H_{res})$ (given by (1) and (2)), so the lower bound of $A(i, j)$ is $(H_{res} \div H_{res})$, and the upper bound is $((H_{task} \times H_{res}) \div 1)$. Hence, we can say that the possible range for any given element of the ETC matrix that generated using the proposed method, is $[1, H_{task} \times H_{res})$, which is same as Braun *et al.*'s range, $[1, \phi_b \times \phi_r)$. For example, given that task heterogeneity, $\phi_b = 100$ and resource heterogeneity, $\phi_r = 10$ for LoLo heterogeneity quadrant in Braun *et al.*'s simulation model [13], the range of any given element of a LoLo ETC matrix is said to be $[1, 1000)$. Using the proposed method, we will obtain a set of gridlets with length, L, which is in the range of $[10, 1000)$, and a set of resources with computing power P, which is in the range of $[1, 10)$. Then the resulting range of any given element of a LoLo ETC matrix is said to be $[1, 1000)$, which is same as Braun *et al.* [20].

Proposition 2: When task heterogeneity (H_{task}) and resource heterogeneity (H_{res}) parameters are used to simulate gridlets and resources in GridSim as in Fig. 1 and 2, the expected value of any given element of the ETC matrix is $\frac{1}{4}(H_{task}+1)(H_{res}+1)$.

Proof: If $X \sim U(a, b)$, then the expected value of X, $E(X)$ is $\frac{1}{2}(b+a)$. Since X_{task} $U([1, H_{task}))$ and L is the product of a random number X_{task} and H_{res}, the expected value of L, $E(L)$ is $\frac{1}{2}(H_{task}+1) \times H_{res}$. Analogously, since $X_{res} \sim U([1, H_{res}))$ and P is the ratio of H_{res} to a random number X_{res}, the expected value of P, $E(P)$ is $H_{res} \div \frac{1}{2}(H_{res}+1)$, which can be reduced to $\frac{(2H_{res})}{((H_{res}+1))}$. It is noted that each element in the ETC matrix that generated in GridSim is the ratio of L to P. Hence, the expected value of the elements in the ETC matrix is the ratio of $E(L)$ to $E(P)$, namely $\frac{\frac{1}{2}(H_{task}+1)\times H_{res}}{\frac{2H_{res}}{(H_{res}+1)}} = \frac{1}{4}(H_{task}+1)(H_{res}+1)$.

Proposition 3: When task heterogeneity (H_{task}) and resource heterogeneity (H_{res}) parameters are used to simulate gridlets and resources in GridSim as in Fig. 1 and 2, the standard deviation of the elements of the ETC matrix is $\frac{1}{12}[3(H_{task}-1)^2(H_{res}+1)^2 + 3(H_{res}-1)^2(H_{task}+1)^2 + (H_{task}-1)^2(H_{res}-1)^2]^{1/2}$.

Proof: Note that each element of the ETC matrix is the ratio of $(X_{task} \times H_{res})$ to $\frac{H_{res}}{X_{res}}$, which can further be simplified and expressed as $(X_{task} \times X_{res})$. From the formula of standard deviation of the product of two random variables, $Var(XY) = Var(X)E(Y)^2 + Var(Y)E(X)^2 + Var(X)Var(Y)$, we can therefore derive the standard deviation of the elements of the ETC matrix: $\frac{1}{12}[3(H_{task}-1)^2(H_{res}+1)^2 + 3(H_{res}-1)^2(H_{task}+1)^2 + (H_{task}-1)^2(H_{res}-1)^2]^{1/2}$.

From the analysis of properties of the ETC matrices that generated in both the proposed simulation model and in [20], it is shown that the ETC matrices in both simulation models have same statistical properties: range, expected value, and standard deviation. It can thus be suggested that the similar concept of heterogeneity quadrant as in [20] is able to be accommodated in GridSim by our proposed simulation model. Surprisingly, it is noticed that the variation of the values (coefficient of variation) of each row and of each column in the ETC matrix that generated in GridSim is constant. This is due to the fact that the computing power of any simulated resource in GridSim is assumed constant for all tasks, which means that the resource with highest computing power will always being the fastest regardless of tasks, and the tasks which have same length will always have the same value of expected execution time with respect to resources. For instance, let us assume that 3 resources and 4 tasks are simulated in GridSim, a 4×3 matrix can be indirectly generated as given in Fig. 3, and by calculating the standard deviation σ and mean μ, the statistic coefficient of variation (CV) can be obtained by $CV = \frac{\sigma}{\mu}$. Fig. 3 demonstrates that all the rows and columns in the ETC that indirectly generated in GridSim have the same coefficient of variation.

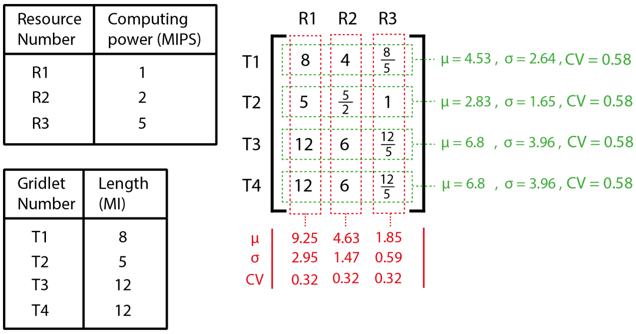

FIGURE 3. A simple example of simulated environment in GridSim that illustrates some statistical properties of the ETC matrix.

VI. EXPERIMENT

Simulation experiments were carried out to validate the effect of incorporating the range-based method into GridSim simulation for evaluating scheduling algorithms. Same values of the task and resource heterogeneity parameters were used as in [20] to simulate four different scheduling cases with respect to heterogeneity for the experiments. 512 gridlets and 16 resources are simulated for each scheduling case. All the simulation experiments were performed in the environment of Window 10 Pro with 64-bit and run on a PC with Intel Core i5-3470 CPU 3.20 GHz and 8 GB RAM. Two simple constructive heuristic-based scheduling algorithms, namely Min-Min and Max-Min, are selected for the experiments. Both the algorithms were repeated run for 30 times to obtain the average makespan results.

From the makespan results in Fig. 4, it is observed that the Max-Min algorithm performs better than Min-Min in all the cases. However, in the simulation study of twelve heuristic-based scheduling algorithms by Braun *et al.* [20], the makespan results obtained by Min-Min was better than Max-Min heuristic for all the cases. According to [20] and [7], Max-Min algorithm has better performance than Min-Min when there are many shorter tasks than the longer ones. Therefore, the contrast in the results can be explained by the imbalance ratio between small tasks and large tasks. Furthermore, since the simulated Grid environment with the proposed simulation model has same size (512 tasks and 16 resources) and same statistical properties (range, expected value, and standard deviation) as Braun *et al.* [20], it can thus be suggested that even with the same degree of heterogeneities in a Grid environment,

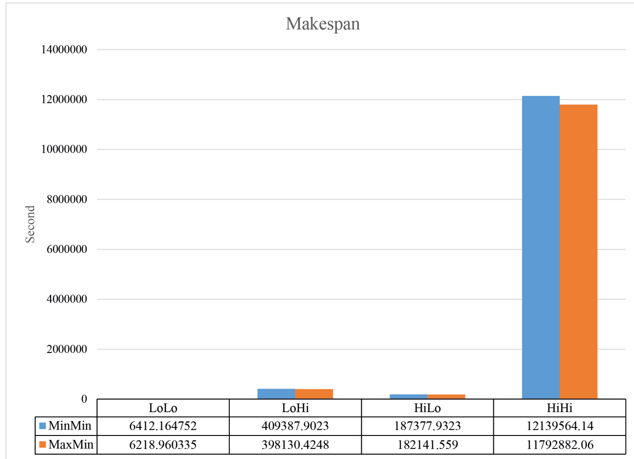

FIGURE 4. The makespan results of Min-Min and Max-Min for four different heterogeneity cases.

variation of CV (coefficient of variation) of rows and columns of ETC matrix could possibly lead to bias in the results of makespan for different heuristic-based scheduling algorithms. Further work is required to verify the reason by investigating the impact of skewness of the length of the simulated tasks.

VII. CONCLUSION

It is known that the main issues of simulation are that of representativeness and generalization. It is crucial to construct realistic simulation in order to increase the precision in the simulation and able to obtain a reliable and trustworthy result. Therefore, in this work, we present a simulation model that incorporates the range-based method into GridSim for modeling and simulating heterogeneous task and resource in order to capture different natures of heterogeneity in real world Grid environments for repetitive evaluation experiments. By using the proposed simulation model, we show that the concept of heterogeneity quadrant is able to be accommodated in GridSim. Overall, the proposed simulation model allows Grid researchers to be able to simulate different scheduling cases with respect to heterogeneity when using GridSim. It is very helpful for Grid researchers to examine the performance of any scheduling algorithms under various Grid scheduling cases with respect to the natures of heterogeneity. Beside heterogeneity, this study reveals another important consideration in simulation study that assesses heuristic-based scheduling algorithms, which is the balance of ratio between small tasks and large tasks. In addition, the analysis of the ETC matrix also exposes a limitation of GridSim, that is, it is only able to simulate Grid computing environment with consistent heterogeneity due to the fact that the computing power of any simulated resource in GridSim is assumed constant for all tasks and also due to lack of features of GridSim for simulating the inconsistency of computing power of any particular resource. It is important to bear in mind that this limitation of GridSim may cause a bias in the performance evaluation of scheduling algorithms. In future work, we will work towards extending the GridSim to simulate resources that have flexible, dynamic, and inconsistent computing power.

REFERENCES

[1] I. Foster and C. Kesselman, *The Grid 2: Blueprint for a New Computing Infrastructure*. New York, NY, USA: Elsevier, 2003.
[2] M. Kalantari and M. K. Akbari, "A parallel solution for scheduling of real time applications on grid environments," *Future Generat. Comput. Syst.*, vol. 25, no. 7, pp. 704–716, 2009.
[3] R. P. Prado, S. García-Galán, A. J. Yuste, and J. E. M. Expósito, "A fuzzy rule-based meta-scheduler with evolutionary learning for grid computing," *Eng. Appl. Artif. Intell.*, vol. 23, no. 7, pp. 1072–1082, 2010.
[4] Y. Hao, G. Liu, and N. Wen, "An enhanced load balancing mechanism based on deadline control on gridsim," *Future Generat. Comput. Syst.*, vol. 28, no. 4, pp. 657–665, 2012.
[5] R. Aron and I. Chana, "Bacterial foraging based hyper-heuristic for resource scheduling in grid computing," *Future Generat. Comput. Syst.*, vol. 29, no. 3, pp. 751–762, Mar. 2013. [Online]. Available: https://www.researchgate.net/profile/Rajni_Aron
[6] Y.-H. Lee, S. Leu, and R.-S. Chang, "Improving job scheduling algorithms in a grid environment," *Future Generat. Comput. Syst.*, vol. 27, no. 8, pp. 991–998, 2011.
[7] L. Y. Tseng, Y. H. Chin, and S. C. Wang, "The anatomy study of high performance task scheduling algorithm for grid computing system," *Comput. Standards Interfaces*, vol. 31, no. 4, pp. 713–722, 2009.
[8] I. Al-Azzoni and D. G. Down, "Dynamic scheduling for heterogeneous desktop grids," *J. Parallel Distrib. Comput.*, vol. 70, no. 12, pp. 1231–1240, 2010.
[9] S. Nesmachnow, H. Cancela, and E. Alba, "A parallel micro evolutionary algorithm for heterogeneous computing and grid scheduling," *Appl. Soft Comput.*, vol. 12, no. 2, pp. 626–639, 2012.
[10] P. Ezzatti, M. Pedemonte, and Á. Martín, "An efficient implementation of the min-min heuristic," *Comput. Oper. Res.*, vol. 40, no. 11, pp. 2670–2676, 2013.
[11] R. Duan, R. Prodan, and X. Li, "A sequential cooperative game theoretic approach to scheduling multiple large-scale applications in grids," *Future Generat. Comput. Syst.*, vol. 30, pp. 27–43, Jan. 2014.
[12] N. M. Reda, A. Tawfik, M. A. Marzok, and S. M. Khamis, "Sort-mid tasks scheduling algorithm in grid computing," *J. Adv. Res.*, vol. 6, no. 6, pp. 987–993, 2015.
[13] S. Selvi and D. Manimegalai, "Multiobjective variable neighborhood search algorithm for scheduling independent jobs on computational grid," *Egyptian Inform. J.*, vol. 16, no. 2, pp. 199–212, Jul. 2015.
[14] F. Dong and S. G. Akl, "Scheduling algorithms for grid computing: State of the art and open problems," School Comput., Queen's Univ., Kingston, ON, Canada, Tech. Rep. 2006-504, 2006.
[15] H. Li and R. Buyya, "Model-based simulation and performance evaluation of grid scheduling strategies," *Future Generat. Comput. Syst.*, vol. 25, no. 4, pp. 460–465, 2009.
[16] H. B. Prajapati and V. A. Shah, "Analysis perspective views of grid simulation tools," *J. Grid Comput.*, vol. 13, no. 2, pp. 177–213, 2015.
[17] R. Buyya and M. Murshed, "GridSim: A toolkit for the modeling and simulation of distributed resource management and scheduling for grid computing," *Concurrency Comput., Pract. Exper.*, vol. 14, nos. 13–15, pp. 1175–1220, Nov./Dec. 2002.
[18] R. K. Armstrong, Jr., "Investigation of effect of different run-time distributions on smartnet performance," Naval Postgraduate School, Monterey CA, USA, Tech. Rep. ADA337730, 1997.
[19] S. Ali, H. J. Siegel, M. Maheswaran, D. Hensgen, and S. Ali, "Representing task and machine heterogeneities for heterogeneous computing systems," *Tamkang J. Sci. Eng.*, vol. 3, no. 3, pp. 195–207, 2000.
[20] T. D. Braun *et al.*, "A comparison of eleven static heuristics for mapping a class of independent tasks onto heterogeneous distributed computing systems," *J. Parallel Distrib. Comput.*, vol. 61, no. 6, pp. 810–837, 2001.
[21] V. Gajera, S. Priyadarshi, R. Gupta, and P. K. Jana, "An effective multi-objective task scheduling algorithm using min-max normalization in cloud computing," in *Proc. 2nd Int. Conf. Appl. Theor. Comput. Commun. Technol. (iCATccT)*, Jul. 2016, pp. 812–816.
[22] S. K. Panda and P. K. Jana, "A multi-objective task scheduling algorithm for heterogeneous multi-cloud environment," in *Proc. Int. Conf. Electron. Design, Comput. Netw. Automated Verification (EDCAV)*, Jan. 2015, pp. 82–87.
[23] S. K. Panda and P. K. Jana, "Efficient task scheduling algorithms for heterogeneous multi-cloud environment," *J. Supercomput.*, vol. 71, no. 4, pp. 1505–1533, 2015.

KAILUN ENG received the B.S. degree in computer science from University Putra Malaysia in 2015, where he is currently pursuing the M.S. degree with the Department of Communication Technology and Networking. His research interests include distributed computing, grid computing, cloud computing, artificial intelligence, and heuristic and optimization with emphasis on scheduling. He received the Overall Best Graduating Student from the Department of Communication Technology and Networking, University Putra Malaysia, in 2015.

ABDULLAH MUHAMMED received the bachelor's degree from University Putra Malaysia, Malaysia, in 1998, the master's degree from Universiti Malaya in 2004, and the Ph.D. degree from the University of Nottingham, U.K., in 2014, all in computer science. He is currently a Senior Lecturer with the Department of Communication Technology and Network, Faculty of Computer Science and Information Technology, University Putra Malaysia. His research interests include grid/cloud computing, and heuristic and optimization.

MOHAMAD AFENDEE MOHAMED received the Ph.D. degree in mathematical cryptography from University Putra Malaysia in 2011. He is currently a Senior Lecturer with University Putra Malaysia. His research interests include both theoretical and application issues in the domain of information security and mobile and wireless networking.

SAZLINAH HASAN received the bachelor's degree in computer science from Universiti Technology Malaysia in1999, and the M.Sc. degree from University Putra Malaysia (UPM) in 2001. She has been a member of the academic staff with the Faculty of Computer Science and Information Technology, UPM, since 2001. As a member of the faculty, she taught several courses for undergraduate students, such as data communication and networks, computer programming, and internetworking. Her research interests include routing ad hoc network, computer networks, and distributed system.