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A New Makespan Estimation Model for Scientific Workflows on Heterogeneous Processing Systems

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ABSTRACT

Scientific workflows epitomizing computation-intensive applications demand heterogeneous processing resources for attaining high performance. Generally, optimal scheduling of the tasks in workflow is well-acknowledged NP-complete problem. In the present work, a new makespan estimation model is proposed to estimate the bounds on the makespan of the workflows using minimal information. The performance of the proposed estimation model is evaluated using four scientific workflows and the estimation of the makespan computed by the model is compared with the actual makespan generated by the most-cited heuristic scheduling algorithms devised for heterogeneous processing systems. The experimental results revealed that the proposed estimation model is effective and can precisely estimate the makespan of the workflows with an error of over 10% and 26% for computation-intensive and data-intensive workflows respectively.

General Terms

High Performance Computing, Workflow Scheduling, makespan estimation

Keywords

scientific workflows; high performance; heterogeneous processing resource; makespan; makespan estimation

1. INTRODUCTION

Large monolithic applications in numerous scientific fields such as knowledge discovery, bioinformatics, computations, weather and climate modeling, earthquake science, genome analysis and astronomy can be broken down into smaller tasks structured with intricate dataflow dependencies among themselves are often structured as scientific workflows. Scientific workflows expedite scientists to nimbly model the computation intensive applications as multi-stage computational tasks usually involving a series of data processing operations such as data retrieving, transformation, analysis and aggregation stages. The complexity and the heterogeneity of the scientific workflows demands Heterogeneous Processing Resources (HPR) to attain high performance. HPR are the most potential platforms for rendering high performance at lower costs.

The contributions of the current work are

- A new makespan estimation model is proposed to estimate the bounds on the completion time, i.e., makespan of the scientific workflows.
- The proposed model estimates the Best-Case Computation Time (BCCT) and Worst-Case Computation Time (WCCT) of the scientific workflows using minimal information.
- The computational complexity of the new makespan estimation model is lesser than the existing models.
- Validation of the model is performed with the most-cited heuristic scheduling algorithms developed for HPR.

In general, workflow scheduling problem is a well-acknowledged NP-Complete problem [1]. However, the available estimation models deal with simple workflows having unit tasks and no dataflow latencies. Hence, the existing models are not viable for scientific workflows. The proposed estimation model is devised using minimal information, i.e., the profile of the scientific workflows. Generally, the profile of the scientific workflows constitutes of the height and the parallelism of the workflow. As the makespan of the workflow highly depends upon the profile of the workflows, these two parameters chiefly contribute for devising good and precise makespan estimation model which can satisfy all the cases.

A makespan estimation model is valid only when BCCT and WCCT functions are admissible. The admissibility of the estimating functions must guarantee that the BCCT never overestimates and WCCT never underestimates the actual makespan of the scientific workflow. Therefore, the estimation model must provide tight bounds on the makespan. The primary aim of the new makespan estimation model is to provide a-priori information of the bounds on the makespan i.e., BCCT and WCCT of the scientific workflows. The a-priori information provided by BCCT and WCCT bound is required to schedule the workflows, provide the resources, and guides in devising the scheduling algorithms.

The remaining paper is structured as follows. In section II, the problem is described, and the overview of the scientific workflows is illustrated in section III. In section IV, the related work is detailed and in section V, the new makespan estimation model is presented. In section VI, the proposed model is evaluated using four scientific workflows and finally section VII summarizes the present work.

2. PROBLEM DESCRIPTION

2.1 Application Model

A workflow W encompasses of a set of tasks which are connected in the form of a Directed Acyclic Graph, W = < T, E >, where T is a set of n tasks < t_1, $t_2 \ldots t_n$ >, and E indicates a set of directed edges < $e_{i,j}, .. e_{m,n}$ > forming no cycles. Each edge $e_{i,j}$ imposes dependency constraint between the tasks t_i and t_j, i.e., the task t_j can be executed only when its predecessor task t_i is completed. Each task $t_i \in$ T is associated with a positive integer w_i which specifies its computation time. Moreover, each edge $e_{i,j} \in$ E is associated with a nonnegative integer $d_{i,j}$ that denotes the dataflow time between the tasks t_i and t_j. A task having no

Table 1. Computation Time Matrix

Task	r_1	r_2
t_0	70	84
t_1	68	49
t_2	78	96
t_3	89	26
t_4	30	88
t_5	66	86
t_6	25	21
t_7	96	26

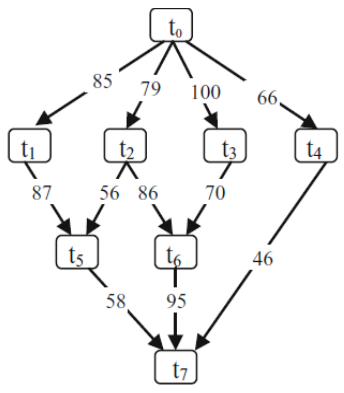


Fig 1: An example workflow

predecessor is termed as the *start task* t_{start} and the task with no successor is the *sink task* t_{sink}. Generally, a workflow includes a *start task* and a *sink task* otherwise a pair of pseudo start, and sink tasks must be connected with pseudo edges to the numerous start and sink tasks. The matrix D of order $n \times n$ is used to represent the dataflow time between the tasks, where each element $d_{i,j}$ in the matrix D indicates the dataflow time between the tasks t_i and t_j.

The organization of the tasks in a workflow describes the structure of the workflow. A task happens to be *free* upon the completion of all its predecessors and after it receives the data from its predecessors it becomes *ready*. As each task becomes *ready* it is placed in the queue for execution. An example workflow is shown in Figure 1.

2.2 HPR Model

A HPR model constitutes of a suite of m resources $< r_1, r_2 ... r_m > \in$ R with varied processing potentials, fully connected with high speed network. Each resource can execute only one task at a time i.e., tasks cannot be preempted. The execution of task t_j and its predecessor t_i on the same resource, i.e., $r(t_i) = r(t_j)$, then the dataflow between the two tasks is assumed as *local* and dataflow time $d_{i,j}$ is zeroed. Since, the output data generated by the task t_i is available at the same resource on which task t_j is to be performed, transferring of the data is not required. Otherwise, i.e., $r(t_i) \neq r(t_j)$, the dataflow is assumed to be *remote*. Moreover, the computations of the tasks and the dataflow between the tasks are carried out simultaneously. The matrix E of order $n \times m$ is used to represent the computation time of n tasks on m resources and each element $w_{i,j}$ denotes the computation time of the task t_i on resource r_j. Table. 1 shows the computation time matrix for the workflow depicted in Figure 1.

The key attributes required to describe the workflow scheduling are the Earliest Start Time (EST) and the Earliest Completion Time (ECT). The EST and ECT of the task t_i on resource r_j are denoted as $EST(t_i,r_j)$ and $ECT(t_i,r_j)$ respectively and computed by (1) and (2) respectively. The EST for a start task t_{start} is zero.

$$EST(t_i,r_j) = max\ \{\ ready(t_i),\ avail(r_j)\ \} \qquad (1)$$

$$ECT(t_i,r_j) = EST(t_i,r_j) + w_{i,j} \qquad (2)$$

where $ready(t_i)$ is the time the task t_i becomes *ready* and $avail(r_j)$ is the time the resource r_j is available to execute the next task. In the equation (2), $ECT(t_i,r_j)$ is computed by $EST(t_i,r_j)$ and $w_{i,j}$, where $w_{i,j}$ is the computation time of the task t_i on resource r_j. The schedule length, i.e., makespan of W is the Actual Completion Time (ACT) of t_{sink}, given by (3)

$$makespan = ACT(t_{sink}) \qquad (3)$$

Definition 1 (Bottom Level). The *bottom level* of task t_i is the length of the longest path from the task t_i to t_{sink}. It is denoted as $bl(t_i)$ and computed by the computation and dataflow times along the path using (4)

$$bl(t_i) = \overline{w_i} + max_{t_j \in succ(t_i)}\ \{\ bl(t_j) + d_{i,j}\ \} \qquad (4)$$

where $\overline{w_i}$ is the average computation time of the task t_i and $succ(t_i)$ is a set of immediate successors of t_i and $d_{i,j}$ is the dataflow times between the tasks t_i and t_j.

Definition 2 (Top Level). The *top level* of the task t_i is the length of the longest path from the start task t_{start} to t_i, excluding the computation time of t_i. It is denoted as $tl(t_i)$ and computed by the computation and dataflow times along the path using (5)

$$tl(t_i) = max_{t_j \in pred(t_i)}\ \{\ tl(t_j) + w_j + d_{j,i}\ \} \qquad (5)$$

where $pred(t_i)$ is a set of immediate predecessors of t_i and $d_{j,i}$ is already explained in the equation (4).

Definition 3: The Critical Path (CP) is the longest path in the workflow and the length of the CP can be computed by the sum of the computation and dataflow times along the path and denoted as CP_l. The computation critical path is computed by the sum of the minimum computation time of each task on CP, it is denoted as CP_c and computed using (6).

$$CP_c = \textstyle\sum_{t_i \in \mathrm{CP}} min_{\ r \in \mathrm{R}}\ w_i \qquad (6)$$

The CP tasks in a workflow can be identified by summing up $bl(t_i)$ and $tl(t_i)$ for each task t_i. All the tasks on CP have same $(bl(t_i) + tl(t_i))$ value which is equal to CP_l.

3. THE RELATED WORK

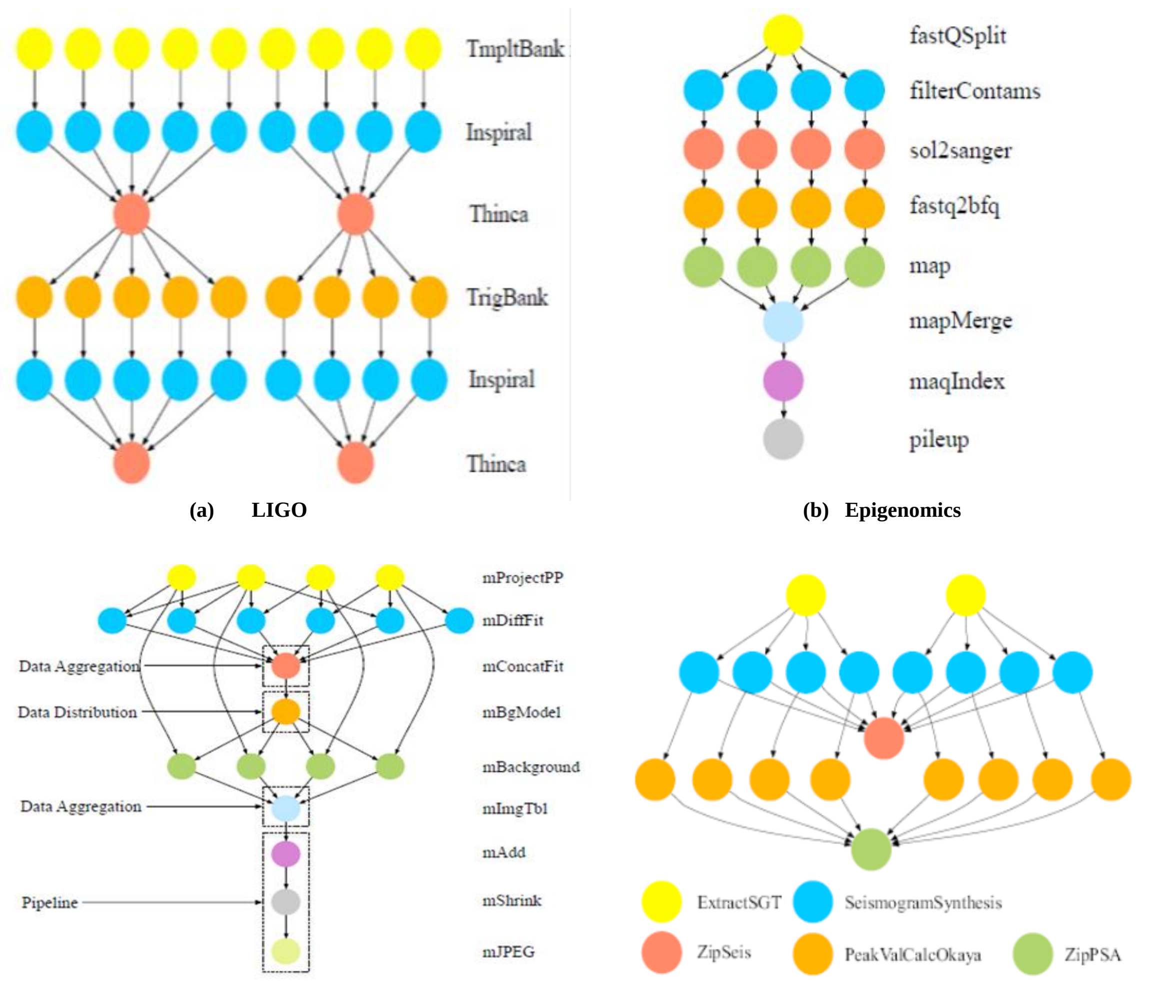
Limited research work has been carried out in estimating the performance of the workflows.

Fernandez et al. [4] were the first to devise lower bounds on the makespan for the workflows with unit sized tasks having no dataflow latencies and performed on homogeneous environments. To compute the lower bound, an interval $[\theta_1,\theta_2]$ during which maximum number of tasks $n' \subset n$ can be executed is considered such that $[\theta_1,\theta_2] \subset [0,\ CP_c]$. For m resources, and n tasks in the workflow, then $m \times (\theta_1 - \theta_2)$

denotes the tasks executed on *m* resources. The excess area is divided by *m* and added to CP_c.

The WCCT, i.e., the upper bound of the workflow was first proposed by Jain et al. [5]. The computation of the upper bound was confined to the workflows consisting of unit computation time tasks having no dataflow overheads and was executed on homogeneous systems. The workflow is partitioned according to the levels and the upper bound for each partition was computed by the summation of the number of ready tasks divided by *m*. Finally, the upper bounds of all the partitions are summed up to obtain the upper bound of the workflow. Moreover, the lower bound is computed by considering a partition in which the maximum number of tasks can be executed and is divided by *m.*

In [8], a level based estimation model is proposed to analyze the computation times of the workflows. The model requires the workflow to be partitioned into levels in both top-down and bottom-up approaches to group the set of tasks which can be performed concurrently. The level computation time is computed by the sum of the computation times of all the tasks



(a) LIGO **(b) Epigenomics**

(c) Montage **(d) Cybershake**

Fig 2: The structure of the scientific workflows

in a level. The makespan for each level is computed by the maximum of the level computation time divided by *m* and the maximum computation time of a task at that level. The performance of the workflow is estimated by the summation of the makespan of all the levels and nominal dataflow latency is added to it.

4. AN OVERVIEW OF SCIENTIFIC WORKFLOWS

Generally, scientific applications are categorized as computation-intensive, data-intensive, memory -intensive, or a combination of these based upon the applications. The computation-intensive workflows consist of tasks which expend most of the time in computations, while the tasks in the data-intensive workflows generate enormous data and therefore involve much in exchanging data rather than computations [6]. The tasks in the memory-intensive workflows demand high physical storage requirements. Most of the scientific applications embrace workflows to epitomize computation- intensive applications for efficient computation on heterogeneous environments which are the most preferred platforms for attaining high performance.

Laser Interferometer Gravitational Wave Observatory (LIGO) is an Inspiral Analysis Workflow [11]. LIGO is a memory bound and heavily computation-intensive workflow that detects gravitational waves generated by numerous events in the universe according to Einstein's theory of relativity. The LIGO workflow structure allows greater parallelism. This workflow is applied to analyze the data acquired by amalgamating of compact binary systems, namely binary neutron stars and black holes. The time-frequency data from any event for each of the three LIGO detectors is fragmented into small chunks and then analyzed. A set of waveforms which belong to the parameter space are generated for each chunk. Matched filter output is computed and triggers if Inspiral is detected which are then tested for consistency by the Thinca jobs. Inspiral jobs are highly computation-intensive. Trigger output generates Template banks. The structure of the LIGO workflow is depicted in Figure 2(a).

Epigenomics [12] is a computation-intensive and largely data parallel pipelined application. This workflow primarily processes pipelined data to execute genome sequence jobs which is utilized by Maq system. The remaining jobs of the workflow include filter of noise and contaminated data, a map job which aligns the current location in a reference genome, which is mostly computation-intensive and generates global map to identify the sequence density at each position in the genome. A simple way to enhance performance is to run Epigenomics on heterogeneous platforms since many tasks of this application can run in parallel and are heterogeneous and the structure of this application is given in Figure 2(b).

Montage workflow is devised by NASA / IPAC [9] is an astronomical image mosaic engine which is more widely studied workflow applications. Montage is designed to take multiple astronomical images from telescopes or any other instruments and amalgamate into a single mosaic that appears to be taken from a single instrument. The input images are re-projected onto a sphere and the overlap of the images is calculated. Subsequently, the images are re-projected to correct the orientation and to normalize the background. Lastly, all the processed images are composed into a single mosaic. Astronomers can tailor the functionalities of Montage workflow and add code according to the requisites. Accordingly, Montage is designed consisting of a set of tasks and mostly, the tasks spend much time in communicating and very lesser amount of time in the computation and hence Montage is described as data-intensive workflow and its structure is shown in Figure 2(c).

Cybershake is a seismological application which is highly data and memory-intensive and its structure is depicted in Figure 2(d). This application is generated by the Southern California Earthquake Center [10] to characterize earthquake hazards in geographical regions using Probabilistic Seismic Hazard Analysis (PSHA) technique. The application utilizes Earthquake Rupture Forecast (ERF) to detect the probable ruptures within 200km of an interested region. For every rupture, rupture definitions are converted from ERF into numerous rupture variations with varying hypocenter positions and slip time distributions to generate Strain Green Tensors (SGT). Subsequently, synthetic seismograms for every rupture variation are computed and peak intensity measures are derived from the synthetics which are then combined with the original rupture probabilities to generate probabilistic seismic hazard curve in the region. The information provided by PSHA is utilized by city planners and building engineers to estimate seismic hazards prior to construction of the buildings.

5. A NEW MAKESPAN ESTIMATION MODEL

Basically, the makespan of the workflow is influenced by the profile of the workflow, dataflow latencies between the tasks in the workflow and the number of resources employed in the computation of the workflow.

The profile of the workflow includes the implicit parallelism and the height of the workflow. The execution of the parallel tasks concurrently on an adequate number of resources can significantly reduce the makespan. On the other hand, the height of the workflow reflects the longest path in the workflow, i.e., the CP. Because of the sequential bottlenecks of the CP tasks, these tasks can only be performed serially and hence provisioning of additional resources may not further minimize the makespan.

The main shortcomings of the existing models in the literature are they do not consider the dataflow latencies among the tasks and hence do not fit for the scientific workflows. On the other hand, the new makespan estimation model is devised considering the Critical Path (CP), and the intrinsic parallelism of the workflow. The proposed estimation model captures the workflow parallelism by effectively identifying the independent branches in a workflow. CP is a global heuristic and the inherent sequential path of the workflow that plays a pivotal role in determining the bounds on the computation time.

Theorem 1: *Let $W = <T,E,w,d>$ be a workflow and CP_c be the compute critical path. For any schedule S of W, the makespan is always greater than CP_c.*

$$makespan > CP_c \qquad (7)$$

Proof: A CP always begins at the *start* task and ends at the *sink* task and it is the longest directed path between a pair of *start* and *sink* tasks. A directed path in the workflow represents the chain of dependent tasks that are to be processed in a sequence. Any other path length in the workflow is at least the length of the computation critical path length. Therefore, the duration of the workflow is at least CP_c regardless of the number of resources provisioned.

Lemma 1: *The maximum number of levels in a workflow in any path cannot exceed the number of tasks on the critical path.*

Proof: Let a workflow W constitutes of k number of levels, $\ell=\{\ell_1,\ell_2,\ell_3, \ldots\ell_k\}$, $1 \le k \le n$. The tasks can be grouped into the levels by topologically ordering the tasks $t_i \in$ T in W $\ni$ for each edge $e_{i,j} \in$ E, if t_i is in the level ℓ_{k-1} then t_j must occur in the level ℓ_k, where $k > j$. Therefore,

$$\ell = \bigcup_{k=1}^{n} \ell_k = \mathrm{T} \qquad (8)$$

As per definition 1, CP is the longest path from the start task to sink task. At most one task from each level ℓ_k, $1 \le k \le n$, lies on CP, i.e., no more than k tasks can be included in CP, which are denoted as $t_{cp,1}$, $t_{cp,2}$,..$t_{cp,k}$, where each task $t_{cp,i}$, $1 \le i \le k$, indicates i^{th} task on CP selected from level ℓ_i. Moreover, there may be more than one CP in a workflow as several paths can have maximal length.

Lemma 2: *The maximum queue length equals the level maximum branching factor of the workflow.*

Proof: The maximum branching factor of the workflow determines the queue length. The maximum queue length is the maximum number of tasks that become free upon the execution of a task. For example, consider the workflow given in the Figure 1 scheduled on two resources. However, the execution of the task t_o at the level 1 frees the tasks t_1, t_2, t_3, and t_4 at level 2. Therefore, the maximum queue length for the given workflow is four.

Lemma 3: *When the ready tasks are more than the number of resources, then in an ideal scheduling system the load is equally balanced on all the resources. The maximum additional load on each resource is no more than the queue length / m, m is the number of resources on HPR.*

Proof: Let $k \subseteq n$ be the number of ready tasks placed in the queue and m be the number of resources on HPR to execute a ~~workflow. During the computation of the workflow, if k~~ exceeds m, then $(k - m)$ tasks fall as additional load on m resources. In an ideal scheduling system this additional load is equally distributed on m resources. Therefore, the additional load on each resource is no more than queue length / m.

For instance, in the given workflow in the Figure 1, if the task t_o at the level 1 at level 1 is executed, frees the tasks t_1, t_2, t_3, and t_4 which are added to queue. Since the workflow is executed on two resources, only two tasks can be executed in parallel. In an ideal scheduling system, the remaining two tasks are distributed to two resources which is the additional load incurred on each resource due to the inadequate resources provisioned for performing the workflow. Therefore, *queue length / m* is the additional load on each resource that eventually leads to the increase in the makespan.

Theorem 2: *The WCCT of a workflow equals the CPl + ε, where ε is the additional load taken by each resource when the number of resources in HPR is less than queue length.*

$$makespan \le \begin{cases} CP_l, & k < m \\ CP_l + \varepsilon, & otherwise \end{cases} \qquad (9)$$

Proof: Generally, the profile of the workflow depends upon two parameters, i.e., CP of the workflow and the number of parallel tasks. As per definition 1, CP is the longest chain of dependent tasks in the workflow and hence these tasks must be performed in succession. According to Lemma 1, the maximum number of levels in a workflow cannot be more than the number of tasks lying on CP. The length of any path in the workflow is always lesser than or equal to the length of CP, i.e., CP_l. Consequently, the constrained sequential computation time of the tasks on the CP is at most the completion time of any path in the workflow. Therefore, the WCCT of a workflow is chiefly contributed by the critical path length with respect to the number of levels.

The second parameter ε represents the number of tasks that can be performed in parallel provided when sufficient resources are provisioned to execute the workflow on HPR. In situations when fewer resources are provisioned, the queue length gradually increases and falls as an additional load on each resource and thus leads to the increase in the makespan. Therefore, ε is the maximum additional load on all the resources, i.e., maximum of queue length / m.

In situations when the maximum branching factor (k) of the workflow is greater than the number of resources (m) provisioned to execute a workflow, i.e., $k > m$, the queue length gradually increases which falls as an additional load on each resource and leads to the increase in the makespan. According to Lemma 3, ε is the maximum additional load on all the resources, i.e., maximum of *queue length / m*, computed as follows.

$$\varepsilon = (k - m) * \overline{w} / m \qquad (10)$$

where $\overline{w}$ is the average execution time of each task in the workflow. The equation (9) establishes a sharp WCCT of the workflow. Therefore, BCCT and WCCT values are chiefly contributed by CP of the workflow and the completion time of a workflow is highly dependent on the structure of the workflow. Figure 3 and Figure 4 present the algorithm for WCCT and BCCT for the workflow.

Algorithm 1. A new makespan estimation model for WCCT of the workflow

Input: A workflow W = < T, E, w_i, $d_{i,j}$ >, T and E are a set of tasks and edges in the workflow. $\overline{w_i}$, is the average computation time of the task t_i and $d_{i,j}$ is the dataflow time between the tasks t_i and t_j.

Output: The WCCT of the workflow.

```
1.  Set the average computation time $\overline{w_i}$ for each task $t_i \in$ T.
2.  Compute bl for $t_i \in$ T tasks in W.
3.  Compute tl for $t_i \in$ T tasks in W.
4.  Compute $rank(t_i) = bl(t_i) + tl(t_i)$ for $t_i \in$ T tasks in W.
5.  Compute $CP_l := rank(t_{start})$, where $t_{start}$ is the start task.
6.  $CP_{set} := t_{start}$ // $CP_{set}$ is the set of CP tasks.
7.  $t_i \leftarrow t_{start}$.
8.  while ($t_i$ != $t_{sink}$) do
9.       Select $t_j$ where (( $t_j \in succ(t_i)$) and ($rank(t_j)$ = = $CP_l$)). // $succ(t_i)$ is the successor tasks of $t_i$
10.      $CP_{set} := CP_{set} \cup \{ t_j \}$
11.      if($k > m$) // where $k$ is the maximum branching factor of the workflow and $m$ is the number of resources provisioned to execute a workflow
12.          $\varepsilon = (k - m) * \overline{w_i} / m$   // where ε is the maximum additional load on all resources
13.          WCCT := WCCT + $\overline{w_i}$ + ε
14.      else
15.          WCCT := WCCT + $\overline{w_i}$
16.      $t_i \leftarrow t_j$
17. end while
```

Fig 3: Algorithm for estimating WCCT of the workflow

Algorithm 2. A new makespan estimation model for BCCT of the workflow

Input: A workflow W = < T, E, w_i, $d_{i,j}$ >, T and E are a set of tasks and edges in the workflow. w_i is the minimum computation time of the task t_i and $d_{i,j}$ is the dataflow time between the tasks t_i and t_j.

Output: The BCCT of the workflow.

```
1.  Set $w_i$ to the minimum computation time of each task $t_i \in$ T.
2.  Compute bl for $t_i \in$ T tasks in W.
3.  Compute tl for $t_i \in$ T tasks in W.
4.  Compute $rank(t_i) := bl(t_i) + tl(t_i)$ for $t_i \in$ T tasks in W.
5.  $CP_l := rank(t_{start})$, where $t_{start}$ is the start task.
6.  $CP_{set} := t_{start}$ // $CP_{set}$ is the set of CP tasks.
7.  $t_i \leftarrow t_{start}$
8.  while ($t_i$ != $t_{sink}$) do
9.      select $t_j$ where (( $t_j \in succ(t_i)$) and ( $rank(t_j)$ = = $CP_l$ )) // $succ(t_i)$ is the successor of $t_i$
10.     $CP_{set} := CP_{set} \cup \{t_j\}$
11.     BCCT := BCCT+ $w_j$
12. end while.
```

Fig 4: Algorithm for estimating BCCT of the workflow

5.1 Time Complexity Analysis

The computation of the WCCT of the workflow includes CP length, i.e., CP_l and ε. The CP includes $n^1 < n$ tasks and $e^1 < e$ edges and hence CP_l can be calculated in time O(n+e) while the computation of ε involves $n^1 < n$ tasks and requires O(n) time. Therefore, the complexity of WCCT of the workflow is O(n + e), where n is the number of tasks and e is the number of edges in the workflow. The computation of BCCT of the workflow entails CP_c. The calculation of CP_c necessities $n^1 < n$ tasks and hence BCCT of a workflow can be computed in time O(n). Generally, the WCCT and BCCT of the workflow are computed recursively adding one task in each iteration.

The WCCT and BCCT values computed for the example workflow depicted in the Figure 1 are 508 and 195 respectively. The makespan for the same workflow generated by the HEFT [2], PETS [7] and MSL[3] scheduling strategies are 446, 446 383-time units respectively.

6. PERFORMANCE EVALUATION

In this section, the performance of the new makespan estimation model is evaluated using randomly generated scientific workflows namely LIGO, Epigenomics, Cybershake, and Montage. Generally, the characteristics required for generating the scientific workflows are as follows.

- Workflow size (n) is the number of tasks in the workflow.
- Dataflow to Computation time Ratio (DCR) is the ratio of the average dataflow time to average computation time in a workflow. The dataflow time in a workflow is computed using (11).

$$\textit{dataflow time} = DCR * \textit{computation time} \qquad (11)$$

  when DCR ≤ 1, computation - intensive workflows can be generated while DCR ≥ 1 workflows are data-intensive workflows.
- Shape parameter (α) determines the structure, i.e., the height and width of the workflow. The height of the workflow, i.e., the number of levels in a workflow is obtained by $\sqrt{n}$ / α and the width of the workflow, i.e., the number of tasks at each level is $\sqrt{n}$ × α. For α < 1values, longer workflows with low parallelism are generated and when α > 1, shorter workflows with high parallelism can be generated.
- Heterogeneity factor (β) determines the variation in the computation times of each the task on m resources. Higher β values cause much deviation in the computation times of the tasks while lesser β values results in the trivial difference in the computation times of the tasks. The computation time of each task t_i on the resource r_j is denoted as $w_{i,j}$, where $1 \le i \le n$, $1 \le j \le m$, is randomly selected from the range computed using the equation (12)

$$\overline{w_i} \times (1- \beta / 2) \le w_{i,j} \le \overline{w_i} \times (1+ \beta / 2) \qquad (12)$$

  where $\overline{w_i}$ is the average computation time of each task in the workflow.

To evaluate the effectiveness of the new makespan estimation model, two sets of randomly generated scientific workflows are used. The first set consists of computation-intensive workflows viz., LIGO and Epigenomics workflows which are generated with workflow size (n) of {40, 56, 72, 88} and {20, 32, 64, 106} respectively.

As these workflows are computation-intensive applications, their DCR values cannot be more than one. Since the structure of the scientific workflows is known, the parameters such as workflow size (n), DCR, heterogeneity factor (β) and average computation time of the workflow ($\overline{w_i}$) are essential for generating the scientific workflows. The characteristics of LIGO and Epigenomics workflow set for the experimentations are depicted in Table 2.

Another set of data-intensive workflows namely Cybershake and Montage with workflow sizes (n) {20, 36, 68, 132} and {20, 38, 59, 98} respectively, are generated. Since these workflows are data-intensive applications, their DCR values cannot be less than one and the parameters are specified in Table 3. The combination of the mentioned parameter values generated 2000 workflows for each scientific workflow. The proposed BCCT and WCCT values for varied resource set are computed for LIGO, Epigenomics, Cybershake and Montage workflows. The BCCT and WCCT are evaluated by considering the best and the worst of the three makespans generated by the HEFT, PETS, and MSL scheduling algorithms.

Table 2. Characteristics of LIGO and Epigenomics workflows

Parameter	**Values**				
DCR	0.1	0.25	0.5	0.75	1.0
β	0.1	0.25	0.5	0.75	1
$\overline{w_i}$	100	150	200	250	
m	4	8	12	16	20

Table 3. Characteristics of Cybershake and Montage workflows

Parameter	**Values**				
DCR	0.1	0.25	0.5	0.75	1.0
β	0.1	0.25	0.5	0.75	1
$\overline{w_i}$	100	150	200	250	
m	4	8	12	16	20

The experimental results are presented in Table 4, 5, 6, and 7 respectively. Each row in these tables represents the average data from 20 workflows obtained with the combination of different β and $\overline{w_i}$ values for each DCR value.

The validation of the new makespan estimation model is performed by comparing BCCT and WCCT values computed for each workflow with the actual makespan of the workflow. The error ξ between WCCT and the actual makespan is denoted as $makespan_{actual}$ and computed using (13)

$$\xi = \left| \frac{makespan_{actual} - WCCT}{makespan_{actual}} \right| \qquad (13)$$

From the Table.4, it can be observed that for the computation-intensive LIGO workflows the error percent increased as DER value increased when the workflow size and the number of resources are same. Moreover, error enhanced as the workflow size increased for the same number of resources (m) and DER values. The error in percent for the workflow size 40 is noted to be 7.65, for 56 tasks it is 8.53, for 72 tasks it is 10.64 and for 88 tasks the error 13.93 percent. An error is observed to be below 10 percent for 70 percent of the cases and overall it is 10.18 percent.

Moreover, the error varied for different number of resources (m). For m = {4,8,12,16,20} and the workflow size 40, the error percent is {8.2,7.9,7.2,7.4,7.5}, while for workflow size 56, it is {7.8,13.0,8.0,6.8,7.1}, for workflow size 72 it is

{7.0,16.6,14.8,8.1,6.8}, and for workflow size 88 it is {6.6,19.1, 20.4,15.3,8.3} respectively. For the same workflow size, the error is observed to vary for different number of resources. The error percent is noted to be high when the workflows attain optimal makespan. This implies that optimal schedules are attained when the number of resources provisioned are sufficient to execute the workflow.

Similar trends in the error values can also be observed for the computation-intensive Epigenomics workflow shown in Table 5. The error values are observed to be increasing with the rise in the DER values. The error percent for workflow size {20, 32, 64, 106} is {10.89,11.33,8.81,10.61} respectively. For various *m* values i.e., {4, 8,12,16 20}, the error percent for workflow size 20 is {9.4,10.9,11.5,11.3,11.4}, for workflow size 32 it is {8.94,10.5,12.4,12.6,12.2}, for workflow size 64 it is {4.5,10.5, 8.8,9.8,10.4} and for 106 tasks it is {1.7,12.6, 16.1,13.3,9.3} respectively. Overall, the error value is noted to be 10.41.

For a data-intensive Cybershake workflow presented in the Table 6, the error in percent for 20 tasks is 13.64, for 36 tasks it is 13.92, for 68 tasks it is 29.6 and for 106 tasks it is 47.2. An overall error is noted to be 26 percent. For various *m* values {4, 8, 12, 16, 20}, the error in percent for workflow size 20 is {17.5, 12.4, 12.8, 12.8,12.7}, for workflow size 36 it is {17.7,18.8, 14.5,9.4,9.2}, for 68 tasks it is {21.8,33.1,34.1,31.2,26.6}and for 132 tasks it is {22.3,43.4,53.5,58.0,58.9} respectively.

Table 4. Performance of the proposed BCCT and WCCT on LIGO Workflow set

n	DER	*m* = 4				*m* = 8				*m* =12				*m* =16				*m* = 20				No. of Work flows
		BCT	Make span	WCT	Error (%)	BCT	Make span	WCT	Error (%)	BCT	Make span	WCT	Error (%)	BCT	Make span	WCT	Error (%)	BCT	Make span	WCT	Error (%)	
40	0.1	1853	2368	2538	7.2	1258	1813	1948	7.4	1100	1729	1844	6.6	1077	1694	1816	7.1	1074	1701	1822	7.1	20
40	0.25	1856	2441	2630	7.7	1252	1928	2075	7.6	1100	1814	1940	6.9	1074	1811	1940	7.1	1066	1772	1907	7.6	20
40	0.5	1849	2476	2686	8.5	1244	1996	2152	7.8	1091	1875	2017	7.5	1082	1871	2011	7.5	1073	1877	2016	7.4	20
40	0.75	1848	2501	2728	9.1	1260	2024	2196	8.4	1100	1969	2115	7.4	1075	1929	2075	7.6	1069	1939	2089	7.7	20
40	1	1823	2533	2754	8.8	1248	2059	2228	8.2	1095	1970	2116	7.4	1082	1967	2115	7.5	1072	1883	2028	7.7	20
56	0.1	2395	2989	3188	6.7	1759	2039	2300	12.8	1222	1825	1964	7.6	1080	1736	1850	6.5	1075	1722	1847	7.2	20
56	0.25	2359	3057	3272	7.0	1772	2125	2397	12.8	1226	1902	2057	8.1	1079	1830	1961	7.1	1068	1815	1955	7.7	20
56	0.5	2362	3073	3319	8.0	1766	2216	2493	12.5	1224	2013	2170	7.8	1084	1947	2073	6.5	1075	1961	2086	6.3	20
56	0.75	2352	3077	3340	8.6	1777	2226	2527	13.5	1230	2061	2235	8.4	1078	2014	2151	6.8	1065	1995	2141	7.3	20
56	1	2345	3096	3360	8.5	1767	2259	2562	13.4	1219	2087	2253	7.9	1080	2021	2162	6.9	1070	1940	2072	6.8	20
72	0.1	2898	3643	3856	5.9	2275	2298	2665	16	1749	1940	2229	14.9	1207	1816	1954	7.6	1078	1769	1880	6.3	20
72	0.25	2881	3655	3903	6.8	2291	2381	2767	16.2	1753	2032	2324	14.4	1213	1921	2077	8.1	1070	1863	1997	7.1	20
72	0.5	2891	3695	3968	7.4	2287	2427	2836	16.9	1731	2118	2424	14.5	1211	1995	2159	8.2	1072	1958	2088	6.6	20
72	0.75	2879	3770	4035	7.0	2305	2470	2879	16.6	1732	2153	2472	14.8	1208	2078	2245	8.0	1066	2008	2150	7.0	20
72	1	2872	3731	4020	7.8	2287	2476	2903	17.2	1736	2166	2500	15.4	1208	2081	2256	8.4	1069	1984	2117	6.7	20
88	0.1	3406	4292	4521	5.3	2804	2588	3062	18.3	2254	2087	2518	20.6	1732	1898	2201	15.9	1201	1809	1955	8.1	20
88	0.25	3398	4258	4541	6.7	2809	2657	3154	18.7	2262	2177	2617	20.2	1726	2027	2328	14.9	1205	1923	2084	8.3	20
88	0.5	3409	4364	4639	6.3	2798	2694	3215	19.3	2254	2264	2725	20.3	1727	2080	2400	15.4	1202	2016	2180	8.1	20
88	0.75	3385	4333	4652	7.3	2799	2718	3253	19.7	2259	2288	2752	20.3	1728	2134	2456	15.0	1204	2084	2247	7.8	20
88	1	3398	4362	4676	7.2	2809	2750	3290	19.6	2263	2301	2772	20.5	1729	2176	2509	15.3	1206	1996	2173	8.8	20

Table 5. Performance of the proposed BCCT and WCCT on Epigenomics Workflow set

n	DER	*m* = 4				*m* = 8				*m* =12				*m* =16					*m* = 20			No. of Work flows
		BCT	Make span	WCT	Error (%)	BCT	Make span	WCT	Error (%)	BCT	Make span	WCT	Error (%)	BCT	Make span	WCT	Error (%)	BCT	Make span	WCT	Error (%)	
20	0.1	1191	1566	1698	8.4	1118	1510	1654	9.6	1086	1464	1611	10.0	1082	1476	1620	9.8	1072	1445	1601	10.8	20
20	0.25	1207	1696	1836	8.2	1114	1553	1721	10.9	1089	1506	1673	11.1	1076	1533	1702	11.0	1069	1513	1684	11.4	20
20	0.5	1196	1679	1847	10.0	1119	1617	1795	11.0	1092	1536	1724	12.2	1075	1560	1741	11.6	1069	1583	1762	11.3	20
20	0.75	1183	1734	1908	10.0	1123	1680	1873	11.5	1096	1613	1814	12.4	1074	1574	1773	12.7	1064	1614	1803	11.7	20
20	1	1193	1735	1914	10.3	1117	1670	1862	11.5	1091	1641	1836	11.9	1039	1530	1701	11.2	1065	1585	1771	11.7	20
32	0.1	2759	3555	3759	7.2	1923	2471	2687	8.7	1372	1837	2041	11.1	1340	1817	2024	11.4	1344	1839	2041	11.0	20
32	0.25	2107	2329	2618	12.4	1917	2503	2756	10.1	1368	1911	2127	11.3	1345	1870	2107	12.7	1333	1889	2112	11.8	20
32	0.5	1633	2045	2271	11.0	1902	2556	2827	10.6	1367	1948	2197	12.8	1348	1938	2190	13.0	1336	1934	2175	12.5	20
32	0.75	1296	1951	2107	8.0	1912	2574	2864	11.3	1364	1983	2251	13.5	1341	2018	2273	12.7	1334	1992	2251	13.0	20
32	1	1108	1895	2011	6.1	1934	2587	2892	11.8	1364	2022	2289	13.2	1346	1996	2260	13.3	1341	1956	2208	12.9	20
64	0.1	2516	3728	3830	2.7	1923	2471	2687	8.7	1372	2060	2219	7.8	1343	1941	2126	9.5	1339	1929	2110	9.4	20
64	0.25	2539	3714	3869	4.2	1917	2503	2756	10.1	1374	2169	2346	8.2	1351	2074	2270	9.5	1342	2038	2246	10.2	20
64	0.5	2537	3793	3967	4.6	1902	2556	2827	10.6	1365	2292	2481	8.3	1345	2162	2371	9.6	1341	2156	2372	10.0	20
64	0.75	2518	3731	3938	5.6	1912	2574	2864	11.3	1367	2307	2520	9.2	1347	2237	2456	9.8	1341	2135	2380	11.4	20
64	1	2526	3779	3985	5.4	1934	2587	2892	11.8	1360	2237	2473	10.6	1348	2202	2440	10.8	1336	2101	2331	11.0	20
106	0.1	3537	5321	5360	0.7	2932	3081	3430	11.3	2388	2412	2750	14.0	1860	2064	2333	13.0	1328	1873	2035	8.7	20
106	0.25	3540	5327	5408	1.5	2932	3120	3495	12.0	2379	2366	2750	16.2	1860	2156	2448	13.5	1331	2018	2188	8.5	20
106	0.5	3560	5349	5446	1.8	2947	3141	3550	13.0	2391	2400	2808	17.0	1887	2022	2216	9.6	1335	2059	2256	9.5	20
106	0.75	3534	5374	5483	2.0	2921	3178	3590	13.0	2387	2486	2896	16.5	1933	2294	2638	15.0	1334	2051	2263	10.3	20
106	1	3503	5299	5434	2.5	2937	3137	3566	13.7	2390	2495	2917	16.9	1851	2203	2539	15.3	1372	2056	2254	9.6	20

Table 6. Performance of the proposed BCCT and WCCT on Cybershake Workflow set

n	DER	*m* = 4				*m* = 8				*m* =12				*m* =16					*m* = 20			No. of Work flows
		BCT	Make span	WCT	Error (%)	BCT	Make span	WCT	Error (%)	BCT	Make span	WCT	Error (%)	BCT	Make span	WCT	Error (%)	BCT	Make span	WCT	Error (%)	
20	1	173	292	342	17.0	165	274	300	9.6	162	269	296	10.2	160	269	297	10.4	158	270	297	10.0	20
20	2	171	374	436	16.4	165	357	392	10.0	162	358	394	10.0	160	357	394	10.2	161	354	392	10.8	20
20	5	172	604	704	16.6	166	601	671	11.7	162	575	651	13.1	160	593	665	12.2	160	607	677	11.5	20
20	7	173	729	859	17.9	166	723	824	14.0	163	728	830	13.9	161	711	814	14.5	159	718	821	14.4	20
20	10	172	896	1072	19.7	164	892	1041	16.7	163	894	1043	16.8	160	904	1053	16.6	160	765	894	16.8	20
36	1	177	439	516	17.6	166	316	390	23.5	164	284	337	18.8	160	285	310	8.7	160	278	303	9.0	20
36	2	174	512	603	17.8	170	404	488	20.9	165	387	447	15.6	160	384	417	8.4	159	385	417	8.5	20
36	5	181	731	862	17.9	168	653	771	18.1	164	662	750	13.2	160	642	705	9.9	159	646	709	9.7	20
36	7	174	858	1017	18.6	165	829	966	16.5	162	812	925	13.9	160	813	896	10.2	159	822	903	9.9	20
36	10	178	1133	1321	16.6	169	1103	1266	14.8	163	1144	1273	11.3	160	1122	1229	9.5	160	960	1047	9.1	20
68	1	177	657	782	22.4	166	396	541	43.1	164	325	459	48.4	160	294	409	45.9	160	286	379	38.4	20
68	2	174	739	873	21.4	170	483	638	37.6	165	415	556	40.1	160	389	511	37.0	159	382	482	30.8	20
68	5	181	929	1102	21.9	168	710	896	30.8	164	655	827	30.7	160	642	792	27.5	159	635	761	23.4	20
68	7	174	1068	1264	21.6	165	848	1057	29.0	162	814	1005	27.6	160	806	975	24.7	159	806	949	20.8	20
68	10	178	1255	1489	21.9	169	1105	1340	25.1	163	1078	1293	23.5	160	1076	1270	21.2	160	926	1078	19.4	20
132	1	148	1171	1439	22.9	139	653	997	52.7	135	481	831	72.6	133	398	737	85.3	132	361	679	88.1	20
132	2	145	1266	1543	21.9	139	734	1090	48.5	135	568	929	63.6	134	492	840	70.6	133	453	779	72.1	20
132	5	149	1458	1780	22.1	141	941	1337	42.0	138	797	1196	50.0	135	734	1116	52.1	134	714	1072	50.1	20
132	7	147	1580	1931	22.2	136	1088	1511	38.9	138	962	1382	43.7	133	902	1304	44.7	132	882	1264	43.3	20
132	10	146	1780	2178	22.3	137	1323	1782	34.7	136	1208	1661	37.5	133	1165	1599	37.2	133	966	1361	41.0	20

Table 7. Performance of the proposed BCCT and WCCT on Montage Workflow set

n	DER	*m* = 4				*m* = 8				*m* =12				*m* =16					*m* = 20			No. of Work flows
		BCT	Make span	WCT	Error (%)	BCT	Make span	WCT	Error (%)	BCT	Make span	WCT	Error (%)	BCT	Make span	WCT	Error (%)	BCT	Make span	WCT	Error (%)	
20	1	322	474	537	13.2	303	468	531	13.3	299	480	537	11.9	295	465	527	13.3	292	459	525	14.3	20
20	2	327	624	718	15.2	308	618	721	16.6	298	609	712	16.8	295	607	712	17.4	292	612	715	16.9	20
20	5	323	817	996	29.2	307	856	1024	32.8	299	857	1023	32.2	295	850	1016	32.4	293	852	1018	32.4	20
20	7	327	870	1142	41.7	304	882	1139	48.4	298	873	1130	48.9	296	892	1143	47.1	295	905	1156	46.4	20
20	10	319	720	1005	79.0	307	726	1007	96.5	300	727	1005	95.8	296	721	1000	96.8	293	673	900	84.5	20
38	1	327	628	714	13.8	310	554	643	16.2	299	548	605	10.3	293	537	595	10.8	293	533	594	11.4	20
38	2	327	779	922	18.4	302	751	894	19.1	298	754	863	14.5	295	747	861	15.3	292	741	853	15.1	20
38	5	320	1135	1459	28.6	303	1138	1431	32.3	299	1156	1410	27.5	294	1139	1409	29.6	293	1129	1400	30.0	20
38	7	322	1370	1822	33.0	301	1374	1781	37.1	301	1377	1765	35.2	295	1328	1746	39.3	293	1367	1757	35.6	20
38	10	320	1640	2218	39.2	303	1619	2185	48.6	298	1629	2165	45.7	294	1645	2171	44.3	294	1388	1829	44.1	20
59	1	324	774	871	12.5	306	582	715	23.0	300	551	657	19.3	299	545	616	13.0	294	541	588	8.8	20
59	2	325	909	1041	14.5	301	736	909	23.5	296	718	860	19.8	298	722	829	14.9	298	716	798	11.5	20
59	5	335	1302	1540	18.2	306	1225	1508	23.1	299	1219	1468	20.4	295	1216	1431	17.7	292	1225	1414	15.5	20
59	7	325	1621	1920	18.5	309	1560	1915	22.7	300	1558	1877	20.5	301	1558	1845	18.5	292	1558	1817	16.6	20
59	10	331	2095	2481	18.4	304	2072	2531	22.1	300	2066	2492	20.6	297	2069	2462	19.0	297	1749	2049	17.1	20
98	1	319	1097	1234	12.5	307	734	961	30.9	298	633	847	33.8	295	597	787	32.0	291	584	741	26.9	20
98	2	321	1188	1392	17.2	305	895	1191	33.0	299	858	1131	31.8	296	855	1092	27.8	293	850	1055	24.1	20
98	5	319	1615	2008	24.4	303	1539	2007	30.4	301	1531	1968	28.5	294	1533	1938	26.5	294	1512	1893	25.2	20
98	7	318	1942	2449	26.1	304	1918	2528	31.8	298	1931	2490	29.0	294	1922	2449	27.4	292	1936	2428	25.4	20
98	10	321	2406	3103	29.0	306	2432	3252	33.7	300	2366	3169	33.9	295	2358	3113	32.0	295	2008	2615	30.2	20

For Montage workflow depicted in the Table 7, for lower workflow sizes the error percent is high and as the workflow size increased the error is observed to decline. It can be observed that error increased with DER values. The error for the workflow size 20 is observed to be 39.72 percent, it is 27.82 percent for 38 tasks, 17.98 percent for 59 tasks, and increased to 28 percent for 98 tasks. And overall error is 28 percent.

7. CONCLUSION

A new makespan estimation model is devised to estimate the bounds on the makespan of the workflows. In the available model's dataflows were either ignored or nominal, hence these models could not be extended for computation-intensive and data-intensive workflows. The proposed makespan estimation model is devised with minimal information considering the profile of the workflow as the makespan of the workflow highly depends on its profile. The proposed estimation model is devised with a complexity of O(n) and O(n+e) for computing BCCT and WCCT respectively. The present model is validated using the scientific workflows. The results of the experiments revealed that the proposed model could precisely estimate the makespan of the scientific workflows. The error for computation-intensive workflows namely LIGO and Epigenomics is observed to be 10.18 and 10.4 percent respectively and for data-intensive workflows namely Cybershake and Montage it is noted to be 26 percent and 28 percent respectively.

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