Context-aware Task Allocation for Fast Parallel Big Data Processing in Optical-Wireless Networks

Context-aware Task Allocation for Fast Parallel Big Data Processing in Optical-Wireless Networks

(Invited Paper)

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***Abstract*—MapReduce architecture has been considered as one of the most promising candidates for efficient and reliable big data mining. While current MapReduce is basically designed for data center and enterprise networks, in which a number of servers are interconnected with optical fiber cables, prospective MapReduce would be applied in optical-wireless environment such as optical-wireless data center network, fiber-wireless (FiWi) access network, and so forth. To modify MapReduce for optical-wireless hybrid network, we need to answer the fundamental research problem, "How does MapReduce architecture use optical and wireless resources for task allocation?" To answer this question, this paper reveals some challenging issues and proposes a context-aware task allocation scheme that is designed by considering characteristics of both optical and wireless communications. Our proposed task allocation scheme can minimize the completion time of big data processing. Numerical results are presented to demonstrate the effectiveness of our proposed method compared with existing task allocation schemes.**

***Index Terms*—Context-aware task allocation, MapReduce, minimizing completion time, optical-wireless network.**

I. Introduction

Throughout the last decade we have witnessed a tremendous increase in data which is generated from whole society. According to the latest statics [1], the number of IP network-connected devices will be three times as high as the global population by the end of 2017. As a result, the amount of annual global traffic will reach 1.4 zettabytes in 2017, almost 16 gigabytes per capita, up from 6 gigabytes per capita in 2012. Furthermore, with the emergence of social networking services and the use of information and communication technologies in various industries, various types of data are being produced (such as social media data, multimedia data, customer data, log data, and so forth) [2]. Such kind of data, called big data, has attracted much attention since it can contain valuable and important information. However, big data has different characteristics from traditional data, i.e., volume (data size of terabytes to petabytes), variety (either structured data or unstructured data), and velocity (requirement of real-time data processing). Therefore, big data cannot be processed in traditional manner using only a single high-spec server (i.e., super computer-based mining).

MapReduce is a superior architecture, which complies with the requirements of big data mining. For efficient and reliable big data mining, MapReduce distributes data to distinct servers and these servers execute data processing in parallel. In comparison with the traditional super computer-based mining, MapReduce can perform more efficient big data processing with cheaper servers. While conventional MapReduce architecture is designed for optical network such as data center and enterprise networks [3], prospective MapReduce needs to be modified to be applicable to optical-wireless hybrid network, in which each server communicates with other servers by using both optical and wireless links.

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As a realistic optical-wireless hybrid network, the following environments are considered. (*i*) With the explosive progression of wireless communications technology, optical-wireless data center network will become the medium choice for future data center networks. In this network, while intra-rack servers communicate by radio, inter-rack communication is conducted via optical fiber cables. (*ii*) In fiber-wireless (FiWi) access networks, which integrate optical and wireless networks (e.g., passive optical network (PON) and wireless fidelity (WiFi)), user terminals and networking devices execute data processing in order to achieve efficient mobile cloud computing [4]. (*iii*) We are developing a disaster resilient network by using movable and deployable resource units (MDRUs), which are deployed to disaster area and provide the information and communications services instead of damaged base stations, optical fiber cables, and data centers [5]. In MDRU-based network, each MDRU connects to other MDRUs with optical fiber cables and connect with users through wireless links.

In order to redesign MapReduce for optical-wireless networks, we need to consider the fundamental research problem "How does MapReduce architecture use optical and wireless resources for task allocation?" In this paper, we propose an optimal task allocation scheme that switches the communication mode (i.e. optical or wireless) by considering its characteristics, such as the differences in multiple access control and transmission schemes (unicast or multicast). The proposed task allocation scheme effectively utilizes the network resource based on network and server load, and minimizes the completion time of big data processing.

The remainder of the paper is organized as follows. First, we survey some relevant research works on MapReduce for combating the task scheduling issue in Section II. Then, we describe our considered future vision of MapReduce in optical-wireless hybrid networks and introduce its challenging issues in Section III. Section IV presents a novel task allocation scheme based on characteristics of both optical and wireless communications, followed by its performance evaluation in Section V. Finally, concluding remarks are provided in Section VI.

II. Related Research Work

An introduction to the first MapReduce for parallel data processing architecture has been presented by Dean *et al.* in [6] in 2004. The architecture has been widely used in many cloud computing frameworks such as Hadoop and nutch. Fig. 1 shows an example of parallel data processing with MapReduce. The nodes are classified into data processing nodes and a master node. While the data processing nodes store data and execute mapping and reduction processes, the master node schedules tasks in both the mapping and reduction processes. When a processing request is injected, the master node finds nodes that store the data appertaining to the injected task (here, nodes A and B). Additionally, the master node selects mappers that execute the mapping process. Nodes A', A" and B', B" are selected as mappers for node A and B, respectively. Then, nodes A and B transmit replication data to each mapper. The mappers perform mapping process that picks out the required information to classify a large amount of information. After the mapping process finishes, the master node selects a reducer, which is a processing node executing the reduction process, from the mappers (here, node A'). The reducer collects the information extracted in mapping process and executes the reduction process that outputs the result data. While MapReduce can execute the data mining at a speed proportional to the number of nodes, the performance depends on task allocation and scheduling schemes. A lot of efficient task allocation schemes have been proposed in literature.

The works [7]–[9] have developed load-aware task allocation and scheduling schemes. In [7], the authors have developed a parallel data processing architecture that allocates tasks to different types of virtual machines, in order to improve the overall resource utilization and reduce the processing cost. The work [8] has proposed a dynamic task scheduling for heterogeneous workloads. In the proposed scheme, three types of queue based on I/O and CPU utilization are used to distribute the heterogeneous workloads. In the work conducted by A. Verma *et al.* [9], a task scheduling algorithm, which optimizes the completion time and cluster resource utilization under realistic workloads, has been proposed.

Another direction to develop network-aware task allocation scheme has been considered in works [10]–[12]. M. Asahara *et al.* have proposed a task scheduling scheme based on network topology that can avoid the network congestion [10]. In [11], the authors have designed a MapReduce framework for wireless data center. Through simulation, they verify the effectiveness of MapReduce in wireless environment. The work [12] has considered radio and computing resources sharing problem and proposed a cooperative resource management to provide an efficient cloud computing in wireless network.

In this paper, one of our contributions is opening up a new direction for MapReduce, i.e., task allocation scheme based on characteristics of both the optical and wireless communications for minimizing completion time. In other words, our work brings up important issue of resource utilization in optical-wireless hybrid networks, which is an issue that is not widely studied but can greatly decrease the performance of conventional MapReduce.

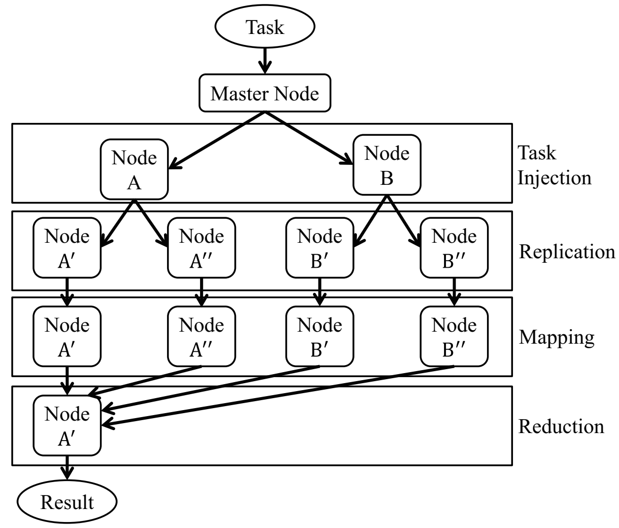


Fig. 1. Conventional parallel data processing architecture with MapReduce.

III. MapReduce in Optical-Wireless hybrid Network

In this section, we present one of optical-wireless hybrid networks, followed by challenging issues of MapReduce in the considered optical-wireless hybrid network.

A. Network model

Our considered optical-wireless data center network is depicted in Fig. 2. Servers in each rack can be classified into two groups. The first group consists of servers that only have a wireless interface, and the other group consists of servers that have wireless and wired interfaces. Although fully wireless data center networks have been proposed in [13], the considered network uses wireless interfaces only for intra-rack communication since wireless communications have a small coverage area and suffer from decreased signal strength due to walls and barricades. Moreover, we suppose that carrier sense multiple access/collision avoidance (CSMA/CA) is used as a multiple access scheme. Inter-rack communication is conducted via a wavelength division multiplex fiber cable with optical path switching in order to provide high quality of service (QoS) [14]. We use distributed optical path provisioning as a path set-up scheme [15].

In case of intra-rack communication, servers transmit data by unicast or multicast. Thus, intra-rack communication effectively utilizes the radio resource by using multicast in the data replication phase. On the other hand, data transmission scheme is unicast in case of inter-rack communication because severs that have wired interface reserve the optical path and transmit data to inter-rack server via the reserved optical path. In the data replication phase, inter-rack communication requires

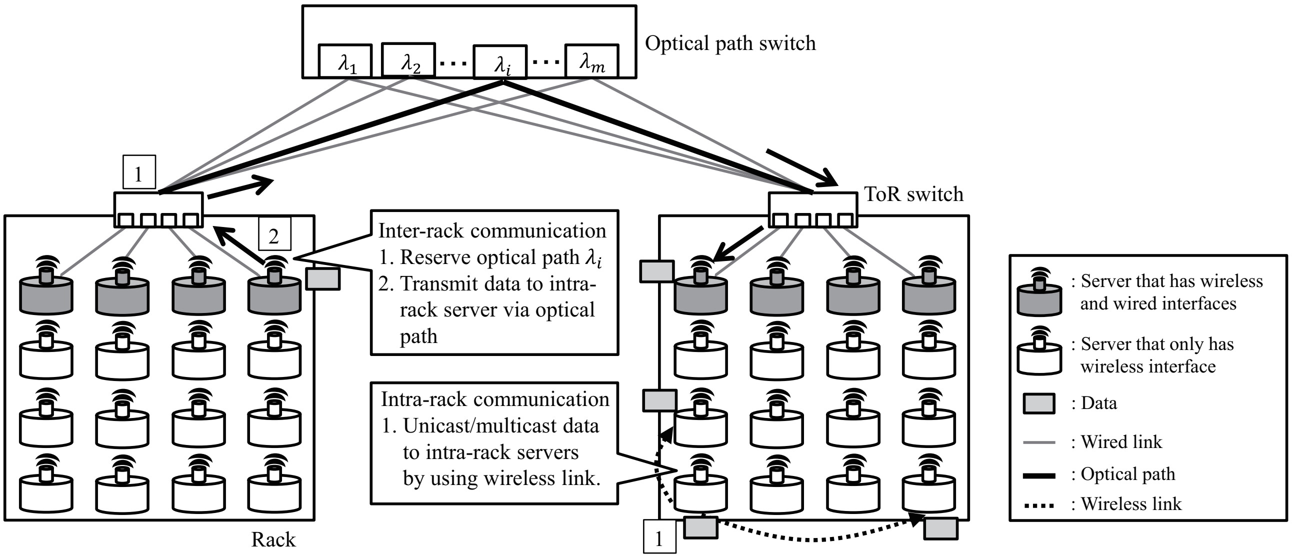


Fig. 2. Considered optical-wireless data center network, and intra-rack and inter-rack communication mechanisms.

the reservation of multiple optical paths. Therefore, efficiency of inter-rack communication is lower than that of intra-rack communication.

For simplicity, we assume that there exists a master node and it is chosen from the servers that have wireless and wired interfaces, whereas other servers act as data processing nodes. Master node allocates tasks by two communication modes, i.e., intra-rack and inter-rack task allocation. In case of intra-rack task allocation, the master node selects mappers and reducer from servers in the intra-rack. In contrast, inter-rack allocation choses them from the inter-rack servers that connect with the top of rack (ToR) switch.

B. Challenging issues

In our envisioned network model, it is required to consider the characteristics of optical and wireless communications and MapReduce in order to achieve data processing with minimum completion time. This section introduces some challenging issues that tackle the development of efficient task allocation schemes.

Communications-aware Task Allocation: It is necessary to clarify the impact of communications mode selection (i.e., either inter-rack or inter-rack communication) on the completion time of parallel data processing. First, we mention task allocation to intra-rack servers with wireless communications. Because the master node transmits data to multiple mappers to execute the mapping process, it is clear that multicast with wireless communications is a better transmission scheme for the mapping process. However, the wireless communication is not suitable for the reduction process, in which multiple mappers transmit data to a reducer. This is because mappers are forced to wait to transmit data with the CSMA/CA mechanism, which results in drastic reduction of system throughput and the emergence of transmission delay. On the other hand, task allocation to inter-rack servers with optical path switching inefficiently uses the resources because optical path provides unicast transmissions. Additionally, the blocking probability increases when the number of provisioned paths increases. Thus, the process of allocating task to inter-rack servers is not suitable for the mapping process, especially when data redundancy, f, is larger. Similarly, inter-rack communication wastes resources in reduction phase. Because optical path reservation requires shorter waiting time for transmissions than that of the CSMA/CA mechanism, task allocation to inter-rack servers effectively uses the resources. It can be noticed that there is a trade-off relationship between intra-rack and inter-rack communications in terms of resource efficiency. Therefore, optimal task allocation can be derived for efficient parallel data processing.

Load-aware Task Allocation: Additionally, server load (CPU and I/O load) should be considered for designing efficient task allocation schemes, similar with many other existing works [7]–[9]. The point that separates our work from those of existing works is the consideration of the impact of communications mode on the server load. Multicasting with wireless communications lacks retransmission schemes, error detection and correction coding, which means much more redundancy is required to ensure the reliability of the processed result. However, server load may increase with higher redundancy. Therefore, optimal redundancy to allocate task is derived by considering both the reliability of result and server load. This aspect should be taken into account for designing effective task allocation.

Context-aware Task Allocation: Various information including communications mode and servers load, (called context) will help with the task allocation design. In optical-wireless hybrid networks, network condition, data size, and data redundancy also produce the beneficial information. Designing task allocation schemes based on context information is required to minimize the completion time of parallel data processing. Our future direction is to discover the new context and integrative development based on context information to achieve smart-MapReduce.

IV. Proposed Context-aware Task Allocation Scheme

In this section, we propose a context-aware task allocation scheme, which can shorten the completion time of big data mining in optical-wireless data center networks.

In conventional MapReduce architectures, task allocation schemes are designed based on server load or network load. While the server load based task allocation scheme reduces the execution time of data processing, the network load based task allocation scheme achieves lower transmission delay. Therefore, by considering the both metrics, we can optimize the task allocation for minimizing the completion time of data processing. Additionally, the conventional network load based scheme allocates tasks by considering available network bandwidth, which is not sufficient to allocate tasks to appropriate processing nodes in optical-wireless network environments since optical and wireless communications have different characteristics, such as multiple access control and data transmission schemes.

Therefore, our proposed task allocation scheme decides the number of tasks that will be allocated to nodes in each rack based on the expected transmission delay by considering the characteristics of optical and wireless communications. In addition to this, our proposed scheme selects adequate nodes that have lower processing load as processing nodes. Through these phases, our proposal can shorten the completion time of big data mining.

A. Determining task load on each rack

In this phase, the master node decides the number of tasks that will be allocated to servers in each rack based on the expected transmission delay by considering the multiple access control scheme of optical and wireless communications and traffic model on mapping and reduction process. We define m and n, which denote the numbers of tasks that will be allocated to intra-rack and inter-rack servers, respectively. The master node calculates $T_{\mathrm{intra}}(m)$ and $T_{\mathrm{inter}}(n)$, which are the expected transmission delays required to allocate tasks to distinct servers in intra-rack and inter-rack, respectively. $T_{\mathrm{intra}}(m)$ and $T_{\mathrm{inter}}(n)$ are expressed as the sum of expected transmission delays in mapping and reduction process.

In case of task allocation to intra-rack servers, servers are forced to wait to transmit data with the CSMA/CA mechanism. According to work [16], throughput of each node with IEEE 802.11, $\alpha(N)$, depends on the number of nodes that transmit data, N. Because the master node transmits m tasks to distinct mappers with wireless multicasting and the $(m-1)$ mappers transmits the processed data to a reducer with unicasting, the master nodes can calculate the transmission delay required to allocate tasks to m intra-rack servers, $T_{\mathrm{intra}}(m)$, which is expressed as follows.

$$T_{\mathrm{intra}}(m) = D_{\mathrm{map}}/\alpha(1) + D_{\mathrm{red}}/\alpha(m-1), \tag{1}$$

where D_{map} and D_{red} indicate data sizes of tasks to be proceeded in the mapping and reduction processes, respectively.

Moreover, $\alpha(N)$ can be calculated by using the probability that a node successfully transmits data, $P_{\mathrm{S}}(N)$, and the theoretical throughput of wireless communication, B_{R}, as follows.

$$\alpha(N) = P_{\mathrm{S}}(N) B_{\mathrm{R}}. \tag{2}$$

Here, the value of $P_{\mathrm{S}}(N)$ is derived from [16].

In case of task allocation to inter-rack servers, the master node allocates data to n inter-rack servers, and n mappers transmit the processed data to a reducer via the reserved optical paths. Because the optical path switch creates an optical path connecting each server having traffic to send to all destinations having traffic destined, the source node waits to transmit data until optical path is provisioned. Let $\tau(N)$ denote the waiting time required to create an optical path when N nodes require optical paths. The value of $\tau(N)$ increases with increase in N because the optical path provisioning is dismissed due to blocking. The master node can calculate the transmission delay required to allocate task to inter-rack servers, $T_{\mathrm{inter}}(n)$, by using following equation.

$$T_{\mathrm{inter}}(n) = D_{\mathrm{map}}/B_{\mathrm{W}} + \tau(n) + D_{\mathrm{red}}/B_{\mathrm{W}} + \tau(n), \tag{3}$$

where B_{W} denotes the capacity of the reserved optical path.

Moreover, $\tau(N)$ can be defined in detail by considering the acceptance probability on optical path provisioning, $P_{\mathrm{A}}(N)$, the time spent for a reservation trial, T_{trial}, and the time spent for reservation retrial, T_{retrial}. Assuming that the ith trial is the first trial that succeeds in optical path provisioning and M is the maximum number of trials, $\tau(N)$ is expressed as follows.

$$\tau(N) = \sum_{i=1}^{M} P_{\mathrm{A}}(N)\{1 - P_{\mathrm{A}}(N)\}^{i-1} \times \{iT_{\mathrm{trial}} + (i-1)T_{\mathrm{retrial}}\}. \tag{4}$$

Here, the detailed derivation of $P_{\mathrm{A}}(N)$ can be found in [17].

In order to minimize the transmission delay for data allocation, the master node decides m and n based on calculation results of $T_{\mathrm{intra}}(m)$ and $T_{\mathrm{inter}}(n)$ for all combination of m and n. In other words, m and n that minimize the larger value in $T_{\mathrm{intra}}(m)$ and $T_{\mathrm{inter}}(n)$ is selected as the optimal numbers of tasks that will be allocated to intra-rack and inter-rack servers, respectively. Additionally n tasks are evenly allocated to each rack. Because the number of interfering nodes in wireless communications and the number of available optical paths in optical communications might affect the decision of the values of m and n, the proposed task allocation scheme dynamically changes task load on each rack based on network condition.

B. Processing nodes selection

While the previous phase minimizes the transmission delay by using characteristics of communications and network condition, this phase aims at minimizing the execution time of data processing. The master node selects m servers that have lower loads as processing nodes from the intra-rack servers and

TABLE I
PARAMETER SETTINGS.

Wireless capacity	7Gbps
Contention window	63
Capacity per wavelength	1Gbps
Number of wavelengths	10
Number of racks	18
Number of servers in a rack	20
Data size	125Mbyte
Number of servers connecting with ToR switch in a rack	3
Number of master nodes	1

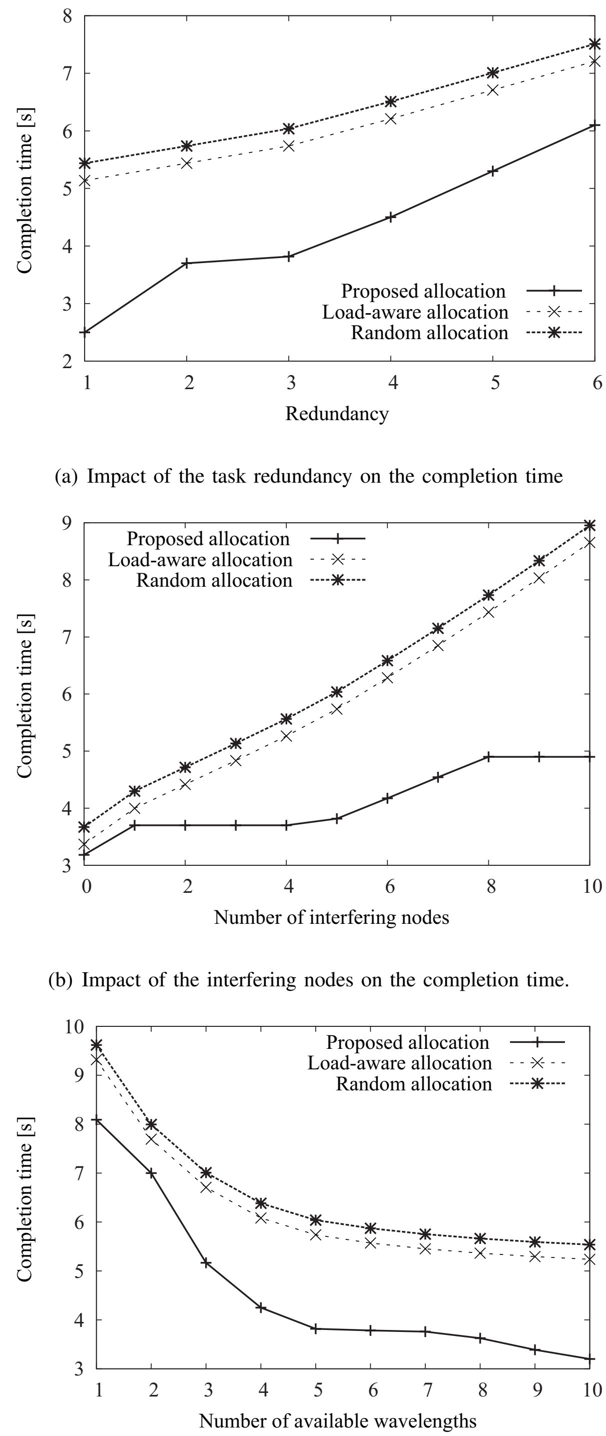
selects n servers from inter-rack servers. However, the master node wastes resources for collecting the load information from all servers. Indeed, throughput of the both communications drastically decreases with load information sharing. To cope with this issue, in our proposed scheme, threshold based information sharing is used. In this scheme, the master node broadcasts the message including threshold of load to all nodes. Nodes that have lower loads than the threshold reply with a message including its task loads information. Thus, the master node knows the candidate for processing nodes.

V. PERFORMANCE EVALUATION

In this section, we confirm the effectiveness of the proposed task allocation scheme through numerical results. The proposal is compared with the load-aware and random task allocation schemes. While the load-aware allocation scheme selects processing nodes based on I/O and CPU utilization, the random allocation scheme selects processing nodes in random manner. In this performance evaluation, we show the results of the completion time in three different scenarios.

A. Parameter settings

The parameter settings are summarized in Table I. In this performance evaluation, we suppose that the topology of optical-wireless data center network follows Fig. 2. In our supposed data center network, there are 20 racks, which are connected with optical fiber links, where the number of wavelengths is 10 and capacity per wavelength is 1Gbps. Intra-rack communication is carried out by 60GHz based IEEE 802.11ad with 7Gbps capacity. Additionally, the contention window is set to 63. There are 20 servers and 3 servers connect with ToR switch, where we assume that links between servers and ToR switch has sufficient bandwidth. Data size of processing tasks for both mapping and reduction process is 125 Mbyte. To model the load heterogeneity, we suppose that the processing time of servers follows the binomial distribution, where average and variance are set to 1.5s and 0.3s, respectively. In this network, we evaluate the completion time when a request is injected. In order to confirm the impact of various environments on the performance of proposal, we consider three different scenarios, i.e., various data redundancy, wireless network condition, and optical network condition.



(a) Impact of the task redundancy on the completion time

(b) Impact of the interfering nodes on the completion time.

(c) Impact of the number of available wavelengths on the completion time.

Fig. 3. Performance comparison in terms of completion time in different scenarios.

B. Numerical results

In the graphs presented in Fig. 3, we demonstrate the performance of the proposed context-aware and existing task allocation schemes in three scenarios. Fig. 3(a) exhibits the completion time when task redundancy is varied from 1 to

6, where the number of interfering nodes that send unrelated data and the number of available wavelengths are set to 5. From the result, it is clear that our proposed scheme achieves shorter completion time regardless of task redundancy. It can be noticed that the slope of proposed scheme changes when redundancy is 2 and 3. From these points, the proposed scheme uses inter-rack servers as processing nodes because the intra-rack communication requires longer transmission delay than that of the inter-rack communication.

Fig. 3(b) demonstrates the result when the number of interfering nodes is varied from 0 to 10, where redundancy and the number of available wavelengths are set to 3 and 5, respectively. Because the proposed scheme changes the number of tasks that will be allocated to each rack with increase in the number of interfering nodes, it is able to keep the lower completion time. On the other hand, the load-aware and random task allocation schemes require more completion time because the load-aware and random task allocation schemes use intra-rack servers as processing nodes in spite of the decrease in wireless throughput.

Fig. 3(c) shows the impact of the number of available wavelengths on the completion time, where redundancy and number of interfering nodes are set to 3 and 5, respectively. Similar to the previous results, the proposed scheme achieves a shorter completion time of data mining. Moreover, the proposed scheme achieves outstanding performance with increase in the number of available wavelengths, i.e., the completion time with the proposed scheme reduces by approximately 61 percent when the number of available wavelengths is 10. From these results, we can conclude that the proposed scheme efficiently allocates tasks and obtains the processing result with shorter completion time in optical-wireless hybrid networks.

VI. Conclusion

An efficient parallel data processing with MapReduce is required to realize more convenient and comfortable big data mining. However, the conventional MapReduce is not suitable to provide the high-speed data processing in optical-wireless hybrid networks because it is designed for optical wired networks. To address this challenge, in this paper, we highlighted the importance on designing appropriate task allocation scheme for efficient data processing in optical-wireless hybrid networks. Additionally, we proposed a simple yet effective task allocation scheme, which is designed based on context information. By deciding the number of tasks that will be allocated to servers in each rack based on the expected transmission delay, the proposed task allocation is able to shorten the completion time of big data processing. Moreover, the results obtained from numerical analysis demonstrated the effectiveness of our proposed task allocation scheme with the significant improvement in completion time. In future, our work will perform further investigations on how to enhance the processing reliability of MapReduce.

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