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Greening Big Data Networks: Volume Impact

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Abstract

Tremendous volumes generated by big data applications are starting to overwhelm data centers and networks. Traditional research efforts have determined how to process these vast volumes of data inside datacenters. Nevertheless, slight attention has addressed the increase in power consumption resulting from transferring these gigantic volumes of data from the source to destination (datacenters). An efficient approach to address this challenge is to progressively processing large volumes of data as close to the source as possible and transport the reduced volume of extracted knowledge to the destination. In this article, we examine the impact of processing different big data volumes on network power consumption in a progressive manner from source to datacenters. Accordingly, a noteworthy decrease for data transferred is achieved which results in a generous reduction in network power consumption. We consider different volumes of big data chunks. We introduce a Mixed Integer Linear Programming model (MILP) to optimize the processing locations of these volumes of data and the locations of two datacenters. The results show that serving different big data volumes of uniform distribution yields higher power saving compared to the volumes of chunks with fixed size. Therefore, we obtain an average network power saving of 57%, 48%, and 35% when considering the volumes of 10-220 (uniform) Gb, 110 Gb, and 50 Gb per chunk, respectively, compared to the conventional approach where all these chunks are processed inside datacenters only.

Keywords- Big Data processing, IP/WDM, MILP, power consumption

I. Introduction

The flourishing in the Internet-enabled technologies is driving the world to be inundating by a colossal amount of data generated from diversified realms such as bioinformatics, health informatics, social media, business and sensors data. The term big data has been devised to describe handling multiple data types generated by numerous data sources.

While it is exceedingly hard to enumerate the volumes of data generated by the current Internet-connected devices, the situation is becoming even more intricate in the near future, as the estimated number of the Internet-connected devices is going to be 100 billion devices by 2020 [1]. Based on IDC report [2], the overall data volume will reach 40,000 Exabyte in 2020. This exponential increase in volumes of data is causing dramatic drops in the percentage of data that is to be processed inside datacentres. Consequently, there will be massive networking power consumption due to transporting unprocessed raw data while the only interest is the extracted knowledge from such data. Further, additional wastage in storage and bandwidth is resulting from transferring raw data, which leads to high financial cost. Managing immense data volumes demands new processing and communications methodologies.

Several efforts are directed towards the minimization of power consumption of processing and transporting such massive volumes of data. In [3] the authors developed a Mixed Integer Linear Programming (MILP) model to analyse the energy efficiency in the cloud-enabled Internet of Things (IoT) networks. The authors in [4] proposed a MapReduce framework to locally process as much data as possible on multiple IoT nodes rather than transmitting the raw data to datacentres (DCs). The authors in [5] presented a processing system for executing a sequence of MapReduce jobs on Geo-distributed datacentres where the treating of jobs is optimized according to time and pecuniary cost. The authors in [6] proposed a dynamic bulk data transfer framework in geo-distributed data canters and planned its design and algorithms depending on Software Defined Network (SDN) architecture. In [7], the authors demonstrated the minimization of overall cost for big data placement, processing, and movement across geo-distributed datacentres. In [8], the authors presented a framework for energy efficient cloud computing services over IP/WDM core networks.

The 4 Vs of big data were coined to grasp various dimensions of big data: Volume (and its effects on power requirements), Velocity (with impact on delay-sensitive and delay-tolerant data), Variety (with different applications that needs various CPU requirements) and Veracity (with trustworthiness and reliability constraints)

In this work, we extend our previous work in [9] and [10] to further investigate the impact of the volumes of big data on network power consumption. We optimize the processing location of different amounts of volumes of data generated by different zones of the core networks so that processing could be achieved at the source core node and/or along the data journey through the core network to the datacentres. We also optimize the lactations of different number of datacentres to evaluate the impact of processing various data volumes on datacentres location. This approach helps to reduce amount of big data traffic transported over the core network each time the data is processed. We developed a MILP model so that the network power consumption is reduced.

II. Greening Big Bata Networks

The concept of greening big data networks is illustrated in Figure 1[9]. Figugre 1(a) displays the conventional techniuqe of proccessing big data where the *Chunks* (the raw data before processing with large volume) are transffered from the source to the datacenters for storing and processing. In green big data networks, see Figure 1(b), Processing Nodes (*PNs*) are attached to the IP over WDM nodes to hundle the *Chunks* and to produce *Infos* (the extracted knowledge from chunks characterized by small volume after processing *Chunks*). A PN consists of limited number of servers, storage, and LAN switches and routers and can process the locall or the data generated by other nodes and forword the results (*Infos*) to datacenters. Note in Figure 1(b) that the data generated by source nodes can either be *Chunks* or *Info*. The latter is the case if the source has processing capability. This type of source core node is referred to as a "Source PN (SPN)". On the other hand, the processing capability placed at intermediate core nodes is refererd to as "Intermediate PN (IPN)".

For realistic considerations, we presume that each PN's processing and storage capacity is limited and vary from one PN to another. On the other hand, datacenters are assumed having a capacity equal to or more than that needed for processing the considered chunks. In equation (1), we introduce the concept of Processing Reduction Ration (PRR). PRR is the ratio of the volume of *Infos* to the volume of *Chunks*. We assume that the volume of a given *Chunk* is reduced by the PRR to produce the *Info* carried by that *Chunk*.

Accordingly, big data traffic is significantly reduced in the network each time these volumes of data processed before reaching their destinations at DCs.

$$Volume\ of\ Info = PRR \times Volume\ of\ Chunk \quad (1)$$

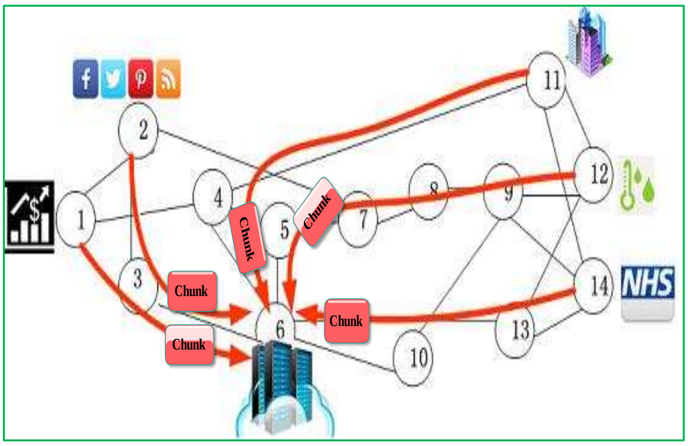

Figure 1(a): Conventional big data networks.

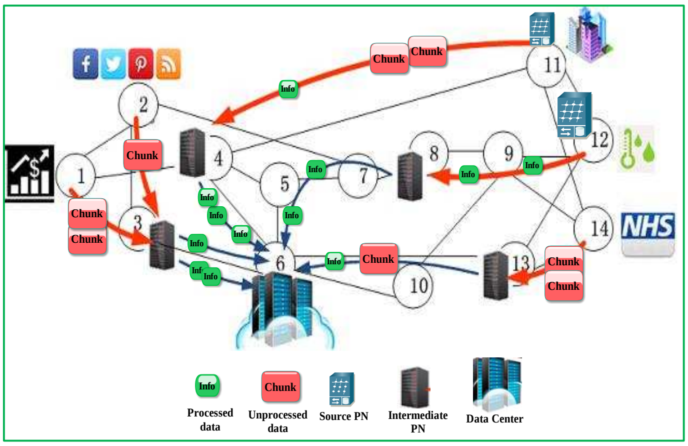

Figure 1(b): Green big data networks.

III. MILP Model Description

In this seciton we descripe a MILP model to optimize the processing resources and processing locations of big data chunks in bypass IP over WDM networks, taking into acount different volume patterns of big data chunks. For details of energy efficient MILP optimization in datacentres and IP over WDM network architectures, see [8], [12]-[24]. We assume that there are capacitated PNs at each core node. Moreover, we optimize the location of two datacenters but with large enough processing and storage capability compared to other PNs. These datacenters are employed to process all extra big data chunks that come from other PNs when all PNs exhaust their resources and to host the results of processed chunks (i.e. infos) generated from the PNs for further analysis.

This paper gives a brief description to the model due to paper length limitation. The objective of our model is to minimize the total power consumption which is the sum of the power consumption of the IP over WDM network, PNs, and DCs as given in eq (2):

$$\text{Minimize: (Total Power Consumption=} \\ \text{IP/WDM network power consumption} + \\ + \text{PNs power consumption} + \text{DCs power consumption)} \quad (2)$$

The IP over WDM power consumption comprises the power consumption of the router ports, transponders, EDFAs, regenerators, and optical switches. The PNs' and DCs' power consumption are composed of the power consumption of the servers, storage, switches and routers. The main features of our model are as follows:

- The model optimizes the location where the processing of each chunk is carried out, in stages by starting the processing locally at the
- SPNs, moving through the IPNs, and finally stepping out towards the datacenters.
- The model optimizes the destination of infos so that each info selects one optimum location of the datacenters.
- The model performs a consolidation process by ensuring that the total CPU utilization in one server allocated to process one or more chunks does not exceed the CPU capacity. This is done by assigning a specific CPU workload per chunk, which is the portion of the CPU required to process a chunk. Accordingly, servers pack as many chunks as possible to reduce the number of oaverall active servers inside a PN.
- The model insures that all servers and storage usage of a given PN do not exceed the processing and storage capacity of that node. For blocking avoidance, the internal LAN switches and routers capacity are assumed to be large enough.

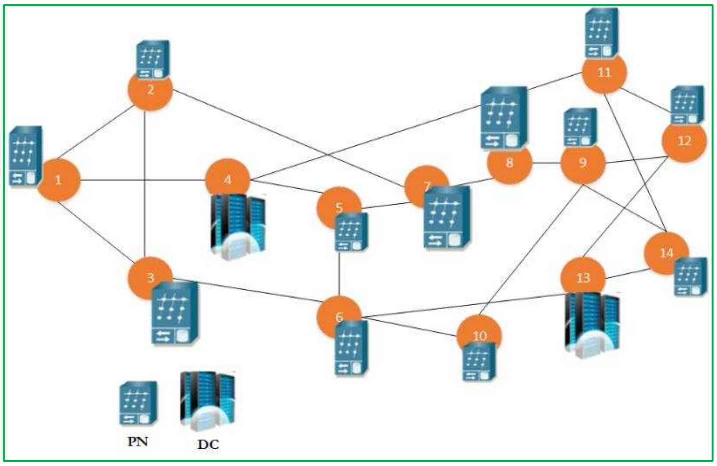

Figure 2 The NSFNET with PNs and two optimum DCs locations

TABLE I INPUT PARAMETERS TO THE MODEL

Number of server per PN	10-30
PNs storage capacity	80 Pb - 600 Pb
Server CPU capacity	4 GHz
Max server power consumption	300 W [8], [9]
Energy per bit of the LAN switch	11.875 W/Gbps [12]
Energy per bit of the LAN router	7.727 W/Gbps [12]
Storage power consumption	0.008 W/Gb [12]
IP/WDM router power consumption	825 W [9] , [19]
IP/WDM regenerator power consumption	222 W [19] , [9]
IP/WDM transponder power consumption	167 W [19] , [9]
IP/WDM optical switch power consumption	85 W [12]-[19]
IP/WDM EFDA power consumption	52 W [12]-[19]
Wavelength bit rate	40 Gbps [12]-[19]
Number of wavelengths per fiber	32 [12]-[19]
Number of chunks generated per PN (β)	10-60

- The model optimize datacenters locations which are used for processing the extra big data chunks when all PNs are fully utilized and for receiving the infos from PNs to store them for further analysis.

The MILP model is evaluated on the NSFNET network shown in Figure 2. The NSFNET network consists of 14 nodes connected by 21 bidirectional links. We assume the capacitated PNs to be located at each core node. Two uncapacitated datacenters locations is optimized as shown in Figure 2. The processing and storage capacities of the PNs are randomly assigned between 10-30 servers (with 4 GHz CPU capacity per server) and 10 PB - 75 PB, respectively. Note that we use processor cycles in GHz as a measure of the total processing capability of a node [11]. Table I summarises the input parameters of the model [8], [9], [12]-[19].

IV. Evaluation and Results

To study the impact of big data volume on the inclusive system performance, three different scenarios are considered in this study. We consider various volume schemas in which we optimize the processing of big data chunks generated by all the NSFNET nodes. We consider number of chunks per PN (β) is varying between 10-60 chunks.

In addition to the existence of these big data chunks in the network, we assume, for realistic considerations, that there is an additional traffic between core nodes named regular traffic. This traffic represents any data that is not intended for big data analytics.

Big data traffic is processed and reduced by the PNs as much as possible and the reduced traffic (i.e. infos) is forwarded to one optimum datacenter. For simplicity, we assume that chunks and infos are transmitted at a data rate equal to their volume per second. Each chunk that is processed inside a PN will produce info after being reduced by the proposed PRR. However, when chunks are processed inside datacenters, the result is stored there for future use. In all scenarios, we consider each chunk demands 3 GHz for processing with 0.01 PRR per chunk.

In the following, we evaluate the impact of volume scenarios on green big data networks:

A. In this scenario, and to reflect more realistic picture in the network, we assume that the volumes of chunks generated by all nodes are uniformly distributed and oscillating between 10 and 220 Gb with an average of around 110 Gb. Table and II summarizes the parameters needed of for this scenario.

TABLE II SCENARIO A PARAMETERS

Number of chunks per PN (β)	CPU workload per chunk in GHz	Chunk volume in Gb (uniform)	Average volume of uniform distribution in Gb	PRR per chunk
10-60	3	10-220	≈110	0.01

Figure 3(a) compares our green big data network power consumption with the network power consumption of the conventional approach where chunks of different volumes are directly fluxed to the datacentres before processing. For all cases, the network power consumption increases when β increases. Presenting the PNs has, however, significantly bounded the growth in power consumption, which results in a maximum network power saving of 64% at β=30 and average power saving of 57% when considering all values of β, compared to the conventional approach when no PNs exist in the network.

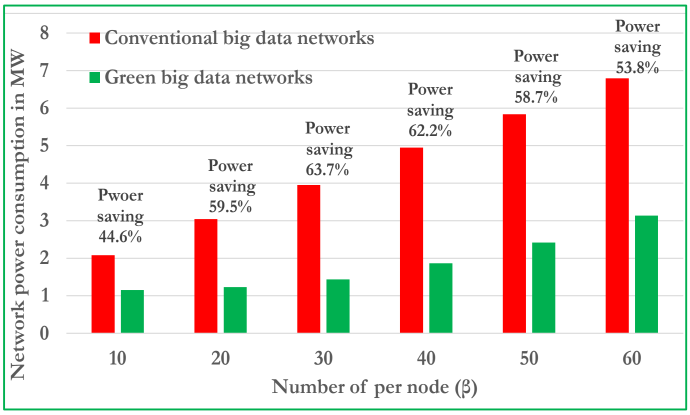

Figure 3(a): Conventional big data network power consumption and green big data network power consumption for scenario A.

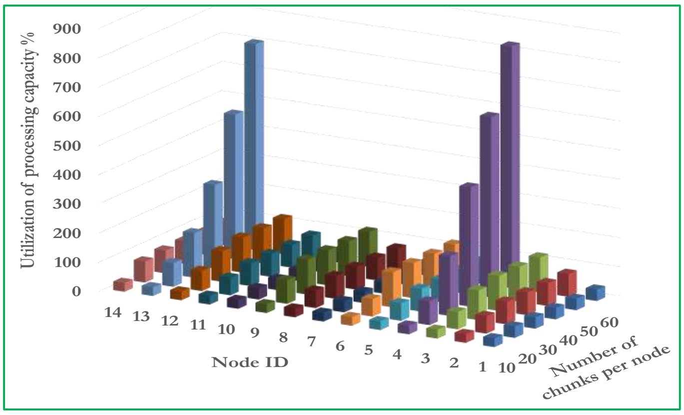

Figure 3(b): Processing utilization of green big data networks with different values of β for scenario A

In the following, we further assess the impact of our scenario on the network power consumption shown in Figure 3(a). When β is between 10 and 20, the network power consumption is small. Here the SPNs have enough capacity to store and process all these chunks locally and only the infos (which have very small size) are optimally aggregated to the datacentres, leading to 44.6% and 59.6 % saving, respectively.

When β reaches 30, the network power consumption slightly increases because few chunks are not processed in the SPNs but forwarded to optimum IPNs. Such a case results in generating a relatively small amount of traffic between the SPNs and the IPNs. However, the power saving reaches the maximum level of 63.7%.

The computing resources of most PNs are fully utilized when β=40 chunk. Such a case requests more router ports because the traffic over the network now is large due to the transmission of chunks and not the inofs, which leads to a scale up of the network power consumption and a scale down of the network power saving. Hence, the power saving is starting to decrease at this point to 62.2%. When the number of chunks surpasses 40 (i.e., β>40) in all PNs, all PNs are fully utilized and these extra chunks will optimally transfer to one of the two optimum datacentres through the energy efficient routes before being processed. Therefore, power saving is noticeably declined to 58.7% and 53.8% at 50 and 60 chunks per node, respectively.

Note that the power saving at β=10 and β=20 is small compared to the power saving at β=30. This is because that in spite of the increase in big data volume at case 30, the available processing capacity is still enough to process all the chunks at PNs. On the other hand, we note a reduction in power saving beyond β=30. This is due to the depletion of most PNs resources, which leads to higher raw data traffic in the network toward the datacentres.

Figure 3(b) depicts the utilization of the processing resources as a percentage at different PNs. It shows that our green big data network methodology selects two optimal datacentres locations at nodes 4 and 13. Note that the reference (100%) is the processing capability of a PN with 30 servers, with a data centre having large enough processing capability. From the data in Figure 3(b), it is obvious that some PNs exhaust their CPUs usage earlier than the others at β=20 such as nodes 1, 7, and 11, whilst the computing resources of other PNs are 100% utilized later at β=40 as appeared in nodes 3, 6, and 9. Thus, the workload of the PNs remains steady after being fully utilized, while the datacentres' processing usage increases gradually to reach a maximum level at 60 chunks. For details of PNs and DCs processing resources utilization, see [9].

B. In this scenario, we reused the same inputs revealed in Table II except the volume of each chunk now is fixed at 110 Gb to further examine the impact of serving different volumes of big data chunks on green big data networks. We used this volume because the average volumes of the previous uniform distribution is around 110 Gb. This enables us to capture the distinct differences with scenario A in terms of network power consumption.

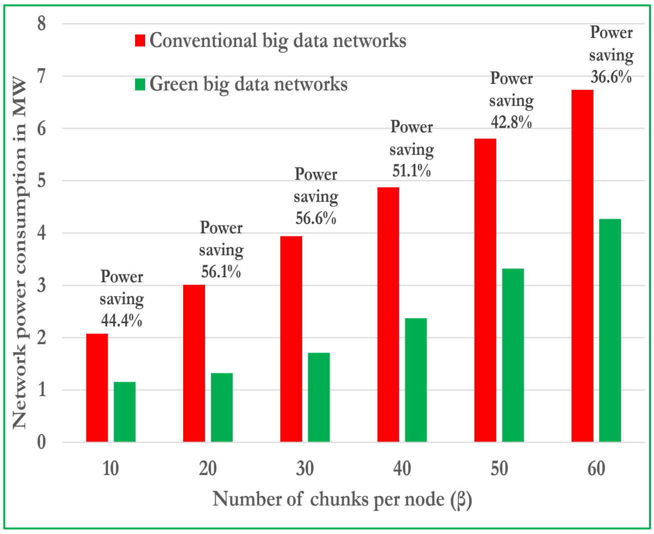

Figure 4: Conventional big data network power consumption and green big data network power consumption for scenario B.

Figure 4 generally shows similar behavior of Figure 3(a) since we obtain a maximum saving of 56.6% at the same stage (30 chunks). However, this saving is less by 7% compared to scenario A. This is because there are number of chunks with larger sizes in scenario A compared to fixed sizes of 110 Gb in scenario B, such as 200 Gb and 220 Gb; Our approach gives the priority to serve chunks with larger sizes as much as possible and forward smaller chunks (such as 10 Gb and 25 Gb) to the datacenters. For example, processing locally a chunk of 220 Gb will produce an info of 2.2 Gb which needs small portion of a single router port, while directly forwarding 220 Gb needs around six router ports. Thus, the number of reduced router port is nearly five ports. On the other hand, transferring a chunk of size 50 Gb before processing needs nearly one router port while its info (0.5 Gb) needs very little space of an active router port. In this case, the reduction of the needed router ports is close to one port only. Accordingly, handling locally and intermediately larger volumes (i.e., > 110 Gb) results in significant reduction in the number of active router ports required to transfer such volumes. For the same reason, the average power saving is decreased by 9% to reach 48% compared to the average power saving in scenario A.

C. To further evaluate the impact of big data volumes on green big data networks, we consider in this scenario a lower volume of 50 Gb per chunk, again we used all other data shown in Table II.

Data in Figure 5 illustrates that a maximum power saving of 41.9% is gained at the same point of previous scenarios where β=30 chunks. This saving is, however, 11% less compared to scenario B. This reduction is due to the larger volume ranges that available for scenario A compare to scenario C. Therefore, there are larger number of chunks with size > 50 Gb for scenario A compared to scenario C which is limited to fixed size of 50 Gb. The average power saving is 35.4% which is around 21% less compare to scenario A.

TABLE III VOLUME SCENARIOS SUMMARY

Scenario	Volume per chunks in Gb	Maximum network power saving	Average network power saving
A	10-220 (Uniform)	63.7%	57%
B	110	56.65%	48%
C	50	41.9%	35.4%

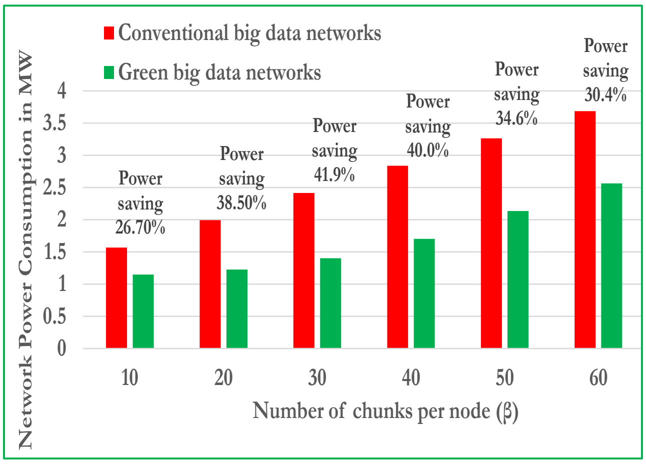

Figure 5: Conventional big data network power consumption and green big data networks power consumption for scenario C.

In all scenarios, changing big data volume patterns in the network has significant impact on network power saving while it has minor effects on optimizing DCs locations as the dominant selected locations are at nodes 3 and 14 in all scenarios due to their strategic locations among nodes. Table III summarizes the network power saving achieved in the three scenarios when applying different big data volumes in the network.

V. Conclusions

In this work, we studied the impact of big data volumes on greening big data networks in IP over WDM networks by describing a MILP model. We proposed to distribute the processing jobs of different volumes of big data chunks generated uniformly at a given node among different nodes connecting the source to the datacenters. Any node that is capable of storing and processing a chunk is called a Processing Node (PN). We also optimized two datacenters locations for processing the incoming PNs chunks and for hosting the results that come from the PNs. The network power consumption is mainly affected by the size of chunks. The results show that serving chunks with volumes of uniform distribution yields higher power saving compared to the power saving when the volumes of chunks is fixed. Consequently, an average network power saving of 57%, 48%, and 35% is gained when considering the volumes of 10-220 (uniform) Gb, 110 Gb, and 50 Gb per chunk, respectively, compared to the conventional approach where all these chunks are processed inside DCs only.

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