DYNAMIC TASK OFFLOADING ALGORITHM FOR OPTIMISING IoT NETWORK QUALITY OF SERVICE IN THE MOBILE-FOG-CLOUD SYSTEM

By

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Thesis Submitted to the School of Graduate Studies, Universiti Putra Malaysia, in Fulfilment of the Requirements for the Degree of Doctor of Philosophy

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Chairman : Associate Professor Rohaya binti Latip, PhD
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The application of the Internet of Things (IoT) is increasing to almost all aspects of human endevour. IoT aims at getting everything (wearable, smart cameras, home appliances, vehicles, and hospital equipment) connected to the Internet. These devices continuously generate a massive amount of data on the network. The IoT (mobile) devices that generate these data are limited in terms of processing capacity and energy, because of these limitations of the mobile devices, they cannot process all generated tasks in the IoT application environment. Cloud computing and Fog computing are introduced to assist mobile devices to respond to environmental demand. Most times, the approach of relying on cloud infrastructure for IoT application analysis may be inefficient in terms of the limited battery life of the mobile devices, resource allocation algorithm delay, and computational offloading processes that sometimes increases the response time. Furthermore, many IoT applications are time sensitive such as health monitory systems, augmented reality services, agriculture, pest control, online natural language processing, smart home applications, smart cities, safe driving, waste management, emergency response systems, and traffic control systems. Therefore, offloading a massive amount of data from mobile devices to the fog or cloud introduces another problem of delay in choosing the optimal resources for processing the tasks resulting in incurring delay by the resource allocation algorithms. This problem sometimes makes the application of IoT inefficient in sensitive cases that require low response time. However, the problem of offloading large data sizes for analysis at the remote processing layer (fog or cloud) and efficient scheduling of tasks and resources is addressed in this study. Therefore, an Energy-Efficient Canonical Polyadic Decomposition (EECPD) scheduling algorithm to minimize the mobile device energy consumption in the system is proposed. Secondly, a hybrid Genetic Algorithm and Enhanced Inertia Weight Particle Swarm Optimization (GAEIWPSO) algorithm for optimal resource allocation to minimize the delay is proposed. Finally, a Dynamic Task Offloading Algorithm (DTOA) based on rank accuracy estimation model to efficiently schedule tasks and resources in the Mobile-Fog-Cloud system is proposed. The proposed

algorithms achieved minimized data reduction ratio, number of deployed tasks, energy consumption, delay; and in addition, increased throughput, and better resource utilization, which in all enhanced the overall network quality of service. The attribute reduction technique is implemented with Matlab. The EECPD and GAEIWPSO algorithms are implemented with Python and Networkx simulators while DTOA algorithm is implemented with iFogSim to demonstrate the efficiency of the proposed scheme. The results proved that the proposed scheme performed better than the benchmark results.

Abstrak tesis yang dikemukakan kepada Senat Universiti Putra Malaysia sebagai memenuhi keperluan untuk ijazah Doktor Falsafah

ALGORITMA PEMUNGGAHAN TUGASAN DINAMIK UNTUK MENGOPTIMALKAN KUALITI PERKHIDMATAN RANGKAIAN IoT DALAM SISTEM PENGKOMPUTERAN KABUS MUDAH ALIH

Oleh

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Aplikasi Internet Benda (IoT) semakin meningkat kepada hampir semua aspek usaha manusia. IoT bertujuan untuk membolehkan segala-galanya (boleh pakai, kamera pintar, peralatan rumah, kenderaan dan peralatan hospital) disambungkan ke Internet. Peranti-peranti ini secara berterusan menjana sejumlah besar data pada rangkaian. Peranti IoT (mudah alih) yang menjana data ini terhad dari segi kapasiti pemprosesan dan tenaga, kerana batasan peranti mudah alih ini, mereka tidak dapat memproses semua tugas yang dijana dalam persekitaran aplikasi IoT. Pengkomputeran Awan dan pengkomputeran Kabus diperkenalkan untuk membantu peranti mudah alih bertindak balas terhadap permintaan persekitaran. Selalunya, pendekatan yang bergantung pada infrastruktur awan untuk analisis aplikasi IoT ini mungkin tidak cekap dari segi jangka hayat bateri yang terhad bagi peranti mudah alih, kelewatan algoritma peruntukan sumber, dan pengkomputeran proses pemunggahan yang kadangkala meningkatkan masa tindak balas. Tambahan pula, banyak aplikasi IoT adalah sensitif masa seperti sistem pemantauan kesihatan, perkhidmatan realiti tambahan, pertanian, kawalan perosak, pemprosesan bahasa semula jadi dalam talian, aplikasi rumah pintar, bandar pintar, pemanduan selamat, pengurusan sisa, sistem tindak balas kecemasan dan sistem kawalan trafik. Oleh itu, memunggah sejumlah besar data daripada peranti mudah alih ke kabus atau awan memperkenalkan satu lagi masalah kelewatan disebabkan pemilihan sumber-sumber yang optimal untuk memproses tugasan yang mengakibatkan kelewatan oleh algoritma peruntukan sumber. Masalah ini kadangkala menjadikan aplikasi IoT tidak cekap dalam kes sensitif yang memerlukan masa tindak balas yang rendah. Walau bagaimanapun, masalah memunggah saiz data yang besar untuk analisis pada lapisan pemprosesan jauh (kabus atau awan) dan penjadualan tugas dan sumber yang cekap ditangani dalam kajian ini. Oleh itu, algoritma penjadualan Penguraian Polyadic Canonical Cekap Tenaga (EECPD) untuk meminimumkan penggunaan tenaga peranti mudah alih dalam sistem dicadangkan. Kedua, Algoritma Genetik hibrid dan Pengoptimuman Partikel Berat Inersia Dipertingkat (GAEIWPSO) untuk peruntukan sumber yang optimum bagi meminimumkan kelewatan dicadangkan. Akhir sekali,

Algoritma Pemunggahan Tugas Dinamik (DTOA) berdasarkan model anggaran ketepatan kedudukan untuk menjadualkan tugas dan sumber dengan cekap dalam sistem pengkomputeran kabus mudah alih dicadangkan. Algoritma-algoritma yang dicadangkan mencapai penurunan nisbah pengurangan data, bilangan tugasan yang diatur, penggunaan tenaga, kelewatan; dan tambahan pula meningkatkan daya pemprosesan serta pengunaan sumber yang lebih baik. Teknik pengurangan atribut dilaksanakan dengan Matlab. Algoritma EECPD dan GAEIWPSO dilaksanakan dengan simulator Python dan Networkx manakala algoritma DTOA dilaksanakan dengan iFogSim untuk menunjukkan kecekapan skema yang dicadangkan. Keputusan membuktikan bahawa skema yang dicadangkan menunjukkan prestasi yang lebih baik daripada keputusan penanda aras.

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ALGORITHMS

LIST OF ABBREVIATIONS

CNN	Convolutional Neural Network
CPD	Canonical Polyadic Decomposition
DTOA	Dynamic Task offloading Algorithm
EECPD	Energy-efficient canonical Polyadic decomposition
GA	Genetic Algorithm
GAEIWPSO	Hybrid genetic algorithm and enhanced inertia weight particle swarm optimisation
NIST	National Institute of Standards and Technology
PSO	Particle Swarm Optimisation
RAEM	Rank accuracy estimation model
UPM	Universiti Putra Malaysia

CHAPTER 1

INTRODUCTION

1.1 Background of the Study

Cloud computing emerged in the field of distributed computing as the provision of on-demand computing services (Shen, Li, Yan, & Wu, 2010). There are so many definitions of cloud computing both in academia and industry, but the U.S. NIST (National Institute of Standards and Technology) definition seems more appropriate because it includes the most common key terms commonly used in the Cloud Computing environment. They defined cloud computing as a model for allowing suitable, access to a shared pool of on-demand network configurable computing devices or resources (such as servers, services, applications, and storage) that can be easily provisioned and released with reduced effort or service provider management interaction (Dillon, Wu, & Chang, 2010). Cloud services range from applications, storage, and networks, to services that are offered over the internet usually on a pay-as-you-use basis. Instead of owning computing infrastructure or data centers, companies may decide to rent access to applications, storage, or processing power from cloud providers. Cloud computing enables organizations to cut costs and the complexity of owning and maintaining their own computing infrastructure, and instead pay for what they use only when they use it. On the other hand, the cloud providers benefits from the significant economies of scale by offering their services to the users of their infrastructures and services. Because of these advancements in the area of distributed computing, the limited processing, storage and high cost of maintenance of IT infrastructures are minimized. These improvements gave rise to the use of IoT devices which are gaining entrance in all sphere of human endevour.

The term IoT covers several topics in the area of the application of sensors to monitor, measure, and communicate environmental information. The architecture always differs from problems to available resources and skills of the administrator. Because of the above reasons, it is always difficult to provide a single architecture to identify the IoT (Di Martino et al., 2018). The use of smart sensors and devices is becoming more common in everyday life. IoT has become a pervasive reality. Smartphones are the most common IoT device which every person carries around. Smartphones with all the sensors have to remain the major means of connection to the internet. There are other smart sensors in our environment used for different applications such as in the smart city, smart home, security, internet of vehicular networks, telemedicine, etc. (Nguyen, Thi, Binh, & Anh, 2019). IoT refers to the ability of smart devices to sense signals from the environment, collect data and sometimes analyze the data and share the data across the internet or local area network and also respond based on the information received from the processed data. One of the main features of IoT devices is sharing data. Sharing is the only way data can be resourcefully handled and used for various purposes. The following are different ways that IoT has been applied:

- wearable and phones are used for tracking movement; registering exercises, habits, and daily activities. Wearable devices can detect dangers if equipped with special sensors and can communicate such dangers to the wearer or other people elsewhere via the internet.

- self-parking cars use proximity sensors to detect nearby objects.
- the vehicle tracking system uses IoT devices with GPS devices or even smartphones to determine the position of the vehicle or to detect traffic congestion on the road.
- domestic gadgets use IoT to provide real smart home experiences like an intelligent bulb that can be turned on or off based on people's movements. Indoor temperature can be controlled based on environmental conditions etc.

However, IoT devices have different approaches to how they interact among themselves and with the outside world. The differences in the approaches are a result of the differences in their characteristics. There are different scenarios or paradigm which is made up of one or combinations of the following:

a. Mobile Computing
b. Mobile Edge Computing or Fog Computing
c. Cloud Computing

There are situations where two or three of the above basic paradigms are combined depending on the need of the network administrator. In all these architectures, if the data is not executed at the user device (mobile computing) then the data needs to be offloaded (moved) from the point of generation to the point of execution. Moving data/offloading involves an additional delay in getting the desired result.

In this research, the problems of mobile devices in mobile edge computing are considered. The study focused on how to optimize the device energy consumption, delay, and response time of the IoT devices by proposing task scheduling, resource allocation, and offloading algorithms respectively to solve the problems. Specifically, this study proposed a canonical Polyadic decomposition-based tasks scheduling algorithm for mobile device energy consumption, an enhanced hybrid meta-heuristics algorithm for minimizing delay, and computation offloading for reducing the response time, improving the network throughput, and resource utilization.

1.2 Motivation for the Study

There are so many IoT devices connected in the present-day cyber-physical environment (smart home, Telemedicine, self-driving cars, smart city, etc.). Within these IoT application environments, various devices are interconnected through advanced wireless technologies for different purposes such as security, communication, social media, surveillance, messaging, defense, health monitoring, etc. These deployments are usually associated with different deployment models including mobile computing, edge computing or fog computing, and cloud computing. All these deployments aim at improving the quality of service in the system in terms of energy consumption of the mobile devices, delay in receiving task request responses, network throughput, and resource utilization. The radical changes in society due to the increasingly pervasive use of information and communications technology in all sphere of human endeavour is raising research concerns. Such advancement is triggered by the introduction of the Internet of Things, in which smart sensing devices can be incorporated into the objects surrounding human daily activities. This increase in the application of mobile devices increases the network traffic, energy consumption of the mobile devices, delay in responding to device requests, and increases the mobile device usage of its processing ability. Internet connection extends IoT further than traditional smart devices like smartphones to a various range of devices and things such as sensors, machines, cars, etc. to accomplish many different applications and services such as healthcare, telemedicine, traffic control, energy management, vehicular networks, etc. The increasing demand for the analysis of the data generated by these IoT devices, manage the data, and store such data by the applications built on top of such sensory networks demands new architectures, such as mobile edge computing or fog computing, cloud computing, or a combination of these architectures, which are presently the hot topics in research (Di Martino et al., 2018). This internet connectivity of IoT devices generates a large volume of data that needs to be processed. These huge amounts of data need to be stored, processed, and analyzed to obtain valuable information needed by the user on time. Again, the number and complexity of applications and services are also growing speedily, which entails more scalable processing approaches.

The limitations of smart devices such as battery life, processing capability, storage, and network resources are the main challenges facing the application of IoT in so many areas, especially when it involves time-sensitive tasks such as health-related areas, traffic, and intrusion detection. These problems can be minimized by offloading time-consuming and resource-intensive tasks to a higher computing platform like Fog computing or Cloud computing while the less time-consuming and low-resource intensive tasks are handled at the smart devices.

The Cloud computing paradigm, which supports ubiquitous access to share and provides resources to users flexibly via virtualization, can be a good platform for IoT applications.

However, when combining IoT and Cloud computing, introduces a new problem, the transmission delay (Nguyen et al., 2019).

According to (John A. Stankovic, Tu Le, and Abdeltawab Hendawi, 2019) the number of IoT devices connected to the internet will increase to 75.4 billion by 2025. With this dramatic increase in the number of connected devices, the traditional centralized Cloud architecture processing characteristics whereby computing and storage resources are centralized at a remote location and placed in several data centers will not be able to service the requirements of IoT applications need. This is because of the distance and bandwidth issues between the Cloud and IoT devices. The data transmission between the IoT devices and the Cloud through the Internet will worsen traffic congestion. The transmission delay will affect the network quality of service (QoS), which will affect the main aim of IoT applications, especially for time-sensitive tasks. To address the transmission delay, cisco introduced Fog computing. The concept of Fog computing is to extend Cloud computing capabilities closer to IoT devices. The devices at the edge of the network such as routers, switches, gateways, smartphones, personal computers, etc. that have more processing capability, communication capability, and storage can be used as Fog devices. Fog computing transforms a network edge into a distributed computing infrastructure, which enables the implementation of IoT applications by the users. Fog computing architecture brings the cloud capabilities closer to the IoT devices thereby reducing the transmission and making the processing and storage faster. Fog devices can be deployed anywhere closer to the user and within the network connectivity such as power poles, vehicles, organization buildings, factory premises, and commercial centers.

With Fog computing, the resources are at the edge of the network closer to the user, the time it takes for data to reach a processing node is therefore reduced hence Fog computing optimizes task transmission time. However, the processing capability of a Fog Node is higher than the processing capability at the user devices but less than the processing capability at the cloud node. Therefore, it is not every task that can be handled at the Fog node. Fog nodes can handle small tasks or processing requests with a short delay while heavy tasks requiring high computational capability will be prioritized to be processed on cloud computing infrastructure. Therefore, Fog computing complements Cloud computing to form a new computing paradigm, Cloud–Fog computing.

Though Cloud–Fog computing architecture has several advantages, such as low response time, reduced network traffic, and more energy efficiency, however, this Cloud–Fog computing architecture also comes with its challenges. The problems of Cloud–Fog computing architecture are computational tasks scheduling, resource allocation, and offloading. Cloud–Fog computing architecture is a highly distributed system that needs efficient and scalable tasks scheduling, resource allocation, and offloading algorithms that can withstand the scalability nature of IoT applications in society today.

1.3 Problem Statement

There are so many mobile devices in the present environment that produce signals, which need to be processed to enable the system to take the necessary action required by the user. Mobile/IoT devices are always limited in power supply as they are powered by batteries. Inefficient task scheduling causes the network to increase the energy consumption of mobile devices. Most of the time, it cannot meet up with the time required to respond to task requests based on the incoming data (H. Li, Ota, & Dong, 2018).

Cloud computing was introduced to ameliorate the limitation of mobile devices. The distance between the mobile devices and the cloud infrastructure together with network bandwidth issues introduced another problem of delay in resources allocation. The fog was introduced to minimize the distance traveled in sending data from the mobile device to the point of processing. Though Fog computing is seen as the cloud closer to the user, it is not a substitute for the cloud. It only complements the cloud because its storage and processing capability cannot be compared to that of the cloud.

Another problem of fog computing is the problem of computation offloading which deals with deciding on which task to offload and where to process the task. The decision on whether to process the task at the mobile layer, fog/edge layer, or cloud layer is known as computation offloading (Gnana Jeevan & Maluk Mohamed, 2018), which is still another problem in this area. Computation offloading is a challenge in Fog computing. This challenge is because the sources of the tasks to be offloaded are many and they are to be offloaded to different processing devices. It is therefore an NP-hard problem (Braun et al., 2001; Madni, Latiff, Coulibaly, & Abdulhamid, 2016). These types of problems do not have one straight solution. To solve this type of problem, there are two approaches which are the heuristics approach and the meta-heuristic approach.

This research focused on the problem of mobile devices' tasks scheduling, resource allocation, and computation offloading to address high energy consumption, delay in selecting the processing device, and high response time in IoT applications. This research also aims at addressing the problem of offloading computational intensive tasks with large data presented in (Alli & Alam, 2019). Solutions are proposed to address the following specific problems at the mobile device in the mobile-fog-cloud computing architecture.

The specific problems addressed in this research are the problems of:-

i. high energy consumption by mobile devices during scheduling large input tasks generated from the environment. This problem is addressed through the data reduction ratio and the number of deployed tasks (H. Li et al., 2018).
ii. choosing the optimal resource by resource allocation algorithms which causes a delay in the IoT environment because the resources are dynamically changing and the resource allocation algorithms need to dynamically recalculate the available processing capacities to determine which resource to be selected for the task processing (Deng, Sun, Li, Luo, & Wan, 2021).
iii. high response time, low throughput, and uneven resource utilization issues resulting from offloading tasks with large data sizes by computation offloading algorithms (Alli & Alam, 2019).

1.4 Objectives of the Study

The aim is to optimize the IoT quality of service. To achieve this aim, an attribute reduction algorithm was proposed to minimize the data size of the scheduled tasks. Followed by a hybrid meta-heuristic algorithm in particular the hybrid genetic algorithm and enhanced inertia weight particle swarm optimization for resource allocation. The optimal device selection algorithm enhanced resource allocation to reduce the overall transmission delay in IoT task processing. Finally, the computation offloading algorithm was proposed to optimize the overall network quality of service in Mobile-Fog-Cloud computing architecture.

The following are the specific objectives of the study:

i. to propose an Energy-Efficient Canonical Polyadic Decomposition (EECPD) algorithm to addresses the problem of tasks scheduling in Mobile-Cloud system which leads to mobile devices' high energy consumption by reducing the input data size at the user device.
ii. to develop a hybrid Genetic Algorithm and Enhanced Inertia Weight Particle Swarm Optimization (GAEIWPSO) algorithm to addresses the transmission delay problem of resource allocation in choosing the optimal device, which prolongs the device usage and increases energy consumption of the device.
iii. to propose a Dynamic Task Offloading Algorithm (DTOA) based on a Rank Accuracy Estimation Model (RAEM) for solving the offloading problems in Mobile-Fog-Cloud system which result to high response time, low throughput, and uneven resource utilization of the existing offloading algorithms.

1.5 Research Scope

The focus of this research is on the task scheduling algorithm, resource allocation algorithm, and computational offloading algorithm used for task processing in Mobile Edge Computing (MEC) and Mobile Cloud Computing (MCC) architecture. The task scheduling algorithm used image data sets for determining the data reduction ratio. The scheduling algorithm is limited to determining the number of deployed tasks on the mobile layer of the MEC environment.

The second algorithm focused on resource allocation. The algorithm focused on a Metaheuristic approach to reduce delay and energy consumption of the mobile layer in a mobile edge computing environment. The last algorithm is the offloading algorithm which focused on reducing response time in MCC that involves 10 mobile devices, five fog devices, and one hybrid cloud.

1.6 Organization of the Thesis

This thesis is on the topic "Computational offloading based on attributes reduction approach for optimization of IoT network quality of service (QoS) in the mobile-fog-cloud system". This work contributed to mobile edge computing task scheduling algorithms, resource allocation algorithms, and computation offloading algorithms. The remainder of this thesis is organized as follows-

Chapter 2 is dedicated to the literature review on cloud computing, fog computing, and mobile computing. The reviews of related work in task scheduling, resource allocation, and computation offloading are also presented, which is the scope of this study. The problems of these areas are presented. The existing solutions in this field are illustrated, discussed, and their drawbacks are highlighted.

Chapter 3 presented the system's model and methodology used for research.

Chapter 4 presented the proposed Energy-Efficient Canonical Polyadic decomposition (EECPD) based task scheduling algorithm, the experimental setup, and the evaluation of the results.

Chapter 5 presented the proposed hybrid Genetic Algorithm and Enhanced Inertia Weight Particle Swarm Optimization (GAEIWPSO) algorithm by discussing the proposed algorithm, experimental setup, and evaluation of results.

Chapter 6 discussed the Dynamic Tasks Offloading Algorithm (DTOA) based on the Rank Accuracy Estimation Model (RAEM), the experimental setup, and the evaluation of the result.

Chapter 7 concluded the study, its research contributions, and recommendations for future works.

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