CLOUDLET DEPLOYMENT AND TASK OFFLOADING IN MOBILE EDGE COMPUTING USING VARIABLE-LENGTH WHALE AND DIFFERENTIAL EVOLUTION OPTIMIZATION AND ANALYTICAL HIERARCHICAL PROCESS FOR DECISION-MAKING

By

DABA LAYTH MUWAFAQ ABDULHUSSEIN

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

September 2023

DEDICATIONS

This thesis is dedicated to my beloved Father and Mother, whose unwavering love, guidance, and sacrifices have shaped me into who I am today. To my supportive Wife and Children, your steadfast belief in me and constant encouragement have been my driving force. To my dear brothers and sisters, your support and friendship have been a continuous source of strength throughout this work. Last, I dedicate this achievement to my beloved first and second countries, Iraq and Malaysia.

Abstract of thesis presented to the Senate of Universiti Putra Malaysia in fulfilment of the requirement for the degree of Doctor of Philosophy

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September 2023

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Mobile edge computing (MEC) is a well-known technique to support delay-sensitive applications at the edge of mobile networks. MEC has shown its potential in real-world computation but is still not fully mature. MEC's main feature is pushing computing resources to the network edges. In MEC environment, cloudlets that represent a relatively powerful computing resource can be collocated with the base station to enable good coverage of computing service due to the high demand and random distribution of users. The problem of **C**loudlet **D**eployment and **T**ask **O**ffloading (**CDTO**) involves deploying a set of cloudlets in an environment and assigning user tasks to optimize various metrics, including energy consumption, quality of service (QoS) and cost. Typically, approaches deal with them separately, which might cause sub-optimality. Furthermore, assuming the fixed location of the cloudlets will limit the dynamic adaptability of the problem. Enabling more optimality and adaptability to the dynamic nature of CDTO, we propose a novel **V**ariable-**L**ength multi-objective **W**hale optimization **I**ntegrated with **D**ifferential **E**volution designated as **VL-WIDE** for joint cloudlet deployment and tasks offloading. Unlike the existing optimization algorithm, VL-WIDE features the capability of searching different lengths of solutions to cover the variable number of cloudlets for deployment. It provides an application-oriented solutions repair operator for repairing non-valid solutions and assuring that all solutions are generated in the feasible region. Furthermore, it enables non-dominated evaluation of solutions based on four objectives using crowding distance for selection. The proposed algorithm with its variable length solution encoding enables moving the cloudlets among pre-defined locations, adding or removing them in order to increase the quality of service according to the change in the user density caused by user mobility. VL-WIDE was also integrated with the solution selection model based on the Analytical Hierarchical Process (AHP) that considers decision-maker preference for the optimized objectives. Comparing this developed algorithm with other algorithms shows its superiority in multi-objective optimization (MOO) evaluation metrics. VL-WIDE has accomplished a higher median value for the domination over state-of-the-art algorithms with a higher number of non-dominated solutions value than all other benchmarks. Three hundred scenarios involving various parameters related to base stations, cloudlets, users, and wireless communications were generated. Additionally, a simulator is used to evaluate the proposed methodology under different deployment scenarios and network conditions. The simulator provides a realistic environment to test the system, and the results are compared with the benchmarks. The improvement percentage in terms of hyper-volume, delta-metric, and the number of non-dominated solutions are (8%), (5%), and (6%), respectively, over the baseline approach. Furthermore, the AHP VL-WIDE solutions were more fulfilling to the desire of the decision-maker compared with other algorithms.

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

PENEMPATAN CLOUDLET DAN PELUCUTAN TUGAS DALAM PENGKOMPUTERAN TEPI MUDAH ALIH MENGGUNAKAN TEKNIK PEMBOLEHUBAH-PELBAGAI 'WHALE' DAN PENGOPTIMUMAN EVOLUSI BERBEZA SERTA PROSES HIRARKI ANALITIK UNTUK PEMBUATAN KEPUTUSAN

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Pengkomputeran tepi mudah alih (MEC) merupakan satu teknik yang terkenal untuk menyokong aplikasi peka-kelewatan pada pengkomputeran tepi mudah alih. MEC telah menunjukkan potensinya dalam pengkomputeran dunia nyata tetapi masih belum sepenuhnya matang. Ciri utama MEC adalah mendorong sumber pengkomputeran ke pinggiran rangkaian. Dalam persekitaran MEC, 'cloudlets' yang mewakili sumber pengkomputeran yang cukup kuat boleh diletakkan bersama stesen pangkalan untuk membolehkan liputan perkhidmatan pengkomputeran yang baik disebabkan permintaan yang tinggi dan taburan rawak pengguna. Masalah Penempatan dan Pelucutan Tugas Cloudlet (CDTO) melibatkan penempatan set 'cloudlets' dalam suatu persekitaran dan menugaskan tugas pengguna untuk mengoptimumkan pelbagai metrik, termasuk penggunaan tenaga, kualiti perkhidmatan (QoS), dan kos. Secara umumnya, pendekatan mengendalikan mereka secara berasingan, yang mungkin menyebabkan sub-optimaliti. Selain itu, menganggap lokasi tetap 'cloudlets' akan membataskan adaptabiliti dinamik masalah ini. Untuk membolehkan lebih optimal dan kebolehan ubai suai kepada sifat dinamik ‘CDTO’, kami mencadangkan satu kaedah terbaru Optimum Berbagai-Objektif Panjang-Berubah ikan paus yang Digabungkan dengan Evolusi Beza yang dikenali sebagai ‘VL-WIDE’ untuk penempatan bersama 'cloudlets' dan pelucutan tugas. Berbeza dengan algoritma optimal yang sedia ada, ‘VL-WIDE’ mempunyai keupayaan mencari peluang penyelesaian yang berbeza untuk merangkumi jumlah 'cloudlets' yang berubah-ubah untuk penempatan. Ia menyediakan operator pembaikan penyelesaian berorientasikan aplikasi untuk membaiki penyelesaian yang tidak sah dan memastikan bahawa semua penyelesaian dihasilkan dalam kawasan yang boleh dilaksanakan. Selain itu, ia membolehkan penilaian yang tidak dikuasai oleh penyelesaian berdasarkan empat objektif menggunakan jarak keramaian untuk pemilihan. Algoritma yang dicadangkan dengan kod penyelesaian panjang yang berubah membolehkan pemindahan 'cloudlets' di antara lokasi yang telah ditentukan, menambah atau mengurangkan untuk meningkatkan kualiti perkhidmatan mengikut perubahan dalam ketumpatan pengguna yang disebabkan

oleh mobiliti pengguna. VL-WIDE juga telah digabungkan dengan model pemilihan penyelesaian berdasarkan Proses Hirarki Analitik (AHP) yang mengambil kira keutamaan pembuat keputusan untuk objektif yang dioptimalkan. Membandingkan algoritma yang dibangunkan ini dengan algoritma lain menunjukkan keunggulannya dalam metrik penilaian optimasi objektif berganda (MOO). VL-WIDE telah mencapai nilai median yang lebih tinggi untuk dominasi berbanding dengan algoritma terkini dengan jumlah nilai penyelesaian yang tidak dikuasai yang lebih tinggi daripada semua penanda ukur lain. Tiga ratus senario yang melibatkan pelbagai pemboleh ubah berkaitan dengan stesen pangkalan, 'cloudlets', pengguna, dan komunikasi tanpa wayar telah dihasilkan. Selain itu, satu simulasi digunakan untuk menilai metodologi yang dicadangkan dalam pelbagai senario penempatan dan keadaan rangkaian yang berbeza. Simulator ini menyediakan persekitaran realistik untuk menguji sistem, dan hasilnya dibandingkan dengan penanda ukur. Peratusan peningkatan dari segi isipadu-tinggi, metrik delta, dan bilangan penyelesaian yang tidak dikuasai adalah (8%), (5%), dan (6%) masing-masing, berbanding dengan pendekatan asas. Selain itu, penyelesaian ‘AHP VL-WIDE’ lebih memuaskan kehendak pembuat keputusan berbanding dengan algoritma lain.

ACKNOWLEDGEMENTS

In the Name of Allah, my utmost thanks and gratitude must first be offered to Almighty Allah for all blessings and for granting me good health throughout this research.

I would like to thank my supervisor Prof. Dr. Nor Kamariah Noordin, for her encouragement and support in all stages of the research work, for providing assistance, and for giving me experiences. Thank you for opening my mind to a new world of knowledge, opportunities, and experiences and giving me a better understanding.

And I would like to thank my supervisory committee, Prof. Dr. Mohamed Othman, Prof. Dr. Alyani Ismail and Assoc. Prof. Dr. Fazirulhisyam Hashim, for their encouragement, support, and constructive feedback.

Also, I would like to thank all of the UPM staff for their wonderful work in organizing student affairs.

Without your unwavering support and encouragement, my success would not have been possible to do this work.

This thesis was submitted to the Senate of Universiti Putra Malaysia and has been accepted as fulfilment of the requirement for the degree of Doctor of Philosophy. The members of the Supervisory Committee were as follows:

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LIST OF SYMBOLS

$\mathrm{e}_{\mathrm{i}}^{\mathrm{t}}$	The required energy for transmitting a task of u_i to its related BS
$E_{i,c}$	The expected energy consumption for executing the task at c_j
$E_{i,d}$	The expected energy consumption for executing task on u_i
$E_{i,u}$	The expected energy consumption by u_i
E_{it}	Energy consumption for transmitting the task from u_i to c_j
N_{BS}	Total number of base stations
N_C	Number of deployed cloudlets
bs_k	base station k
c_j	Cloudlet j
e_i^c	Energy consumption for executing tasks generated from u_i at c_j
e_i^u	Energy consumption for executing tasks generated from u_i at his device
p_i	Transmission power of u_i
r_i^u	Transmission rate of u_i
u_i	User i
u_t	Step of random walk at moment t
x_t	The x position of the user at moment t
y_{a_i}	The actual resulted value from executing the solution
y_t	The y position of the user at moment t
$z_{i,j}$	Probability of assigning the task generated from u_i to c_j
α_i	The input data size of the task of u_i
β_i	Exponential resource demand of tasks generated from u_i
λ_i	Average task arriving rate generated from u_i

ξ^c	Effective switching capacitance of the CPU of c_j
ξ_i	Effective switching capacitance of the CPU of u_i
σ^2	The variance of the user mobility random walk model
τ_i^c	Average waiting time composing of the queue waiting time and the execution time at c_j
φ^c	Computing capacity (CPU cycles/second) of each cloudlet
φ_i^u	Computing capacity of u_i
BS	Number of base stations
C	Number of cloudlets
L	The maximum number of currently operating cloudlets $L \leq N_C$
N	The number of data points corresponding the experiment
S	Performance score
TS	Total score
U	Number of users
m	Alternative
w	Weight
y	The desired value by the decision maker
μ	Maximum workload (CPU cycles/second) of each cloudlet

LIST OF ABBREVIATIONS

AHP	Analytical Hierarchical Process
BSs	Base Stations
CDTO	Cloudlet Deployment and Task Offloading
DE	Differential Evolution
MCDM	Multi-Criteria Decision Making
MEC	Mobile Edge Computing
MECE	Mobile Edge Computing Environment
MGW	Modified Guided-population-archive Whale-optimizer-based cloudlet deployment and task offloading
MOEAD	Multi-Objective Evolutionary Algorithm based on Decomposition
MOO	Multi-Objective Optimization
NRIM	Normalized Relative Importance Matrix
NSGA-II	Non-dominated Sorting Genetic Algorithm-II
NSGA-III	Non-dominated Sorting Genetic Algorithm-III
PSO	Particle Swarm Optimization
RIM	Relative Importance Matrix
RMSE	Root Mean Square Error
VL-WIDE	**V**ariable-**L**ength multi-objective **W**hale optimization **I**ntegrated with **D**ifferential **E**volution
WMANs	Wireless Metropolitan Area Networks
WOA	Whale Optimization Algorithm

CHAPTER 1

INTRODUCTION

1.1 Overview

Mobile edge computing (MEC) is a well-known technique to support delay-sensitive applications at the edge of mobile networks. In recent years MEC has received significant attention from the academic and industrial communities [1]. MEC alleviate the shortcomings of traditional cloud computing by minimizing the delay of computation services and saving energy for mobile devices. One of MEC's critical challenges is selecting an efficient placement of the cloudlet [2] and task offloading decision [3].

In the Mobile Edge Computing Environment (MECE), cloudlets can be collocated with the base station in the wireless metropolitan area network (WMAN) [4]. The latter is a wide area network consisting of many base stations (BSs) that allow mobile devices to access their needed services. On the one hand, the deployment of the base station is not a random process; rather, it is based on conducting certain optimization for selecting the best location for the base station to accomplish the maximum coverage [5]. On the other hand, deploying cloudlets at a certain base station should also result from an optimization algorithm aiming to maximize or minimize several factors. Hence, researchers have considered the problem of cloudlet deployment as one of the sub-problems of MEC [6]. However, a minority of studies have considered mobile cloudlets in order to enable dynamic deployment by moving cloudlets based on the temporal condition of MEC [7].

Cloudlet is a new computing paradigm introduced to the Mobile Edge Computing (MEC) service framework. It allows computing resources to be closer to mobile devices [8]. Cloudlets can be placed close to the end device to reduce communication delays of mobile devices. The cloudlets location is essential to the delay tolerance of mobile devices, primarily in a large-scale Wireless Metropolitan Area Network (WMAN) that consists of hundred Base Stations (BSs) [9], where mobile devices can access the cloudlets. The capacity of cloudlet is much smaller than cloud computing as edge computing is supplied with one or a few servers due to the limitation of space and cooling requirements [10]. Cloudlets can contain one or more servers collocated with the BSs.

Offloading is a technique used in the MEC environment to increase the effectiveness of mobile device applications by moving resource-intensive activities to nearby cloudlets [7]. Offloading in MEC mostly refers to running resource-intensive applications on behalf of local mobile devices to minimize workloads, overhead, and processing costs compared to local computing. To perform compute offloading, mobile devices and cloudlets must operate offloading frameworks [11].

In the MEC context, computation offloading problems are a very difficult challenge [12]. The primary drawback of offloading work to a remote cloud is the latency, which disrupts user experiences in interactive applications like mobile gaming [13]. Cloudlets get around this problem by giving users low-latency access to network-edge computing resources, which significantly boosts the efficiency of mobile applications [14]. The primary issue with WMAN is the deployment of fewer cloudlets with good services to end user. From the perspective of network management, it is costly to place a cloudlet at each BS to service end users [20], [16].

In the real-world problems, optimization often involves minimizing or maximizing the objective functions. The optimization algorithm provides systematic and efficient methods for producing and comparing new solutions to achieve the optimal solution [17]. Optimizing one aspect of a certain system is irregular in real-world applications due to more than one user satisfaction perspective [18]. This has led researchers to develop the concept of Pareto-optimization, which assesses a certain decision regarding the system using a set of satisfaction metrics, e.g., delay, cost, energy and quality of service. Consequently, instead of dealing with one optimal solution, we consider a set of non-dominated solutions that are provided to the decision maker or to an automated process for selecting one of them to be enabled according to certain criteria [19]. Some famous algorithms for multi-objective optimization are the non-dominated sorting genetic algorithm (NSGA-II) [20], NSGA-III [21], and multi-objective evolutionary algorithm (MOEA) [22].

Multi-objective optimization techniques are an excellent approach in this situation. In multi-objective optimization, as opposed to single-objective optimization, the search is for a collection of non-dominated solutions known as the Pareto optimal set rather than a single optimal solution, which must be optimized [23]. The non-dominated objective solutions are the ones that provide the best potential compromises between the many objectives of the problem (i.e., these solutions cannot enhance one objective without affecting another). The decision-makers, in this case, the service providers, are given access to such non-dominated solutions so that they may choose the one that caters to their specific demands and requirements in the most effective manner [24]. The computational methods that are currently available to solve multi-objective optimization problems include meta-heuristics and high-level strategies governing underlying techniques. These computational methods are the most effective for searching for optimal or near-optimal solutions to a specific optimization problem [25].

Traditional meta-heuristic optimization algorithms consider a fixed length of solution space, but this does not apply to many real-world problems. The reason is that certain values of some decision variables might generate or disable other decision variables, which causes the variable-length nature of solution space caused by different lengths of solutions [25]. Dealing with such types of problems requires a special type of operators that are aware of the length variability of the solution space and capable of covering all dimensions of solutions while searching. Variable-length algorithms are better since their solution vectors can vary in length [25].

The outcome of multi-objective optimization is a set of non-dominated solutions designated as the Pareto front. It contains a set of non-dominated solutions, all of which are considered to be optimal [24]. However, the process has to select one of them to be operated in the system at one time. Accordingly, selecting one solution requires prior knowledge about the preference of the decision-makers [26]. The decision maker will provide the system with preference relative weighting of the objectives. Hence, using this information is required to be combined with the outcome of the optimization to select one solution to operate in the system.

In the Mobile Edge Computing (MEC) environment, it is essential to consider various scenarios and parameters related to base stations, cloudlets, users, and wireless communications [27]. These scenarios help assess how well the algorithms perform under different conditions and deployments. In order to evaluate the proposed methodology effectively, a simulator should be employed. This simulator should be designed to replicate real-world conditions and network environments [28]. It should be capable of testing the system's performance in comparison of the proposed algorithm with the benchmark algorithms, such as MGW [29], NSGA-II, NSGA-III, MOEAD, and PSO [30]. One important aspect to consider is the use of a variable-length approach for deploying cloudlets. This means that the number of the deployed cloudlets can vary based on the computing requirements of the mobile users in the MEC environment. This adaptability ensures that the system can efficiently allocate resources where they are needed most which optimizing performance and resource utilization.

1.2 Problem Statement

The problem of cloudlet computing optimization involves deploying set of servers named cloudlets in a geographical region and managing user computing requests by offloading them through base-station and assigning them to cloudlets for execution. The result is evaluated based on different factors such as execution time, energy consumption for both user and cloudlet, and cost. This problem is considered as non-convex optimization problem with dynamic nature. Two factors are considered as significantly important in cloudlet computing optimization. The first one is the deployment of cloudlet which is when deployed in a static way, it will limit the performance from the perspective of dynamic handling. In other words, the nature of computing demands is that they are subject to dynamical changes in their source and volume which might be in-efficient to keep the cloudlet deployed in the same location. The second one is the heterogeneity and composite nature of tasks which might require off-loading one task on more than one cloudlet for load balancing between cloudlets.

Unfortunately, based on literatures (see Table 2.3 and Table 2.4), none-of the existing approaches have jointly and dynamically addressed the cloudlet deployment and task offloading. More specifically, the joint of cloudlet deployment and task-offloading has been addressed by only a few previous works, such as [2], [31] and [29]. However, they have not considered cloudlet mobility, only [7] considered cloudlet mobility but used a fixed number of cloudlets. Furthermore, enabling joint optimization of cloudlet deployment, deactivation and activation by moving, task offloading, and inter-cloudlet flow is an optimization problem with the variable number of decision variables. Hence, this optimization is regarded as a special class of optimization algorithm that needs careful study. Furthermore, it becomes more complex when considering its multi-objective nature due to various performance criteria, including energy consumption, cost and latency with a self-conflict nature.

Tackling the variable number of cloudlets and the multi-objective nature of problem, it is found that the optimization algorithm should support it. However, majority of the previous algorithms (see Table 2.5) were developed to support a single objective except for the work of [32], which suffers from weak interclass interaction between the solutions and the work of [33] that is based on an evolutionary algorithm and was applied only on a bi-objective real-world problem. Hence, the literature lacks a multi-objective swarm-based algorithm with variable-length feature. We fill this research gap by developing a novel variable-length whale optimization algorithm with supportability of multi-objective aspects.

The last aspect of the problem is selecting one from the set of solutions generated from the optimization. Typically, a multi-objective optimization algorithm provides a set of non-dominated solutions named Pareto front. Ultimately, one of the provided solutions must be operated or enabled. The selection of one of the Pareto solutions is another problem that has been tackled in the literature by using Multi-Criteria Decision Making (MCDM) models. It is found that Simple additive weighting SAW is the most used one as it is shown in Table 2.6. However, SAW assumes the availability of an absolute description of the weights of the objectives, which is not feasible. The decision maker can generally provide a relative importance matrix between the criteria or objectives. In order to handle this, the solution selection should be based on the representation of relative importance between the objectives.

1.3 Research Questions

The following questions are forwarded in this research to optimize cloudlet computing in the MEC environment:

1. How to optimize cloudlet computing in the MEC environment?
2. What new approach is needed to provide new solutions for best optimization with enabling adequate degree of freedom by changing the number of cloudlets and satisfying multi-aspects of performance?
3. How to select one solution out of the set of non-dominated solutions in order to fulfill the decision maker preference?

1.4 Research Objectives

The ultimate goal of this research is accomplished cloudlet computing optimization. This goal is accomplished by the following objectives:

1. To design a novel framework for Cloudlet Deployment and Task Offloading in the MEC environment. The framework supports dynamic environment and multi-criteria decision-making.

2. To solve the optimization given in the framework based on variable-length multi-objective optimization algorithm that support changing in the number of deployed Cloudlets based on computing requirements in the environment.

3. To provide the possibility of selecting the appropriate solution from the set of non-dominated solutions using multi-criteria decision-making method based on the decision-maker's preferences.

1.5 Research Motivation

The demand for computing resources at the network edge is growing annually. Previous studies have underscored the significance of computing requirements at the edge of the network. As depicted in Figure 1.1, almost all service providers in the Heavy Reading survey [34] either have worked or are working on a distributed cloud strategy at the edge. The number of mobile devices at the network edge is constantly increasing, with billions of such devices now in use. These devices generate massive amounts of data that require processing. Furthermore, modern applications have high processing demands. Mobile devices can save time and reduce energy by offloading their tasks to nearby cloudlets for processing, which is more efficient than processing on the device itself or sending the data to a remote Cloud. Consequently, optimizing Cloudlet computing in the MEC environment has become increasingly important, and has attracted the attention of many researchers in recent years.

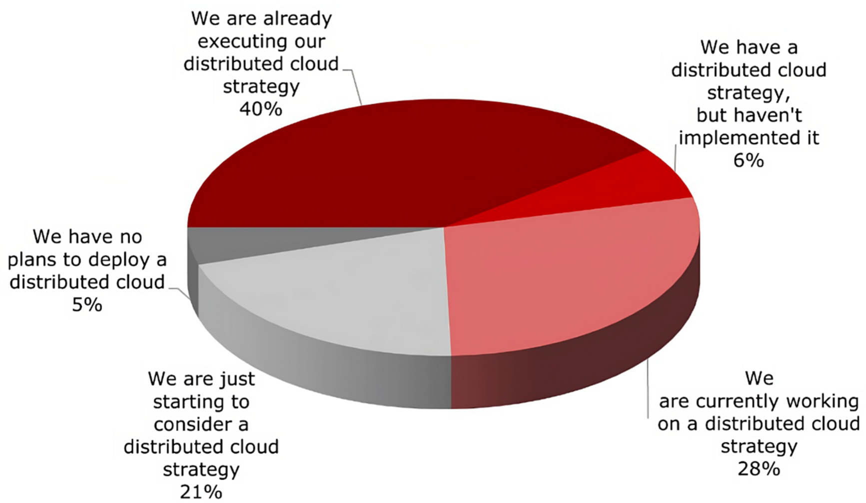

Figure 1.1: Status of Distributed Cloud Strategy (Infrastructure at the Edge). [34]

1.6 Research Contributions

This research offers the following contributions:

1. This research enables to solving the problem of cloudlet-based computing with an additional degree of freedom that enables not only deploying the cloudlets in optimal locations but also moving them according to the geographical demands information and integrating this with task offloading between more than one cloudlet for better load balancing.

2. It presents a novel formulation of the optimization problem of cloudlet-based computing using the variable-length of solution space. This enables reserving a compact representation of the decisions regarding the variables needed for locating the cloudlets and offloading the tasks from the user to the cloudlets.

3. It provides an application-oriented solution repairing operator for fixing non-valid solutions and assuring that all solutions are generated in the feasible region.

4. It incorporates variable-length searching within a hybrid framework combined with multi-objective whale optimization and differential evolution. Hence, it provides the literature with the first variable-length searching of multi-objective hybrid whale-differential evolution optimization.

5. It provides one solution selection from the multi-objective optimization algorithm using MCDM approach that relies on the relative importance between the objectives, i.e., AHP. This is distinguished from the existing approaches in the literature that ignores this information in the solution selection. Furthermore, this enables the online operation of the algorithm without the need for human-based decision-making, which supports real-time operation.

In Figure 1.2, we present a block diagram that illustrates the interplay between the problem statement, the objectives, and our research contributions. The diagram provides a visual representation of how these parts are interconnected.

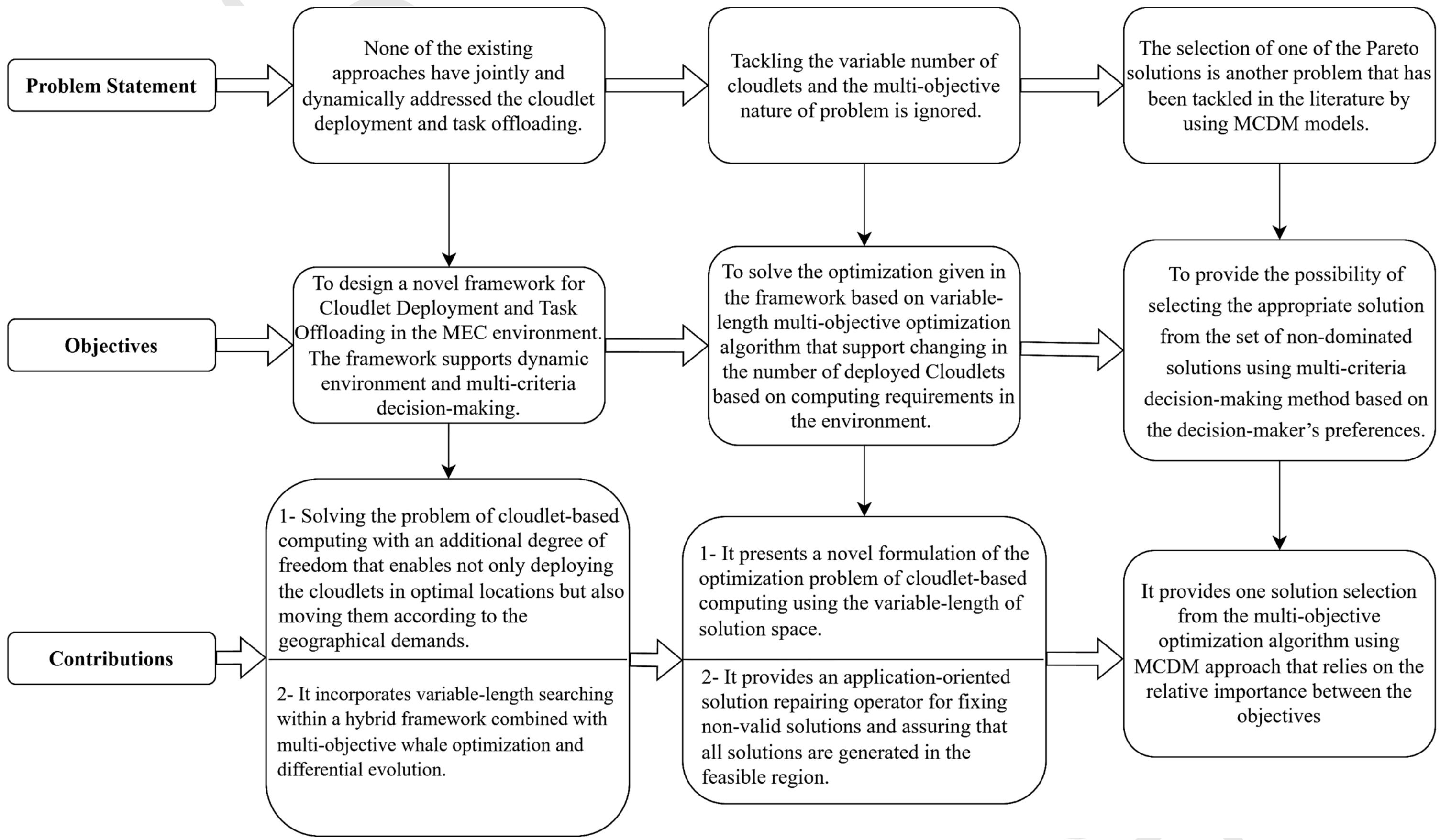

Figure 1.2: Block diagram of interconnected between problem statement, objectives and research contributions

1.7 Scope of the Research

This research is scoped down to optimize cloudlet computing in the MEC environment. It determines the maximum number of cloudlets to be inserted given budget range. Furthermore, determine which base station to link the inserted cloudlet, subset of BS is selected to deploy mobile cloudlet, and each cloudlet is allowed to move for N_m times within one day where, $N_m \geq 0$. The cloudlet associate users given task nature and user mobility. The users are walking in the environment in the random walk model. Each inserted cloudlet is connected to each other via the network connection. The task flow depends on the state of the cloudlets, and the user applications are dynamically partitioned into discrete off-loadable tasks that can be processed at any of the cloudlets where the user will offload tasks to a nearby base station with a cloudlet, and the cloudlet can either choose to add the task to its own queue (if the cloudlet is under loaded) or to redirect it to another cloudlet (if the cloudlet is overloaded) in the network.

Another scope of this research is to enable satisfaction of decision maker preference by proposing method for selecting solution from the Pareto front based on the desire relative importance of all performance aspects by decision maker.

1.8 Thesis Organization

The rest of this thesis is structured as follows. Chapter 2 provides an overview of cloudlet deployment and task offloading in the MEC environment. It also discusses the algorithms and techniques used to address different objectives, such as cost, energy, and latency. Chapter 3 describes the research methodology, including the framework, formulation, algorithm and technique used to address the objectives. Chapter 4 provides the obtained results, their analysis, and related discussions. Chapter 5 provides a conclusion to the research and offers suggestions for possible future research directions.

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