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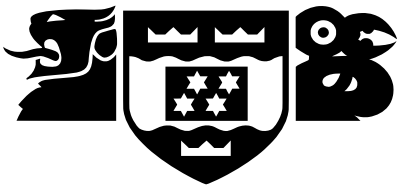

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Multi-objective PSO for service location-allocation

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Submitted in partial fulfilment of the requirements for
Master of Computer Science.

Abstract

In recent years, web services technology is becoming increasingly popular because of the convenience, low cost and capacity to be composed into high-level business processes. The service location-allocation problem for a web service provider is critical and urgent, because some factors such as network latency can make serious effect on the quality of service (QoS). This paper presents a multi-objective optimization algorithm based on multi-objective PSO to solve the service location-allocation problem. A stimulated experiment is conducted using the WS-DREAM dataset. The results are compared with a multi-objective genetic algorithm (NSGA-II). It shows multi-objective PSO based algorithm can provide a set of best solutions that outperforms NSGA-II.

Contents

Chapter 1

Introduction

Modern enterprises need to respond effectively and quickly to opportunities in today's competitive and global markets. To accommodate business agility, companies are supposed to utilise existing business processes while exposing the various packaged applications found spread throughout the enterprise in a highly standardized manner. A contemporary approach for addressing these critical issues is embodied by (Web) services that can be easily assembled to form a collection of autonomous and loosely coupled business processes [23].

The emergence of Web services developments and standards in support of automated business integration has driven major technological advances in the integration software space, most notably, the service oriented archiecture (SOA) [5]. In an SOA, software resources are packaged as web services, which are well defined, self-contained modules that provide standard business functionality and are independent of the state or context of other services [24].

A Web service is a software system allowing to expose services via Internet. The SOA promotes the composition of coarse-grained web services to build more complex web applications using standards such as WS-BPEL [22]. Because of the convenience, low cost [1] and capacity to be composed into high-level business processes, web service technology is becoming increasing popular.

Web services were hosted in heterogeneous server clusters or co-location centers that were widely distributed across different network providers and geographic regions. In recent years, web services are increasingly being deployed in infrastructure-as-a-service (IaaS) clouds such as Amazon EC2, Windows Azure, and Rackspace, According to [9], 4% of Alexa's top 1 million use EC2/Azure and 96% web services were hosted in other platforms.

With the ever increasing number of functional similar web services being available on the Internet, the web service providers (WSPs) are trying to improve the quality of service (QoS) to become competitive in the market. QoS, also known as non-functional requirements to web services, is the degree to which a service meets specified requirements or user needs [31], such as response time, security and availability. Among numerous QoS measurements, service response time is a critical factor for many real-time services, e.g. traffic service or finance service. Service response time has two components: transmission time (variable with message size) and network latency [14].

Study [13] shows that network latency is a significant component of service response delay. Ignoring network latency will underestimate response time by more than 80 percent [26], since network latency is related to network topology as well as physical distance [11]. To reduce the network latency, WSPs need to allocate web services to a user concentrated area so that the overall network latency is minimized.

According to [9], 96% of Alexa's top 1 million web services were hosted in heterogeneous server clusters or co-location centers that were widely distributed across different network

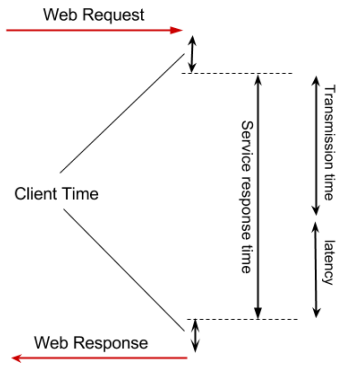

Figure 1.1: Service response time

providers and geographic regions. Hence, it is not only necessary but urgent to provide an effective web services allocation guide to WSPs so that they can be benefited.

Ideally, WSPs could deploy their services to each user center in order to provide the best quality. However, the more services deployed, the better the quality and the higher cost.

The main goal of Web service location-allocation is providing a web service allocation plan to WSPs so that it minimizes the cost as well as remains high quality of services.

1.1 Original Plan

We set up two objectives in original plan. Firstly, developed a model for location-alloation problem so that it can be tackled by evolutionary multi-objective optimization (EMO). Secondly, developed a multi-objective particle swarm optimization based algorithm to solve this probelm.

1.2 What has been learned

In the first trimester, we modelled the service location-allocation into a matrix-representation model so that it can be solved by EMO algorithms. Based on this model, we further developed a multi-objective particle swarm optimization based algorithm to solve this problem. We conducted a series of experiement that runs on different parameter settings and test cases. The experimental results were compared with a NSGA-II-based approach.

During the study we discovered that there is no common model that generally fits all multi-objective optimization algorithms. Although most EMO algorithms share similar representation, there are many subtle differences that prevent them share a general model. Genetic algorithm (GA) uses a string-liked representation (e.g., matrix A') that naturally good at solving discrete problem (e.g., binary problem). However, in PSO, particles are "moving" in a continuous hyperplane. Therefore, the representation of particle (e.g., matrix A) is continuous.

$$A = \begin{array}{c} \\ s_1 \\ s_2 \\ s_3 \end{array} \begin{array}{c} \begin{array}{ccc} j_1 & j_2 & j_3 \end{array} \\ \begin{bmatrix} 0.12 & 0.87 & 0.42 \\ 0.07 & 0.32 & 0.95 \\ 0.76 & 0.64 & 0.27 \end{bmatrix} \end{array} \qquad A' = \begin{array}{c} \\ s_1 \\ s_2 \\ s_3 \end{array} \begin{array}{c} \begin{array}{ccc} j_1 & j_2 & j_3 \end{array} \\ \begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \\ 1 & 1 & 0 \end{bmatrix} \end{array}$$

In order to cope with the subtle differences between two algorithms, we employed a transfermation technique with a parameter: threshold.

$$x_{id} = \begin{cases} 1 & \text{if } x_{id} > threshold \\ 0 & \text{otherwise} \end{cases} \tag{1.1}$$

This transfermation is applied on each variable of a particle before evaluation, transform from continuous representation A to A'. As a result, the fitness functions could be applied on PSO-based algorithm as well as genetic algorithm-based algorithm.

However, it completely changed the explanation of the original representation.

In the originl design, A' represents a particle or chromosome which denotes a solution or service deployment plan where a_{sj} is a binary value 1 or 0 to indicate whether a service s_i is allocate to a location j_i or not. In continuous representation A, each entry represents a probability of service s_i NOT allocate in a location j_i. We could manipulate the solutions by adjusting the threshold. For example, the solution is different by applying different threshold values.

We employed this approach and the experimental results show that the threshold profoundly affect the final solution set. Therefore, it leads to a new problem, how to choose an appropriate threshold.

So far, we considered two approaches. First, based on current model, developing a dynamic threshold which automated adjust its value along with the iteration. Second, developed a binary PSO based algorithm which could directly applied the binary-matrix representation.

Chapter 2

Background Survey

2.1 Related work on Service Location-allocation

2.1.1 Traditional Service Location-allocation Methods

Very few researches have studied the service location-allocation problem and most of the researchers treat this problem as a single objective problem. [1] [26] try to solve the problem by using integer linear programming techniques. In particular, [26] solved this problem by employing greedy and linear relaxations of Integer transpotation problem. However, the major problem for this approach is that linear programming is not scaling.

2.1.2 EC Approaches(Non-PSO) for Service Location-allocation

Huang [10] proposed an enhanced genetic algorithm (GA)-based approach, which make use of the integer scalarization technique to solve this problem. This algorithm solves the problem with one objective and one constraint. However there are some deficiencies in the integer scalarization techniques [2]. Firstly, decision makers need to choose appropriate weights for the objectives to retrieve a satisfactorily solution. Secondly, non-convex parts of the Pareto set cannot be reached by minimizing convex combinations of the object functions.

In previous research, we proposed a NSGA-II [6] based approach to web service location-allocation problem.

NSGA-II is a multi-objective algorithm based on GA [20]. It is one of the most widely used methods for generating the Pareto frontier, because it can keep diversity without specifying any additional parameters [7]. When used for problems with only two objectives, NSGA-II performs relatively well in both convergence and computing speed. However, NSGA-II has been criticized for its high computational cost and bad performance on applications with more than two objectives [8].

We discovered that the NSGA-II based approach is effective to produce a set near-optima solutions for the web service location-allocation problem. Also, NSGA-II based approach are more efficient than GA-based approach for problem with big number of user centers and server locations. Future work will investigate the scalability of our proposed approaches for big datasets.

2.2 Particle Swarm Optimization (PSO)

PSO proposed by Kennedy and Eberhart in 1995 [16]. Similar to evolutionary algorithms (EA), PSO is a population based technique inspired by the swarm behavior of birds and fishes during their search for food. PSO is a meta heuristic in which each individual, called

a particle, flies in its own direction and velocity searching for a good solution in the search space. The underlying phenomenon of PSO is optimized by social interaction in the population where all particles communicate their information to direct their movement.

$$x_{id}^{t+1} = x_{id}^{t} + v_{id}^{t+1} \tag{2.1}$$

$$v_{id}^{t+1} = w * v_{id}^{t} + c_1 * r_{1i} * (p_{id} - x_{id}^{t}) + c_2 * r_{2i} * (p_{pg} - x_{id}^{t}) \tag{2.2}$$

PSO is based on the principle that each solution can be represented as a particle in the swarm. Each particle has a random initial position in the search space which is represented by a vector $x_i = (x_{i1}, x_{i2}, \ldots, x_{iD})$, where D is the dimensionality of the search space. Particles move in the search space to search for the optimal solutions. Each particle has a velocity, represented as $v_i = (v_{i1}, v_{i2}, \ldots, v_{iD})$ which is limited by a predefined maximum velocity, v_{max} and $v_{id} \in [-v_{max}, v_{max}]$. During the search process, each particle maintains a record of position its previous best performance, called pbest. The best position of its neighbours is also recorded, which is gbest. The position and velocity of each particle are updated according to the following equations:

In the two equations, t shows the t^{th} iteration. $d \in D$ shows the d^{th} dimension. w is the inertia weight used to balance the local search and global search abilities of PSO. c_1 and c_2 are acceleration constants. r_{1i} and r_{2i} are random constants uniformly distributed in $[0, 1]$. p_{id} and p_{gd} denote the values of pbest and gbest in d^{th} dimension.

2.3 PSO based multiobjective algorithms

Several multiobjective optimization algorithms are based on Particle Swarm Optimization such as Multi-objective Particle Swarm Optimization (MOPSO) [3], Nondominated Sorting Particle Swarm Optimization (NSPSO) [19]. The performance of different multi-objective algorithms was compared in [3] using five test functions. These algorithms are NSGA-II, PAES [18], Micro-GA [4] and MOPSO. The results show that MOPSO was able to generate the best set of nondominated solutions close to the true Pareto front in all test functions except in one function where NSGA-II is superior.

Raquel and et al. [25] proposed a multi-objective Particle Swarm Optimization with crowding distance (MOPSOCD) that extends the MOPSO. The mechanism of crowding distance is incorporated into the algorithm specifically on global best selection and in the delection method of an external archive of nondominated solutions. The diversity of nondominated solutions in the external archive is amintained by using the mechanism of crowding distance together with a mutation operator. The performance shows that MOPSOCD is highly competitive in converging towards the Pareto front and has generated a well-distributed set of nondominated solutions.

Chapter 3

Work Done

This chapter presents a comprehensive description of the current status of the project. To complete objective one, we designed a matrix-based representation for the service location-allocation problem. A Multi-objective PSO-based approach is then proposed to solve the problem. The experimental results reveal the effectiveness and efficiency of our approach in comparison with our previous NSGA-II-based approach.

3.1 Problem Description , Assumptions and Modeling

In this section, we first describe the service location-allocation problem, then we will present models for the services location-allocation problem.

3.1.1 Problem Description

Web service location-allocation problem is to determine reasonable locations for web services so that the deployment cost of WSP can be minimized while service performance can be optimized. In this paper, to optimize service performance we consider to minimize network latency.

The task of service location-allocation has two objectives:

- To minimize the total cost of the services.
- To minimize the total network latency of the services.

3.1.2 Assumptions

To model the service location-allocation problem, we consider the following assumptions:

Stakeholder Web Service Providers, User Centers and Candidate Locations

There are two types of WSP, the first type WSP has existing facilities, the second type WSP is startup company that has no facility. We consider the problem faced by a WSP who has existing facilities but wishes to use the collected data to re-allocate their services in order to maximum their profit.

The WSP must decide on facility locations from a finite set of possible locations. In order to make a decision, the WSP must first analyze the data collected from current use of services. The collected data should include the records of Web request from each unique IP address. Therefore, based on these data, the WSP could summarize several customer demands concentrated on n discrete nodes [1], namely user centers. We assume that the

WSP has already done this step and a list of user centers and candidate locations are given. Candidate location is the geometric location that is suitable to deploy services. Candidate locations are selected based on other criterions such as facilities or deployment cost. User centers and candidate locations can be overlapping, in fact, since web serivce users receive best QoS services if the web serivces are deployed locally. Therefore, the WSPs would like to choose user centers as candidate locations. In addition to deciding which locations to deploy, information about network latency between user centers and candidate locations are needed.

The list below shows some critical information that should be providered by the WSPs.

1. A list of user centers
2. A list of candidate locations
3. Service invocation frequency from user centers to services
4. Average network latency from user centers to candidate locations
5. Web service deployment cost for each candidate location

Worth noting that service invocation frequency are changing over time. For example, a service was popular in some regions may be unfrequented after a few months. That's the main reason for WSPs re-allocate their services. Network latency highly depends on the network traffic and may be very different during periods of a day. However, as long as there is no significant changes in the network topology, the average network latency remain stable. Therefore, the average network latency for a period of time should be representative.

Static deployment vs. Dynamic deployment

As virtual machine technology and infrastracture-as-a-service (IaaS) are becoming more and more popular. Dynamic web service deployment become possible [15]. On the other hand, static deployment is still the mainstream because of a majority of web serivce are deployed on local infrastracture [9]. In this paper, we made an assumption that WSPs periodicaly change the web service deployment since the user centers are changing over time.

3.1.3 Model Formulation

To model service location-allocation problem, we need to make use of a set of matrices, to present input information and output solutions.

For service location-allocation problem, we need information of service usage, network latency, and service deployment cost to decide service location-allocation so that the overall network latency can be minimized with minimal deployment cost and within constraints. Assume a set of $S = \{s_1, s_2, ...s_s, s_x\}$ services are requested from a set of locations $I = \{i_1, i_2, ...i_i, i_y\}$. The service providers allocate services to a set of candidate facility locations $J = \{j_1, j_2, ...j_j, j_z\}$.

In this paper, we will use the following matrices.

Matrices	
L	server network latency matrix $L = \{l_{ij}\}$
A	service location probability matrix $A = \{a_{sj}\}$
A'	service location matrix $A' = \{a'_{sj}\}$
F	service invocation frequency matrix $F = \{f_{is}\}$
C	cost matrix $C = \{c_{sj}\}$
R	user response time matrix $R = \{r_{is}\}$

A *service invocation frequency matrix*, $F = [f_{is}]$, is used to record services invocation frequencies from user centers, where f_{is} is an integer that indicates the number of invocations in a period of time from a user center to a service. For example, f_{13} = 85 denotes service s_1 is called 85 times in a predefined period of time.

$$F = \begin{array}{c} \\ i_1 \\ i_2 \\ i_3 \end{array} \begin{array}{c} \begin{array}{ccc} s_1 & s_2 & s_3 \end{array} \\ \begin{bmatrix} 120 & 35 & 56 \\ 14 & 67 & 24 \\ 85 & 25 & 74 \end{bmatrix} \end{array} \qquad L = \begin{array}{c} \\ i_1 \\ i_2 \\ i_3 \end{array} \begin{array}{c} \begin{array}{ccc} j_1 & j_2 & j_3 \end{array} \\ \begin{bmatrix} 0 & 5.776 & 6.984 \\ 5.776 & 0 & 2.035 \\ 0.984 & 1.135 & 2.3 \end{bmatrix} \end{array}$$

A *network latency matrix* $L = [l_{ij}]$, is used to record network latencies from user centers to candidate locations. For example, the network latency between user center i_2 with candidate location j_1 is 5.776s. These data could be collected by monitoring network latencies [29] [30].

The cost matrix, $C = [c_{sj}]$, is used to record the cost of deployment of services to candidate locations, where c_{sj} is an integer that indicates the cost of deploying a service to a location. For example, $c_{12} = 80$ denotes the cost of deploying service s_1 to location j_2 is 80 cost units.

$$C = \begin{array}{c} \\ s_1 \\ s_2 \\ s_3 \end{array} \begin{array}{c} \begin{array}{ccc} j_1 & j_2 & j_3 \end{array} \\ \begin{bmatrix} 130 & 80 & 60 \\ 96 & 52 & 86 \\ 37 & 25 & 54 \end{bmatrix} \end{array} \qquad A = \begin{array}{c} \\ s_1 \\ s_2 \\ s_3 \end{array} \begin{array}{c} \begin{array}{ccc} j_1 & j_2 & j_3 \end{array} \\ \begin{bmatrix} 0.12 & 0.87 & 0.42 \\ 0.26 & 0.13 & 0.78 \\ 0.67 & 0.98 & 0.33 \end{bmatrix} \end{array}$$

To model the service location-allocation problem, we consider the following assumptions:

1. The new WSP decides where to locate his facilities regardless of there is existed functional similar services from other WSPs.
2. The decision of service location-allocation is made only considering two factors: total network latency and total cost.
3. A static allocation policy is used by WSPs. In practice, Web services typically offer clients persistent and interactive services, which often span over multiple sessions. Therefore, a dynamic reallocation scheme is not practical as it may disrupt the continuity of the services.

A *service location-allocation probability matrix* $A = [a_{sj}]$ represents the probability of a service s_i allocate to a candidate location j_i. a_{sj} is a real value, $a_{sj} \in (0, 1)$ indicate the probability of a service is **NOT** allocate to a candidate location.

A *service location-allocation matrix* $A' = [a'_{sj}]$ represents a solution for web service location-allocation, a'_{sj} is a binary value, a'_{sj} either 1 or 0, indicates whether a service is allocate to a candidate location.

A' can be easily derived from A by using a transformation threshold function with a predefined threshold:

$$a'_{sj} = \begin{cases} 1 & \text{if } a_{sj} > threshold \\ 0 & \text{otherwise} \end{cases} \tag{3.1}$$

Using service location allocation matrix $A' = [a'_{sj}]$ and network latency matrix $L = [l_{ij}]$, we can compute user response time matrix $R = [r_{is}]$,

$$r_{is} = MIN\{l_{ij} \mid j \in \{1, 2, ..., z\} \text{ and } a'_{sj} = 1\} \tag{3.2}$$

For example, we can use the two example matrices L and A presented above to construct the response time matrix R. For each service s, by checking matrix A, we can find out which

location the service has been deployed. Then we check matrix L, to find out its corresponding latency to each user center i. If there is more than one location, then the smallest latency is selected. Therefore, we can construct the response time matrix R as:

$$R = \begin{array}{c} \\ i_1 \\ i_2 \\ i_3 \end{array} \begin{array}{c} \begin{array}{ccc} s_1 & s_2 & s_3 \end{array} \\ \begin{bmatrix} 5.776 & 6.984 & 0 \\ 0 & 2.035 & 0 \\ 1.135 & 2.3 & 0.984 \end{bmatrix} \end{array}$$

Summary

Input:

- L: network latency from user centers to candidate locations
- F: service invocation frequency from user centers to web services
- C: deployment cost for services in different candidate locations

Temporary variable:

- A: service location-allocation probability matrix
- R: user response matrix is a temporary variable generated during the optimization process

Output:

- A': the solution matrix

3.2 MOPSOCD for Web Service Location Allocation

To apply MOPSOCD to the service location-allocation problem, the first step is to define variables in MOPSOCD (i.e., to identify particle and the fitness functions).

3.2.1 Particle Representation and Constraints

We model the service location matrix $A = [a_{sj}]$ as a particle. In our case, we set one basic constraint. The service number constraint requires that each service is deployed in at least one location.

$$\sum_{x \in S} a'_{xj} \geq 1 \tag{3.3}$$

Fitness Function

In order to accomplish these two objectives, we design two fitness functions to evaluate how good each particle meets the objectives. We use *CostFitness* to calculate the overall cost of deploying services under an allocation plan

$$CostFitness = \sum_{s \in S} \sum_{j \in J} c_{sj} \times a'_{sj} \tag{3.4}$$

where c_{sj} is the cost of deploying service s at location j, a'_{sj} represents the deployment plan. The sum of the multiplication of c_{sj} and a'_{sj} is the total deployment cost.

$$LatencyFitness = \sum_{i \in I} \sum_{s \in S} r_{is} \times f_{is} \tag{3.5}$$

Normalise function

To indicate the goodness of an allocation solution we normalise *CostFitness* and *LatencyFitness* according to the largest and minimum values of *CostFitness* and *LatencyFitness*. Normalised fitness values can also be used to compare results from different approaches. Since the maximum and minimum values for total cost and total latency are deterministic, we use exhaustive search to find out the $Latency_{max}$. $Latency_{min}$ is zero for we assume each service could be deployed in each user center. $Cost_{min}$ is the cost of allocating each of services at a location that leads to the minimal cost and $Cost_{max}$ is the cost of allocating each service is allocated to all the locations.

$$CostFitness' = \frac{CostFitness - Cost_{min}}{Cost_{max} - Cost_{min}} \tag{3.6}$$

$$LatencyFitness' = \frac{LatencyFitness - Latency_{min}}{Latency_{max} - Latency_{min}} \tag{3.7}$$

For example, we use the above mentioned matrices F and R.

$LatencyFitness = f_{11} * r_{11} + f_{12} * r_{12} + f_{13} * r_{13} + ... + f_{33} * r_{33}$
$= 120 * 5.776 + 6.984 * 35 + 0 * 56 + ... + 0.984 * 74$
$= 1300.696$

3.2.2 MOPSOCD based algorithm for service location-allocation

In this section we present our MOPSOCD based algorithm for service location-allocation as Algorithm 1.

3.3 Experimental Studies

3.3.1 Dataset

Latency matrix was derived from WS-DREAM [29, 30], which is a historical dataset on QoS of Web services from different locations. It contains the data of latencies from 339 different user locations invoked 5824 web services scattered over different locations.

A cost matrix is generated from a normal distribution with mean as 100 and standard deviation as 20. A frequency matrix is generated from a uniform distribution over [1, 120].

3.3.2 Environment

The algorithm was coded in R [21] using existed packages: NSGA2R, MOPSOCD. The program was run on a 3.40GHz desktop computer with 8 GB RAM.

3.3.3 Test case

Four different service location-allocation problems were designed with different complexities.

Algorithm 1 MOPSOCD for service location-allocation

Inputs: Cost Matrix C, Server network latency matrix L, Service invocation frequency matrix F

Outputs: Pareto Front: the *Archive* set

Initialize a population P with random real values $\in (0, 1)$
Each individual i in P using the fitness function
Initialize personal best of each individual i.
Initialize $GBEST$
Initialize *Archive* with nondominated vectors found in P
repeat
    Compute the crowding distance values of each nondominated solution in the *Archive*
    Sort the nondominated solutions in *Archive* in descending crowding distance values
    for (**do** each particle)
        Update the $GBEST$ by randomly select a particle from top 10% of P
        Compute the new velocity
        Update its position
        If it goes beyond the boundaries, then multiply its velocity by -1
        If($t < (MAXT * PMUT)$), apply Mutation
        Evaluate fitness
        Update its $PBESTS$
    end for
    Insert new nondominated solution into *Archive*, remove dominated solutions from *Archive*
until maximum iterations is researched
return *Archive*

Table 3.1: Test Cases

problem	number of service	number of candidate location	number of user center
1	20	5	10
2	50	15	20
3	100	25	40
4	200	40	80

3.3.4 Parameter

Parameter settings for MOPSOCD are as follow. The population size is 50 and the maximum number of generations is 50. The mutation rate P_m is 0.5. The inertia parameter w is 0.4. $c1$ and $c2$ are set to 1. The archive size is 250. The transformation threshold is set to 0.7.

Parameter setting for NSGA-II are, population size is 50 and the maximum number of generations is 50. The tournament size is 3. The cross probability P_c is 0.8 and the mutation probability P_m is 0.2.

3.3.5 Evaluation metrics

To compare the result of MOPSOCD and NSGA-II, we first derive the Pareto front by using the approach in [28, 27], and then compare the results using approach in [12]. In Xue's approach, 40 sets of solution achieved by each multi-objective algorithm are firstly combined into one set. Secondly, we apply nondominated sort on each solution set and generated final solution set. Thirdly, we use cost fitness value and latency fitness value as x, y coordinate,

plot the final solutions on a graph. Our goal is to minimize both cost and latency. Therefore, better solution should locate closer to the origin.

3.3.6 Experimental Results

This section presents an analysis for the proposed MOPSOCD-based approach in solving the service location-allocation problem. Figure 3.1 shows the experimental result for the four test cases.

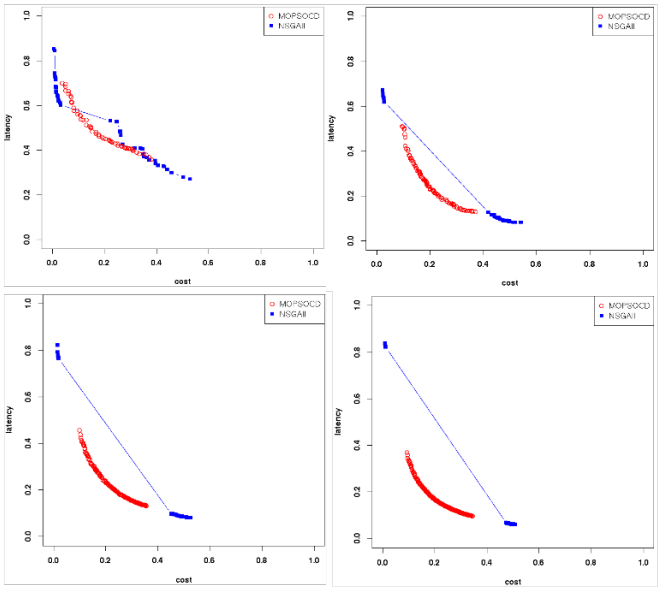

Figure 3.1: Experiments results

It is easy to notice that in the first two experiments, the number of variable are relatively small, 200 and 1000 respectively. Both algorithms were able to handle the problem and generated a pareto front. In both cases, MOPSOCD presents better results. In terms of quality, the pareto front generated by MOPSOCD is clearly under the NSGA-II which means its closed to optimal solution. In terms of distribution, pareto front of MOPSOCD is well-distributed along with the true pareto front. Although in some cases, it sacrificed quality (e.g., upper part of problem 1). On the other hand, NSGA-II form a nonuniform pareto front.

In the last two experiments, the number of variable are huge, 4,000 and 16,000 respectively. Both algorithms show limitations on such scale of variables. As the results show, NSGA-II try to keep diversity in the solution set. As a consequence, the solution set shows polarity among solutions. This is certainly an undesirable solution. In constrast, the result from MOPSOCD shows relatively good coverage of optima pareto front.

Table 3.2 shows the efficiency of the two algorithms.

Table 3.2: Execution Time (s)

problem 1		problem 2		problem 3		problem 4	
MOPSOCD(s)	NSGA-II(s)	MOPSOCD(s)	NSGA-II(s)	MOPSOCD(s)	NSGA-II(s)	MOPSOCD(s)	NSGA-II(s)
20.6347 $\pm$ 0.27 $\uparrow$	32.79 $\pm$ 0.59	110.26 $\pm$ 0.70 $\uparrow$	323.49 $\pm$9.13	533.72 $\pm$ 8.63 $\uparrow$	2064.127 $\pm$69.65	3416.83 $\pm$ 244.03 $\uparrow$	18980.26$\pm$801.454

As the result shows, MOPSOCD is clearly much efficient than NSGA-II in every test case. Specifically, NSGA-II roughly takes 4 times longer than MOPSOCD in problem 3 and problem 4.

Chapter 4

Conclusion and Future work

4.1 Conclusion

This paper first developed a model for serivce location-allocation problem so that it can be tackled by evolutionary multi-objective optimization (EMO). Secondly, we developed a multi-objective PSO-based algorithm to solve the problem. The experiments show that our algorithm is both effecient and effective than NSGA-II-based algorithm. However, the main disadvantage is that the decision of the value of the transformation threshold is an ad-hoc problem. There is no systematic approach to determine the optimal transformation threshold. In order to solve this problem, we mainly consider a binary-based PSO (BPSO) approach. It is natural to apply BPSO on a binary-based representation, therefore BPSO and NSGA-II could use the same representation. In the future, we will further investigate the use of binary PSO approach on serivce location-allocation.

So far we have completed the first two objectives. As we found more problems, two additional objectives has been added to the project. A Gantt chart showing the brief plan for the rest of the project is illustrated as follows.

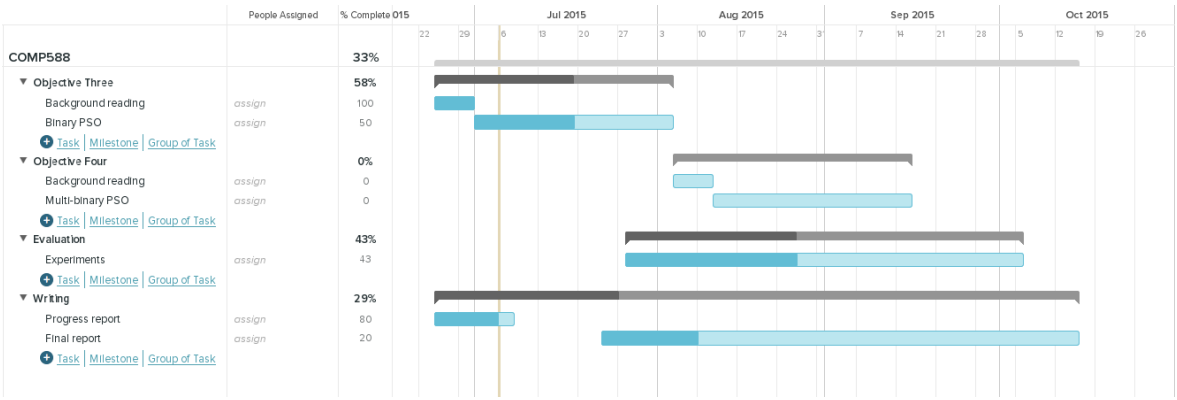

Figure 4.1: A Gantt chart for the rest of the project

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