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Resource Allocation in Mobile Cloud Computing using Optimization Techniques

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ABSTRACT

Mobile Cloud computing has become a new age technology. Mobile Clouds can make it possible to access applications and associated data from anywhere. Mobile cloud service providers are able to charge resources from cloud for storage and other computational purposes. Resources in mobile cloud computing are radio and computing resources. These radio and computing resources is heart to the mobile cloud computing. Resource allocation is performed with the objective of minimizing the costs associated with it. Resources allocation means how much resources are allocated to the end user from available resources. Optimization techniques are used for allocating resources to user in this paper. Different optimization techniques are used in different situations for optimizing the resources.

Key words: Cooperation formation, Linear programming, Mobile cloud computing, Robust optimization.

1. INTRODUCTION

Now a day mobile phone is like a mini computer and it provides the services as like a computer. Many of new terms are introduced in few decades with development of information technology industry. Mobile Cloud Computing (MCC) creates revolution along with the mobile phones across the globe. Delivering cloud services in a mobile environment is a principle issue. Mobile cloud computing is the summation of cloud computing [1] and a mobile computing environment. MCC implementation is difficult in real time. Absence of standards, access schemes, security and elastic application models are some of issues related to MCC [2]. Open issues related to MCC are energy efficiency, security, better service and task division. The mobile cloud computing system is shown in Figure.1. Mobile application and computing is a key role in mobile cloud computing. Mobile cloud computing is combination of mobile computing, cloud computing and wireless networks. Mobility has become a very popular word in today's computing area. Mobile computing is based on a collection of three major concepts: hardware, software and communication. Signal disturbance, security, hand-off delay, limited power, low computing ability and Quality of Service are the different challenges in mobile cloud computing. A mobile database system (MDS)[4] provides full database and mobile communication functionality. It allows a mobile user to access from anywhere. In fully connected information space each node of the information space has some communication capability, some node can process information, some node can communicate through voice channel and some node can do both. MDS mean Distributed system with mobile connectivity. MDS have full database system capability, complete spatial mobility, built on PCS/GSM platform and wireless and wired communication capability. Mobile cloud computing is simply use of cloud computing technology on mobile devices. Mobile Email is perhaps the example of mobile computing that most people can connect with. Mobile email allows user to view, manage and response to email without ever accessing an office network.

Resource Allocation is utilizing and allocating resources within the limit of cloud environment to meet the needs of the cloud application. In resource allocation assign the type and amount of resources in order to complete a user job. An optimal Resource Allocation Schema (RAS) should need to avoid two applications trying to access the same resource at the same time and also to handle limited resources and isolated resources.

Figure 1: Mobile Cloud Computing

Three optimization techniques are using for allocating resources in MCC

i) Linear programming
ii) Stochastic optimization
iii) Robust optimization.

i) Linear programming*:* A linear programming problem may be defined as the problem of maximizing or minimizing a linear function subject to linear constraints. The constraints may be equalities or inequalities. This model applies when all the resource allocation parameters are deterministic.

ii) Stochastic programming: Stochastic optimization is a process of maximizing or minimizing the objective function, when input parameters are random. If the parameters are random then stochastic programming is used. The stochastic programming model requires the probability distributions of the random parameters.

iii) Robust optimization: A robust model solves the uncertain data of linear optimization problem. When the parameters are range of values then robust optimization is used

2. RELATED WORK

Mobile cloud computing is latest technology. It is divided into two parts, General Purpose Mobile Cloud Computing and Application Specific Mobile Cloud Computing. Mobile cloud computing architecture, applications, benefits, and different issues in mobile cloud computing were discussed in [3]. Software as a Service (SaaS) is a model in which an application is hosted as a service to customer via the Internet. For example web user can use Google doc and they do not need to install any application for that. Platform as a Service (PaaS) services include application design, development, testing, deployment and hosting. In this not only services (application software etc) but server, memory and other platforms can be used and subscriber needs to pay as per terms and conditions [5]. The mobile devices are facing many challenges in their resources (e.g., battery life, storage, and bandwidth) and communications (e.g., mobility and security) [6].

Battery is one of the main resources for mobile devices. Many of solutions are evaluated to increase life time of battery in mobile phones. Computation offloading technique is used for transforming the large computations and complex processing from mobile devices to servers in clouds. This avoids taking a long application execution time on mobile devices. Evaluating the effectiveness of offloading techniques [7] shows that up to 45% of energy consumption can be reduced for large matrix calculation. A compiler optimization for image processing [8] can reduce 41% for energy consumption of a mobile device. Also, using Memory Arithmetic Unit and Interface (MAUI) to migrate mobile game components [9] to servers in the cloud can save 27% of energy consumption for computer games and 45% for the chess game.

3. SYSTEM MODEL

In the MCC environment wireless base stations are $A = \{1, . . . , A\}$ where A is the total number of areas. The set of base stations is denoted by $B = \{1, . . . , B\}$, where B is the total number of wireless base stations. The set of data centers is denoted by $D = \{1, . . . , D\}$, where D is the total number of data centers. The set of applications is denoted by $P = \{1, . . . , P\}$, where P is the total number of available mobile applications.

The providers set is denoted by $N = \{1, . . . , S\}$ where S is the total number of providers. Let $K_{b,s}{}^{bw}$ denote the registered bandwidth of provider s at the base station b. Let $K_{d,s}{}^{cp}$ denote the number of servers which are registered by provider s at the data center d. Let $R_p{}^{bw}$ denote the bandwidth required per instance of application p. In this paper, $R_p{}^{cp}$ represents the server utilization required per instance of application p. Let V_p denote the revenue generated per instance of running mobile application p for the provider.

1) **Linear programming formulation**

The objective function of the linear programming is expressed below

$$v(\mathbb{C}) = \max_{x_{a,b,d,p}} \sum_{a\in\mathcal{A}}\sum_{b\in\mathcal{B}}\sum_{d\in\mathcal{D}}\sum_{p\in\mathcal{P}} x_{a,b,d,p} V_p \tag{1}$$

The objective function defined in (1) is to find out the number of application instances to be supported to maximize the revenue. v(C) is denoted the total revenue of coalition C. From (1), $x_{a,b,d,p}$ is the number of application instances.

$$\sum_{a\in\mathcal{A}}\sum_{d\in\mathcal{D}}\sum_{p\in\mathcal{P}} x_{a,b,d,p} R_p^{\mathrm{bw}} \le K_b^{\mathrm{bw}}(\mathbb{C}), \quad b \in \mathcal{B}. \tag{2}$$

$$\sum_{a\in\mathcal{A}}\sum_{b\in\mathcal{B}}\sum_{p\in\mathcal{P}} x_{a,b,d,p} R_p^{\mathrm{cp}} \le K_d^{\mathrm{cp}}(\mathbb{C}), \quad d \in \mathcal{D}. \tag{3}$$

$$\sum_{b\in\mathcal{B}}\sum_{d\in\mathcal{D}} x_{a,b,d,p} \le D_{a,p}^{\mathrm{dm}}(\mathbb{C}), \quad a \in \mathcal{A}, p \in \mathcal{P}. \tag{4}$$

The constraint in (2) ensures that the total amount of required bandwidth to support application instances must be less than or equal to the available bandwidth at coalition. The constraint in (3) ensures that the total amount of required servers to support application instances must be less than or equal to the available servers. The constraint in (4) ensures that the number of instances must be less than or equal to the total demand. $D^{dm}{}_{a,p}$(C) is the number of users' requests for application p from area a at coalition C.

$$\sum_{d\in\mathcal{D}}\sum_{p\in\mathcal{P}} x_{a,b,d,p} \le M\alpha_{a,b}, \quad a \in \mathcal{A}, b \in \mathcal{B}. \tag{5}$$

$$\sum_{b\in\mathcal{B}} x_{a,b,d,p} \le M\beta_{a,d,p}, \quad a \in \mathcal{A}, d \in \mathcal{D}, p \in \mathcal{P}. \tag{6}$$

$$x_{a,b,d,p} \geq 0, \quad a \in \mathcal{A}, b \in \mathcal{B}, d \in \mathcal{D}, p \in \mathcal{P}. \tag{7}$$

The constraint in (5) ensures that the users from area *a* can access base station *b*. *M* is the maximum number of application instances. The constraint in (6) ensures that the instances from area *a* running an application *p* can access the server from data center *d*. The constraint in (7) ensures that $x_{a,b,d,p}$ are non-negative numbers.

2) Stochastic Formulation

The linear programming model does not take the uncertainty of resource allocation parameters into account. If some parameters (e.g., users' demand) are unknown and random, a stochastic programming model [11] is used for calculating the revenue. This model is performed in two-stages. In the first stage, a decision is made on the number of application instances to be offered (i.e., $x_{a,b,d,p}$) based on the partial information. In the second stage, the exact values of the random parameters are found. The coalition determines the number of application instances that it is unable to support (denoted by $y_{a,b,d,p},\tilde{\omega}$) due to insufficient resources.

$$v(\mathbb{C}) = \max \sum_{a\in\mathcal{A}}\sum_{b\in\mathcal{B}}\sum_{d\in\mathcal{D}}\sum_{p\in\mathcal{P}} x_{a,b,d,p}V_p - E\left[\mathcal{Q}(x_{a,b,d,p},\tilde{\omega})\right] \tag{8}$$

$$\text{where} \quad \mathcal{Q}(x_{a,b,d,p},\tilde{\omega}) = \max_{y_{a,b,d,p,\tilde{\omega}}} \sum_{a\in\mathcal{A}}\sum_{b\in\mathcal{B}}\sum_{d\in\mathcal{D}}\sum_{p\in\mathcal{P}} y_{a,b,d,p,\tilde{\omega}}C_p \tag{9}$$

The objective function (8) is to maximize the difference between the revenue and the cost for all cooperative providers in the coalition C. the objective function is divided into two parts. The first part $\sum_{a\in\mathcal{A}}\sum_{b\in\mathcal{B}}\sum_{d\in\mathcal{D}}\sum_{p\in\mathcal{P}} x_{a,b,d,p}V_p$ is the revenue generated from offering of instances. In this, decision is to be made without knowing the exact amount of available resources. The second part is an expectation over random variables. The second part accounts for the cost (i.e., penalty) for being unable to run the offered application instances.

$$\sum_{a\in\mathcal{A}}\sum_{d\in\mathcal{D}}\sum_{p\in\mathcal{P}} (x_{a,b,d,p} - y_{a,b,d,p,\tilde{\omega}})R_p^{\mathrm{bw}} \leq K_{b,\tilde{\omega}}^{\mathrm{bw}} \quad b \in \mathcal{B}. \tag{10}$$

$$\sum_{a\in\mathcal{A}}\sum_{b\in\mathcal{B}}\sum_{p\in\mathcal{P}} (x_{a,b,d,p} - y_{a,b,d,p,\tilde{\omega}})R_p^{\mathrm{cp}} \leq K_{d,\tilde{\omega}}^{\mathrm{cp}}(\mathbb{C}) \quad d \in \mathcal{D}. \tag{11}$$

The constraint in (10) ensures that the required bandwidth for the supported application instances (i.e., $x_{a,b,d,p} - y_{a,b,d,p},\tilde{\omega}$ is the number of supported instances) does not exceed the available bandwidth). The constraint in (11) ensures that the required number of servers for the supported application instances does not exceed the number of available servers in the resource pool.

$$\sum_{b\in\mathcal{B}}\sum_{d\in\mathcal{D}} x_{a,b,d,p} \leq D_{a,p}^{\mathrm{dm}}(\mathbb{C}), \quad a \in \mathcal{A}, p \in \mathcal{P}. \tag{12}$$

$$x_{a,b,d,p} \geq y_{a,b,d,p,\tilde{\omega}}, \quad a \in \mathcal{A}, b \in \mathcal{B}, d \in \mathcal{D}, p \in \mathcal{P}$$

$$x_{a,b,d,p}, y_{a,b,d,p,\tilde{\omega}} \geq 0, \quad a \in \mathcal{A}, b \in \mathcal{B}, d \in \mathcal{D}, p \in \mathcal{P}. \tag{13,14}$$

The constraint in (12) is to ensure that the number of instances is not more than the users demand. The constraint in (13) ensures that $x_{a,b,d,p}$ has to be greater than or equal to $y_{a,b,d,p},\tilde{\omega}$. The constraint in (14) ensures that the decision variables are non-negative numbers.

Deterministic Formulation*:*

The SP model involving the random variable $\tilde{\omega}$ in (8)-(14) can be transformed into its equivalent deterministic problem.

$$v(\mathbb{C}) = \max_{x_{a,b,d,p}} \sum_{a\in\mathcal{A}}\sum_{b\in\mathcal{B}}\sum_{d\in\mathcal{D}}\sum_{p\in\mathcal{P}} x_{a,b,d,p}V_p - \sum_{\omega\in\Omega} P(\omega)\Big(\sum_{a\in\mathcal{A}}\sum_{b\in\mathcal{B}}\sum_{d\in\mathcal{D}}\sum_{p\in\mathcal{P}} y_{a,b,d,p,\omega}C_p\Big) \tag{15}$$

The objective function in (15) is to maximize the difference between the expected total revenue and the cost.

$$\sum_{a\in\mathcal{A}}\sum_{d\in\mathcal{D}}\sum_{p\in\mathcal{P}} (x_{a,b,d,p} - y_{a,b,d,p,\omega})R_p^{\mathrm{bw}} \leq K_{b,\omega}^{\mathrm{bw}}(\mathbb{C}) \quad b \in \mathcal{B}, \omega \in \Omega. \tag{16}$$

$$\sum_{a\in\mathcal{A}}\sum_{b\in\mathcal{B}}\sum_{p\in\mathcal{P}} (x_{a,b,d,p} - y_{a,b,d,p,\omega})R_p^{\mathrm{cp}} \leq K_{d,\omega}^{\mathrm{cp}}(\mathbb{C}) \quad d \in \mathcal{D}, \omega \in \Omega. \tag{17}$$

$$\sum_{b\in\mathcal{B}}\sum_{d\in\mathcal{D}} x_{a,b,d,p} \leq D_{a,p}^{\mathrm{dm}}(\mathbb{C}), \quad a \in \mathcal{A}, p \in \mathcal{P}. \tag{18}$$

$$x_{a,b,d,p} \geq y_{a,b,d,p,\omega}, \quad a \in \mathcal{A}, b \in \mathcal{B}, d \in \mathcal{D}, p \in \mathcal{P}, \omega \in \Omega. \tag{19}$$

$$x_{a,b,d,p}, y_{a,b,d,p,\omega} \geq 0, \quad a \in \mathcal{A}, b \in \mathcal{B}, d \in \mathcal{D}, p \in \mathcal{P}, \omega \in \Omega. \tag{20}$$

The constraints in (16), (17), (18), (19) and (20) are similar to those in (10), (11), (12), (13) and (14) respectively. The only difference is that the random variable $\tilde{\omega}$ is replaced by the scenario ω.

3) Robust optimization Model

The robust optimization model [10] for resource allocation on coalition C is to obtain the worst-case solution. The model considers the resource requirement uncertainty of application instances (i.e., required bandwidth and server) for coalition C. Let $R^{\mathrm{bw}}p$ and $R^{\mathrm{cp}}p$ denote the nominal values of the bandwidth and server requirements.

$$v(\mathbb{C}) = \max_{x_{a,b,d,p}} \sum_{a\in\mathcal{A}}\sum_{b\in\mathcal{B}}\sum_{d\in\mathcal{D}}\sum_{p\in\mathcal{P}} x_{a,b,d,p}V_p \tag{21}$$

The objective function (21) is to find out the number of application instances to be supported to maximize the revenue.

$$\sum_{a\in\mathcal{A}}\sum_{d\in\mathcal{D}}\sum_{p\in\mathcal{P}} x_{a,b,d,p}\overline{R}_p^{\mathrm{bw}} + u_b^{\mathrm{bw}}\Gamma_b^{\mathrm{bw}} + \sum_{a\in\mathcal{A}}\sum_{d\in\mathcal{D}}\sum_{p\in\hat{\mathcal{P}}_{\mathrm{bw}}} q_{a,b,d,p}^{\mathrm{bw}} \le K_b^{\mathrm{bw}}(\mathbb{C}), \quad b\in\mathcal{B}. \tag{22}$$

$$\sum_{a\in\mathcal{A}}\sum_{b\in\mathcal{B}}\sum_{p\in\mathcal{P}} x_{a,b,d,p}\overline{R}_p^{\mathrm{cp}} + u_d^{\mathrm{cp}}\Gamma_d^{\mathrm{cp}} + \sum_{a\in\mathcal{A}}\sum_{b\in\mathcal{B}}\sum_{p\in\hat{\mathcal{P}}_{\mathrm{cp}}} q_{a,b,d,p}^{\mathrm{cp}} \le K_d^{\mathrm{cp}}(\mathbb{C}), \quad d\in\mathcal{D}. \tag{23}$$

The constraints in (22) and (23) ensure that the total amount of required bandwidth and the total number of required servers are less than or equal to the available bandwidth and servers in the resource pool respectively.

$$u_b^{\mathrm{bw}} + q_{a,b,d,p}^{\mathrm{bw}} \ge \hat{R}_p^{\mathrm{bw}} k_{a,b,d,p}, \quad a\in\mathcal{A}, b\in\mathcal{B}, d\in\mathcal{D}, p\in\hat{\mathcal{P}}_{\mathrm{bw}}. \tag{24}$$

$$u_d^{\mathrm{cp}} + q_{a,b,d,p}^{\mathrm{cp}} \ge \hat{R}_p^{\mathrm{cp}} k_{a,b,d,p}, \quad a\in\mathcal{A}, b\in\mathcal{B}, d\in\mathcal{D}, p\in\hat{\mathcal{P}}_{\mathrm{cp}}. \tag{25}$$

$$x_{a,b,d,p} \le k_{a,b,d,p}, \quad a\in\mathcal{A}, b\in\mathcal{B}, d\in\mathcal{D}, p\in\mathcal{P} \tag{26}$$

The constraints in (24) and (25) ensure that in presence of uncertainty the bandwidth and server requirements do not exceed the corresponding bounds.

$$\sum_{b\in\mathcal{B}}\sum_{d\in\mathcal{D}} x_{a,b,d,p} \le D_{a,p}^{\mathrm{dm}}(\mathbb{C}), \quad a\in\mathcal{A}, p\in\mathcal{P}. \tag{27}$$

$$x_{a,b,d,p}, k_{a,b,d,p} \ge 0, \quad a\in\mathcal{A}, b\in\mathcal{B}, d\in\mathcal{D}, p\in\mathcal{P}. \tag{28}$$

$$u_b^{\mathrm{bw}}, u_d^{\mathrm{cp}} \ge 0. \tag{29}$$

The constraint in (27) ensures that the number of instances must be less than or equal to the total demand. The constraints in (28) and (29) ensure that the decision variables are nonnegative numbers. $X^{\dagger}_{a,b,d,p}$ denotes the solution of the robust optimization model.

4. EXPERIMENTAL RESULTS

In this section of the paper the experiment results are discussed. The experimentation is carried out using the resources provided in Table 1. It contains the available bandwidth and servers at base station and data center. The three service providers are A, B and C and their bandwidth are 10, 5 and 15 and the available servers are 5,8 and 6 respectively.

The required number of bandwidth and servers are shown in Table.2. It contains the two applications and their bandwidth and servers. The required bandwidth of two applications is 1 mbps and 2 mbps respectively and servers are 2 and1 respectively.

Linear programming

The service provider A provides the services of application 1 to the end user. The service provider gets the revenue per application of 50 from the end user.

Table 1: Bandwidth and servers of providers

Name	bandwidth	servers
A	10 mbps	5
B	5 mbps	8
C	15 mbps	6

Table 2: Required bandwidth and servers for Applications

Name	bandwidth	servers
App1	1 mbps	2
App2	2 mbps	1

Table 3: Revenue generated by using linear programming. TB – Total Bandwidth, TS – Total no.of Servers, RB – Required Bandwidth, RS – Required no.of Servers, TI – Total no.of application instances, SI – Supported Instances

TB	TS	RB	RS	TI	SI	revenue
10	5	1	2	10	2	100
10	8	1	2	10	4	200
10	10	1	2	10	5	250
10	12	1	2	10	6	300
10	15	1	2	10	7	350
10	18	1	2	10	8	400
10	20	1	2	10	10	500
10	24	1	2	10	10	500
10	26	1	2	10	10	500
10	28	1	2	10	10	500

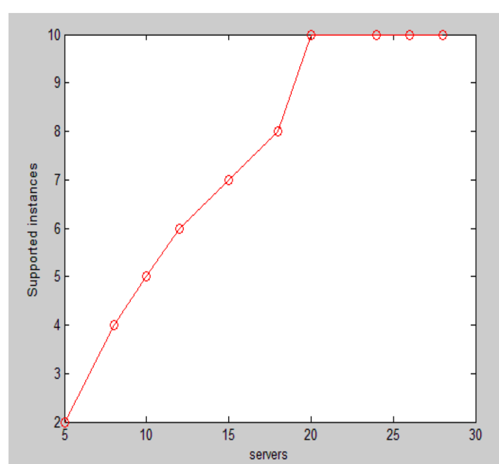

Figure 2: Increase in application instance with total servers

From Table.3, it is observed that when the number of servers increase by the values 5,8,10,12,15,18,20,24,26 and 28, then the supported applications get increased by the values 2,4,5,6,7,8,10,10,10 and 10. Maximum supported applications are 10 because the available instance is 10.

Figure 2 shows the application instances with respect to total available servers. It is observed that the supported application instances get increased up to 10 and after that there is no improvement, because of insufficient bandwidth and application instances at cloud.

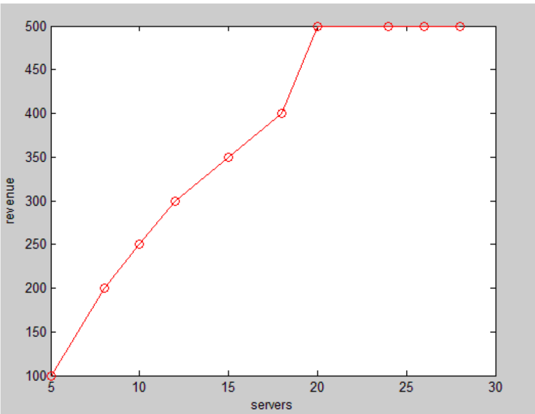

Figure 3: Increase in revenue with total servers

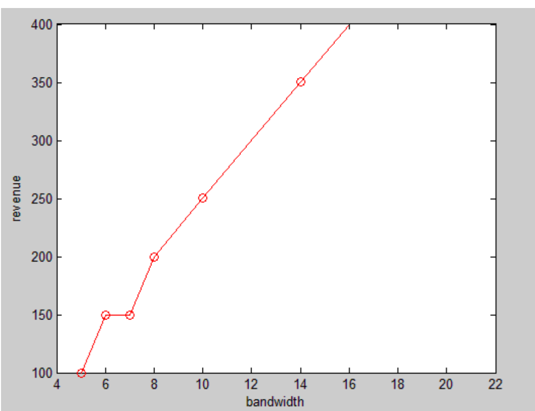

Figure 4: Revenue increase with respect to bandwidth

Table 4: Increase in revenue with respect to bandwidth
TB – Total Bandwidth, TS – Total no.of Servers, RB – Required Bandwidth, RS – Required no.of Servers, TI – Total no.of application instances, SI – Supported Instances

TB	TS	RB	RS	TS	SI	revenue
20	20	1	2	15	10	500
20	24	1	2	15	12	600
20	26	1	2	15	13	650
20	28	1	2	15	14	700
20	30	1	2	15	15	750
20	32	1	2	15	15	750

Table 5: Available resources of provider2 and required resources of application 2
TB – Total Bandwidth, TS – Total no.of Servers, RB – Required Bandwidth, RS – Required no.of Servers, TI – Total no.of application instances, SI – Supported Instances

TB	TS	RB	RS	TI	SI	revenue
5	8	2	1	10	2	100
6	8	2	1	10	3	150
7	8	2	1	10	3	150
8	8	2	1	10	4	200
10	8	2	1	10	5	250
14	8	2	1	10	7	350
16	8	2	1	10	8	400
18	8	2	1	10	8	400
20	8	2	1	10	8	400
22	8	2	1	10	8	400

Figure 3 shows the increase in the revenue of the coalition with respect to the total servers available at coalition. It is observed that when the total number of servers gets increased, the revenue of the coalition gets increased. The revenue becomes constant after it reaches the threshold, because of insufficient resources at coalition.

From Table 4, it is observed that when the number of application instances gets increased to 15 and total bandwidth to 20, the revenue gets increased up to 750 and after that it remains constant because of insufficient application instance.

Table 5 shows the increase in the revenue and supported instances with respect to bandwidth. It shows information related to the service provider 2, the available resources and required resources of applications 2 and the supported instances and revenue generated

Figure 4 shows the increase in the revenue of the coalition with respect to bandwidth available at coalition. It is observed that when the bandwidth gets increased, the revenue of the coalition gets increased. The revenue becomes constant after it reaches the threshold, because of insufficient resources at coalition

Stochastic programming

Stochastic programming is used for getting the fair revenue. In this stochastic programming both supported application and unsupported applications are considered for getting the fair revenue. Revenue generated per application is 50 for supported application and penalty cost for unsupported instance is 51.

Table 6 shows the revenue generated from stochastic programming. Total revenue is given by the difference between the revenue of the supported instances and penalty cost for unsupported application instances.

Table 6: Revenue generated from stochastic method
TB – Total Bandwidth, TS – Total no.of Servers, RB – Required Bandwidth, RS – Required no.of Servers, TI – Total no.of application instances, SI – Supported Instances, USI – Unsupported Instances

TB	TS	RB	RS	TI	SI	USI	Total revenue
10	5	1	2	10	2	8	-308
10	8	1	2	10	4	6	-106
10	10	1	2	10	5	5	-5
10	12	1	2	10	6	4	96
10	15	1	2	10	7	3	197
10	18	1	2	10	8	2	298
10	20	1	2	10	10	0	500
10	24	1	2	10	10	0	500
10	26	1	2	10	10	0	500
10	28	1	2	10	10	0	500

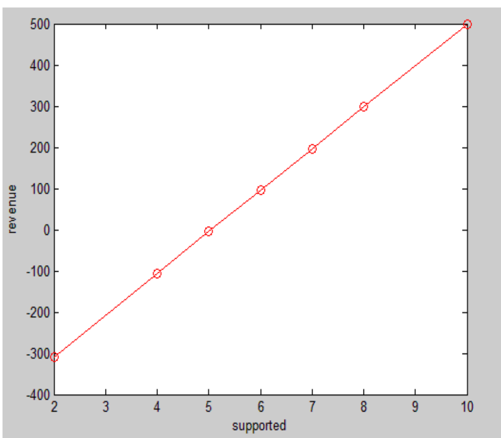

Figure 5: Revenue with supported application instances

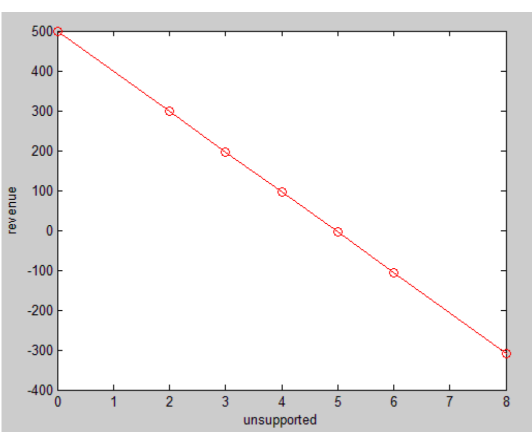

Figure 6: Revenue with unsupported application instances

Figure 5 shows the revenue generated with supported application instances. In this figure when the number of application instances gets increased the revenue also increases and if supported application decreases the revenue also decreases.

Figure 6 shows the revenue generated with respect to the unsupported applications. In this figure when the unsupported application increases the revenue decreases and if the unsupported applications decrease the revenue increases.

Robust optimization

The robust optimization method is used when the parameters are uncertain. If the parameters are range of parameters then the robust method is used. The required resources are uncertainty and values are range of values. The bandwidth required and servers required get changed.

Figure 7 shows the comparison among the three models of revenue. It is observed that linear programming gives more revenue compared to other two models.

Table 7 shows the revenue change with respect to required number of bandwidth and servers. When the required bandwidth and servers are changed the revenue gets changed. It is the worst case to generate revenue by using robust optimization method.

Table 7: Revenue generated by using robust method
TB – Total Bandwidth, TS – Total no.of Servers, RB – Required Bandwidth, RS – Required no.of Servers, TI – Total no.of application instances, SI – Supported Instances

TB	TS	RB	RS	TI	SI	revenue
10	5	1	2	10	2	100
10	8	1	3	10	2	100
10	10	2	2	10	5	250
10	12	2	2	10	5	250
10	15	3	2	10	3	150
10	18	1	4	10	4	200
10	20	1	2	10	10	500
10	24	4	2	10	2	100
10	26	2	2	10	5	250
10	28	1	2	10	10	500

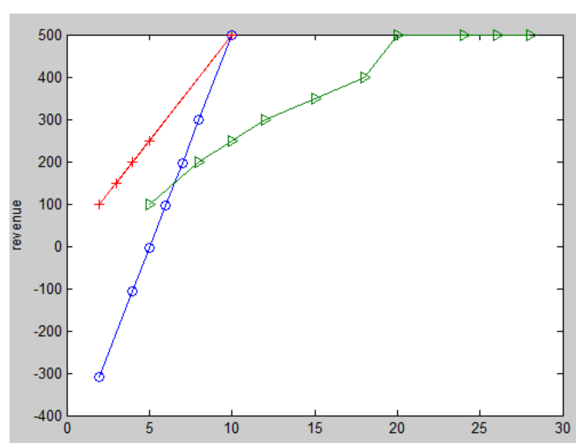

Figure 7: Comparing three models of revenue, ► is the linear programming line, ○ is the stochastic line, + is the robust line

5. CONCLUSION

Recently, mobile cloud computing has a more response. Mobile Cloud Computing (MCC) is a development and extension of Cloud Computing and Mobile Computing. The ultimate goal of MCC is to provide wealthy mobile computing through faultless communication between front-users (cloud-mobile users) and end-users (cloud providers). In this paper allocating the resource allocation is the how much resource is allocated to the required application instances. In this resources allocation is done by using three optimization techniques in three different situation, if the parameter are deterministic linear programming is used, parameters are random stochastic model is used and robust model is used when there is a range of parameters.

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