Optimal Device Selection for Offloading Application Mobile Codes in Pervasive Environments

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Abstract

With fast growing research in the area of application partitioning for offloading, determining which devices to prioritize over the other for mobile code offloading is fundamental. Multiple methods can be adopted using both single-criterion and multiple-criteria strategies. Due to the characteristics of pervasive environments, whereby devices having different computing capability, different level of privacy and security and the mobility nature in such environment makes the decision-making process complex. To this end, this paper proposes a method using a combination of AHP to get weights of the criteria for each participating device and fuzzy TOPSIS to determine the priorities of the devices in the decision-making process. An evaluation of the method is also presented.

Keywords: application partitioning, device selection, pervasive environments, AHP, fuzzy TOPSIS

1. Introduction

In next generation pervasive environments, devices that will potentially host mobile codes of partitioned applications [1][2] will vary from simple everyday household units such as smart washing machine, smart refrigerator, smart television and so on to more powerful devices such as desktop computers, laptops and home desktop servers among others. Also, a variety of devices with different characteristics will be emerging to support the infrastructure. Therefore, it is essential to decide which devices to prioritize over others. It is no secret that application partitioning and offloading will be so natural and pervasive unlike current situation at the time of writing of this paper.

The objective of this work is to present a method to find the optimal participating devices in the user's surrounding among a certain class of heterogenous devices that provide the same service, so as to perform the mobile code migration best. Compared to existing work that uses only one criterion, the methods of Analytic Hierarchy Process (AHP) [3] and fuzzy technique for order preference by similarity to ideal solution (TOPSIS) [4] are based on multiple criteria to find the optimal participating device for migration.

In this work, we first demonstrate the optimal device selection based on one criterion. Next, to be able to make a decision while considering simultaneously multiple criteria, we proposed a method based on the combination of AHP and fuzzy TOPSIS techniques.

The rest of the paper is organized as follows: Section 2 describes the problem of making device selection decision based on a single and multiple criterion. In Section 3, we proposed the combination of AHP and fuzzy TOPSIS to ease the process of multi-criteria decision making. Section 4 analyzed the proposed method and finally Section 5 concludes the paper.

2. Problem Statement

2.1 System environmental overview

Devices (as mentioned above) that are readily available to host mobile codes of a partitioned application are usually diverse and not comparable. Here, we consider a certain class of participating devices that provide the resources of computation, networking and storage. Offloading the same mobile codes to different participating devices may result in different amounts of computing within the same time period due to the different speeds of the devices, and may cost different communication time due to the wireless network and devices' availability. Thus, a method for optimal participating device selection is required.

The execution time of offloading mobile codes in pervasive environments is greatly reduced when the optimal device is prioritized over other potential participating devices. The bandwidth of the network, the participating devices speedup (F) (since not all devices have the same CPU and amount of memory), the communication failure rate (due to mobility) along with the security aspect should be considered while selecting the optimal device for offloading. Since remote participating devices (laptops, desktops and servers) may be more resourceful than the source mobile device, F_i would normally be greater than 1.

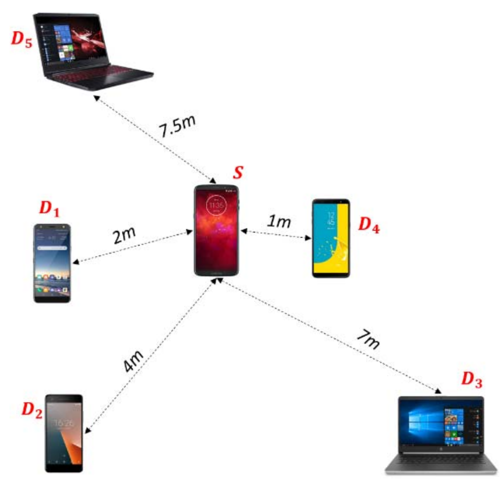

Figure 1. Potential remote participating devices

Figure 1 shows five remote participating devices (D_1, D_2, D_3, D_4 and D_5) that are within the reach of the source mobile device S running the partitioned application. Each device has got a different speedup factor since normally laptops are more powerful than smartphones. The nearest device is 1 meter and the farthest is 7.5 meters away from S. Thus, the bandwidth and communication failure rate are also different from each other.

In view of performance improvement, the offloading time t_o should be less than the time it takes for the application to execute on the source mobile device t_s. The offloading time is the addition of the communication time and the computation time on the remote device. Hence, time is saved when offloading the mobile codes if the following condition is true [5]:

$$t_s > t_o = \frac{t_s}{F_i} + (1 + X_i^U).\frac{D_i^U}{B_i^U} + (1 + X_i^D).\frac{D_i^D}{B_i^D}$$

where $i \in 1, 2, \dots, N$; B_i^U and B_i^D are the upload and download bandwidth speeds respectively; D_i^U and D_i^D represents the upload and download data transfer rates respectively and finally X_i^U and X_i^D are the upload and download failure rates respectively.

$\frac{D_i^D}{B_i^D}$ is the communication time. The bandwidth and failure rate for both upload and download might not be the same, that is, $B_i^U \neq B_i^D$ and $D_i^U \neq D_i^D$. Multiple strategy exists [6] to find out the optimal device such as (1) bandwidth: choosing the remote device with the highest bandwidth (2) Failure rate: choosing the remote device with the lowest failure rate (3) Speedup factor: choosing the remote device with the highest speedup factor.

2.2. Simulation and performance analysis

The algorithm is implemented to help make a device selection decision and the results are compared. The parameters used are as follows: the bandwidth B_i is consistently selected from $[32kb/s, 256kb/s]$ and the failure rate X_i is consistently selected from $[0.01, 0.2]$. The data transfer rate for upload and download are $D_i^U = 2000kb$ and $D_i^D = 1500kb$ respectively. The speedup factor F_i is consistently selected from $10s$ to $200s$ [11]. The number of participating devices is 10. The simulation is run 100 times. The average time t_o of the 3 device selection algorithms is shown in Figure 2 below. We can that the lowest failure rate algorithm costs much more time than the highest bandwidth algorithm.

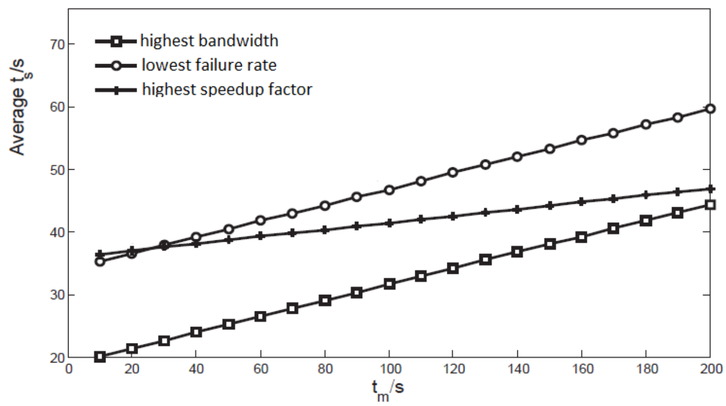

Figure 2. Average t_o for the three device selection algorithms

2.3. Device selection problem

The author in [5] prioritized servers based solely on energy savings for computation offloading. The analysis presented previously, again only one criterion is considered at a time in selecting the optimal remote device. Other factors are ignored. However, for an optimal selection of participating devices, multiple criteria need to be taken into consideration simultaneously. Some of the QoS criteria from the Cloud Services Measurement Initiative Consortium (CSMIC) [8].

A. *Bandwidth*: how fast the data is transferred depends on the wireless connection between the source mobile device and the participating devices [9].
B. *Performance*: performance viewed in terms of speed, accuracy and service response time should be considered. Speed means how fast a participating device for computing is. Accuracy refers simply to the degree of closeness to what the user expected actual value or result generated by using the participating device.
C. *Availability*: refers to the ability to connect or access a remote participating device. It is associated to connection failure and participating device availability during the migration process [10].
D. *Security*: to make sure that the partitioned application codes running on the remote participating devices are safe and privacy is well preserved. Migrating application code and data to participating devices does raise security and privacy issues, like tracking user's location using location-based navigation data.

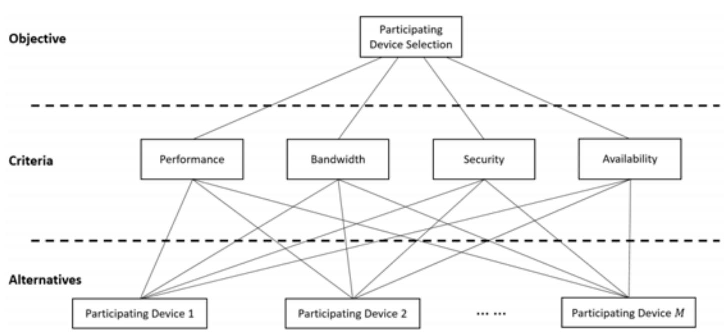

Figure 3. Decision hierarchy of participating device selection

Figure 3 shows the decision pyramid for the participating device selection along with all the relevant criteria discussed and sub-criteria. Three hierarchy levels are illustrated. The first level is called the objective hierarchy, that is, what the objective is. The objective is to select the optimal participating nodes among other available participating devices in a priority order. The second level of the hierarchy is called the criteria hierarchy and four criteria are considered for participating device selection such as bandwidth, performance, availability and security. Also, the performance criteria are quantitatively defined as speed, memory and storage, while the security criteria is defined as data privacy, data integrity and data loss. The third and last level of the hierarchy is about making the final decision about which physical participating device to select for code offloading and in which order.

3. Proposed technique for combining AHP and Fuzzy TOPSIS for Multi-Criteria Decision Making

In this section the methods of analytic hierarchy process (AHP) and fuzzy technique for order preference by similarity to ideal solution (TOPSIS) are combined to ease the process of multi-criteria decision making [11]. AHP is used to get weights of the criteria for each participating device and fuzzy TOPSIS is used to determine the priorities of the devices in decision-making process [7].

3.1. The AHP Method

Analytic hierarchy process (AHP) is a method for determining the relative importance of a set of alternatives in a multi-criteria decision problem. Evaluations are converted to numerical values so that they can be processed and compared, and derives a priority for each element of the hierarchy. The outcomes of the pairwise comparison on N criteria can be expressed in an evaluation matrix as follows:

$$A = \left(a_{ij}\right)_{N\times N} = \begin{pmatrix} a_{11} & a_{12} & \cdots & a_{1N} \\ a_{21} & a_{22} & \cdots & a_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ a_{N1} & a_{N2} & \cdots & a_{NN} \end{pmatrix}, a_{ii} = 1, a_{ji} = \frac{1}{a_{ij}},$$

where element a_{ij} is based on a standardized comparison scale of nine levels as shown in Table 1 [11]. As for the relative weights, they are given by eigenvector (w) corresponding to the largest eigenvalue (λ_{max}) as:

$$Aw = \lambda_{max} w \qquad (4.1)$$

Definition	Intensity of Importance
Equally importance	1
Moderate importance	3
Strong importance	5
Very strong importance	7
Extreme importance	9
Intermediate	2, 4, 6, 8

Table 1 Level of importance scale

The output of AHP is strictly related to the consistency of the pairwise comparison. The consistency index (CI) is:

$$CI = \frac{\lambda_{max} - N}{N - 1} \qquad (4.2)$$

To conclude whether the evaluations are adequately consistent, the consistency ratio (CR) is used and is calculated as follows:

$$CR = CI/RI, \qquad (4.3)$$

where the random index (RI) is only relevant with the matrix order. To meet the consistency, CR must be less than 0.1.

3.2. The Fuzzy TOPSIS Method

Technique for order preference by similarity to ideal solution (TOPSIS) is extensively used to solve decision problems in real and virtual scenarios. Why to use adopt fuzzy TOPSIS here is because it is intuitively easy for the decision-makers to use and calculate through a triangular fuzzy number, which is proved to be an effective way for formulating decision problems [7]. Fuzzy TOPSIS stages can be outlined as follows [11]:

1. Build a decision matrix for the ranking. The matrix is structured as follows:

$$\begin{array}{c} \\ A_1 \\ A_2 \\ \vdots \\ A_i \\ \vdots \\ A_M \end{array} \begin{pmatrix} C_1 & C_2 & \dots & C_j & \dots. & C_N \\ x_{11} & x_{12} & \dots & x_{1j} & \dots & x_{1N} \\ x_{21} & x_{22} & \dots & x_{2j} & \dots & x_{2N} \\ \vdots & \vdots & \dots & \vdots & \dots & \vdots \\ x_{i1} & x_{i2} & \dots & x_{ij} & \dots & x_{iN} \\ \vdots & \vdots & \dots & \vdots & \dots & \vdots \\ x_{M1} & x_{M2} & \dots & x_{Mj} & \dots & x_{MN} \end{pmatrix}$$

where C_j is the j^{th} criterion, A_i is the i^{th} participating device. Normalization is not required since the triangular fuzzy number $x_{ij}\epsilon[0,1]$. Figure 4 illustrates membership functions of linguistic values, which are used for evaluation of alternative weapons in this step, and the corresponding triangular fuzzy numbers are listed in Table 2.

2. Calculate the weighted normalized decision matrix. The weighted normalized value v_{ij} is calculated as follows:

$$v_{ij} = x_{ij} \times w_j,\ i = 1,2,\cdots,M,\ j = 1,2,\cdots,N \tag{4.4}$$

where w_j represents the weight of the j^{th} criterion, which is obtained from the AHP method.

3. Determine the positive-ideal (A^+) and negative-ideal solutions (A^-), respectively:

$$\mathrm{A}^+ = \{\mathrm{v}_1^+, \mathrm{v}_2^+, \cdots, \mathrm{v}_N^+\} = \{(\max_j \mathrm{v}_{ij} \,|\, \mathrm{i} \in \mathrm{I}), (\min_j \mathrm{v}_{ij} \,|\, \mathrm{i} \in \mathrm{I}')\}, \tag{4.5}$$

$$\mathrm{A}^- = \{\mathrm{v}_1^-, \mathrm{v}_2^-, \cdots, \mathrm{v}_N^-\} = \{(\min_j \mathrm{v}_{ij} \,|\, \mathrm{i} \in \mathrm{I}), (\max_j \mathrm{v}_{ij} \,|\, \mathrm{i} \in \mathrm{I}')\}, \tag{4.6}$$

For normalized positive triangular numbers, we can define the fuzzy positive-ideal and negative-ideal solutions. As for benefit criterion, we have $v_j^+ = (1,1,1)$ and $v_j^- = (0,0,0)$, while for cost criterion, $v_j^+ = (0,0,0)$ and $v_j^- = (1,1,1)$.

4. Calculate the distance of each alternative from A^+ and A^- using the Euclidean distance:

$$D_i^+ = \sum_{j=1}^{N} d(v_{ij}, v_j^+), i = 1,2,\dots,M, \tag{4.7}$$

$$D_i^- = \sum_{j=1}^{N} d(v_{ij}, v_j^-), i = 1,2,\dots,M, \tag{4.8}$$

where $d(v_{ij}, v_j)$ calculates the Euclidean distance between v_{ij} and v_j.

5. Compute the relative closeness to ideal solution, denoted as:

$$C_i^* = \frac{D_i^-}{D_i^+ + D_i^-} \tag{4.9}$$

6. Rank the alternatives in descending order according to C_i^*. As the value of C_i^* approaches 1, this means the better the performance of the alternatives.

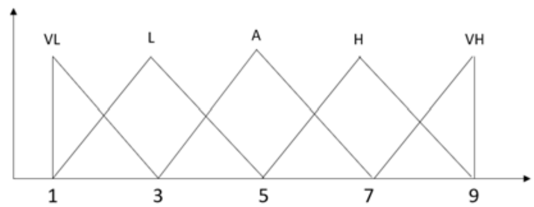

Figure 4. Membership functions of linguistic values

Linguistic values	Fuzzy ranges
Very Low (VL)	1, 1, 3
Low (L)	1, 3, 5
Average (A)	3, 5, 7
High (H)	5, 7, 9
Very High (VH)	7, 9, 9

Table 2. Fuzzy Membership Functions

4. Computing the Weights of Criteria

Criteria weights calculation is subjective. It is what matters most in improving the overall application performance from the user's mobile perspective. For example, if the data to be sent to an offloaded partition on a remote participating device is neither private nor highly sensitive, in such situation, the security factor is the least important among the four criteria mentioned in section 2.3. In the context of application partitioning and offloading, bandwidth is the most important criteria because it will largely impact the communication cost. Next, performance is also crucial as it does impact the application's execution time and directly affects battery usage. A slow participating device (in terms of CPU speed and memory available) would imply a longer execution time and more energy consumption for the source mobile device in terms of idle time. Thus, the relevant criteria for the selection of participating devices are prioritized and ranked as follows: bandwidth $>$ performance $>$ availability $>$ security. However, the ranking of the criteria can vary depending on the context.

As per the level of importance scale illustrated in Table 1, a pairwise comparison matrix is generated as shown in Table 3.

Criteria	*Bandwidth*	*Performance*	*Availability*	*Security*
Bandwidth	1	3	5	7
Performance	0.33	1	3	4
Availability	0.2	0.33	1	2
Security	0.14	0.25	0.5	1

Table 3. Pairwise comparison matrix

Using the AHP process described in section 3.1, the criteria weights are calculated, see Table 4 using random index $RI = 0.9$ for four criteria.

Criteria	*Weights*	
Bandwidth	0.57	$\lambda_{max} = 4.0487$
Performance	0.2544	$CI = 0.0162$
Availability	0.11	$RI = 0.9$
Security	0.0656	$CR = 0.018$

Table 4. Criteria weights, λ_{max}, consistency index (CI) and consistency ratio (CR)

Note that bandwidth the most important criteria, in our context, is given an importance weight of 57% while the least important one, that is, security is given an importance weight of approximately 7%. Also, the consistency ratio (CR) is 0.018 which is well less than 0.1, which is the criteria checking point. Hence, the weights calculated by the AHP process is consistent and can be used for further calculations.

The outputs of the fuzzy weighted decision matrix are detailed in Table 5 below.

Remote Device	bandwidth	performance	availability	security
remote device 1	A	L	H	H
remote device 2	L	H	A	H
remote device 3	VH	H	VH	A
remote device 4	H	A	H	A
remote device 5	VH	VH	VH	VL
criteria weights	0.57	0.2544	0.11	0.0656
remote device 1	3, 5, 7	1, 3, 5	5, 7, 9	5, 7, 9
remote device 2	1, 3, 5	5, 7, 9	3, 5, 7	5, 7, 9
remote device 3	7, 9, 9	5, 7, 9	7, 9, 9	3, 5, 7
remote device 4	5, 7, 9	3, 5, 7	5, 7, 9	3, 5, 7
remote device 5	7, 9, 9	7, 9, 9	7, 9, 9	1, 1, 3
remote device 1	0.19, 0.3167, 0.4433	0.0283, 0.0848, 0.1413	0.0611, 0.0856, 0.11	0.0364, 0.051, 0.0656
remote device 2	0.0633, 0.19, 0.3167	0.1413, 0.1979, 0.2544	0.0367, 0.0611, 0.0856	0.0364, 0.051, 0.0656
remote device 3	0.4433, 0.57, 0.57	0.1413, 0.1979, 0.2544	0.0856, 0.11, 0.11	0.0219, 0.0364, 0.051
remote device 4	0.3167, 0.4433, 0.57	0.0848, 0.1413, 0.1979	0.0611, 0.0856, 0.11	0.0219, 0.0364, 0.051
remote device 5	0.4433, 0.57, 0.57	0.1979, 0.2544, 0.2544	0.0856, 0.11, 0.11	0.0073, 0.0073, 0.0219
A^* (FPIS)	0.4433, 0.57, 0.57	0.1979, 0.2544, 0.2544	0.0856, 0.11, 0.11	0.0364, 0.051, 0.0656
A^- (FNIS)	0.0633, 0.19, 0.3167	0.0283, 0.0848, 0.1413	0.0367, 0.0611, 0.0856	0.0073, 0.0073, 0.0219

Table 5. Weighted computation decision matrix for the five remote devices

The outputs of the fuzzy TOPSIS analysis are shown in Table 6.

Remote Device	d^*	d^-	C_i^*	Rank
remote device 1	1.0435	0.6523	0.3847	4
remote device 2	1.0675	0.5043	0.3208	5
remote device 3	0.2716	1.3431	0.8318	2
remote device 4	0.8162	1.0352	0.5591	3
remote device 5	0.1671	1.2947	0.8857	1

Table 6. Outputs of fuzzy TOPSIS

Using equations 4.7 and 4.8, D_i^+ and D_i^- are computed. Thus, using the C_i^* values, the ranking of the remote participating devices can be made as follows: D_5, D_3, D_4, D_1 and D_2. D_5 holds the highest C_i^*, that is, $C_5^* = 0.8857$. Therefore, we can conclude that based on the four criteria considered simultaneously, remote participating device D_5 is the optimal choice among the other four potential devices available for the source device S. That is, the middleware running on S should choose D_5 to offload the mobile codes of the partitioned application concerned.

5. Conclusion

Selecting only one criterion as previous algorithms work is limited. Both single and multiple criteria analysis were performed. We proposed a method that considers multiple criteria such as bandwidth, performance, availability and security in determining the optimal remote device for code offloading. The method uses a combination of AHP and fuzzy TOPSIS. AHP is used to get weights of the criteria for each participating device and fuzzy TOPSIS is used to determine the priorities of the devices in the decision-making process. This work aims to help researchers in the area of software partitioning for offloading in ranking the list of available participating devices to host mobile codes. Hence, making the overall offloading system performance more effective.

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