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Multi-objective Optimization Model in Mobile Data Communication Scheduling

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***Abstract*—The paper describes a multi-objective model to optimally schedule a service on a mobile device that requires data communication with the external data repositories.**

Keywords—scheduling; multi-objective optimization; mobile device; real-time data access.

I. Introduction

Mobile device usage is growing as is their ability to provide sophisticated services. The primary reason for the growing popularity of the mobile devices is their ability to support relationships among the peers through the connectivity and communication anywhere and anytime mantra [1, 2, 3]. However, the mobile devices have noticeable resource constraints and users are often concerned about the communication costs, battery life and device busy periods.

One common approch to handle the problems with multiple goals is to assign weigths to each of the objectives the users value. A consolidated single score can be computed by taking the weigthed sums of the individual scores. However, such an approach would be unsuitable for detrmining the optimal schedule for data communication from mobile devices. The mobile users do not have the same preferences; and more importantly, their prefernce mix would vary widely based on the service initiating the data-communication. For example, a user's interest in a mobile service dependent on the alternates available to the user. Further, the available services may vary over time and geographical location of the user of the mobile service. This makes the use of weigthed sum approach for estimating potential benefits to a user impractical.

The paper describes a model that aids in finding the Pareto optimal schedules for the data communication dependent services available through the mobile devices.

To motivate, we present the following made-up problem: A mobile device user accidently meets the President holidaying on a remote island and is invited for a breakfast with the first family. The user has a number of pictures that she is eager to share them with her social groups. What is the best schedule to upload these pictures?

The paper is organized as follows. The section II describes the decision variables and other parameters that determine the behavior of the communication episode. The objective functions of interest to the mobile users are listed and modeled in section III. Section IV describes the use of the model to determine the Pareto efficient values for the decision variables. The last section provides other potential applications and extensions for the model.

II. Multi-Objective Model for Mobile Data Communication

Several studies have been conducted to identify and understand the satisfaction factors of the mobile device users [2, 3, 4]. However, these studies do not explain how the mobile device users can optimize the access to a service by scheduling it for better outcomes. The problem of optimizing the access to a service through a mobile device can be set as a multi-objective optimization problem since there are more than one satisfaction factors required to be optimized and these satisfaction factors are conflicting with each other.

A mobile user has two primary decision variables controlling the access to mobile services: the postpone interval (delay) and the communication mode to use for the data communication (mode). The postpone interval, delay, represents the length of the period by which the data communication is delayed after the need for a data communication outside the mobile device is first noted; in this paper, the time at which the data communication need is first noted is marked as time 0. The communication mode, mode, as the second decision variable represents the use of a wired, Wi-Fi or a cellular data network to contact the data repository. These communication modes may have further specializations determined by their speed, noise or price characteristics. In this paper, we will use the following identifiers and functions in the equations:

size(data)	Size of the data to be communicated by the mobile service.
batteryCharge(t)	MilliAmpere hours (mAh) of the electric charge stored in the mobile device battery at time t.
dischargeRate(mode)	Battery discharge rate mAh/s in communication mode *mode*.

speed(mode)	Communication speed for communication mode *mode*.
qdr	Quiescent discharge rate for the device battery to keep the device active
nextChargeTime(t)	Time for the next battery charge opportunity at or after time t
available(mode, t)	Boolean function; true if the mobile user can use communication mode, *mode*, at time t. A mobile user may avoid a live communication mode if it is considered unsecure. Thus, the function captures security needs.

III. OBJECTIVE FUNCTIONS

When accessing a service requiring data communication from a mobile device, the device owner seeks to choose values for the decision variables delay and mode to use the best data communication outcomes for the service. The proposed model defines five objectives to find the Pareto-optimal solutions: data access cost, service efficacy, battery charge depletion, depleted battery charge encumbrance, and device unavailable duration.

A. Minimizing Data Access Cost

A high cost for the mobile Internet access discourages the users from accessing the Internet from their mobile device [4, 5]. The cost of the mobile Internet access is determined by the amount of data communicated and is dependent on the available communication modes and the time of the access. Since the cost of communication varies across many different network providers, a lower data communication cost can be achieved by delaying the communication for a particular interval of time in order to get a cheaper available connection.

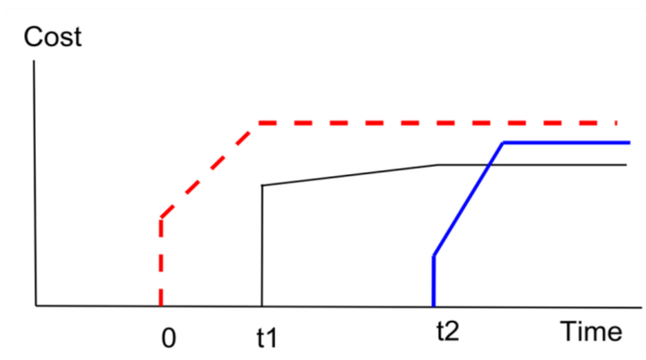

Fig. 1. Data access cost.

A simple model for the communication cost that approximate common arrangements available to mobile users can be based on a fixed per service cost with variable component determined by the amount of data. The specific service accessible to the user may depend on time and location. As shown in Figure 1, a mobile user may control cost by accessing service at an opportune time.

In mathematical notation the cost objective goal can be represented as:

$$\textit{Minimize cost(delay, mode)} = \textit{fixedCosts(delay, mode)} + \textit{varCosts(delay, mode)} * \textit{size(data)} \quad (1)$$

B. Maximizing Service Efficacy

Mobile users and applications place a significant premium on the immediacy of the data interaction and servicing. In this respect, the data communication requirements have the characteristics similar to the real-time applications. The full benefits of the service are derived if the data can be transferred before a user or service specific deadline; titled festive deadline. However, if the service is delayed past a later deadline, titled obsolesce deadline, the mobile user derives little benefit from the service. Basic real-time schedulers approximate the benefits from a service completed between these two deadlines using a linearly decaying service efficacy function [6, 7]. Figure 2 provides a easy to understand picture to explain our model.

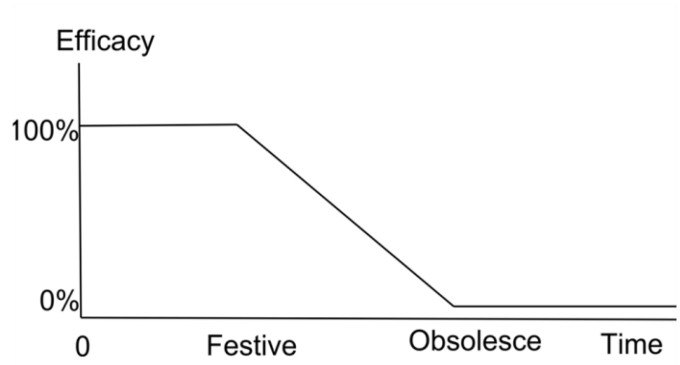

Fig. 2. Service efficacy.

Thus, the service efficacy objective is expressed as:

Maximize efficacy(delay, mode), where

$$\textit{efficacy(delay, mode)} = 1 \quad \text{when } \textit{delay} < \textit{festive}$$

$$\textit{efficacy(delay, mode)} = (\textit{obsolesce} - \textit{delay})/(\textit{obsolesce} - \textit{festive}) \quad \text{when } \textit{festive} \leqslant \textit{delay} \leqslant \textit{obsolesce} \quad (2)$$

$$\textit{efficacy (delay, mode)} = 0 \quad \text{when } \textit{delay} > \textit{obsolesce}$$

IV. OBJECTIVE FUNCTIONS RELATED TO THE BATTERY STATUS

Battery status is a fundamental constraint of the mobile devices resulting from the requirements for the mobile devices to be small and light. The battery power is required not only to run the mobile device to perform user started operations but also to keep the device functioning and continuing its quiescent services. Therefore, an adequate amount of remaining battery life is essential for the satisfied device owners.

The battery charges drain at a slow constant rate (*qdr*) to keep the device active and functioning. However, each data communication episode uses significantly larger amount of battery power to radiate signals and to perform the related computational activities. This demand is determined by a number of factors including the communication mode, duration and the noise characteristics of the communication channel. However, drained battery charge is not a permanent liability. The battery levels are restored by recharge of the device batteries. Considering the importance of the remaining battery charge for the mobile device, a number of objectives exist in the model.

C. Minimize Battery Charge Depletion

The remaining electric charge in the battery after a data communication episode is a function of three arguments: the state of the battery before the communication episode, the communication mode used for the data communication, and the duration of communication. The communication duration is primarily determined by the amount of data transfer and the transmission speed for the communication mode. However, transmission speed is also affected by the environmental conditions such as the channel noise and congestion. Smaller battery discharge in completing the data communication needs of a service leaves more charge for other services; thus (See Figure 3):

$$\begin{aligned}&\textit{Minimize batteryDischarge (delay, mode)} = \\ &\textit{dischargeRate(mode)*size(data)/speed(mode)}\end{aligned} \tag{3}$$

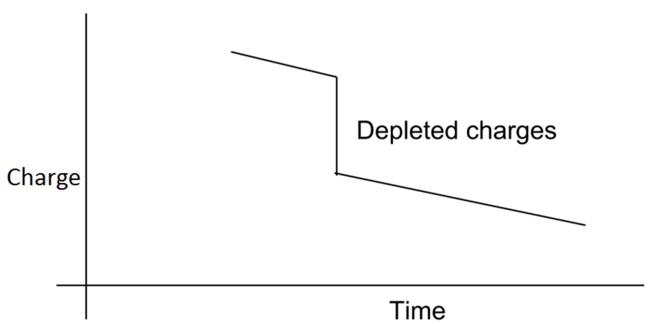

Fig. 3. Depleted charges.

Closely related to this objective are the constraints that determine the feasibility of the communication episode. Firstly, the communication mode should be available over the period *delay* to *delay + size(data)/speed(mode)* for the data to be communicated. Secondly, the battery should have enough charge to complete the data communication. These requirements are expressed in the constraints below:

$$\begin{aligned}&\textit{available(mode, t)} \quad \textit{delay} \leqslant t \leqslant \textit{delay} + \\ &\textit{size(data)/speed(mode)} \\ &\textit{batteryCharge(delay)} \geqslant \\ &\textit{dischargeRate(mode)*size(data)/speed(mode)}\end{aligned} \tag{4}$$

D. Minimize Depleted Battery Charge Encumbrance

If a resource is used for a purpose, it is not available for the alternate purposes. Economists describe the idea as an opportunity cost. A similar dilemma is also faced by the user of a mobile device. Battery life is an important resource and a mobile device becomes inoperative once the battery has run down below a low charge threshold. The savvy mobile users take significant care to preserve the battery life. It is not uncommon to notice the mobile users minimizing the device usage to preserve the battery charges to the time when the device battery can be recharged.

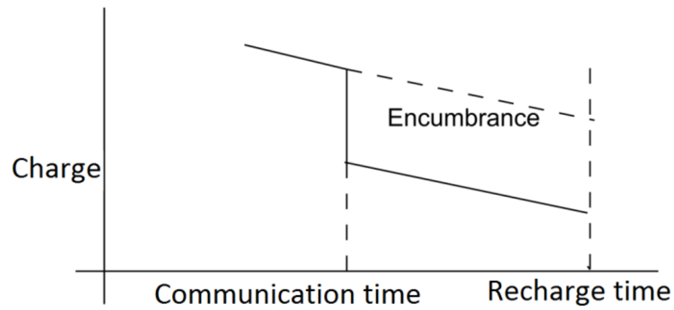

Fig. 4. Charge encumbrance.

This objective is modeled by the area under the battery charge line plotted against the time.. Each data communication episode reduces the area; and, this reduction in the area defines the depleted battery charge encumbrance for the mobile user. The idea of encumberance is depicted in Figure 4 and affects the users quite distictly from the depleted charges as shown in Figure 3.

The encumbrance reduces the future opportunities to use the mobile device due to the reduced remaining battery charges. As the common mobile devices use rechargeable batteries, the encumbrance is cleared at the next battery recharge.

$$\begin{aligned}&\textit{Minimize encumbrance(delay, mode)} = \\ &\textit{(nextRechargeTime(delay) – delay)*} \\ &\textit{dischargeRate(mode)*size(data)/speed(mode)}\end{aligned} \tag{5}$$

E. Minimizing Device Unavailable Duration

A mobile device is not fully available to its user when it is busy in a data communication based service. This limitation is a consequence of the constraints on the computational resources as well as the limited communication bandwidths available to the mobile devices. A long access time is annoying and lowers user satisfaction [4, 8]. A longer access period also drains more battery charges [9].

The device busy interval is the time interval required to successfully transmit the data using the available communication modes – this also is a period of significantly restricted availability of the mobile device. Thus, the objective:

$$\begin{aligned}&\textit{Minimize deviceUnavailable(delay, mode)} = \\ &\textit{size(data)/speed(mode)}\end{aligned} \tag{6}$$

The constraints listed earlier with the objective function battery charge depletion apply to this objective too. However, there is another cause leading to a potential device unavailable situation. The events leading to this situation are described as follows: if the battery charge is depleted by a data communication episode, the remaining charges on the battery may not sustain the device in the active mode till the next recharge time. In this case a period may occur, before the next recharge, where the device is unavailable because the device battery charges have drained to their low threshold level. The situation may be cared for in the model by augmenting the constraints on the feasible solutions.

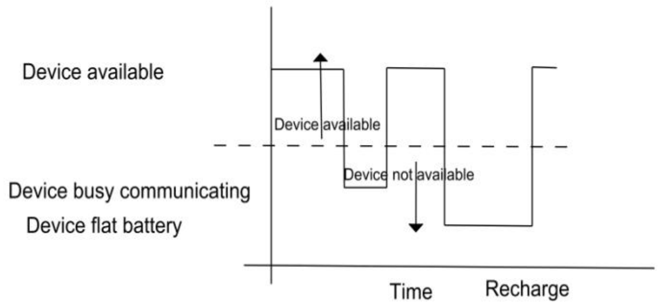

Fig. 5. Device availability.

Therefore, each feasible decision must ensure:

$$BatteryCharge(delay) \geqslant dischargeRate(mode)*size(data)/speed(mode) + (nextRechargeTime(delay) - delay)*qdr \quad (7)$$

If the inequality is not satisfied, the device battery will discharge to a level below the minimum threshold and cause the device to become unavailable. Thus, the function to be minimized when the condition is not met is:

$$Minimize\ deviceUnavailable(delay, mode) = size(data)/speed(mode) + (nextRechargeTime(delay) - (BatteryCharge(delay) - ischargeRate(mode)*size(data)/speed(mode))/qdr) \quad (8)$$

V. How to Use Model to Schedule communication

In this section we describe how the objective functions can be used to determine a communication schedule to suit the service requirements. Using realistic operational parameters for costs and speeds available to the Australian users of mobile devices in 2012, we set a simulation study. A data communication requirement was determined and fed into the simulation software. The Pareto optimal (Refernce) solutions were identified. Pareto optimal solutions are the tuples that are not dominated by the other feasible solutions. A solution p is said to dominate the other solution q, is p performs on at least one criterion better than q and performs at least as well as q on all other criteria.

To further help explanation, a simulation scenario is constructed in order to compare the optimum solutions produced by our model with the possible unaided solutions which ~~are~~ a user might chose for this case. An unaided or blind solution in this case is a solution where the device owner performs the data communication activity immediately. Most mobile device data communication today operates in this mode. We compare these blind and optimum solutions based on the five objective functions that we have explained earlier. The following figures show the solutions comparison for this case.

In order to construct the simulation model, jMetal framework is used as the building blocks. jMetal stands for Meta-heuristic Algorithms in Java, it is a framework for constructing and solving a multi-objective optimization problem using evolutionary algorithms. The framework is based on Java programming language and has been used in a wide range of applications since it was built as an easy to use, flexible, and extendable software package. The ease of use, flexibility, and extendibility can be achieved by jMetal since it takes full advantage of the capabilities that Java offers and is structured in a way that a problem can be developed as an independent class from the algorithm that solves it. A wide range of core classes which can be used as the building blocks of multi-objective meta-heuristics are provided by this framework in order to take advantage of code-reusing. In addition, the evolutionary multi-objective algorithms in this framework are tested for their performance with standard multi-objective optimization problems [10].

VI. Discussions and Conclusions

The paper has presented a multi-objective model for scheduling the data communication based services on the mobile devices. As these objectives are incomparable with each other and represent different needs they cannot be assigned meaningful weights to generate a single outcome. Even if such weights were feasible, each mobiles user will attach different weight of importance to these objectives. Indeed, one would expect the same user to assign different weights to these objectives at the different times. Pareto optimal solutions provide the best option for determining efficient schedules.

Using realistic parameter values and cyclic lifecycle of the mobile users we have run several test scenarios. The experiments support the common wisdom of preferring a wired data communication mode over a Wi-Fi mode and preferring the Wi-Fi communication over the cellular communication. This rule receives support as these preferred modes also frequently overlap with the battery recharge opportunities.

The Pareto efficient schedules, however, tend to occur over the disjoint time periods. The efficient periods are separated by the periods of time where the decisions deliver less satisfying (dominated) outcomes.

The increasing adaption of the cloud computation and resources would make the services on the mobile devices even more dependent on the externally located data. The models for scheduling the data communication would be helpful in optimizing the use of mobile device resources and capabilities.

VII. Future Works

For the future works of this research, there are several possibilities that can and need to be explored.

The simulation model in this research can be augmented in order to handle multiple transfers and multiple data access. The enhanced model may be used to schedule the data transfer in an optimized way. Alternatively one may propose an algorithm to

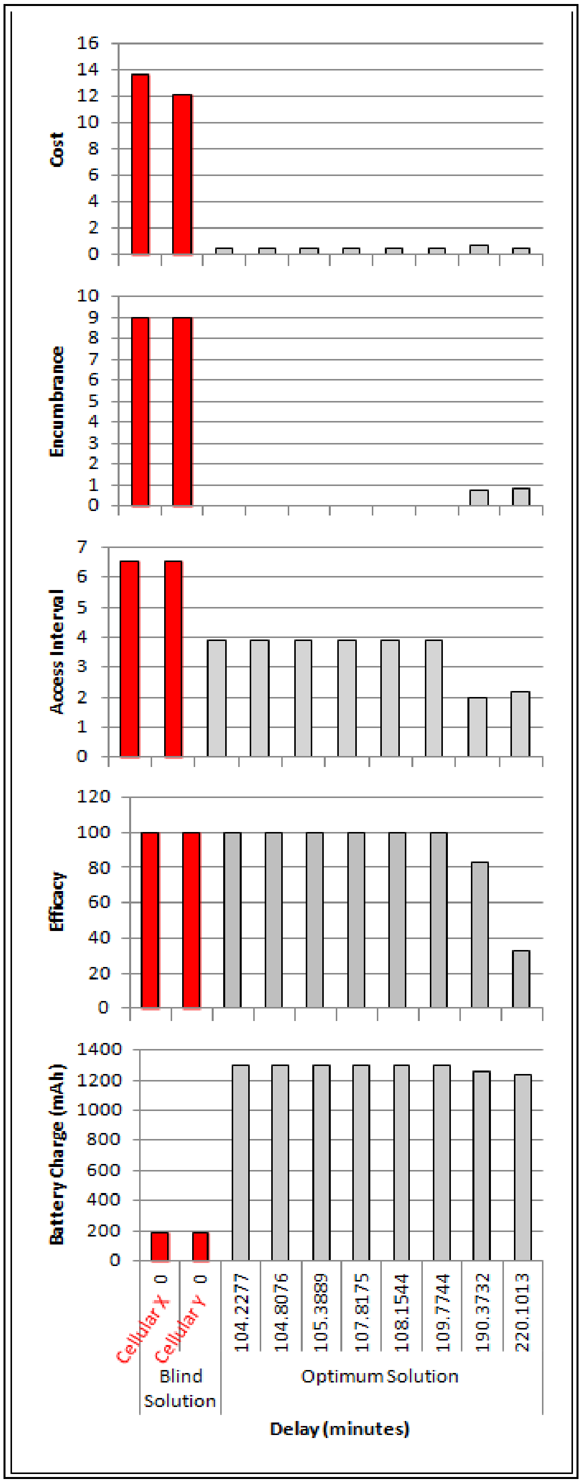

Fig. 6. Evaluation result.

priorities the transfers and choose a subset of them for actual transfer consistent with the expected cost and benefit outcomes.

A machine learning capability can be integrated into this model to predict the mobile user's daily activity in order to generate a more accurate resource availability schedule/table. A simulator tool may also be of value to monitor the device and its usage to provide accurate and precise estimates of various parameters used in the model.

Sensor devices are often deployed in remote locations without 24x7 accesses to resources. Their data transfer operations may be subject to natural and unpredictable activities. For example long periods of cloudy weather may reduce the charge in the battery. Data communication may be subject to the availability of a base station. The model can be extended to optimize data collection activity for remote sensors.

Cloud computing resources also have access patterns that are subject to interruption quality variations similar to the issues modeled in this research. The model can be extended to optimize and streamline access to cloud resources for cost, reliability, security and availability benefits.

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