Performance Aware Adaptation in Open Corpus E-Learning Systems

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Abstract. This paper presents a Performance Oriented Adaptation Agent (POAA) architecture that improves adaptive selection of Learning Objects stored in distributed knowledge repositories. This approach can enhance adaptation process in the Open corpus Adaptive Educational Hypermedia System (OAEHS) Server. The focus is on enhancing existing adaptive selection process by considering network performance factors at a session level. The solution involves taking into consideration not only the user's characteristics and preferences but also throughput conditions on relevant connection links. Introduction of performance oriented DER selection minimises download latency and in turn increases the user's quality of experience.

1 Introduction

Adaptive Hyper-media Systems (AHS) are web-based solutions that identify user categories and deliver differentiated content tailored to individuals or groups based on user characteristics such as skills, goals, capabilities, knowledge, interests and preferences [3]. Possible adaptations include content modifications (the content is adapted to best suit the users) and link adjustments (the link structure is tailored to guide the users towards relevant and interesting information) [3]. Adaptive Educational Hypermedia Systems (AEHS) such as AHA! [8], ELM-ART [24] and InterBook [5] seek to optimise learner experience with their online course material by personalising this material to the learner's individual learning requirements. All these systems are stand-alone systems dealing with a limited number of well-structured resources known at system design time (so-called closed corpus systems) and although deployed in the Web context, provide no support to incorporate information from arbitrary Web locations.

Open Adaptive Educational Hypermedia Systems (OAEHS), such as KBS [12], are AEHS that operate with existing information resources such as Digital Educational Repositories (DER). These systems use an open corpus of documents and adapt hypermedia documents to the individual needs of the user regardless of the origin or location of the materials. For example, the materials may be part of a tutorial, may refer to content from a personal Web page or could be Learning Objects (LOs) that belong to an open repository of learning material. Such information space must be searchable, interoperable and accessible.

Web-based educational systems, including OAEHS are distributed by nature and their response time depends on the underlying network performance. Download latency can be defined as the time that elapses from the user requesting a page to the moment the user receives the requested page. A number of surveys [22], [1], [11] indicate significant adverse effects of long download waiting times, resulting in the changes in users' attitudes, behaviour (e.g. decision to abandon a web page or intention not to visit the site again) and perceptions including the perception of web pages' quality and usability [18]. Consequently, the user's performance suffers resulting in work of inferior quality and accuracy. Even delays as short as four seconds decrease performance and change behavioural intentions [10]. Today's Web users use "devices ranging from mobile phones to domestic appliances" [6], and at the same time, they "expect a usable presentation regardless of the device's capabilities or the current network characteristics [14]. Same can be applied to today's learners and despite continuous improvements in infrastructure "users continue to discover new applications that consume these additional resources" [21]. The Web users' expectations grow each year, and their demands continue to increase, out-pacing the provision of the Web infrastructure.

Traditionally, learning systems content is tailored with large screen devices (PC, laptop) and uninterrupted network availability in mind. Today's learning devices are limited in terms of screen size, network connection cost and quality, user input/output modalities, platforms supported, battery life and processing/storage power. AH research in the area of education places very little emphasis on delivery performance and its effect on the learning process. Context-related issues are addressed by Smith [23] who focuses on the end-user device and Muntean [16] who considers different network-related factors. Muntean et al [17] enrich content authoring process by considering the end-user device's display resolution, battery power, colour depth, CPU power and multimedia support. Existing terminal-aware adaptive hypermedia systems include APeLS [7], [2], MobiLearn [13], iClass [19]. Learning systems should consider different, sometimes orthogonal properties during the adaptation process, for example, an learning system should balance the user's interest, LO's suitability, the user's device capabilities and network connection in order to produce most suitable content in the best possible way on a small screen size device under poor network conditions.

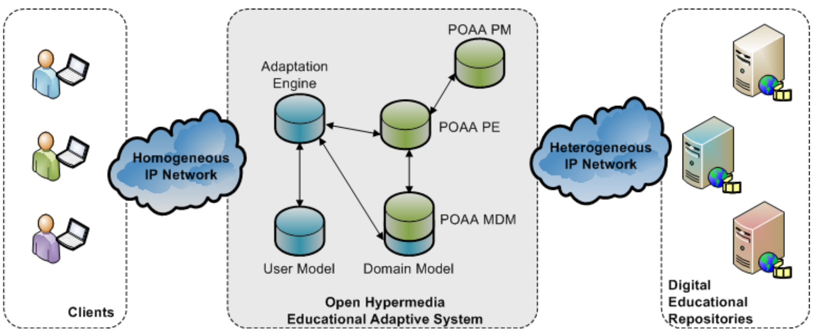
Our approach considers Learning Object's suitability (to the learner's needs) and network conditions to produce most smoothly delivered and presented learning material at any given time. This work considers the case where a learner wishing to get learning content uses an Open Adaptive Educational Hypermedia System (OAEHS) to access a choice of available multimedia learning content possibly stored in multiple Digital Educational Repositories (DERs). The matchmaking mechanism to find the set of LO providers is implemented within an OAEHS, and we can focus on request allocation only. The OAEHS maintains multiple simultaneous connections with a number of DERs, the links differ in quality and nature. DERs are not mirrors, however a level of duplication exists and copies of a number of LOs reside on multiple DERs. It is assumed that the user has a free access to any material accessed through the OAEHS in question and the cost aspect of providing learning content is not considered. It is also assumed that every user has a patience limit and will only be willing to wait so long for the download of the requested learning content before they become dissatisfied and consequently, in the worse case abandon the page. This approach prioritise LO requests in order to minimise download delays for more suitable learning objects.

2 Performance Aware Adaptive Solutionin Open Corpus E-learning System

2.1 Architecture

The learning content selection process is triggered at every user's request for learning content. At that time the list of suitable LOs is generated by OAEHS. OAEHS front-end server selects learning objects with matching learning objectives from various sources, it then builds a presentation suitable for the learner and finally, delivers the presentation to the end user device. A POAA [20] is installed on OAEHS front-end server to enhance the adaptation process by minimising download latency. The POAA monitors network conditions between the OAEHS front-end server and DER servers to determine network performance without employing an agent at DER side. Network parameters considered are related to the delivery performance and include download time and delay. They are inferred from ten most recent sessions with DERs storing requested LOs. The block-level architecture for the OAEHS with POAA is shown in Fig. 1.

Fig. 1. Block Level Architecture



POAA consists of two components, namely POAA Performance Model (POAA PM) and POAA Performance Engine (POAA PE).

POAA Performance Model Performance Model is the passive POAA component. At the user request, OAEHS generates a list of Suitable and Relevant LOs (SRLO) List. The LO's suitability is based on the OAEHS user model while the LO's relevance depends on the characteristics of the user's current request. It is assumed that the SRLO list contains the following information for each suitable LO:

- LOID - LO's identification code (unique within OAEHS Domain Model)
- LOURI - LO's Universal Resource Identifier (URI)
- LOSR - LO's Suitability Rating, ranging from 0 (not suitable) to 100 (perfect match for the learner)

Performance adaptation starts when POAA receives the SRLO list. The list is processed starting from the most suitable LO to less suitable ones. The POAA Performance Engine, described in Section 2.1 calculates performance ratings and generates Performance data enriched SRLO (PSRLO) list. The list is extended with LO's performance rating, size, alternative locations and type. The following attributes (metadata) are elicited by POAA:

- LOPR - LO's Performance Rating (ranging from 0 to 100)
- LOT - LO's type, namely Text, Image (Graphics) and Multimedia streams (Audio or Video)
- LOS - LO's size in KiloBytes (KB)
- LOAL - A list of alternative locations (DERs that store the LO)

Sample content of an PSRLO list is given in Table 1.

Table 1. PSRLO List: Sample Content

LOID	LOPR	LOT	LOS	LOAL
Mat980	83	Video	450	LOS03
Mat344	69	Image	5	LOS04

Where LOS03 and LOS04 are lists containing alternative URIs for LO1 (Mat980) and LO2 (Mat344) respectively.

Each DER is assigned an unique ID. The POAA Performance Engine maintains a history log for each connected DERs (DER log). The log is a sliding-window structure that contains readings for ten most recently requested LOs from a given DER. The following readings are maintained for each DER:

- LOID - LO identifier
- Loss - the number of lost packets

– Delivered - the number of received packets
– RTT - Round Trip Time in milliseconds
– Duration - the difference between the delivery and request time in milliseconds
– Time Stamp - the date and time when the LO is requested

Sample content of a DER log is given in Table 2.

Table 2. DER Log: Sample content

LOID	Loss	Delivered	RTT	Duration	Time Stamp
Mat980	2	448	0.2	0.8	2008-10-30 08:30
Mat344	0	69	0.002	0.01	2008-10-30 10:45

POAA Performance Engine POAA Performance Engine (POAAPE) is the active part of POAA. It calculates performance ratings for all LOs given in SRLO List at each learner's request. The structure of updated SRLO is given in Section 2.1. Furthermore, POAA PE selects DERs to be contacted and schedules requests for each LO in SRLO list.

Performance rating is based on the network condition, therefore POAA PE continuously seeks information on the state on the links to the connected DERs. The amount of additional traffic introduced with this process should be minimal as it may be resource consuming and wasteful in the ever changing Internet environment. The idea is to collect as much information as possible without employing agents on the DER and client sides. Therefore POAA PE collects details for each LO requested and delivered, the details are stored in DER logs. The structure and content of DER logs is outlined in Section 2.1.

Performance Aware Selection Process On a learner's request, OAEHS typically generates a list of suitable and relevant Learning Objects - SRLO. It is assumed that the OAEHS is aware of DERs that contain different learning objects. POAA PE will identify the most efficient DER based on the DER's performance factors. The adaptaton algorithm makes sure to select the most efficent LOs. The DER's performance factors (average throughput and delay) are calculated based on the history collected over ten most recent connections. The values of these parameters are collected and stored separately for each DER in a sliding window-like structure. Every time a learning object is selected and new performance information is acquired, the relevant DER's sliding window is updated. All readings are of same importance. For each LO_j within the provided SRLO List, starting from the most suitable one, POAA PE calculates expected delivery times ($expectedDeliveryTime_{LOjDERi}$) for every DER_i on which the LO resides. The expected download time is calculated based on the following formula:

$$expectedDeliveryTime_{LO_j DER_i} = \frac{Size_{LO_j}}{estThroughput_{DER_i}} + estDelay_{DER_i} \quad (1)$$

The repository DER_S with the shortest expected delivery time for LOj is selected and sent a request for LOj. The selected DER's (DER_S) estimated throughput is updated based on the size and expected delivery time of the requested LO as given in Equations 2. The estimated throughput is updated when the requested LOj arrives to OAEHS.

$$estThroughput_{DER_S} = estThroughput_{DER_S} - Size_{LO_j} \quad (2)$$

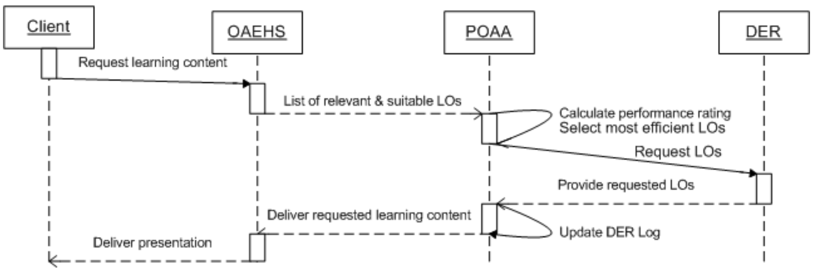


Fig. 2. Test sequence diagram

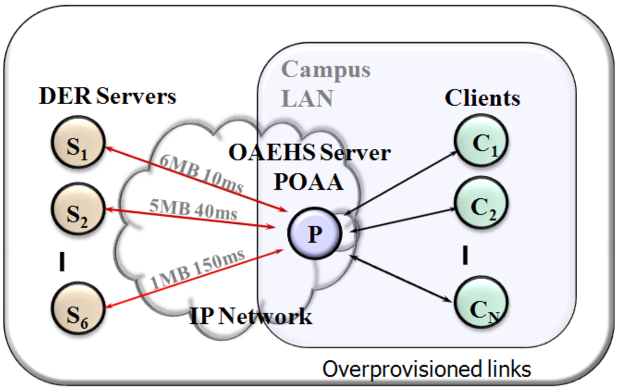
3 Modelling and Simulation

Preliminary tests are currently performed using Network Simulator version 2.29 - NS2 [15]. NS2 is a discrete event simulator, with substantial support for simulation of protocols at various levels of the TCP/IP networking model over wired and wireless networks.

3.1 Test Bed

This paper presents tests which involve one client only. The test setup is presented in Fig. 3. Clients (C_1, C_2 , ..., C_N) and DER servers (S_1, S_2, ..., S_6) are connected to a OAEHS server (P) on which POAA was deployed. In order to evaluate the efficiency of the POAA employment the following simulation was performed. This simulation models a university campus situation, where POAA resides on the university proxy server and learners are using personal computers within the campus local area network. The network links between the server and the clients (P-C_i) are over-provisioned such that no loss or significant delays

Fig. 3. Simulation topology



are expected. The network connections from the server P to the DER servers (P-S_i) differ in terms of bandwidth and propagation delay. This model deals with homogeneous clients in terms of the end-user device and network connection. Certain delays will occur while sending the content from the server (P) to the clients, however, it is assumed that these delays will be constant and the same due to the homogeneity of the clients and therefore not considered in this setting. Assuming that the last leg (P-C) has no major impact on the delivery performance, the calculated performance rating is based on the measurements gathered monitoring the communication between the server (P) and the DER servers (S_i).

The test configuration details are as follows:

– **Characteristics of links.** Three different DERs are considered, and measurements are taken for the appropriate links (P-Si, i in 1, 2, 3, 4, 5, 6). These links are of different bandwidth and delay. The link (P-S1) between the server (P) and DER1 (S1) has the best characteristics (6 MB, 10 ms), the quality of other links is gradually decreased (1MB smaller bandwidth and 30 ms longer delay), finally, the sixth link (P-S6) exhibits the worst characteristics (1 MB, 150 ms). Links between the server (P) and client is overprovisioned, assuming on-campus use.
– **Characteristics of LOs.** It is assumed that copies of LOs (matching learning output and suitability rating) reside on all six servers. TCL random-uniform function is used to generate LO sizes (pseudo-random numbers) which are effectively distributed according to the uniform distribution. The minimum value of the distribution is set to be 1KB, while the maximum value is 100KB - U(1000,100000).
– **Characteristics of requests.** All LOs selected by OEAHS (SRLO List) are requested. All requests originate from a single client.

3.2 Test Scenario

In each simulation, the number of LO requested was varied from one to twenty. The size of requested LOs is kept constant i.e. the same LOs are requested in all three cases. To compare systems performance, the delivery time is measured. Current adaptation aims at delivering every LOs given in SRLO List.

The sequence of the testing process is presented in Figure 2. When a learner requests some learning content, POAA acting as a broker, contacts the OAEHS requesting the learning content. It is assumed that the OAEHS is aware of the content stored on distributed DERs. The OAEHS sends back a list of relevant and suitable LOs and their sources - SRLO List. The relevance of the LO is determined based on the current request for learning content, while the suitability is based on the current user's model maintained by OAEHS. Once provided with the list of suitable LOs and the DERs where they reside, POAA based on DER's performance ratings assigns performance rating to each provided LO as described in Section 2.1. Finally, POAA requests LOs from most efficient DERs, which guarantees that selected LOs are delivered in an optimal/seamless manner with minimal latency. The learning content is delivered by the server (P). Caching would further improve the performance enhanced adaptation, however current tests do not employ caching at OAEHS Server side. The aim of these tests is to compare the delivery performance in terms of download time for a system that deploys the proposed POAA against those measured for a system that does not employ any intelligent selection of the content based on performance. The simulation involved three different scenarios with three different DER selection approaches.

- Case 1: OAEHS System deploys POAA to select source DERs.
- Case 2: OAEHS System randomly selects source DERs.
- Case 3: OAEHS System gets all requested LOs from the most efficient DER.

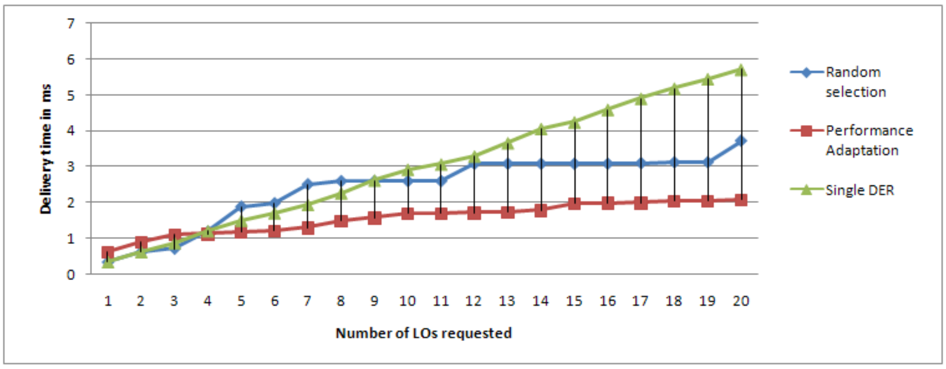
3.3 Results and Result Analysis

The recorded download times are compiled in Fig. 4. Current, preliminary results indicate a significant improvement in performance (reduced download times) when using the POAA-based system in comparison with the other two classic systems. There is no significant difference in download times when the number of requests is low (less than 5). However, the reduction in delivery time grows as the number of LOs increases. For example, when 10 LOs are requested, POAA enhanced system delivers requested LOs 35% faster than system with random selection of DERs and 42% faster than a system using a single DER. The difference in dowload times is even more significant for 20 requested LOs, namely 44% for randomly selected DERs and 64% for single DER systems.

4 Conclusion

This paper describes the architecture of a Performance Oriented Adaptation Agent (POAA) for Open corpus Adaptive Educational Hypermedia Systems

Fig. 4. Delivery Latency



(OAEHS). POAA enhances the existing selection process of learning objects by taking into consideration not only the user personal characteristics but also network delivery conditions. The preliminary test results given here illustrate a significant reduction in download times when using POAA. The time for download reduces up to 44% in comparison with systems without POAA (random selection of DERs), and up to 64% in comparison with a single DER systems. The use of POAA for OAEHS minimises download latency and is expected to improve overall learners' satisfaction and learning outcomes due to shorter waiting times and better quality of the delivered content.

The proposed agent could be used with existing distributed AEHS such as Knowledge Tree [4] to augment the current adaptation process. Furthermore, it can enhance performance of systems that enable personalised access to distributed heterogeneous knowledge repositories, an example of which is Smart Space for LearningTM (SS4L) [9].

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