

Semantic-Based Dynamic Service Adaptation in Context-Aware Mobile Cloud Learning

S. Muhamad, N. Admodisastro, H. Osman, N. M. Ali

Dept. of Software Engineering and Information System, Faculty of Computer Science and Information Technology, 43400 Universiti Putra Malaysia, Malaysia

E-mails: sufry@upm.edu.my novia@upm.edu.my hafeez@upm.edu.my hayati@upm.edu.my

Abstract: *Self-adaptable system concerns on service adaptation whenever errors persist within the system. Changes in contextual information such as networks or sensors will affect the system's effectiveness because the service adaptation process is not comprehensively handled in those contexts. Besides, the correctness to get the most equivalence services to be substituted is limitedly being addressed from previous works. A dynamic service adaptation framework is introduced to monitor and run a reasoning control to solve these issues. Hence, this paper presents a case study to proof the dynamic service adaptation framework that leverages on semantic-based approach in a context-aware environment. The evaluation of the case study resulted in a significant difference for the effectiveness at a 95% confidence level, which can be interpreted to confirm that the framework is promising to be used in operating dynamic adaptation process in a pervasive environment.*

Keywords: *Semantic-based, dynamic service adaptation, context-aware.*

1. Introduction

Numbers of dynamic service adaptation frameworks have been developed in a pervasive environment such as e-Health, e-Commerce transaction, smart building system, e-government, and many others. These frameworks have considered context-aware elements using a semantic-based approach in the dynamic service adaptation process for serving personalized services according to the users' needs.

The context-aware system is also being employed in the education domain such as Mobile Cloud Learning (MCL) application system. MCL facilitates learners to have a personalized learning environment based on their knowledge level, background, and their cognitive abilities [1]. Nevertheless, those frameworks [2-9] do not have sufficient information for the dynamic service adaptation process which then makes the frameworks became less effective. The specific adaptation criteria need to be derived as guidance and basic elements for creating a new framework in a context-aware environment for any discipline.

It is of great interest to measure the effectiveness of the frameworks in terms of their adaptation process according to adaptation criteria within expert reviewers. To

quantify the effectiveness of the adaptation process, a One-way non-parametric ANalysis Of VAriance (ANOVA) (Kruskal-Wallis test) [10] will be used to test the difference between the means of two or more independent (unrelated) groups.

The remainder of the paper is organized as follows. Section 2 discusses the background studies and related works of the research such as the dynamic service adaptation, context-aware, QoS, semantic-based approach, MCL frameworks. Section 3 details the framework. This section described the essential process in the framework. Section 4 explains the methodology of the evaluation process as well as the variables and measurement. Section 5 discusses the analysis of the results followed by Section 6, the conclusion.

2. Background and related works

This section discusses the dynamic service adaptation, context-aware, QoS, semantic-based approach, and MCL frameworks.

2.1. Dynamic service adaptation

Adaptation in the context of information system can be defined as:

...*“a process of modification, substitution or removal of the services in SBAs to satisfy new requirements, to fit with the new situation dictated by the environment, or violation of Service-Level Agreement (SLA)”* [11].

There are two classification of adaptation which are dynamic adaptation and static adaptation. Static adaptation refers to the process of shutting off the system where manual adaptation would be required, whereas dynamic adaptation refers to an automation process of changing the system without shutting down the system and with no human-in-the-loop [12].

Dynamic service adaptation is defined as:

...*“an execution process that dynamically changes the service composition by adding, removing, or replacing the services”* [13].

The dynamic service adaptation process is substantial in the dynamic adaptation lifecycle because the system requires no human intervention and no interruption whenever new requirements or change in the user's context is detected. The service engineering lifecycle [14] is separated into two parts which are the evolution part and the adaptation part. The evolution part highlights the design iteration, whereas the adaptation part concerns on the adaptation whenever needed. Thus, during the dynamic adaptation process, contextual information and QoS are considered to provide personalized services to the user.

2.2. Context-aware

Context is formally defined as:

... *“any information that can be used to characterize the situation of an entity. An entity can be classified as a person, object or place that interacts between a user and application including user and application themselves.”* [15].

Several categories of context have been defined by researchers to classify the contexts according to their behaviour. They categorized contexts into two dimensions

which are extrinsic and intrinsic [15]. External dimension also known as extrinsic refers to the context that can be measured by sensors such as temperature, touch, sound, location, light, and many others. Intrinsic or internal context refers to the user's interaction, emotional state, learner's objectives and task to complete [16, 17].

Extrinsic and intrinsic contexts can either be static or dynamic contexts [18]. A static context element is a context that does not change over time such as operating system capability, Central Processing Unit (CPU) memory requirement, and others, whereas a dynamic context element is a runtime context that can change over time such as network speed, battery status, and others. Thus, context-aware systems can be described as software systems that can adapt their behaviours according to the perceived context or situation, without explicit user intervention [19]. Besides the consideration of contextual information, QoS has also been considered during dynamic service adaptation. QoS is discussed in the next subsection.

2.3. Quality of service

Most of the research have considered QoS to select and rank the most equivalent service during runtime. There is research that considers availability, cost, reputation, and throughput in selecting the service [20]. These QoS are the most used in dynamic adaptation web service selection. Service availability and reputation have become critical factors in internet-based services and application successes as it provides the best services to the users [21, 22]. The availability of the service has a direct impact on the service's reputation [23]. As service discovery has a list of functionalities to match services, then ranking and selection of the service are often made based on the QoS attributes value such as availability, reliability, price, and rating. Availability and reputation are two QoS that most of the research use for service ranking and selection.

Service is available when it is reachable, and functions as expected. Availability is the probability of the system running and it is correlated to reliability. It can be measured as stated in the equation [24]

$$(1) \quad A = \frac{\langle \text{upTime} \rangle}{\langle \text{totalTime} \rangle} = \frac{\langle \text{upTime} \rangle}{(\langle \text{upTime} \rangle + \langle \text{downTime} \rangle)},$$

where:

A is referring to the availability of the service;

$\langle \text{upTime} \rangle$ is the total period during the measurement period when the system running;

$\langle \text{downTime} \rangle$ is the total period of the system that has been shut off and unavailable for use during the measurement period;

$\langle \text{totalTime} \rangle$ is the sum of the measurement time $\langle \text{upTime} \rangle$ and $\langle \text{downTime} \rangle$.

On the other hand, reputation level is ranked from low to high (i.e., 1, 2, 3, 4, and 5). Scores of 1, 2, and 3 are considered low while 4 and 5 are considered high scores. Services with low reputation scores will be taken as untrustworthy services and they will not be considered for service selection [25]. The reputation score can be measured as stated in the equation [26]

$$(2) \quad \bar{x}_n = \frac{1}{n} \sum_{i=1}^n x_i,$$

where:

\bar{x} denotes the average of n rating;
 x_i denotes a rating according to a time sequence;
 $i = 1, 2, \dots, n$.

Thus, service discovery is based on functionality matching and the ranking of the service is in accordance with the QoS requirement. The ranking and selection of the service may vary in techniques and approaches. The contextual information and QoS then can be transformed in a meaningful way using semantic-based approaches.

2.4. Semantic-based approaches

This is an implicit approach to provide a complete representation and description of the services to support the adaptation process while system is running [27]. There are six basic techniques in semantic-based approach as pre-discussed in some research. The techniques are the *Model Driven, Code-Level Approach, Ontology-Based Solution, Message Interception, Rule-Based Reasoning and Middleware Solution* [19, 28].

These techniques can be combined to provide better expressiveness of the contextual information and to support the reasoning process. The learning process will be flexible when mobile device is used, as it comprises mobile context such as social context, temporal, and physical interaction. These contexts can be modelled as an ontology to classify the learning goals and learning resources with different levels of granularity, and context of mobile data [29, 30].

A hierarchical relationship between learning goals, learning resources and mobile context can be formulated. The hierarchical concept can visualised the relationship between contexts which is learner contextual information and device contextual information from British educational ontology [30].

This contextual information can be semantically transformed using web ontology languages. The common web service ontologies such as Web Ontology Language for Web Services (OWL-S) [31], Web Service Modeling Ontology (WSMO), and Semantic Web Service Description Language (WSDL-S) have been discussed [20, 32-34].

2.5. Mobile Cloud Learning (MCL) systems

MCL is a collaboration of mobile learning and cloud computing that enables the mobile device to connect to the network access for education purposes [35, 36]. The main objective of MCL is to provide learners with a customized learning resources based on their level of background knowledge and cognitive capabilities. MCL consists of four recursive components, which are *Assessment, Learning, Communication, and Analysis*.

Since context-aware is applied in MCL, it helps in the reasoning control of acquiring and supplying the personalized educational resources for learners [36]. Context-aware facilitates MCL to be more adaptable and allows for adjustments according on the learners' needs. Here are nine related studies having been reviewed. The Personalized and Adaptive Context-Aware Mobile Learning (PACAML) [2], Personalized Context-Aware Learning System (PCALS) [3], Mobile Cloud Computing (MCC) [7], Accessible and Personalized Mobile Learning System

(APMLS) [9], Units of Learning mobile Player (UoLmP) [5], Mobile Semantic Web Assessment Personalization (MobiSWAP) [6], Personal Data Locker (PDL) [8], Mobile Response System (MRS) [4], and Web-based Learning Platform (WLP) [16].

Based on the reviewed studies, most of the research has acquired intrinsic and extrinsic contexts to carry out adaptation such as user's location, user's profile, language, device's status, goals, or time. The usage of technologies varies across the frameworks, most of them using OWL-S to represent their context. In terms of the type of automation in the adaptation process, most of the frameworks are self-adaptive [2, 3, 16, 4, 6-9] and only UoLmP [5] requires human intervention.

The frameworks [2-9] have followed the design process of dynamic adaptation lifecycle [14] as well as adaptation taxonomy [37, 38]. However, those frameworks have not thoroughly considered what is needed in dynamic service adaptation in a context-aware environment, which makes those frameworks less effective since the frameworks have not completed the whole cycle of the adaptation process. Table 1 shows the derivation of the respective adaptation criteria. These criteria are proposed as guideline to create framework in a context-aware or pervasive environment.

Table 1. Criteria in a dynamic service adaptation framework

No	Criteria	Adaptation lifecycle		Supported research
		S-Cube service engineering lifecycle [14, 9, 12, 34]	MAPE-K [35, 36]	
1	Usage of Adaptation ⇒ Adaptive adaptation (Context-Aware Adaptation)	X	x	[13, 41-45]
2	Stage of Adaptation ⇒ Run-Time (Reactive, Proactive, Post-Mortem)	X	✓	[42-46]
3	Adaptation Lifetime ⇒ Continuous monitoring	✓	✓	[12, 42-45, 47]
4	Object to Adapt ⇒ Application ⇒ Middleware	X	✓	[42-45, 48]
5	Subject of Adaptation ⇒ Context Acquisition (Static, Dynamic) ⇒ Context Representation	✓	✓	[18, 42-45]
6	Adaptation Strategy ⇒ Reasoning Process ⇒ Service Discovery	✓	✓	[42-45, 49, 50]
7	Decision Mechanism ⇒ Service Ranking (QoS consideration) ⇒ Service Selection (Dynamic or Involved human-in-the-loop)	✓	✓	[42-45, 51, 52]

The classification of these criteria is based on fundamental adaptation taxonomy [53, 37] that comprises 12 main different criteria. By considering these criteria, the dynamic adaptation in Service-Based Applications (SBAs) will achieve greater flexibility and effectiveness in a context-aware environment in related disciplines [50, 51]. According to Table 1 seven criteria have been selected based on their pertinence with a context-aware environment along with two adaptation lifecycles

which are the S-Cube service engineering lifecycle [9, 12, 34] and MAPE-K lifecycle [35, 36]. MAPE-K, on the other hand, is a structural adaptation model that comprises: (i) Monitor, (ii) Analyser for context detection, (iii) Planner, (iv) Executer for adaptation plan, and (v) Knowledge manager to share relevant information. The seven criteria are the Usage of Adaptation, Stage of Adaptation, Adaptation Lifetime, Object to Adaptation, Subject of Adaptation, Adaptation Strategy, and Decision Mechanism in the adaptation process.

3. The case study: DACAMoL in Mobile Cloud Learning

This section presents the case study that leverage on Dynamic service Adaptation in Context-Aware Mobile cloud Learning (DACAMoL) framework [17]. The case study is a mobile learning application that provides services for learning resources for learners. The case study uses a semantic-based approach to represent the contextual information, services, and QoS in the adaptation process. It is designed for a run-time environment to sense and react to contexts through a mobile device to provide specific learning resources. According to Fig. 1, the architecture of the mobile cloud learning application comprises of three main components, which are the device, the server, and the service provider.

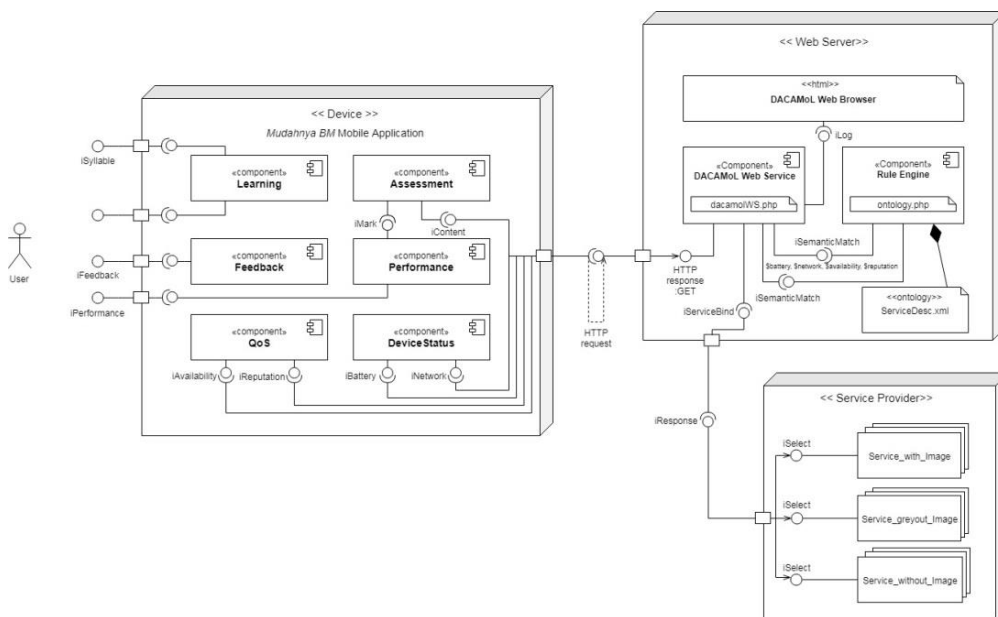


Fig. 1. Architectural framework of the case study

The device component is a front-end that acquires any changes in the scanned contexts such as learner's input, learner profile, network status, device status, and QoS. The component is integrated with the web server, plugged in DACAMoL. Dynamic Adaptation Management (DAM) and Learning Contextual Information Technology are two main components in the DACAMoL tool. This component is responsible to provide the correct learning resources starting from acquisition of the

contextual information, ontology reasoning control, the discovery of the service and service selection, followed by service adaptation.

3.1. Device component

The first component that interacts with users and sense with the environment's context is called device component. This component comprises of six components named learning, assessment, feedback, performance, QoS and device status. To sense the changes in the contextual information, the device will acquire the contextual information based on (i) automatically sense, and (ii) manually provided by the learners or users. The context such as battery level and network are two contexts that sense automatically. These contexts are stored in the device's local repositories, which are *Learner*, and *Device Repository*. Whereas name, age, gender, and preferred language are manually provided context by the users. This manual method can be used to collect as much as data that we want according to our needs.

In the present case study, the context is divided into four groups, which are *Learner Profile*, *Learner Input*, *Network Status*, and *Device Status*. We treat learner profile and learner input as intrinsic dynamic contextual information whereas network status and device status an extrinsic dynamic contextual information. The QoS that have been acquired are availability and reputation. *Learner Profile* consists of learner's background such as name, age, gender, and preferred language(s). Name and gender are considered as inputs to the system, whereas age and preferred language(s) are considered as contextual information. Input can be treated as contextual information if we represent them into semantic representation and their changes may affect the adaptation process.

Learner Input deals with any input from users throughout their learning process such as their mark from 0 to 100 %. In this case, the learner's mark is considered as a context since the changes of the mark may affect their learning contents. *Network Status* on the other hand deals with network bandwidth whether the device is connected to a strong network or vice versa. Finally, *Device Status* is the main source to determine the hardware and software capabilities of handheld devices such as operating system, battery level, screen resolution, and available memory to provide the right execution and operational profile for the accessed services. QoS feature deals with availability and the reputation of the provided services. This contextual information is described in Table 2.

Table 2. The required contextual information

Context element	Data instance	Data storage
Learner profile	String: {age, language}	Learner repository
Learner input	IntegerMark: 0 to 100	Learner repository
Network status	String: {strong, poor}	Device repository
Device status	Low-level context to high-level context (Battery level) String: {low, medium, high, full, charging}	Device repository

Device status converts their context from low-level context to high-level context to simplify the complexity of the rules and structure systematically. Low-level context is defined as an atomic context that is directly acquired from an entity without any derivation [56].

3.2. DACAMoL web service component

After the transformation of the context in the device components, the process will continue with the mapping with the Semantic-Web Server component. Based on Fig. 1, DACAMoL web service consists of *Learning Contextual Information Ontology* that described learner, device specification, QoS, and content that is modified based on *British educational ontology* [30].

Learning Contextual Information Ontology defines the contextual information using upper ontology space that comprises of four ontologies – *Learner Ontology*, *Device Ontology*, and *QoS Ontology* that are blended along with properties linked together with *Content Ontology* as shown in Figs 2-5.

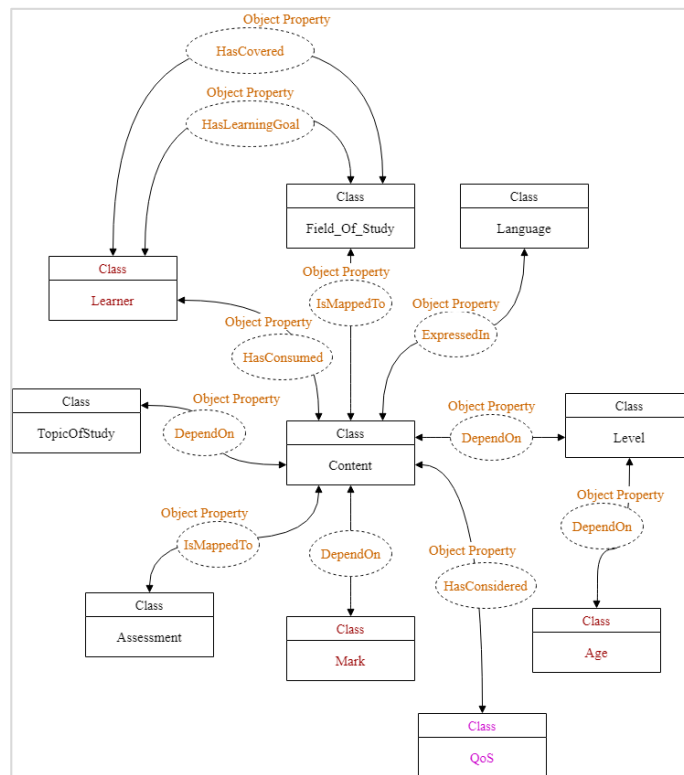


Fig. 2. Content ontology

The *Field_Of_Study* class is the ontology core class that is mapped to the content class as depicted in Fig. 2. *IsMappedTo* is used to annotate the specific contents that are corresponded with the field of study. Another important property is *ExpressedIn*, which is associated with the language class that uses to express the learning contents in a specific language. Content class is associated with the level class as well as the *TopicOfStudy* class through *DependOn* property.

The level of the Content depends on learners, as it is associated through *DependOn* property. Whereas the Assessment class is mapped with the Content class through *IsMappedTo* property. The Content class is also associated with the QoS class through *HasConsidered* property.

Learner ontology is depicted in Fig. 3 where this ontology is used to capture knowledges about learner that enable the system to dynamically adapt and deliver the most equivalence and relevant content based on their needs, preferences, and background. Device class is associated with the Learner class through ConductedLearningActivityIn property where every learning content will be displayed in the learner’s device, and it is used to track the previously conducted learning interaction by the learners. Learner information such as age is captured through HasAge data property in string format. Mark class is linked with Learner class which explains on learner’s mark via HasGain object property.

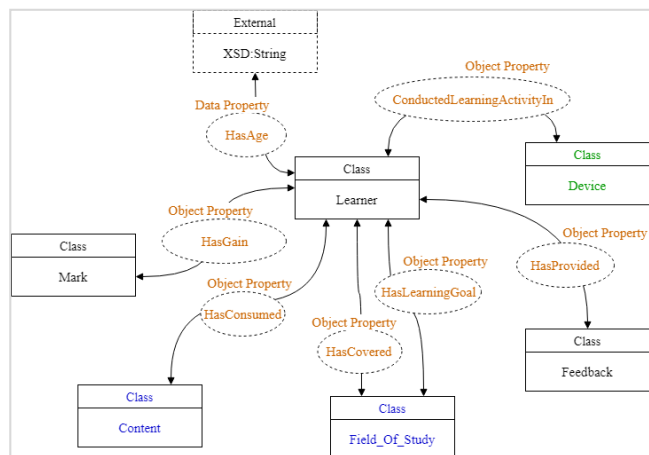


Fig. 3. Learner ontology

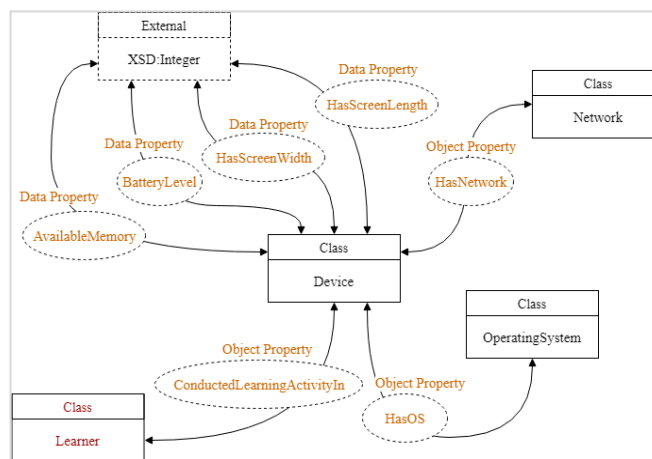


Fig. 4. Device ontology

The device ontology is used to represent the device’s status and information. The learner’s contextual data is useful to discover the learning contents to match with the characteristics of the currently used device. The characteristic of the device such as available memory, battery level, and screen resolution (i.e., screen resolution) are defined in integer format through AvailableMemory, BatteryLevel, HasScreenWidth, and HasScreenLength data properties respectively as shown in Fig. 4.

The other ontology is QoS ontology as illustrated in Fig. 5. This ontology is used to capture data on QoS which are availability and reputation. This data is important to rank the candidate of service before selecting the best service to be adapted. The data type of the QoS values is in Integer format. Class QoS is associated with Content class through HasConsidered property.

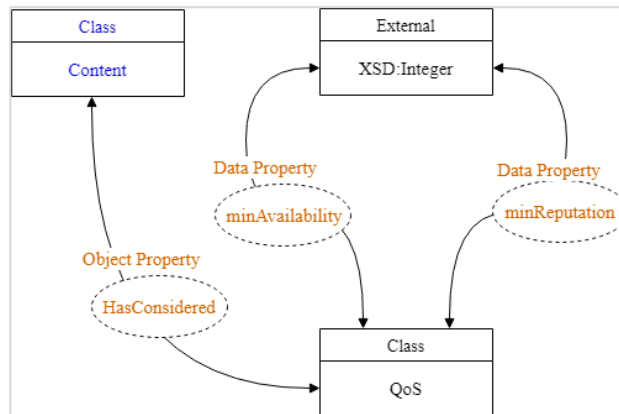


Fig. 5. QoS ontology

3.3. Rule engine component

The results from the DACAMoL web service component are sent to Rule Engine component to search for available and equivalence service from *Service Repository*. The Rule-based technique is used to discover available services from the repository. After find the available and equivalence services from the repository, if-then-else rules is used to rank the services according to their QoS to provide personalized learning resources. Three different rules; Rule 1 (i.e., service discovery rule), Rule 2 (i.e., service ranking rule) and Rule 3 (i.e., service binding rule).

The discovery of the services is based on the user's contextual information where Rule 1 will be used. Rule 1.1 concerns on learner's age, Rule 1.2 for the learner's mark, Rule 1.3 for network connection, and Rule 1.4 triggers based on the device's battery level. The discovery process will return an empty result if there is no match with the contextual information. The ranking of the candidate of services will use Rule 2, which is based on the QoS information (i.e., availability, reputation) stored in the UDDI registry of service description. Rule 2 states that high availability of the service when it is 98% and more, whereas high reputation of the service when it is 4 and 5. The services with higher QoS scores are returned to the user and will be adapted using Rule 3.

The flow of activity for service discovery and selection is depicted with their respective rule, context changes, and QoS consideration as shown in Fig. 6. There are three levels involved:

- (1) Service Discovery level that discovers available services according to network status, device's battery level, and learners mark by using Rule 1;
- (2) Candidate Service Ranking that ranks the candidate of services according to their QoS score of availability and reputation by using Rule 2;

(3) Serving Binding activity that binds the selected service with the service provider by using Rule 3.

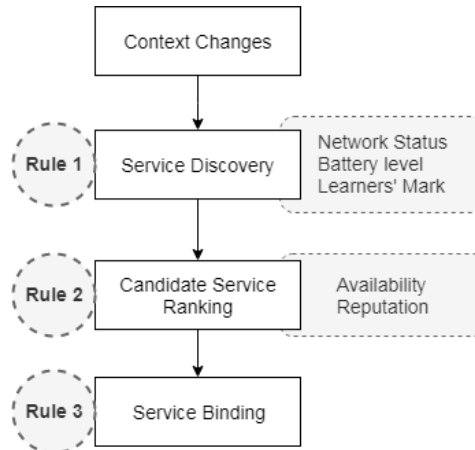


Fig. 6. Service adaptation flow of activity

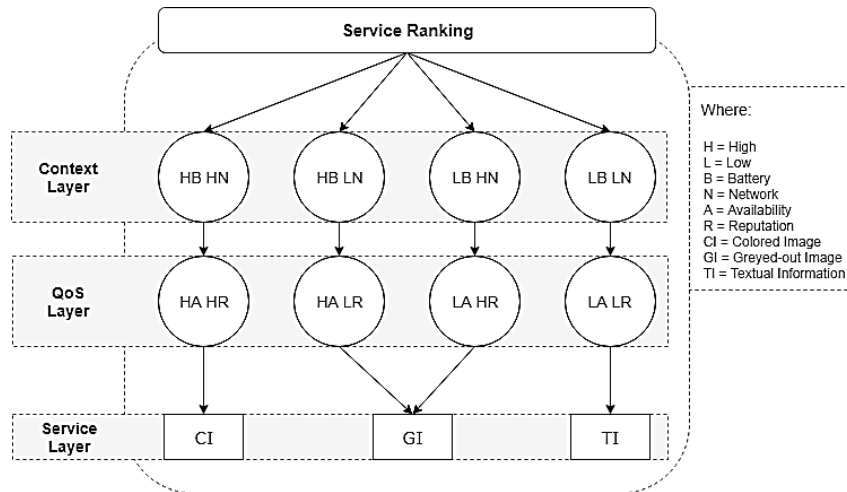


Fig. 7. Tree structure of service ranking

The tree structure of service ranking that shows the flow of decisions to rank the services is presented in Fig. 7. The tree structure of service ranking comprises three layers, which are Context Layer, QoS Layer, and Service Layer. When contexts changes are triggered, the ranking process will start at Context Layer. The ranking is based on the value of device battery level and network status either high or low. After this process is completed, their QoS will be ranked in QoS Layer according to the availability and reputation score whether high or low. QoS availability will be checked first before QoS reputation. Availability is the higher priority ranking for service selection where the services should be in the available state that scores 98% or higher. Hence, candidates of services will be filtered and ranked based on their reputation score. The most equivalence service will be bind accordingly. The services

are Coloured Image service (i.e., CI), Greyed-out Image service (i.e., GI), and Textual Information service (i.e., TI).

3.4. Service provider component

After the discovery and selection of the service are completed, the service adaptation process begins in Service Provider component. This component enables the binding of the selected service with the service provider. The best mobile cloud learning application is the application that can provide learning resources based on learners' background knowledge, their preferences, goals as well as learner's device status. Context changes are referred to as the data instances that are accumulated from Device component (i.e., age, answer, network status, battery level). Whereas adaptation decision is a process that is performed based on the context changes accordingly.

Network status is categorized into two different scales, which are poor and strong. The network is considered as poor if it is 66 kilobits per second (Kbps) and below [56]. Higher than this value is considered a strong network. Apart from that, the battery level is considered low if the value is 49% and below [17]. The low battery can cause system failure. Thus, these context changes are important for battery-saving purposes. Thus, three different types of LRs are distinguished according to the network strength, battery levels, and QoS values, which are (1) LRs with colored images, (2) LRs with greyed out image and (3) LRs with no image.

4. Methodology of evaluation

The objective of this evaluation is to evaluate the case study that leverage on DACAMoL compared to other dynamic adaptation frameworks in terms of their effectiveness in the adaptation process, according to adaptation criteria. The effectiveness of the process flow of the framework should meet this definition. Effectiveness is defined as “...a measure of the ability of a system to meet its specified needs (or requirements) from a particular viewpoint. This measure may be quantitative or qualitative and it allows comparable systems to be ranked. These effectiveness measures are defined in the problem space. Implicit in the meeting of problem requirements is that threshold values must be exceeded.” [57]

To achieve the stated evaluation objective, hypotheses are derived in Table 3.

Table 3. Research question and hypothesis

Hypothesis	<p>Null Hypothesis (H_0): $\mu_{DACAMoL} = \mu_{MobiSWAP} = \mu_{ULF} = \mu_{WLP} = \mu_{UoLmP}$</p> <p>There is no significant difference in compliance of all stipulated conditions for DACAMoL and the other four frameworks. Thus $\mu_{DACAMoL} = \mu_{MobiSWAP} = \mu_{ULF} = \mu_{WLP} = \mu_{UoLmP}$</p> <p>Alternative Hypothesis (H_1): $\exists x \in z: \mu_{DACAMoL} > \mu_x$</p> <p>There is a significant difference in compliance of all stipulated conditions for DACAMoL and the other four frameworks. Given $z = \{MobiSWAP, ULF, WLP, UoLmP\}$, x is a framework belongs to z.</p>
------------	--

The evaluation is performed according to the procedure that is discussed in this section. Prior to this expert review study, a pilot study has been conducted with two expert reviewers. The result and comments from this pilot study are used to improve the evaluation process. This evaluation is a Quasi-experiment where we prior select eight expert reviewers that should possess minimum of five years of experience in software development. In addition, they should know what Service Oriented Architecture (SOA) is, web services, and how services are being adapted in the service adaptation process. Expert reviewers are given a short briefing and a set of checklists to compare the DACAMoL framework with four other frameworks. They need to evaluate the effectiveness of the process of the framework by considering contextual information and QoS based on the evaluation criteria.

The seven criteria are the *Usage of Adaptation*, *Stage of Adaptation*, *Adaptation Lifetime*, *Object to Adaptation*, *Subject of Adaptation*, *Adaptation Strategy*, and *Decision Mechanism* in the adaptation process. After reviewing these five anonymous frameworks, they need to answer the given checklist. They should leave a mark at the respective framework if the framework possesses any of the criteria.

5. Result analysis

In this section, the effectiveness of the adaptation process of DACAMoL compare with other dynamic adaptation frameworks according to the adaptation criteria is discussed and analysed. Statistical tests have been conducted using IBM SPSS Statistics version 21.0 to determine the acceptance or rejection of the null hypothesis with a given significance level.

The descriptive table provides descriptive statistics for expert reviewers' score for five types of frameworks is described in Table 4. It consists of mean, standard deviation, and 95% confidence intervals (5% significance level) for the dependent variable (i.e., Expert_Score) for each separate group (i.e., framework 1, 2, 3, 4, and 5), as well as when all groups are combined (i.e., Total).

Table 4. Descriptive table Expert_Score

No	N	Mean	Standard deviation	Standard error	95% confidence interval for mean		Minimum	Maximum
					Lower bond	Upper bound		
1	8	10.00	0.000	0.000	10.00	10.00	10	10
2	8	7.50	0.756	0.267	6.87	8.13	7	9
3	8	7.50	0.535	0.189	7.05	7.95	7	8
4	8	8.00	0.000	0.000	8.00	8.00	8	8
5	8	8.63	0.744	0.263	8.00	9.25	8	10
Total	40	8.33	1.071	0.169	7.98	8.67	7	10

The result of the one-way non-parametric ANOVA (Kruskal-Wallis's test) is shown in Table 5. Based on the table, there is significant evidence of the difference between each of the Expert_Score with the Framework which the significance value is $p=0.00$. A 5% significance level has been adopted (i.e., 95% confidence level).

Table 5. Kruskal-Wallis's test result

No	Null hypothesis	Test	Sig.	Decision
1	The distribution of Expert_Score is the same across categories of Framework	Independent samples Kruskal-Wallis Test	0.000	Reject the null hypothesis

Asymptotic significances are displayed. The significance level is 0.05

Total N	40
Test statistic	27.861
Degrees of freedom	4
Asymptotic Sig. (2-sided test)	0.000

Table 6. Pairwise comparison of framework

Sample1-Sample2	Test statistic	Std. error	Std. test statistic	Sig.	Adj. sig.
2.000-3.000	-0.312	5.501	-0.057	0.955	1.000
2.000-4.000	-7.062	5.501	-1.284	0.199	1.000
2.000-5.000	-13.375	5.501	-2.431	0.015	0.150
2.000-1.000	24.562	5.501	4.465	0.000	0.000
3.000-4.000	-6.750	5.501	-1.227	0.220	1.000
3.000-5.000	-13.062	5.501	-2.375	0.018	0.176
3.000-1.000	24.250	5.501	4.408	0.000	0.000
4.000-5.000	-6.312	5.501	-1.148	0.251	1.000
4.000-1.000	17.500	5.501	3.181	0.001	0.015
5.000-1.000	11.188	5.501	2.034	0.042	0.420

Each row tests the null hypothesis that the Sample 1 and Sample 2 distributions are the same.
Asymptotic significances (2-sided tests) are displayed. The significance level is 0.05

The multiple comparisons in which groups differ from each other are shown in Table 6. Dunn's post hoc test is carried out to investigate which framework is significantly different from each other. Based on Table 6, the Dunn-Bonferroni test is shown on each pair of groups. The last column, which is the Adj. Sig. the column, adjusts for multiple testing (Bonferroni error correction). The significant differences are highlighted using an orange colour where their p -value is less than 0.05. There is a statistically significant difference in expert reviewer score of frameworks 1 to 2 ($p = 0.00$), 1 to 3 ($p = 0.00$), and 1 to 4 ($p = 0.015$). However, there were no differences between framework 2 to 3, 2 to 4, 3 to 4 and 4 to 5 ($p = 1.00$), 2 to 5 ($p = 0.15$), 3 to 5 ($p = 0.176$) and framework 5 to 1 ($p = 0.42$).

Based on the pairwise comparison, there are significant differences between frameworks 1 to 2, frameworks 1 to 3 and framework 1 to 4 because the frameworks have differences in their adaptation criteria makes framework 1 is better than other frameworks. Thus, there is a statistically significant difference between groups as determined by Kruskal-Wallis's test. The post-hoc test reveals that the expert reviewer score has been statistically significantly lower after comparing framework 1, DACAMoL (10.0 ± 0.00 , $p = 0.000$), framework 2, MobiSWAP (7.500 ± 0.755929 , $p = 0.000$), framework 3, ULF (7.500 ± 0.534522 , $p = 0.000$), framework 4, WLP (8.00 ± 0.00 , $p = 0.000$) and framework 5, UoLmP (8.625000 ± 0.744024 , $p = 0.000088$).

Based on one-way non-parametric ANOVA test, the means are different from one another but it does not indicate how different means are from one another. The difference may be very large, or it may be very small. Effect size helps to estimate

how large or how small the difference is. The calculation of the effect size is stated below:

$$(3) \quad \begin{aligned} E_R^2 &= \frac{H}{(n^2-1)/(n+1)}, \\ E_R^2 &= \frac{27.861}{(40^2-1)/(40+1)}, \\ E_R^2 &= \frac{27.861}{39}, \\ E_R^2 &= 0.71. \end{aligned}$$

Hence, based on the Epsilon-Squared value, 0.71 is considered as a high effect size value. This shows that there is a large meaningful difference between the five groups. Based on the analysis and discussion, the adaptation process by DACAMoL is effective compared to the other four frameworks.

6. Conclusion

The framework has been evaluated and tested in a case study related to Mobile Cloud Learning (MCL) environment. The main objective of the experiment is to measure the effectiveness of the dynamic adaptation framework in terms of their adaptation process according to adaptation criteria. The experiment results demonstrate significant differences for the effectiveness at a 95% confidence level, which can be interpreted to confirm that DACAMoL is promising to be used in operating dynamic adaptation process in a context-aware environment. With these regards, developers are the main beneficiaries of the framework. They can use the tool to plug into their service system as a web service to handle the dynamic adaptation process. They can also use the adaptation criteria as a guideline to – propose any new frameworks in a context-aware environment.

References

1. Blagoev, I., G. Vassileva, V. Monov. A Model for e-Learning Based on the Knowledge of Learners. – Cybernetics and Information Technologies, Vol. **21**, 2021, No 2, pp. 121-135.
2. Gumbheer, C. P., K. K. Khedo, A. Bungalee. Personalized and Adaptive Context-Aware Mobile Learning: Review, Challenges and Future Directions. – Educ. Inf. Technol., 2022, No 0123456789. DOI: 10.1007/s10639-022-10942-8.
3. Chen, C. M., Y. L. Li. Personalised Context-Aware Ubiquitous Learning System for Supporting Effective English Vocabulary Learning. – Interact. Learn. Environ., Vol. **18**, 2010, No 4, pp. 341-364. DOI: 10.1080/10494820802602329.
4. Fuad, M. M., D. Deb. Cloud-Enabled Hybrid Architecture for In-Class Interactive Learning Using Mobile Device. – In: Proc. of 5th IEEE Int. Conf. Mob. Cloud Comput. Serv. Eng., 2017, pp. 0-3. DOI: 10.1109/MobileCloud.2017.15.
5. Gomez, S., P. Zervas, D. G. Sampson, R. Fabregat. Context-Aware Adaptive and Personalized Mobile Learning Delivery Supported by UoLmP. – J. King Saud Univ. Comput. Inf. Sci., Vol. **26**, 2014, No 1, pp. 47-61. DOI: 10.1016/j.jksuci.2013.10.008.
6. Harchay, A., L. Cheniti-Belcadhi, R. Braham. A Context-Aware Approach for Personalized Mobile Self-Assessment. – J. Univers. Comput. Sci., Vol. **21**, 2015, No 8, pp. 1061-1085.
7. Karadimce, A., D. Davcev. Adaptive Multimedia Content in Mobile Cloud Computing Environment. – In: Proc. of IEEE 1st Int. Conf. Cloud Netw. (CLOUDNET'12), 2012, pp. 209-211. DOI: 10.1109/CloudNet.2012.6483690.

8. Karoudis, K., G. Magoulas. Ubiquitous Learning Architecture to Enable Learning Path Design across the Cumulative Learning Continuum. – *Informatics*, Vol. **3**, 2016, No 4, p. 19. DOI: 10.3390/informatics3040019.
9. Madani, H. H., L. Jemni, B. E. N. Ayed, M. Jemni, D. G. Sampson. Towards Accessible and Personalized Mobile Learning for Learners with Disabilities. – In: Proc. of 4th Int. Conf. Inf. Commun. Technol. Access., 2013.
10. Bhawna, Gobind. Research Methodology and Communication. – *IOSR J. Res. Method Educ.*, Vol. **5**, 2015, No 3, pp. 48-51. DOI: 10.9790/7388-05344851.
11. Lane, S., P. Lago, Q. Gu, I. Richardson. Adaptation of Service-Based Application: A Maintenance Process? – The Irish Software Engineering Research Centre, No 03, 2011.
12. Alferez, G. H., V. Pelechano, R. Mazo, C. Salinesi, D. Diaz. Dynamic Adaptation of Service Compositions with Variability Models. – *J. Syst. Softw.*, Vol. **91**, 2014, No 1, pp. 24-47. DOI: 10.1016/j.jss.2013.06.034.
13. Baroudi, T., Y. Benamar, A. Bendimera. Dynamic Service Adaptation Architecture. – *Softw. - Pract. Exp.*, Vol. **8**, 2017, No 4, pp. 30-35. DOI: 10.14569/IJACSA.2017.080405.
14. Lane, S., Q. Gu, P. Lago, I. Richardson. Towards a Framework for the Development of Adaptable Service-Based Applications. – *Serv. Oriented Comput. Appl.*, Vol. **8**, 2014, No 3, pp. 239-257. DOI: 10.1007/s11761-013-0136-4.
15. Dey, A. K., G. D. Abowd. Towards a Better Understanding of Context and Context-Awareness. – *Comput. Syst.*, Vol. **40**, 1999, No 3, pp. 304-307. DOI: 10.1007/3-540-48157-5_29.
16. Curum, B., N. Chellapermal, K. Kumar. A Context-Aware Mobile Learning System Using Dynamic Content Adaptation for Personalized Learning. – *Emerg. Trends Electr. Electron. Commun. Eng.*, Vol. **416**, 2017, No 1, pp. 379-384. DOI: 10.1007/978-3-319-52171-8.
17. Muhammad, S., N. Admodisastro, H. Osman, N. M. Ali. Dynamic Service Adaptation Framework for Context Aware Mobile Cloud Learning Using Semantic-Based Approach. – *Int. J. Eng. Technol.*, Vol. **7**, 2018, No (4.31), pp. 182-190.
18. Mizouni, R., M. A. Matar, Z. Al Mahmoud, S. Alzahmi, A. Salah. A Framework for Context-Aware Self-Adaptive Mobile Applications SPL. – *Expert Syst. Appl.*, Vol. **41**, 2014, No 16, pp. 7549-7564. DOI: 10.1016/j.eswa.2014.05.049.
19. Guermah, H., T. Fissaa, H. Hafiddi, M. Nassar, A. Kriouile. An Ontology Oriented Architecture for Context Aware Services Adaptation. – *IJCSI International Journal of Computer Science Issues*, Vol. **11**, 2014, Issue 2, pp. 24-33.
20. Agarwal, V., P. Jalote. From Specification to Adaptation: An Integrated QoS-Driven Approach for Dynamic Adaptation of Web Service Compositions. – In: Proc. of IEEE 8th Int. Conf. Web Serv. (ICWS'10), 2010, pp. 275-282. DOI: 10.1109/ICWS.2010.39.
21. Mohamed, R., T. Perumal, M. N. Sulaiman, N. Mustapha, M. N. S. Zainudin. Modeling Activity Recognition of Multi Resident Using Label Combination of Multi Label Classification in Smart Home. – In: Proc. of AIP Conf., Vol. **1891**, 2017, No October. DOI: 10.1063/1.5005427.
22. On, G., J. Schmitt, R. Steinmetz. On Availability QoS for Replicated Multimedia Service and Content on Availability QoS for Replicated Multimedia Service and Content. – In: *Protoc. Syst. Interact. Distrib. Multimedia, IDMS 2002. Lect. Notes Comput. Sci.* Vol. **2515**. 2002, Berlin, Heidelberg, Springer, pp. 313-326. DOI: 10.1007/3-540-36166-9.
23. Mehdi, M., N. Bouguila, J. Bentahar. Trust and Reputation of Web Services Through QoS Correlation Lens. – *IEEE Trans. Serv. Comput.*, Vol. **9**, 2016, No 6, pp. 968-981. DOI: 10.1109/TSC.2015.2426185.
24. Gunther, N., R. F. By-Jain. *The Practical Performance Analyst*. McGraw-Hill, 1998.
25. Qiu, W., Z. Zheng, X. Wang, X. Yang, M. R. Lyu. Reputation-Aware QoS Value Prediction of Web Services Reputation-Aware QoS Value Prediction of Web Services. – In: Proc. of IEEE 10th Int. Conf. Serv. Comput., 2013, No June. DOI: 10.1109/SCC.2013.43.
26. Wu, Yan, et al. A Novel Method for Calculating Service Reputation. – *IEEE Trans. Autom. Sci. Eng.*, Vol. **10**, 2013, No 3, pp. 634-642. DOI: 10.1109/tase.2013.2238231.
27. Sakunthala Prabhha, K. S., C. Mahesh, S. P. Raja. An Enhanced Semantic Focused Web Crawler Based on Hybrid String Matching Algorithm. – *Cybernetics and Information Technologies*, Vol. **21**, 2021, No 2, pp. 105-120.

28. Peinado, S., G. Ortiz, J. M. Doderó. A Metamodel and Taxonomy to Facilitate Context-Aware Service Adaptation. – *Comput. Electr. Eng.*, Vol. **44**, 2015, pp. 262-279. DOI: 10.1016/j.compeleceng.2015.02.004.
29. Al-Yahya, M., R. George, A. Alfaries. Ontologies in e-Learning: Review of the Literature. – *Int. J. Softw. Eng. its Appl.*, Vol. **9**, 2015, No 2, pp. 67-84. DOI: 10.14257/ijseia.2015.9.2.07.
30. Casals, A., S. Paulo, A. Alves Franco Brandão. Modeling a Mobile Learning Context Data Ontology. – In: *Proc. of IEEE World Eng. Educ. Conf.*, 2017.
31. Aslam, M., M. A. Auer, S. Shen, J. Herrmann. Expressing Business Process Model as OWL-S Ontologies. – In: *Proc. of 2nd Int. Work. Grid Peer-to-Peer Based Work. (GPWW'06) Conjunction with 4th Int. Conf. Bus. Process Manag. (BPM'06)*, No September, 2006.
32. Meditskos, G., N. Bassiliades. Structural and Role-Oriented Web Service Discovery with Taxonomies in OWL-S. – *IEEE Trans. Knowl. Data Eng.*, Vol. **22**, 2010, No 2, pp. 278-290. DOI: 10.1109/TKDE.2009.89.
33. Nitzsche, J., T. Van Lessen, D. Karastoyanova, F. Leymann. BPEL for Semantic Web Services (BPEL4SWS). – In: *Proc. of OTM Confed. Int. Conf. Move to Meaningful Internet Syst., Part I*, 2007, pp. 179-188. DOI: 10.1007/978-3-540-76888-3_37.
34. Wang, B., X. Tang. Designing a Self-Adaptive and Context-Aware Service Composition System. – In: *Proc. of IEEE Comput. Commun. IT Appl. Conf. (ComComAp'14)*, 2014, pp. 155-160. DOI: 10.1109/ComComAp.2014.7017188.
35. Gurung, R. K., A. Alsadoon, P. W. C. Prasad, A. Elchouemi. Impacts of Mobile Cloud Learning (MCL) on Blended Flexible Learning (BFL). – In: *Proc. of International Conference on Information and Digital Technologies (IDT'16)*, 2016, pp. 108-114. DOI: 10.1109/DT.2016.7557158.
36. Wang, M., Y. Chen, M. Jahanzaib Khan. Mobile Cloud Learning for Higher Education: A Case Study of Moodle in the Cloud. – *J. Educ. Pract.*, Vol. **7**, 2016, p. 6 (online). <http://files.eric.ed.gov/fulltext/EJ1099593.pdf>
37. Paktinat, S., A. Salajeghe, M. A. Seyyedi, Y. Rastegari. Service-Based Application Adaptation Strategies : A Survey. – *International Journal of Computer, Electrical, Automation, Control and Information Engineering*, Vol. **8**, 2014, No 8, pp. 1321-1325.
38. Papazoglou, M., M. Parkin, K. Pohl, A. Metzger. *Service Research Challenges and Solutions for the Future Internet*. Springer, 2010.
39. Soukkarieh, B., F. Sèdes. Dynamic Services Adaptation to the User's Context. – In: *Proc. of 4th Int. Conf. Internet Web Appl. Serv. (ICIW'09)*, 2009, No iii, pp. 223-228. DOI: 10.1109/ICIW.2009.39.
40. Parra, C., X. Blanc, L. Duchien. Context Awareness for Dynamic Service-Oriented Product Lines. – In: *Proc. of 13th Int. Softw. Prod. Line Conf.*, 2009, pp. 131-140. DOI: 10.1145/1753235.1753254.
41. Fredj, M. Dynamic Reconfiguration of Service-Oriented Architectures Manel Fredj to Cite This Version : HAL Id : tel-00491041. – *Informatique, Télécommunications et Électronique de Paris*, 2010.
42. Bucchiarone, A., A. Marconi, M. Pistore, A. Sirbu. A Context-Aware Framework for Business Processes Evolution. – In: *Proc. of IEEE Int. Enterp. Distrib. Object Comput. Work. EDOC*, 2011, pp. 146-154. DOI: 10.1109/EDOCW.2011.47.
43. Bouguessa, A., L. A. Mebarki, B. Boudaa. Context-Aware Adaptation for Sustaining Disaster Management. – In: *Proc. of 12th Int. Symp. Program. Syst. (ISPS'15)*, 2015, pp. 164-173. DOI: 10.1109/ISPS.2015.7244980.
44. Adel, A., S. Laborie, P. Roose. Semantic Context-Aware Adaptation Platform Architecture. – *Procedia Comput. Sci.*, Vol. **32**, 2014, pp. 959-964. DOI: 10.1016/j.procs.2014.05.518.
45. Hind, L., D. Chiadmi, L. Benhlilma. How Semantic Technologies Transform e-Government Domain. – *Transform. Gov. People, Process Policy*, Vol. **8**, 2014, No 1, pp. 49-75. DOI: 10.1108/TG-07-2013-0023.
46. Bandara, A., T. Payne, D. De Roure, T. Lewis, C. Science. A Semantic Approach for Service Matching in Pervasive Environments. University of Southampton, Tech. Rep. Number ECSTR-IAM07-006, 2007.
47. Ibrahim, N., F. Le Mou. Semantic Service Substitution in Pervasive Environments. – *Inderscience Enterp., Ltd*, 2015, pp. 1-26. DOI: 10.1504/IJSEM.2014.068244.

48. Bekkouche, A., S. M. Benslimane, M. Huchard, C. Tibermacine, F. Hadjila, M. Merzoug. QoS-Aware Optimal and Automated Semantic Web Service Composition with User's Constraints. – Serv. Oriented Comput. Appl., Vol. **11**, 2017, No 2, pp. 183-201. DOI: 10.1007/s11761-017-0205-1.
49. Kazhamiakin, R., S. Benbernou, L. Baresi, P. Plebani, M. Uhlig, O. Barais. Adaptation of Service-Based Systems. – Serv. Res. Challenges Solut. LNCS 6500, 2010, pp. 117-156.
50. Salehie, M., L. Tahvildari. Self-Adaptive Software: Landscape and Research Challenges. – ACM Trans. Auton. Adapt. Syst., Vol. **5**, 2009, No March, pp. 1-40.
51. Benlamri, R., X. Zhang. Context-Aware Recommender for Mobile Learners. ABC 2019, 2014, pp. 1-34.
52. Smith, N., T. Clark. A Framework to Model and Measure System Effectiveness. – In: Proc. of 11th ICCRTS Coalit. Command Control Netw. Era, 2004.

*Received: 15.02.2022; Second Version: 22.06.2022; Third Version: 26.07.2022;
Accepted: 02.08.2022*