Energy-Aware Mobile Learning: Opportunities and Challenges

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***Abstract*—As mobile devices are becoming more powerful and affordable they are increasingly used for mobile learning activities. By enabling learners' access to educational content anywhere and anytime, mobile learning has both the potential to provide online learners with new opportunities, and to reach less privileged categories of learners that lack access to traditional e-learning services. Among the many challenges with mobile learning, the battery-powered nature of mobile devices and in particular their limited battery life, stands out as one issue that can significantly limit learners' access to educational content while on the move. Adaptation and personalisation solutions have widely been considered for overcoming the differences between learners and between the characteristics of their mobile devices. However, while various energy saving solutions have been proposed in order to provide mobile users with extended device usage time, the areas of adaptive mobile learning and energy conservation in wireless communications failed to meet under the same umbrella. This paper bridges the two areas by presenting an overview of adaptive mobile learning systems as well as how these can be extended to make them energy-aware. Furthermore, the paper surveys various approaches for energy measurement, modelling and adaptation, three major aspects that have to be considered in order to deploy energy-aware mobile learning systems. Discussions on the applicability and limitations of these approaches for mobile learning are also provided.**

***Index Terms*—Adaptive mobile learning, energy measurement, energy simulation, energy modelling, energy-aware adaptation.**

I. INTRODUCTION

WITH the rapid growth and development of the information and communication technologies, *e-learning* has seen a fast evolution over the past decade. Being a viable alternative to traditional in-class learning, as well as a cost-effective training solution even in difficult economic circumstances, e-learning is increasingly adopted by educational, corporate and governmental worlds. In this context, the worldwide e-learning services market is projected to grow from $32.1 billion to $49.9 billion between 2010 and 2015 [1]. More recently, mobile devices such as smartphones and tablets have become increasingly affordable and powerful. Not only that sales of such devices are increasing fast with smartphones already outpacing computer sales globally [2], but mobile devices are projected to become the primary means for accessing the Internet over the next few years [3].

Mobile technologies have also changed radically the online learning landscape. Predominantly concentrated in a reduced number of selected countries just a couple of years ago, *mobile learning (m-learning)* has been increasingly adopted worldwide, with a global market for m-learning services expected to grow from $3.2 billion in 2010 to $9.1 billion by 2015 [4]. While e-learning users in developed countries gradually shift from traditional desktop-based e-learning towards mobile learning, users in developing countries may skip e-learning completely in favor of m-learning [4].

E-learning was the first to facilitate learning through technology. Among the many advantages of e-learning, the independence in time and space are considered to be important characteristics. M-learning increased this independence to the extent that learners can move their learning environment as they move, to the extent that learning can be conducted *anytime* and *anywhere*, across *different contexts* [5]. However, along with the advantages brought by mobility, a number of issues and challenges are posed by the multitude of users, learning contexts and technologies involved. Apart from mobile devices, mobile learning uses various other technologies such as, data transport technologies (e.g., WiFi, UMTS, WiMAX, LTE, etc.), and media technologies (e.g., video, audio, images, text, flash animations, etc.). An example scenario of ubiquitous mobile learning, where learners can access the educational content from various locations, using various devices and wireless networks, is illustrated in Fig. 1. Ideally, m-learning applications should be able to automatically detect the different learning contexts and adapt to the needs of different learners and their technological limitations, in order to maximise their learning experience and learning outcomes.

The availability of sufficient battery power is a prerequisite for access to educational content and successful mobile learning. The battery-powered nature of mobile devices and in particular their limited battery capacity, still represents one of the key limitations of mobile devices, despite the significant effort that is being made to create low-power device components, more energy efficient applications and protocols, as well as new battery technologies. Low battery situations can negatively impact the learning outcome, as well as learner's satisfaction with the m-learning application, since learners may run out of battery power before completing a learning activity or they may choose to postpone it in order to keep the power for other activities. However, despite the fact that many adaptive solutions have been proposed to overcome learners' technological limitations, the available energy level has not been considered as an input in the adaptation process.

A. Survey Novelty and Contributions

As indicated by a number of recent surveys (e.g., [6]–[14]), energy efficiency receives increasing research attention

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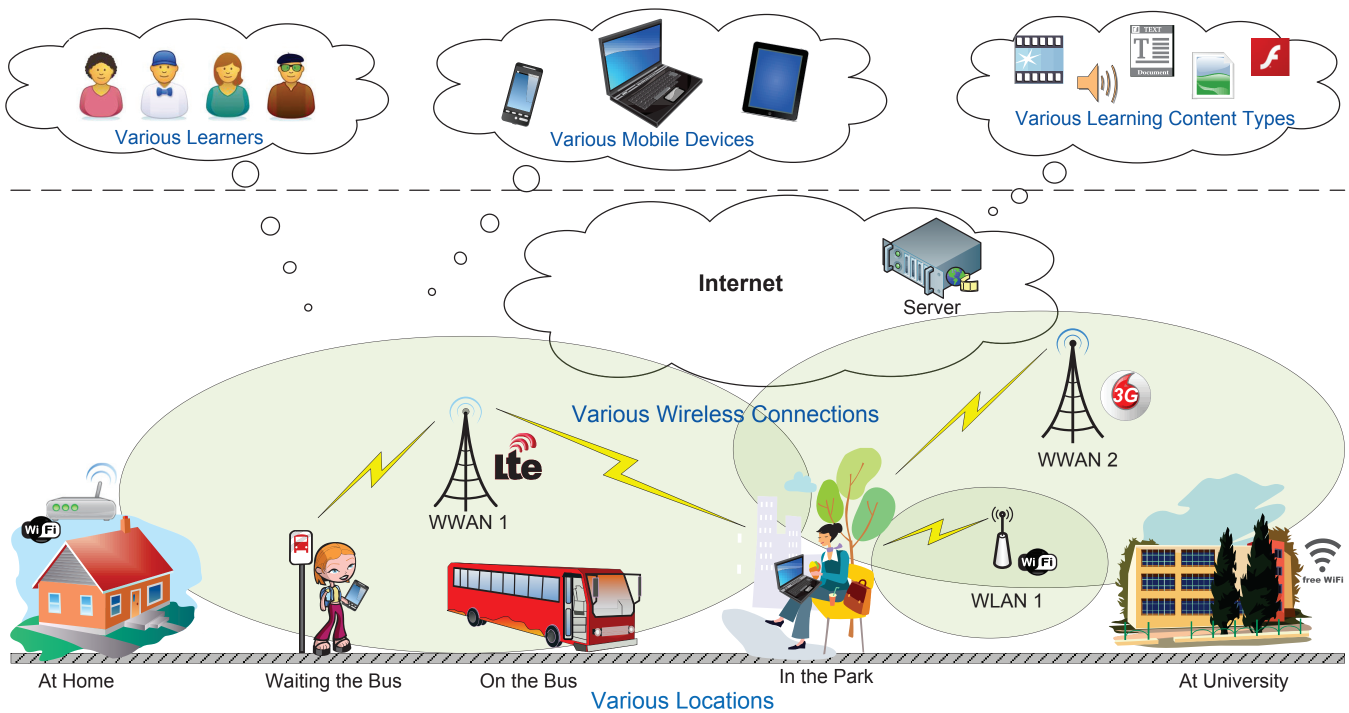


Fig. 1. Ubiquitous mobile learning in heterogeneous wireless environments – generic architecture and example scenario.

in regard to a number of aspects related to wireless data communications, from servers and data centers, to wireless networks and mobile devices. Various energy-saving solutions related to servers, communication links and mobile devices can be considered in order to deploy green energy-aware e-learning and mobile learning systems. However, from a learning point of view, the highest benefit provided by such systems would be to extend the learning time and support the learners to maximise their learning outcome. In consequence, out of the significant body of research on energy saving in the area of wireless communications and mobile devices, this paper narrows down the survey to solutions focused on extending the mobile devices usage time.

Several recent surveys [10]–[14] address energy efficient mobile computing and applications, and overlap in part both between them and with this survey. The latest is due to the fact that, since energy efficiency was not addressed by research works from the area of mobile learning, this survey had to rely as well on research works presenting general solutions related to energy efficient mobile computing. However, there are several different aspects that differentiate this survey from the existing ones.

First, the existing surveys focus on general mobile device energy management techniques [10], on particular applications such as multimedia streaming [11]–[13], or on particular scenarios such as wireless content distribution with mobile-to-mobile cooperation [14]. In contrast, this survey targets mobile learning systems and applications that involve wireless delivery, processing and displaying of educational content that can have different media types such as text, audio and video.

Second, this survey covers several different aspects that are essential to be understood and addressed in order to propose, test and deploy energy efficient mobile learning applications and systems. These are *energy measurement* (i.e., external measurement and built-in measurement) and *simulation*, *energy modelling* (i.e., battery, device and user modelling), and *energy-aware adaptation (energy saving)*. Significant more attention is paid to the measurement and modelling aspects which are key prerequisites to energy saving, but were not the primary focus of the other surveys. While two other surveys have also addressed in part energy modelling this paper differentiates itself from these, through two novel approaches:

- Overviewing and discussing various energy modelling concepts and different approaches for battery, device and user modelling, while directing the reader to relevant studies for more details.
- Rather than detailing individual research studies surveyed, it summarises through tables their most important findings with regard to energy consumption patterns of mobile device components, use-cases, and mobile users, which can be exploited to enable m-learning energy modelling in particular, and improve energy modelling in general.

Furthermore, since the energy saving aspect was the major focus of the existing survey papers, we refer the reader to them for more comprehensive review of various energy saving techniques, while limiting this part to briefly summarising some adaptive approaches, classifying them with regard to when the energy is saved (i.e., during content delivery, computation or displaying).

More importantly, this paper connects the energy measurement, modelling and adaptation aspects to m-learning by showing where each of these fits in a proposed generic framework of an Energy-aware Adaptive M-learning System (EAMLS). The applicability to mobile learning and the limitations of the presented energy measurement, modelling and adaptation approaches are also discussed in detail.

B. Survey Structure

The rest of this paper is structured as follows:

- Section II sets the context of the paper by arguing for the need of energy-aware mobile learning solutions.
- Section III aims to briefly familiarise the reader with the current state of the art in the adaptive mobile learning area and with the general architecture of an adaptive m-learning system.
- Section IV proposes a generic framework of an Energy-aware Adaptive M-learning System, and also briefly shows where and how the various energy-related aspects (energy measurement, modelling and adaptation), fit within this framework.
- Sections V, VI and VII survey, classify and discuss various general approaches for energy measurement, modelling and adaptation respectively, and further discuss their applicability to mobile learning.
- Section VIII concludes the paper and provides a broader overview on the energy measurement, modelling and adaptation approaches that are most suitable for deploying energy-aware mobile learning systems, discussing their opportunities as well as the challenges that will have to be addressed.

II. The Need for Energy-Aware Mobile Learning

A. Evolving Devices and Users

With mobile technologies' global adoption on a fast rise, Internet and computing are arguably in the middle of a mobile revolution age. Mobile devices are getting smaller and more compact, with the latest devices packing high-resolution touchscreen displays, dual/ quad-core CPU's, powerful GPU's capable to render complex 3D games, increased storage space, as well as HD video and photo cameras. They may also have multiple wireless connectivity (e.g., Bluetooth, WiFi, UMTS, LTE, etc.), and multiple sensing capabilities such as GPS, accelerometer, gyroscope, proximity sensor, ambient light sensor, compass, barometer and even eye-tracking [15].

Being more powerful and complex also means that mobile devices are increasingly used by their users. Mobile devices have become mobile work, learning and entertainment centres, being used for communicating, web browsing, social media, photos and videos capturing, music/ radio listening, multimedia playback/ streaming, GPS navigation, mobile payments, playing games or using any of the hundreds of thousands of apps available on various online app stores dedicated to different platforms such as Android, iOS and Windows Phone.

B. Discrepancies between Users' Power Requirements and Batteries' Capacity

Batteries, in particular Li-Ion batteries, are the "de facto" energy source currently powering the mobile devices. Some technological advances have been made in terms of improved battery capacity density and charging cycles [16]. However, revolutionary promises often found in the literature with regard to battery capacities [17] and battery charging cycles [18] orders of magnitude higher, combined with significantly faster battery charging times [19], continue to fail to materialise in the end products [20].

Moreover, the increasing capabilities and functionalities of mobile devices combined with their increased usage, and decreasing space left for battery, places additional strain on the battery, so that mobile devices' power requirements were growing significantly faster than batteries' capacity over the past few years [21]. Additionally, despite next generation of wireless networks such as LTE offering additional bandwidth benefits, this usually comes at the expense of significantly higher battery power drain [7], [22].

While users expect their device battery to last at least a full day without recharging, currently the latest top-of-the-line devices can achieve that only with relative moderate usage as compared to their usage potential. For example, the iPhone 4S smartphone has a battery rated at 6 hours of Internet usage over 3G or 10 hours of video playback [23]. In practice however, the battery life will be considerably reduced below these ratings when conducting more intensive applications such as for example, playing videos streamed over 3G. Furthermore, the battery may also deplete faster due to various problems with the device itself [24], or in time due to the decreasing capacity as a result of the battery aging effect. In this context, the short battery life continues to represent one of the biggest factors contributing to users' dissatisfaction with mobile devices [25].

C. Evolving Mobile Learning

While initially mobile learning applications were predominantly based on text and low-resolution images, more recently these have evolved to include high quality multimedia, graphics, as well as mobile educational games. In particular, multimedia content has started to be increasingly used in e-learning generally and mobile learning in particular, being projected to increase exponentially over the coming years [26].

There are many forms of creating multimedia educational content such as: lecture and lab sessions recordings, screencasts and video explanations, educational animations, etc. Multimedia content has the advantage of providing a rich display of information and can be used to further enforce the understanding of the concepts being taught. More recently, as video streaming was shown to be as well a viable alternative solution for games delivery across different platforms, educators have started to see its potential for delivering educational games and reach an increased number of learners [27].

However, delivering rich multimedia content to mobile devices connected to wireless networks is a very resource intensive task. Significant network bandwidth and computational power are required to decode, receive, and display a multimedia clip. This in turn drains the device battery power quicker, and leads to situations when the battery runs low and the learner cannot finish the online learning session. The learner needs either to charge the battery or to use another device in order to be able to continue the learning session. This interruption can be annoying, a source of frustration and has negative effects on the learning process in general. In fact, short battery life is a major factor contributing to students' decision to abandon mobile learning tasks [28]. There are many other activities for which users may prefer to use their last remaining battery resources, and the users might actually consider postponing important mobile learning activities if not provided with additional power resources.

In this context, we argue that learners' device battery energy is an important factor to be considered when deploying mobile learning systems and applications.

III. Adaptive M-learning Systems

A. Overview

Mobile learning is an interdisciplinary field that covers computer science and wireless communications, as well as education [29]. The transfer of traditional learning into the electronic environment is a complex task, and this requires an interdisciplinary approach. As it has become clear that a "one-size-fits-all" approach [30], cannot satisfy the specific requirements of all learners and technologies, adaptation and personalisation have gradually been brought to the forefront of the research in the area of e-learning in general and m-learning in particular.

The various adaptation and personalisation solutions that have been proposed address aspects related to the learner profile (e.g., goals, preferences, knowledge level, learning styles, etc.), the learning context (e.g., location in time and space, learner psychological properties such as engagement, motivation, confusion, level of attention, etc.), and/ or technological aspects such as the mobile device characteristics (device screen size and resolution, CPU speed, memory, I/O interfaces, formats supported, etc.), and the network connectivity (e.g., network type, coverage, available bandwidth, etc.) [31].

Adaptation based on the learner profile has received much research interest in the area of e-learning in general, with a significant number of Adaptive E-learning Systems (AELS) being proposed over the past decades [32], [33]. Adaptive mobile learning builds on this knowledge, and extends it with new solutions addressing issues characteristic to mobile learning, mainly due to the high variety of mobile devices and their characteristics, the variable network conditions and the changing learning context.

Particular device-related adaptive m-learning solutions that have been proposed include deploying device independent user interfaces by using device independent languages (e.g., XML, HTML, SMIL, etc.) [34], or enabling delivery of interactive lecture recordings by using various multimedia adaptation techniques (e.g., transcoding, cropping, segmentation, etc.) [35]. Wireless networks-related adaptive solutions include various catching strategies to predict and download in advance learning materials, in order to provide learners with access to educational content when they lack network coverage [36], or to reduce the waiting time associated with low-speed wireless networks [37]. Adaptive solutions addressing the learning context and in particular the learner location, make use of technologies such as RFID for object tagging, GPS for outdoor positioning, or WiFi-based positioning for detecting learners' indoor location [38].

B. Generic Architecture

The generic architecture of an Adaptive M-learning System (AMLS), which adapts to the learner's profile and the learner's device is illustrated in Fig. 2. The main components of such a system are the User Model, the Domain Model, the Adaptation Model, the Device Model and the Adaptation Engine. While many adaptive systems would follow this generic architecture, this does not necessarily mean that all the adaptive systems present all components. Instead, particular systems may present one or more of these components, and they may even have additional components depending on the type of adaptation and personalisation being performed.

The *User Model* maintains information about the learners such as: demographic data (e.g., name, age, gender, etc.), knowledge level on the studied material, goals, preferences, learning styles, evaluation results, etc. The user model is built automatically based on information received explicit from the user (e.g., through forms, questionnaires), or implicit through monitoring.

The *Domain Model* stores the educational content and the relationships between content items. It may be organised in a hierarchical structure of concepts or learning objects. At the lowest level, each learning object corresponds to a specific piece of educational information (e.g., a text, an image, a media clip, a podcast, a flash animation, etc.). Multiple elementary concepts can be grouped in order to create more complex learning concepts.

The *Adaptation Model* defines how the system adapts to a particular User Model. It may comprise a set of condition-action rules which express adaptive strategies based on the learner characteristics and/ or the device characteristics. Various navigational, layout and content adaptation techniques have been applied in order to adapt to each particular learner's needs [39]. Such techniques include link hiding, annotation or disabling, and have the role to guide the learner towards the relevant information, while hiding the information that is inappropriate or non-relevant for the learner.

The *Device Model* stores information about the capabilities and characteristics of the mobile devices used by the learners, in form of device profiles. The profiles contain information about the devices characteristics (e.g., device model and type, screen size and resolution, CPU speed, memory, I/O interfaces, formats supported, etc.). The device and its characteristics may be detected by asking the user to fill a simple form the first time s/he accesses the system, and by matching the answers to one of the devices available in a database [40]. Alternatively this information can be retrieved from an online device repository, based on user agents retrieved automatically when learners access the server [41].

The *Adaptation Engine* performs the personalisation and adaptation of the educational content and the learning process, for example by selecting from the Domain Model the educational concepts that are suitable to a specific learner, based on the adaptation rules.

IV. Making Adaptive M-learning Systems Energy-Aware

Extending adaptive m-learning systems and applications, and making them energy-aware has the potential to signif-

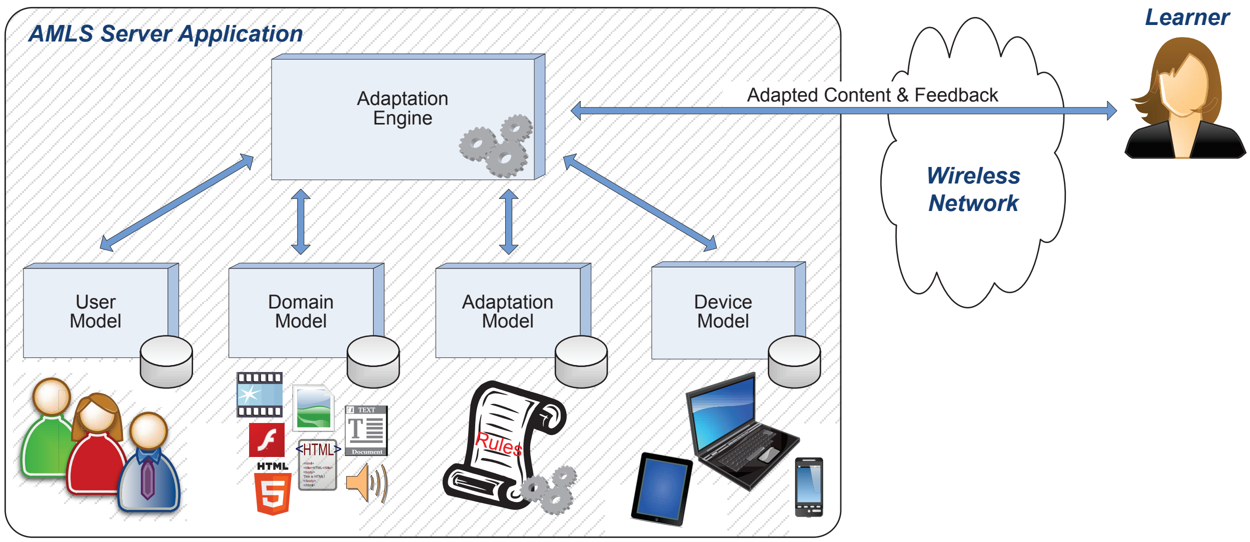


Fig. 2. Generic architecture of an Adaptive M-Learning System (AMLS).

icantly increase the learning outcome as well as learners' satisfaction and experience with m-learning. However, due to the multitude of learners and technologies with different characteristics, a complex multi-dimension approach is required. There are three main dimensions that need to be considered in order to deploy energy-aware mobile learning systems and applications. The first refers to what data is collected, as well as how this is collected and stored. The second dimension is concerned with data reasoning, or how the raw data is analysed and processed in order to have a good knowledge about learners' available battery energy and their energy needs. The third dimension is concerned with the energy-saving actions that can be taken for supporting learners to complete their learning activity or to increase their learning time.

A generic framework of an Energy-aware Adaptive M-learning System (EAMLS), which extends the AMLS architecture with new components characteristic to the three dimensions is presented in Fig. 3. While the framework illustrates various sources of information and energy modelling and adaptation techniques, the list is not an exhaustive one and has more of an illustrative purpose. Furthermore, one system or another may consider only few sources of information and modelling/ adaptation techniques.

A. Data Collection for Energy Modelling

Mobile learning involves various learners with different needs and preferences, using different mobile devices to access educational content over wireless networks with different properties. There are a multitude of factors that can influence a learner's available battery energy resources, as well as his energy requirements. Relevant information about these factors is required in order to accurately predict learners' energy needs, and to apply energy saving actions for supporting them in maximising their learning outcome. A complete mobile learning energy characterization cannot be made without considering at the same time information about the learners, the mobile learning application, the mobile devices used, as well as the network connectivity.

To access the educational content, learners may use a variety of mobile devices with different characteristics and different battery capacity. Static information about the learner device characteristics (e.g., device manufacturer, name, CPU speed, network interfaces, media formats supported, Java/ HTML/ XML support, security, etc.), could be automatically retrieved from device databases such as WURFL (Wireless Universal Resource FiLe) [42], based on device user agents. Other relevant but dynamic information such as for example the running applications, CPU and memory usage, wireless interface states, etc., can be gathered from the Operating System and/ or through tracing the system calls of the applications [43], and delivered to the EAMLS server through a feedback module. Furthermore, both static information (e.g., battery model, capacity, chemistry, optimum charging/ discharging parameters, etc.), and dynamic information (e.g., battery level, voltage, temperature, current drain, etc.), about the battery could be retrieved through the smart battery interface [44] and delivered to the server via the feedback module. Various energy measurement and to less extent energy simulation solutions, as well as their applicability in EAMLSs are presented and discussed in Section V.

The energy consumed by the mobile device to receive the learning content can vary significantly based on the content type, the protocol used for transmission, as well as the wireless network type and its conditions. Relevant information about the wireless network may include the technology type, coverage, capacity, latency, signal strength, available bandwidth, etc. Various techniques have been proposed for measuring the end-to-end available bandwidth based on sending probing packets to the client [45]. One example is to estimate the available bandwidth by analysing how the time distance between two probing packets changes during their transmission to the receiver. Estimating the bandwidth of the wireless connections is significantly more difficult than for wired connections. Wireless networks share the physical medium and their service is highly affected by interferences and the unreliability of the wireless signal due to fading, reflections, refraction,

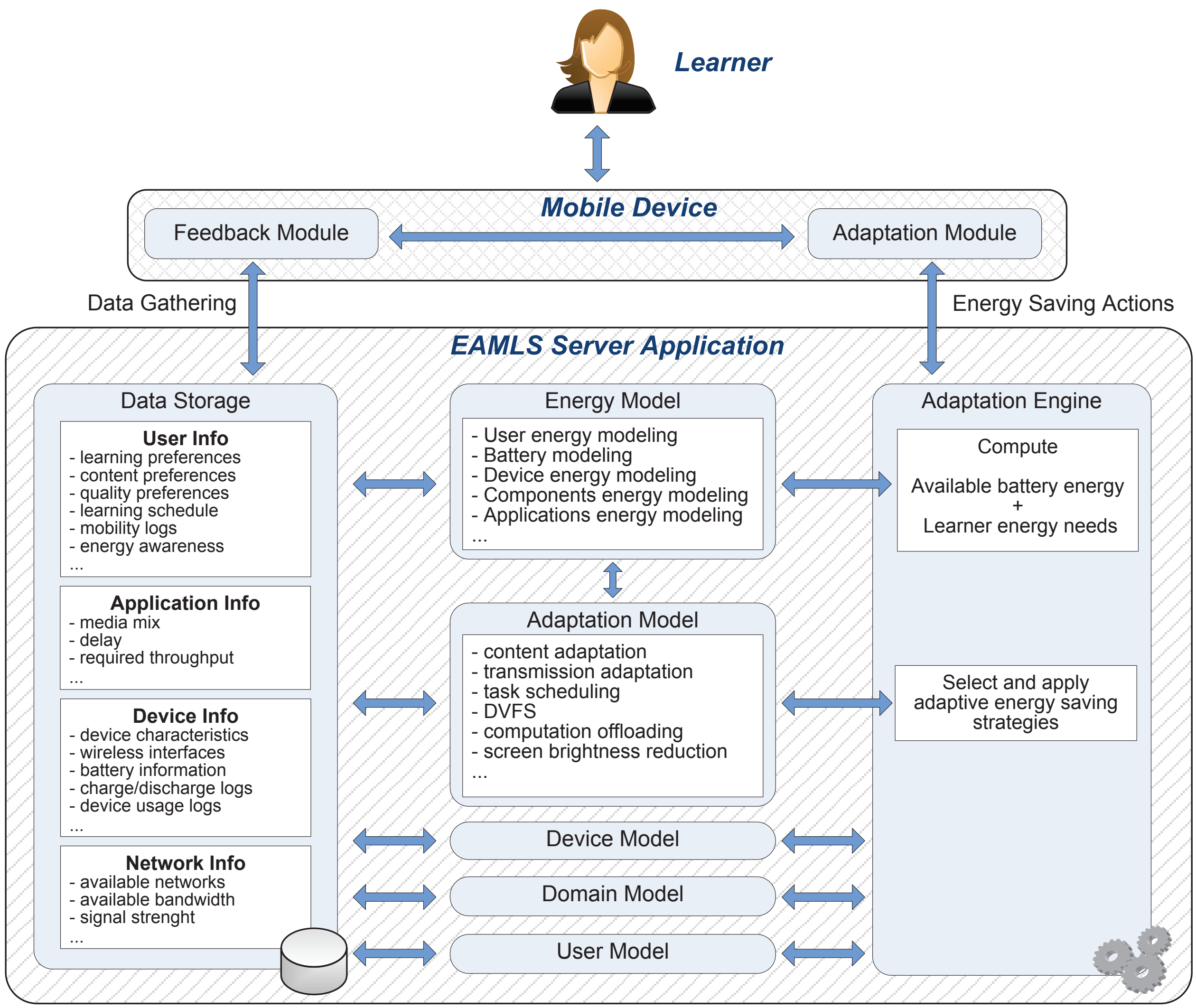


Fig. 3. Generic framework of an Energy-aware Adaptive M-Learning System (EAMLS).

absorption, etc. While the bandwidth estimation techniques should provide accurate values, it is also important for the estimation to be done in a non-intrusive way (i.e., low probing traffic), and considerably fast especially for applications that have critical time response requirements [46].

Information about the learning applications such as for example the media content types used, the maximum delay and the throughput required for providing a certain quality, are also necessary in order to make a good compromise between energy saving and learners' Quality of Experience (QoE) [47].

Learner preferences could also be considered as an important input in the energy-aware adaptation. Information with regard to, e.g., learning styles, preferred media types for presenting the learning content, quality preferences, energy awareness, etc., could be collected for example by asking learners to fill in some questionnaires at the time of registration with the m-learning system. Furthermore, in order to be able to predict learners' future energy requirements, various information needs to be collected over time with regard to their learning schedule, their device charging habits, their roaming across different locations, etc.

B. Energy Modelling

Characterising the energy consumption of mobile learners is fundamental in order to be able to predict if and when they will run out of power before completing their learning activity, and to efficiently manage the available energy provided by their mobile device battery. This requires energy models to be build and integrated with the adaptive m-learning system.

Energy modelling can take as input various data collected about users, applications, devices and/ or networks. Due to the multitude of mobile learning scenarios and the complex interaction between learners and technologies, selecting the most relevant information and using it as input in energy modelling is a complex process. While very accurate energy models may need to consider many parameters, in practice usually only a limited number are considered. This is due to the trade-off between the accuracy and the complexity of the models, in order not to spend undesirable levels of energy with collecting, processing and sending the required data to the system.

There are two main aspects that need to be considered for building energy models: (i) modelling the energy provided by the device battery, and (ii) modelling the energy consumption. The first aspect is necessary in order to be able to accurately estimate the learner's available battery energy at different moments in time, and how much of this can be actually used. The batteries powering the mobile devices, mainly Lithium-based batteries, are complex energy sources [16]. The battery capacity decreases over time due to the ageing effect as well as with every charge-discharge cycle, while the energy released by the battery to the device is influenced by a number of factors such as the discharge current and the temperature. All these aspects need to be considered in order to have an accurate battery modelling.

Energy consumption modelling is essential in order to accurately estimate the energy needed by the learners for completing specific mobile learning activities. This involves many different aspects that would need to be considered such as modelling the energy cost of applications and the energy consumption of mobile devices and their components under different workloads. However, predicting learners' future energy would also require modelling learner related aspects such as their device usage patterns, battery charging/ discharging patterns, mobility patterns, etc. Research work related to energy modelling is presented and discussed in more details in Section VI.

C. Energy-aware Adaptation

Apart from being able to predict when learners will need additional energy resources in order to complete their learning activities, an energy-aware m-learning system should be able to take adaptive decisions in order to manage the available battery energy more efficiently.

Therefore the Adaptation Model is extended with new rules describing various strategies for saving specific amounts of battery energy based on information provided by the Energy Model. Energy saving strategies may include among others content adaptation, dynamic voltage and frequency scaling, computation offloading, adapting the wireless traffic flow or sending the data over a more energy efficient network in range, reducing the screen brightness, etc. For example, the system may decrease the technical quality of the learning content or present this with alternative media types which are less energy expensive to receive and compute. Having information available about multiple wireless networks that are frequently accessed by a learner, the system may compile a list of alternative solutions for transmitting the data, and send a command to the device or a recommendation for the learner to switch to a more energy efficient network in range. Specific energy-saving techniques that have been proposed and their applicability to mobile learning are presented and discussed in Section VII.

The Adaptation Engine (AE) is extended to include mechanisms to continuously compute and monitor learners' available battery energy and their energy needs. This is done based on the energy models stored and continuously updated by the system, and additional real-time information. The AE should also integrate mechanisms for selecting and applying energy-saving strategies when a lower available energy than the one needed by the learners is predicted. The selection among the many available energy-saving techniques is a complex task that would consider different factors such as the amount of energy needed to be saved, learner preferences, context dependent factors such as learner location, etc.

V. Energy Measurement and Simulation

To efficiently manage the energy provided by learners' mobile device battery, good knowledge about the remaining battery capacity, as well as good understanding of where and how the energy is consumed by the device is required. Measuring the device energy consumption under different workloads is the most basic way to evaluate the energy cost of applications and device components. By integrating pre-built energy models, simulators offer a quick and cheap alternative for testing energy saving theories without having to implement complex energy measurement set-ups.

A. Energy Consumption Measurement

Rechargeable batteries powering the mobile devices supply a voltage that decreases around a nominal (average) value (i.e., 3.7V for Lithium-Ion batteries), as the battery charge depletes [16]. Using a number of conditioning circuits such as DC/DC converters, reference regulators and capacitors, the voltage supplied by the battery is regulated, converted and distributed to the various components depending on their voltage supply requirements [48].

Energy measurement can be done at a device-level or at a component level. The instantaneous power consumption of the mobile device can be determined by measuring the battery voltage and the battery current draw and multiplying the two measures. The energy consumed by the device during a specific learning activity can be determined by multiplying the average power consumption with the time duration of that activity.

Similarly, the energy consumption of individual components could be measured if their supply voltage and current draw can be measured. Alternatively, the energy consumption of individual components can be estimated by running a number of benchmarks and comparing the device total energy consumption between different carefully selected cases. As the contribution of different components in the overall energy consumption may vary significantly and some tasks have very short execution times, accurate and fine-grained measurements are necessary in order to provide relevant input data for EAMLS's energy modelling and energy-aware adaptation. There are two main ways in which the device energy consumption can be measured: externally to the device by using additional hardware equipment, or built-in through software access to measurements provided directly by the battery.

1) Device-external Energy Measurement: Device-external energy measurement is an intrusive approach that requires physical access to the mobile device and the use of external equipment for measuring the device voltage and current supply. A number of different current measurement approaches such as current shunt, current mirror, current probe and charge transfer are presented in [48].

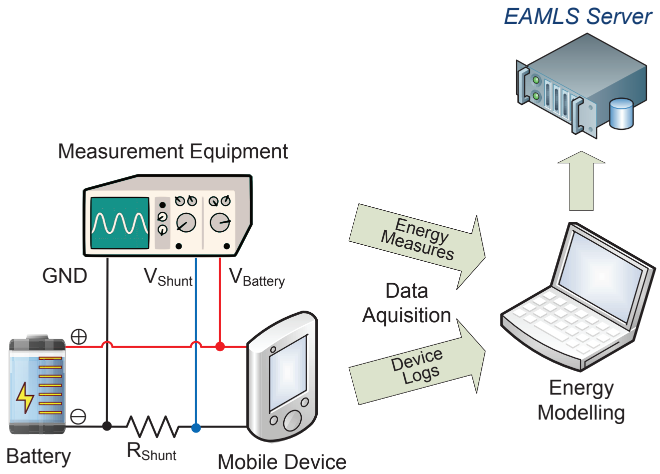


Fig. 4. Generic set-up for external measurement of mobile devices energy consumption, using the low-side shunt resistor method.

Current shunt methods are the most popular in the literature, and are based on measuring the voltage drop across a low-value and high-precision shunt resistor (e.g., 0.01Ω resistance, $\pm 1\%$ tolerance), inserted either on the supply wire (high-side), or on the ground wires (low-side). The high-side approach offers the advantage that one can isolate the current draw of specific device components, as it overcomes the risk for current leakage in other components of the system [49]. Its disadvantage is represented by high common-mode voltages being present on both sides of the shunt in some situations, which may damage the measuring equipment if not provided with high voltage input protection. The low-side approach eliminates the need to account for potential high common-mode voltages, at the expense of less accurate measurements if there is current leakage in the system.

Voltage measurement is usually done using software-driven hardware equipments, which enable to save the data at high sampling rates for further processing. Particular examples of equipments that have been used in the literature range from expensive National Instruments data acquisition systems (DAQ) [50], which enable measurements with up to 24-bit resolution (1.67 million independent values), at sampling frequencies raging from tens of kHz to MHz, to significantly more affordable but less accurate Arduino boards (10-bit resolution, at maximum 10kHz) [51] (see Table VI).

Fig. 4 illustrates the generic setup for measuring the power consumption of a mobile device, using the low-side current shunt method. Two separate measurement equipments or preferably two separate inputs of the same equipment are used for measuring the voltage drop across the battery terminals ($V_{Battery}$), and across the shunt resistor (V_{Shunt}), at a specific sampling frequency.

Having the shunt resistor value R_{Shunt} known, the device power consumption $P[n]$ corresponding to a specific sample n, as well as the device overall energy consumption E for a time duration between the n_1 and n_2 measurement samples, are estimated as in (1) and (2) respectively.

$$P[n] \triangleq \frac{V_{Shunt}[n] \cdot V_{Battery}[n]}{R_{Shunt}} \tag{1}$$

$$E \triangleq \frac{1}{n_2 - n_1 + 1} \sum_{k=n_1}^{n_2} P[k] \tag{2}$$

While the power consumption of individual components could also be measured directly by inserting shunt resistors on their power supply rails, this is possible only with prototyping or open source devices such as Openmoko Neo FreeRunner, for which place-holders for the shunt resistors have been specially designed in advance [52]. A less intrusive method to measure the current consumption without the need to cut the supply wires would be to use current probes such as for example the AIM I-prober 520, which enables measuring the current passing through wires or PCB tracks, as small as 10mA, with an error smaller than $\pm 1\%$ and at sampling frequencies of up to 5MHz [53]. However such probes cost hundreds of dollars and they connect to additional expensive equipments such as oscilloscopes. To eliminate the impact of the battery on the device energy consumption measurements a solution is to power the device from an external source [52], such as for example the Agilent 66319D, a dedicated commercial equipment for testing battery-powered mobile devices, which integrates data logging and battery emulation functionalities [54].

2) Built-in Energy Measurement: In order to be able to accurately measure and monitor the device energy consumption, software applications running on the mobile device need to have access to low-level battery information, such as the battery State-of-Charge (SoC), voltage, current draw and temperature [55].

Important steps towards enabling more accurate software measurements are taken with the increasing adoption and standardisation of smart batteries. Smart batteries are rechargeable batteries commonly found in portable devices, which integrate additional circuits aimed "to provide detailed information to the host device about its state and history so that optimum charging and discharging can be achieved" [56].

Currently there are two specifications describing such batteries: the Smart Battery System (SBS) [57] and the Battery Interface (BIF) [58]. SBS dates back to 1995 and consists of several components describing the data communicated by a smart battery, the smart battery charger, the SBS Manager used for controlling multiple smart batteries in the same system, and the System Management Bus (SMBus) over which the communication between the various components and the host device is made.

BIF was recently introduced by the Mobile Industry Processor Interface (MIPI) Alliance, with the aim to enable wider adoption of smart batteries, as well as to reduce their cost and environmental impact. As opposed to SBS, BIF targets mobile devices specifically, and uses a single wire for data communication instead of two. BIF also offers a number of additional features such as fast battery insertion/ presence/ removal detection, support for legacy and low-cost non-smart batteries, advanced battery authentication and temperature monitoring for enhanced security and safety, and a scalable data structure with software access to all battery data and functions [44].

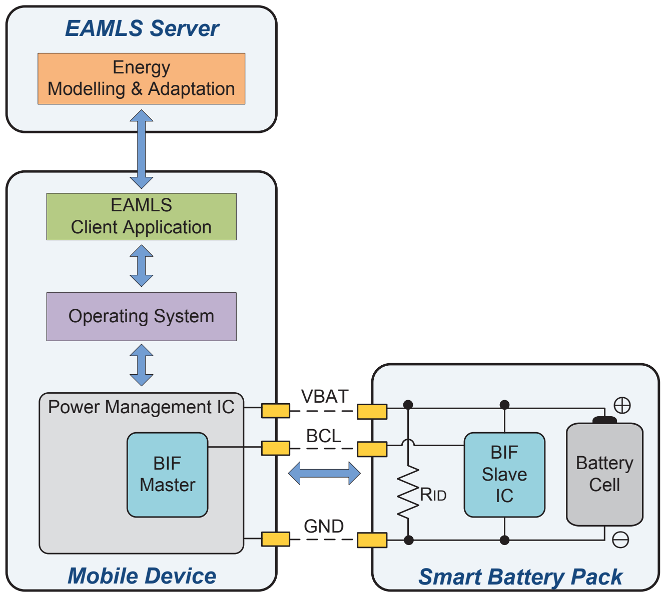


Fig. 5. BIF architecture [44] extended with the possible communication between an EAMLS and a smart battery-equipped mobile device.

Fig. 5 presents the BIF architecture, and how an EAMLS could communicate with a smart battery-equipped mobile device in order to retrieve information about the battery and real-time energy measures. The BIF Master, which can be placed in the power management integrated circuit (PMIC) of the mobile device, communicates with the BIF Slave over the single wire communication line (*BCL*) using the BIF protocol. The value of the R_{ID} pull-down resistor which is connected between the battery positive (*VBAT*) and negative (*GND*) terminals, is used to determine the battery presence, if the battery is smart or low-cost, as well as certain information about the battery chemistry and electrical characteristics.

For a smart battery, additional information is stored in the BIF data structure. This may include generic battery identification information (e.g., manufacturer ID, product ID, etc.), information about the battery functions (e.g., function version, function type such as BIF-predefined or manufacturer specific), capabilities (e.g., monitoring the battery SoC, voltage, current, temperature, authentication, etc.), as well as information about the battery and its field usage history stored as data objects (e.g., battery model, capacity, chemistry, optimum charging and discharging parameters, number of charge/discharge cycles, battery ageing information, etc.) [44]. This information can be accessed by the EAMLS client side application through the smart battery software driver, and passed to the server for further processing.

B. Energy Simulation

Energy simulation software offers a quick way to assess the impact of various factors on energy consumption and to test theories without the need to have access to various mobile devices, nor having to implement time-consuming and complex measurement set-ups. Similarly to energy measurement, simulations can be carried out at a device or component level, depending on how complex and detailed the energy models implemented by the software programs are.

Examples of open source or freeware software packages for simulating mobile devices' energy consumption during wireless transmissions include the Energy Model for ns-2[1] [59], the Energy Framework for ns-3[2] [60], and the Energy Framework for OMNeT++[3] [61]. Additional extensions for ns-2, including an analytical battery model that takes into consideration non-linear battery characteristics such as the recovery effect and the rate capacity effect [62], as well as legacy power management functions defined by the IEEE 802.11 wireless networks standard [63], have also been proposed.

A number of commercial solutions such as Altera PowerPlay [64] and Synopsys Power Compiler [65], are also available for simulating and optimizing the dynamic and static energy consumption of integrated circuits such as FPGAs. However, these are mainly targeted at integrated circuit designers for improving hardware design. For optimizing the energy consumption of software applications in general and mobile learning applications in particular, more suitable solutions would be for example the ARM Development Tools [66]. Application processors and system-on-chips based on the ARM architecture are currently the most widely used in mobile devices. Furthermore the development tools enable developers to evaluate the impact of their application on power consumption, by integrating models that correlate power consumption measurements to the processor usage statistics.

With the increasing integration as a result of decreasing size in the semiconductor manufacturing process and the lack of heatsinks in compact mobile devices, the static energy consumption due to leakage currents increases, and has to be increasingly considered along with the dynamic energy consumption characteristic to actual utilisation. A freely available software that can be used to estimate the static power consumption of system-on-chips through accurate thermal modelling is HotSpot [67].

Freeware and commercial solutions for battery simulation are also available. Dualfoil is a freely available Fortran program that can be used to simulate how the batteries properties change depending on the load profile [68]. The program includes models for various battery chemistries such as lithium-metal, lithium-ion, sodium-ion, and nickel metal-hydride. While the models are very accurate, using the program requires advanced knowledge of the batteries to be modelled, as the user needs to appropriately set tens of battery-related parameters such as for example, the number of current changes, the temperature of the battery and of the ambient air, the thickness of the electrodes, the resistance of the anode and cathode films, the density and columbic capacity of the positive/negative materials, etc. The most notable example of a commercial battery simulation solution is Battery Design Studio, which integrates over 15 electrochemical and equivalent circuit battery models [69].

[1]The Network Simulator - ns-2: http://isi.edu/nsnam/ns/.
[2]ns-3: http://www.nsnam.org/.
[3]OMNeT++ Network Simulation Framework: http://www.omnetpp.org/.

C. Applicability to Mobile Learning

The main applicability of device external energy measurement is that this allows collecting more accurate and high-resolution data, thus enabling building more accurate battery and device energy modelling of learners' mobile devices. However, these require having physical access to learners' devices which is hardly the case with mobile learning. Even if it would be possible to gain this access, it would still not be feasible to create or validate the models for the multitude of devices learners may use. Such an approach will add significant monetary cost in the deployment of the m-learning system. Apart of the cost due to the measurement equipments that could cost hundreds to thousands of dollars, a lot of additional work will be required for collecting and analysing the data used for building the energy models. Furthermore, since these solutions do not enable continuously collecting measurements from the learners, the models built solely on experimental data would not be as accurate when applied to real-life mobile learning scenarios.

The main advantage of built-in energy measurement approach is that it enables automatic, non-intrusive and real-time data collection, which can be used for continuously updating the EAMLS energy models and as an input for the energy-aware adaptation. The main limitation of this approach comes with mobile devices' fragmentation characterised by multiple manufacturers with competing interests, and multiple Operating Systems and devices with different characteristics and capabilities. While the power consumption can be measured with reasonable accuracy for some devices, for others it is not possible due to technological limitations and/ or restricted access of applications to battery measures. For example, the Nokia Energy Profiler [70] is a mobile application and API for Symbian S60 devices, which enables displaying, saving and sending to other applications information such as the battery voltage, current and power consumption, CPU activity, RAM usage, WiFi/ cellular network speed and signal strength, at a 4Hz sampling rate. As opposed, other devices such as for example the increasingly popular ones based on Apple iOS and Google Android, provide access only to a limited number of battery measures (e.g., current consumption not provided along with battery SoC, voltage, and temperature). Furthermore, it is often the case that the measures provided by the smart batteries are averaged over specific durations (e.g., 10, 30 or 60 seconds), before being passed to the applications [71]. Therefore, accurate real-time measurements are not possible for such devices.

Despite the lower accuracy as compared to external energy measurement solutions, built-in solutions are more suitable for mobile learning, as they can be easily integrated with EAMLS for continuously collecting input data for modelling the learners' energy consumption and applying energy saving solutions. Furthermore, by availing of real-world data even at lower resolution, more accurate energy models can be built and more tailored adaptation strategies can be applied.

The main advantage of energy simulations is that these enable a relatively fast and inexpensive way to evaluate energy saving strategies and to assess the energy impact of various factors related to the wireless communication, the battery and/ or the device. Network simulators also enable assessing the energy impact of factors that may be otherwise difficult to control in real experiments (e.g., interferences, amount of packets retransmissions, learner mobility, signal strength, etc.), or to overcome limitations due to the lack of access to technologies. For example, assessing the energy consumption of a learner's device when retrieving the same educational content over different wireless technologies such as WiFi, UMTS and LTE, could be done without having access to each of these technologies, to mobile devices and measurement equipments. This approach however, presents a number of limitations and drawbacks, including: the high cost of commercial simulation applications, the simplicity of some models that do not reflect real measurements, as well as the requirement for the user to have a good energy modelling understanding and programming knowledge.

Therefore, while simulations are suitable for testing energy saving solutions in the early stages of designing energy-aware mobile learning systems and applications, they cannot replace actual energy measurements, which are necessary for validating these solutions in real-life usage scenarios.

Table I summarises the applicability of energy measurement and simulation approaches to mobile learning as well as the limitations that may arise.

VI. ENERGY MODELLING

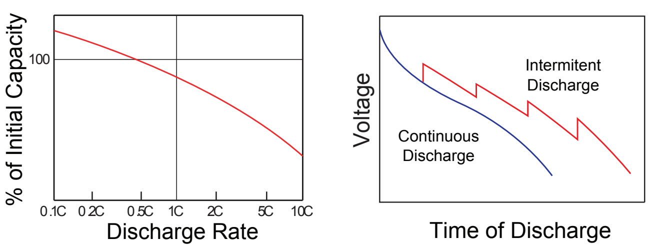
In the context of mobile computing in general and mobile learning in particular, energy modelling is concerned with accurately estimating the available battery energy that can be spent by a user, as well as predicting when the user will deplete this energy. Since having a good understanding of energy consumption and good energy modelling are key ingredients towards deploying efficient energy saving strategies, these aspects are discussed in more details. However, accurate energy modelling and prediction is not a trivial task, since this needs to consider many aspects related to batteries' behaviour, the energy consumption of mobile devices and their individual components, as well as the energy consumption patterns of the different users. Battery modelling [72] can be integrated with the battery management systems for accurate estimation and reporting of the battery state-of-charge, as well as for optimum charging in order to prolong batteries' life [73]. EAMLSs need also to integrate energy models in order to estimate the available battery charge when accurate values are not provided by the battery itself, as well as the remaining usage time in order to be able to efficiently manage the learners remaining battery energy.

A. Energy Modelling Concepts

Accurately estimating the available battery capacity and predicting the remaining usage time on this energy is a complex task, due to the nonlinear battery behaviour, and the time-varying nature at which mobile devices draw power from the battery. The total charge released by the battery is highly influenced by the physical and chemical characteristics of the battery, as well as by a number of nonlinear battery effects [74].

TABLE I
APPLICABILITY OF ENERGY MEASUREMENT AND SIMULATION APPROACHES TO MOBILE LEARNING.

Approach	Applicability	Limitations
Device-external energy measurement	• Collecting high-resolution measurements for offline building of more accurate m-learning energy models.	• Difficulty to build generic energy models applicable to the multitude of devices used by mobile learners. • Added monetary cost in the development of EAMLS. • Cannot be used for collecting energy measurements during real-life mobile learning scenarios.
Device built-in energy measurement	• Collecting energy measurements during real-life usage of m-learning systems for online building and updating of the m-learning energy models. • Can be easily integrated with EAMLS. • Real-time evaluation of energy saving strategies during real-life m-learning scenarios.	• Built-in energy measurements not available for all the devices used by mobile learners. • Lower measurement accuracy and resolution. • Added energy consumption with continuously monitoring and reporting to the EAMLS server of the battery measurements.
Energy consumption simulation	• Rapid testing of energy saving strategies in a variety of simulated mobile learning scenarios using a variety of technologies.	• The need for good expertise due to the difficulty of using simulators. • Not very accurate real-life like energy models are build in simulators.



(a) (b)

Fig. 6. Non-linear battery effects: (a) Rate capacity effect; and (b) Recovery effect [75].

Fig. 6 illustrates two important nonlinear battery effects: the rate capacity effect and the recovery effect [75]. Rate capacity effect consists in part of the battery capacity being lost at higher discharge rates C (i.e., C = 1000mA for a battery with a 1000mAh rated capacity). The recovery effect as opposed, consists in part of the battery charge being recovered by the battery during idle periods.

Temperature is another factor affecting the battery performance. Above room temperature the released capacity increases with the temperature due to higher chemical activity and decrease of the battery internal resistance [76]. Below room temperature the released capacity decreases with the temperature decrease, while prolonged extreme low and high temperatures can permanently affect the battery performance.

Batteries loose part of their capacity during long periods of inactivity. However, this is not an important concern for energy modelling targeting mobile devices, since these are used almost continuously and they are usually powered by lithium batteries, which loose little capacity during inactivity. A more important effect to be considered is the capacity fading consisting of the battery capacity gradually decreasing from its original value with the age and with every charge-discharge cycle, due to reactions taking place inside the battery such as for example the electrolyte decomposition, which in turn increase battery's internal resistance [77].

There are three aspects that are important to be considered in order to have a more accurate and generic energy model: the battery *state-of-charge*, the battery *state-of-health* and the *remaining run-time*. While the first two reflect the available battery energy, the last is an indication on how much time the user has left depending on the activity type.

1) Battery State-of-Charge (SoC): Battery SoC represents the amount of charge present in the battery relative to the maximum possible charge. Making abstraction of the battery operating efficiency and ageing, the SoC can be expressed mathematically as in (3) [78].

$$SoC = \frac{Q_{releaseble}}{Q_{nominal}} \cdot 100\ [\%] \qquad (3)$$

where, $Q_{releaseble}$ is the released capacity of an operating battery when this is completely discharged, and $Q_{nominal}$ is the nominal battery capacity as provided by the manufacturer and usually expressed in ampere-hours (Ah).

Since the maximum releasable capacity of the battery gradually decreases from the nominal value with the battery ageing, the SoC estimation needs to be gradually adjusted to account for these changes. Various solutions for estimating the battery SoC are presented and discussed in [79] and [80]. The advantages and disadvantages of various SoC estimation methods are summarised in Table II.

A complete discharge-charge test under controlled conditions is the most reliable method as it does not depend on the battery state-of-health [79]. However, this is an offline and time consuming method that cannot be used for real-time applications and thus it has little applicability in EAMLSs. Online methods that are more suitable for estimating the SoC of mobile devices batteries during the device utilisation, and thus have a higher potential applicability for EAMLSs, include direct measurements, coulomb/ ampere-hour counting, or adaptive solutions.

The most simple *direct measurement* method involves measuring the battery voltage and estimating the SoC based on a lookup table expressing the relationship between the two [81]. However, the battery voltage is highly affected by factors

TABLE II
SUMMARY OF SoC ESTIMATION METHODS [79], [80].

Method	Advantages	Disadvantages
Discharge Test	• Easy and accurate; • Independent of SoH.	• Offline, time intensive, loss of energy; • Modifies the battery state.
Direct Measurement	• Online, easy.	• Performance varies with battery chemistry, SoH, temperature; • Requires lookup tables with V-SoC/ EMF-SoC relationships; • Need long rest time.
Coulomb Counting	• Online, easy; • Accurate if enough recalibration points and good current measurements are available.	• Needs accurate current measures and regular recalibration; • Needs model for losses and initial SoC.
Fuzzy Logic	• Online, robust.	• Memory expensive in real world applications.
Neural Networks	• Online, ability to learn and represent non-linear relationships from the data.	• Needs training data of a similar battery; • Expensive to implement.
Kalman Filters	• Online, dynamic, flexible, accurate.	• Computation intensive, needs a good battery model; • Difficult to implement filtering algorithm that considers all features (e.g., non-normalities and nonlinearities).

such as temperature, discharge current, or battery ageing. Furthermore, different battery chemistries present different voltage profiles, with some chemistries such as for example lithium-iron-phosphate exhibiting extremely flat profiles [82]. Since many of the assumptions made for voltage modelling do not hold for batteries with flat voltage profiles [83], for such batteries the voltage can only indicate the complete battery discharge when a steep voltage drop occurs, while differentiating between different intermediate SoC levels based on the voltage alone is not possible.

A more accurate direct measurement method consists of estimating the SoC based on the electro-motive force (EMF), the driving force of a battery for providing energy to a load [80]. While EMF is less affected by temperature and battery ageing, this approach requires a detailed lookup table describing the EMF-SoC relationship, as well as an accurate solution to compute the EMF. One possible solution is to estimate the EMF based on the battery voltage, current and impedance, while differentiating between the linear and hyperbolic regions of the battery discharge curve [84].

The solutions based on *coulomb/ ampere-hour counting*, involve measuring the total current that flows in and out of the battery, and integrating this current in order to estimate the battery SoC. The SoC can be expressed mathematically as in (4) [79].

$$SoC(t) = SoC(0) - \frac{1}{Q_{nominal}} \int_{0}^{t} I(t)\ dt \qquad (4)$$

where, $SoC(0)$ and $Q_{nominal}$ represent the initial SoC and the nominal battery capacity respectively, while $I(t)$ represents the measured current (positive current when the battery is discharged and negative when charged).

The coulomb-counting method is suitable for batteries with high charge-discharge efficiency such as lithium batteries, and is widely used for portable electronics thanks to its computation simplicity. However, it also presents a number of disadvantages. In order to accurately estimate the battery SoC, accurate and fine-grained current measures are needed, while the initial state-of-charge $SoC(0)$ needs also to be known or accurately estimated through a separate method. Fine-grained current measurements are usually not possible through built-in solutions, since smart batteries usually average the current and report the values at specific intervals, while current measurement errors may further affect the SoC estimation. Furthermore, various factors affecting the battery's maximum releasable capacity such as the temperature effect, rate capacity effect and the battery ageing, need also to be considered for accurate SoC estimation.

To overcome its limitations coulomb-counting is often combined with direct measurement methods. For example Codeca *et al.* [85], have proposed a mixed solution that makes use of voltage measurement and knowledge about the V-SoC relationship, in order to correct the estimation errors of the coulomb-counting approach. By combining coulomb-counting with EMF measurement, Pop *et al.* [86] have shown that the battery SoC and remaining-run-time can be determined within 1% accuracy.

The *adaptive solutions* [87] aim to improve the accuracy of the SoC estimation by accounting for the unpredictable behaviour of batteries and of the users. The solutions make use of direct measurements and/ or coulomb-counting, as well as computation intelligence techniques such as Fuzzy logic (e.g., [88], [89]), artificial neural networks (e.g., [88], [90], [91]), or Kalman filters (e.g., [91], [92]). Due to their self-learning ability, the adaptive systems are capable to draw useful conclusions from ambiguous or imprecise data with a multitude of variables, and in this way to respond to the time-varying behaviour of batteries and users. While these solutions usually enable a higher SoC estimation accuracy, this comes at the cost of significant higher computation complexity.

2) Battery State-of-Health (SoH): Battery SoH represents the condition of the battery with regard to its ability to hold and deliver a specified charge as compared to an identical new battery and can be expressed mathematically as in (5) [78].

$$SoH = \frac{Q_{max}}{Q_{nominal}} \cdot 100\ [\%] \quad (5)$$

where, Q_{max} represents the maximum capacity that can be released by the fully charged battery, and $Q_{nominal}$ is the nominal battery capacity specified by the manufacturer.

The SoH is close to 100% for a new battery, since a Q_{max} approximately equal to $Q_{nominal}$ can be released if making abstraction of nonlinear effects affecting the battery performance during its operation.

However, batteries gradually loose part of their nominal capacity due to the ageing effect as well as when subjected to abusive treatment (e.g., extreme operating temperatures, complete frequent discharges, etc.). Furthermore, different batteries have different characteristics and different mobile users use their device batteries differently. Therefore, accurately estimating the battery SoH cannot be made without considering both information about the battery behaviour and its usage history.

Battery SoH is often addressed alongside battery SoC in adaptive solutions for more accurate estimation of the battery's actual capacity. In general, these solutions take as input information about the battery characteristics (e.g., nominal capacity, chemistry, physical properties, etc.), the changes that occur in the battery with ageing (e.g., through impedance spectroscopy [93]), and/ or charge/ discharge history (e.g., through charge-discharge cycle count, coulomb count [78], [94]), and estimate the battery SoC and SoH by using techniques such as Fuzzy logic, artificial neural networks, and/ or Kalman filters.

An example of an alternative solution aimed at embedded systems with low computation power was proposed by Mircea *et al.* [95], which estimates the battery SoH based on stored information about the maximum battery capacity as a function of the charge/ discharge cycles and making use of curve modelling and polynomial regression.

3) Remaining Run-Time (RRT): Remaining run-time can be defined as the duration of time for which the battery can supply current to the mobile device before it will stop functioning. For a constant current load and making abstraction of the nonlinear battery effects, RRT can be obtained by dividing the battery releasable capacity ($Q_{releaseble}$) measured in ampere-hour (Ah) to the current I measured in ampere (A) [86], as in (6).

$$RRT = \frac{Q_{releaseble}}{I}\ [h] \quad (6)$$

However, constant current loads rarely occur in real mobile device usage scenarios, which are rather characterised by highly variable current loads due to variations in terms of the device utilisation both in time and between different users. Due to the nonlinear battery effects such as rate capacity effect and recovery effect, the released capacity by the same battery can greatly vary between two scenarios with different variable current loads (also known as load profiles). During intervals with high current loads part of the maximum releasable capacity is lost, and the loss is partially recovered during idle intervals or intervals with low current loads.

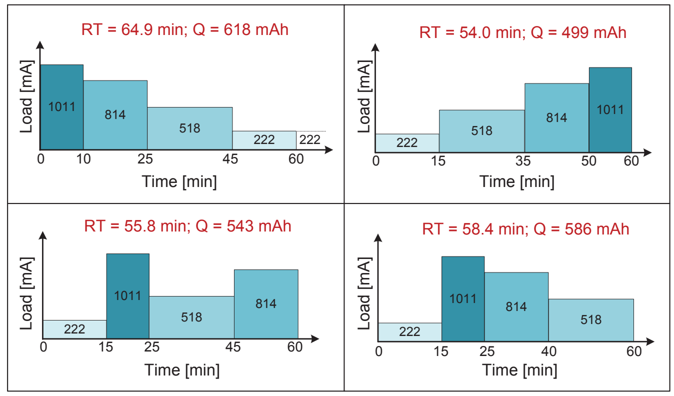


Fig. 7. Explanatory figure illustrating the performance of a mobile device lithium-ion battery for different load profiles (note the variation in terms of battery run-time RT, and released capacity Q). For each profile the battery with a nominal capacity of 640 mAh, was completely discharged from fully-charged to the cut-off point [96].

For example, Rakhmatov and Vrudhula [96] have conducted a number of experiments in order to assess how the run-time and the released capacity of a mobile device lithium-ion battery vary when discharged at various load profiles. Summarizing some of their results, Fig. 7 shows that simply by changing the order of four activities with different constant current loads (i.e., 1011, 814, 518 and 222mA) and different durations (i.e., 10, 15, 20 and 15 minutes respectively), the run-time of a battery with a 640mAh nominal capacity can vary between scenarios with as much as 11 minutes, which translates in a 20% releasable capacity loss between the two best and worst performing scenarios. However, note that these load profiles are still very simple as compared to real-world ones, for which high current variations occur even during the same activity, and intervals of inactivity with very low currents are also common.

Accurate estimation of the RRT requires accurate modelling of the relationship between the load profile and the battery releasable capacity, which even for similar load profiles may vary from device to device. Moreover, constructing an accurate load profile requires detailed knowledge about the user's future activities, as well as where and how their mobile device consumes energy during these activities. Therefore, estimating learners' available battery energy and accurately predicting when they will deplete their available energy resources cannot be made without considering at the same time aspects related to the battery, device and user in the energy modelling. Having a good energy model, various current load decrease and/ or task scheduling strategies [97] can then be applied in order to maximise the battery releasable capacity, better managing learners' available energy resources and eventually allowing them to complete their learning activities.

B. Battery Modelling Approaches

There is a substantial body of research proposing solutions for modelling the battery behaviour and important aspects such as the battery voltage, SoC, SoH, and RRT for specific load profiles. Depending on their particularities, the multitude of battery models that have been proposed can be classified

TABLE III
SUMMARY OF BATTERY MODELLING APPROACHES.

Models	Advantages	Disadvantages
Empirical	• Simple; • Low computation complexity.	• Very low performance; • Do not accurately model nonlinear battery effects.
Electrochemical	• Most accurate; • Account for battery characteristics and internal processes.	• Very complex with high number of parameters and variables; • Difficult to configure and implement; • Computation expensive.
Electrical-circuit	• Simple and intuitive; • Easy to implement with mobile systems.	• Very complex for high accuracy; • Need lookup tables with stored relationships between parameters; • Difficult to configure for multiple battery types.
Mathematical	• Robust; • Battery properties modelled using few equations.	• Abstract, often with low practical meaning; • Lower accurately for modelling electrical battery characteristics.
Mixed/ Hybrid	• Improved accuracy; • Combine advantages of different models.	• May be difficult to implement; • Computation intensive.

in: empirical, electrochemical, electrical-circuit, mathematical, and mixed/ hybrid models [76], [98]. Presenting detailed studies corresponding to each of these categories is out of the scope of this paper, as it can be the subject of a separate survey on its own. Instead, a brief overview with regard to the main characteristics, advantages and disadvantages of the different modelling approaches will be provided, while directing the reader to selected relevant research studies, some of which compare the performance of multiple models, for additional details. The advantages and disadvantages of the various categories of battery models are summarised in Table III.

1) Empirical Models: Empirical battery models (e.g., [99], [100]) describe the battery behaviour through simple equations with parameters usually fitted to match experimental data. In case of an ideal battery whose voltage stays constant during operation and drops to zero only when the battery is completely discharged, and whose released capacity is the same independently of the load profile, the battery life (run-time) could be expressed through a simple equation as in (6). Since this is not the case with real batteries, empirical models attempt to capture the nonlinear effects by extending the ideal model equation with parameters derived from experimental data.

Dating back to 1897, Peukert's law is probably the most well known empirical model, which expresses the battery life as a nonlinear function of its discharge rate [76], as in (7).

$$L = \frac{Q}{I^{\alpha}} \tag{7}$$

where, Q represents the battery capacity, I the discharge current, while α is a constant that depends on the battery type and generally increases with the battery age.

For a variable discharge current $I(t)$, Peukert's law can be extended by using the average current from t = 0 (battery fully charged), to $t = L$ (battery fully discharged) [98], as in (8).

$$L = \frac{Q}{\left(\frac{1}{L}\int_{0}^{L} I(t)\ dt\right)^{\alpha}} \tag{8}$$

Peukert's law however, was found to generally underestimate the battery capacity and life for variable discharge currents and variable operating temperature, as is often the case with mobile devices lithium batteries [101].

2) Electrochemical Models: Electrochemical battery models also called physical models (e.g., [102], [103]), are usually the most accurate ones. This is because the battery behaviour and its important parameters are modelled at the lowest level by taking into consideration the particular characteristics of each battery type being modelled, as well as the chemical, physical and thermodynamic processes taking place inside the battery. Their accuracy however, comes at the expense of very high complexity and is common for these models to include tens of parameters and variables. Electrochemical models are difficult to configure and implement since they require good knowledge about the behaviour of the particular batteries to be modelled, and being computationally expensive, they are slow and often not feasible to be integrated with mobile devices energy management systems.

3) Electrical-circuit Models: Electrical-circuit battery models (e.g., [104], [105]), aim to provide equivalent representations of the battery using circuits consisting of various components such as voltage sources, resistors and capacitors. These models require lookup tables storing the relationships between battery parameters (e.g., voltage-SoC relationship), and can include circuits that discharge the battery capacity, and discharge-rate normalisers that determine the lost capacity at high current loads. Various electrical-circuits models with different complexity have been proposed, ranging from simple models to complex nonlinear and dynamic models [106]. The electrical battery properties can be modelled with good accuracy using this approach, as electrical-circuit models were shown to outperform a number of mathematical models [107].

These models are especially applicable in case of mobile systems, since mobile devices can also be represented through equivalent-circuits thus obtaining a complete device-battery energy model. However, due to the need for look-up tables and the experimental data needed to create them, electrical-circuit models may also imply significant configuration and implementation effort, especially when multiple device types with different battery characteristics need to be considered, such as would be the case with EAMLS.

4) Mathematical Models: Mathematical battery models (e.g., [108]–[111]) make use of equations and/ or other mathematical methods such as stochastic processes, to describe the battery behaviour at a higher level of abstraction than electrochemical and electric-circuit models.

Analytical models such as for example the KiBaM model based on the chemical kinetics process [108], and Rakhmatov and Vrudhula's model based on the diffusion of ions in electrolyte [109], express the battery properties using a reduced set of equations with very few parameters, and were shown to offer good performance under different workloads with less than 10% errors when compared against a detailed electrochemical model [98].

In contrast, stochastic models represent the battery as a finite number of states (i.e., charge states), while the battery behaviour is modelled as the transition between the various states using stochastic processes such as Markov chains [110]. The approach enables modelling both the battery discharge as transitions to lower charge states and nonlinear battery effects such as the recovery effect as transitions from lower to higher charge state.

While mathematical models provide high analytical insight being suitable for performance analysis, and are not very difficult to implement, they are often too abstract and have low practical meaning as they do not well connect to the battery electric, physical and chemical processes.

5) Mixed/ Hybrid Models: The mixed or hybrid battery models aim to offer a better compromise between performance and complexity by exploiting the advantages provided by different modelling approaches. Examples include extending analytical models with stochastic workload representations for more accurate estimation of the RRT under variable current loads [75] [112], or combining electrical-circuit models that are more accurate in predicting the dynamic circuit characteristics of the battery, with analytical models that are more accurate in predicting the nonlinear battery capacity effects [113].

C. Device Energy Analyses and Modelling

Along with having a good knowledge about the available battery charge and how this varies with the operating conditions and the load profile, having accurate load profiles is equally important in order to be able to compute the device run-time for different applications. Creating accurate load profiles in turn, requires a good understanding on where and how the battery energy is consumed by the mobile device, and how the device current draw varies with its utilisation and application load.

However, mobile learners may use a multitude of devices, and the increasing complexity and fragmentation of these devices makes it very difficult to construct a generic device-battery-energy model capable to estimate the RRT with good

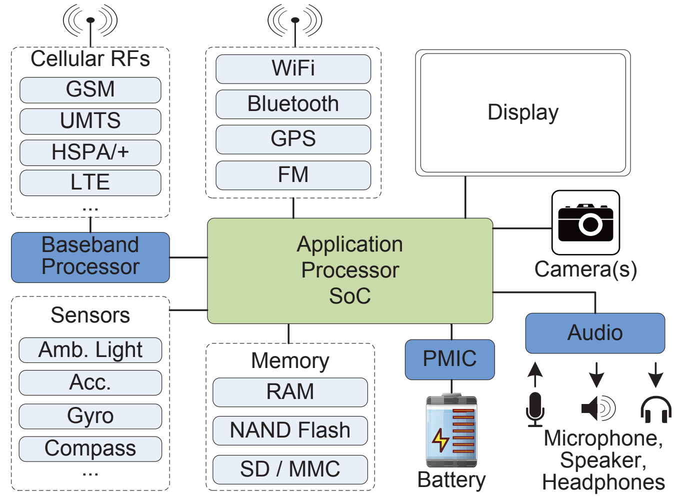


Fig. 8. Generic block diagram of a modern mobile device (e.g., smartphone, tablet).

accuracy for all devices while maintaining its complexity at a feasible level. Modern mobile devices such as smartphones and tablets can run on various operating systems (e.g., Android, iOS, Windows Phone, Symbian, BlackBerry OS, etc.), and are very complex technological equipments. A generic block diagram of a modern mobile device is illustrated in Fig. 8.

It is common nowadays for various mobile device subsystems such as single/ multi-core CPU and GPU to be integrated in the Application Processor system-on-chip. Modern devices also integrate multiple wireless technologies such as WiFi (802.11b/g/n/ac), Bluetooth, NFC, GSM/ EDGE/ UMTS/ HSPA/ HSPA+/ LTE/ WiMAX/ W-CDMA, with many of these usually integrated in the same chips [114]. Some devices use additional external memory cards for data storage, while others rely solely on internal flash storage. Furthermore, it has become a norm for mobile devices to integrate a multitude of sensors such as GPS, accelerometer, gyroscope, ambient light sensor, compass, and/ or barometer, as well as one or multiple photo/ video cameras.

1) Mobile Devices Energy Consumption: Several research studies aimed to provide a better understanding on where and how the battery energy is consumed by mobile devices. Some of these studies have concentrated to assess the device overall energy consumption under various workload situations, without necessarily trying to understand the contribution of each of the different components to this energy. Other studies have tried to break down the device overall energy consumption by assessing the individual energy consumption of one or several components commonly present in mobile devices.

Rather than describing each individual study (a common practice among other surveys), a summary of the most relevant findings with regard to the energy consumption characteristics of different device components is presented in Table IV. The energy consumption characteristics of typical mobile learning applications usually combining audio-video (e.g., podcasts, screencasts, lecture recordings, etc.), and/ or static web educational content (e.g., images, text), are presented in Table V.

TABLE IV
ENERGY CONSUMPTION CHARACTERISTICS OF VARIOUS COMPONENTS COMMONLY FOUND IN A MOBILE DEVICE.

Component	Energy Consumption Characteristics
General	• Mobile device components present low power states (i.e., sleep, idle), to which they are usually turned when not in use. • Part of the battery energy is lost in the process of converting it to the levels required by the various components [52]. • Up to 50% of total power consumption in modern devices is static energy, consumed by components in Idle states when not actively used; turning these components to sleep or completely OFF leads to significant power saving [52]. • Display, CPU, WiFi/ Cellular networks are usually the highest energy consumers [52]. • RAM, Flash, Audio, Sensors have smaller impact (still good to be turned OFF when not in use, since they add up) [52].
Display	• Significant energy consumption increase with the brightness level (nonlinear/ linear increase, depending on device) [52], [117]. • Nonlinear increase with content luminance and chrominance (significantly higher for OLED than for LCD displays) [52], [117].
CPU	• Nonlinear increase in dynamic power consumption with the CPU frequency for the same application load [117]. • Significant variation with the application load for the same CPU frequency [52]. • Running some applications at lower frequency, decreases the power consumption but may increase the overall energy consumption (due to lower performance) [52]. • Decreasing dynamic power consumption and increasing static power consumption due to decreasing nanometer manufacturing scales, and increased integration of multiple subsystems in system-on-chips [118].
RAM Memory	• Presents significant variation with the memory frequency and the application load [52].
Flash Memory	• The energy consumed to read/ write the same amount of data decreases with the read/ write throughput [52]. • Data write (slower) is less energy efficient than read (faster) [52]. • External flash storage such as SD card is slower and is less energy efficient than internal storage (faster) [52]. • Most of the energy consumed to read/ write data is actually spent by CPU and RAM (higher share for internal than external storage) [52].
WiFi	• Power consumption can be up to 14 times higher in idle than in sleep state for 802.11n [119]. • Data transmission (Tx) is more energy expensive than data reception (Rx) [119]. • Doubling the channel width (i.e., from 20MHz to 40MHz), doubles the bitrate with small impact on power consumption [119]. • Transmit power has little impact on energy consumption [119], [120]. • Using multiple antennas significantly increases energy consumption and can lead to energy saving only for large packets and strong links. Receiving short packets with a single antenna at lower bitrate, can be twice as energy-efficient than receiving them as fast as possible with three antennas [119]. • Energy consumption increases with the time increase between successive transfers [121]. • Energy consumed to connect to the network is higher for dynamic than static addressing [122].
Cellular (GSM, UMTS, LTE, etc.)	• Cellular networks are less energy efficient than WiFi [121], [123]. • GSM accounts for significant power consumption in the sleep and idle device states [52]. • GSM is more energy efficient than 3G, but only when transferring low amounts of data [121], [124]. • Often handover between various cellular technologies leads to energy being wasted (handover from GSM to 3G is faster and more power intensive than from 3G to GSM, but approximately the same energy is spent in both cases) [124]. • GSM and 3G present significant loss due to tail energy (wireless card is maintained in a high-power state for several seconds after the actual data transfer), and to less extent due to ramp energy (energy required to switch to the high-power state) [121]. • Energy consumption of 3G increases with the time increase between successive transfers [121].
Bluetooth	• Moderate power consumption (usually below 50mW), which increases with the distance between sender and receiver [52].
Camera, GPS, Sensors (Gyro, Accelerometer, etc.)	• Usually lower but relatively constant power consumption when turned ON and in use [52], [117], [125]. • GPS usually more power hungry than other sensors; independent power consumption with the signal strength [52], [117].
Audio (Codec, Amplifier)	• Nonlinear increase with the volume level [117]. • Higher power consumption when using the built-in speakers at high volume levels [117]. • Low increase in power consumption with volume when using external earphones [117].

A mobile learning application may use several different device components at the same time, with each of these exhibiting different power consumption patterns. Some device components such as WiFi/ cellular network cards, Bluetooth, CPU, RAM and display present high energy consumption variation in time, being influenced by various application and content related factors (e.g., download/ upload size, computation complexity, content/ interface luminance and chrominance, etc.), as well as by the context (e.g., signal strength, network load, etc.). Other components such as photo/ video camera, GPS and the various sensors, present relatively constant power consumption once turned on, and although this might be lower than of other components such as CPU and wireless card, they can lead to significant battery drain if used for longer periods of time. Mobile learning applications may also use such components for supporting personalised and context based learning (e.g., GPS for determining the learner location, camera to communicate with peers, ask for feedback or upload their own content, etc.) [115]. Therefore, energy modelling should address the energy consumption characteristics of all the different components.

Mobile devices may present multiple wireless and cellular interfaces with different energy consumption characteristics. The energy consumption of a wireless interface may vary

TABLE V
ENERGY CONSUMPTION CHARACTERISTICS OF COMMON MOBILE LEARNING USE-CASES.

Use-case	Energy Consumption Characteristics
Podcasts (Audio Playback/ Streaming)	• Very small amount of energy consumed by the audio codec and amplifier; most of the device energy consumption is represented by the static contribution of other device components which are not actively used (e.g., GSM, CPU, Graphics, LCD, etc.) [52]. • Wireless network cards account for significant energy consumption in case of audio streaming.
Video Lectures, Screencasts (Video Playback/ Streaming)	• For local video playback the display accounts for the highest amount of energy consumed, followed by CPU and graphics [52]. • Playing the video from internal rather than external flash storage has little impact on energy consumption [123]. • Energy consumption significantly increases with video quality settings (e.g., resolution, frame rate, and bitrate) [117], [126]–[129]. • Some video codecs are more energy efficient than others (e.g., H.263 more efficient than H.264), while the file formats has little impact on energy consumption [127]–[129]. • Energy consumption varies with content characteristics (e.g., temporal dynamicity, colors, etc.) [129], [130]. • Streaming as opposed to locally playing the video can up to double the device energy consumption [117], [126]–[128]. • Downloading then locally playing the video is more energy expensive than streaming [123]. • UDP streaming more energy expensive than TCP streaming [126]. • Poor wireless network signal strength increases the energy consumption (higher impact on TCP than UDP) [126]. • Energy consumption increases with the network traffic load (higher impact on TCP than UDP) [126].
Online Lectures (Web Browsing)	• Display and graphics have the highest contribution in the device energy consumption [52]. • Wireless transmission accounts for significant amount especially when using low speed networks such as GPRS [52].

depending on different factors such as the operation state (i.e., Transmit, Receive, Idle or Sleep), the channel width, the number of antennas used, or the transmit power (see Table IV). Short-range networks tend to be more energy efficient than long-range networks [14], such as for example Bluetooth being more energy efficient than WiFi, and WiFi more energy efficient than 3G. Some network interfaces such as 3G present energy losses due to tail energy or the device remaining in a high-power for few seconds after the actual data transfer has ended. Other factors related to the wireless network such as signal strength and traffic load can also impact the energy consumption of the wireless card.

Therefore, all these aspects should be considered in energy modelling and different energy models should be built for different wireless networks. Accurate energy consumption models for each of the mobile device's wireless interfaces extended with information on the condition of the available networks are necessary for deploying energy saving techniques, such as for example choosing the most energy efficient network for delivering the content.

Only part of the energy provided by the device battery is actually used by the device when conducting a certain learning activity such as playing an educational video clip (dynamic energy). Part of the battery energy is lost in the process of converting the non-linear battery voltage to constant levels required by the different components, as well as static energy when the device components are in low power states and not actively used. The dynamic energy consumption of the same application varies from device to device, and even on the same device in different situations (e.g., depending on background applications, device settings, network speed, background traffic, etc.).

The device components usually present low power sleep states and mobile operating systems usually have very aggressive policies to turn the components to these states when not in use. However, faulty implementations ("ebugs") may prevent accurate state changes and lead to unnecessary energy consumption [116]. Energy modelling needs to account for both the dynamic and static components in order to obtain accurate load profiles.

2) Device Energy Models: Various research studies have attempted to model the energy consumption of mobile devices, device components or applications. A summary of some relevant studies is presented in Table VI. A common approach in the literature relies on deriving empirical equations from experimental data using simple methods such as linear regression. The major limitation of this approach is that the equations describing the energy consumption as a function of very few parameters (e.g., OLED screen power consumption as a function of screen brightness and pixels brightness [117]), present constants derived from empirical data that are specific to a particular device(s) being used for constructing the model. Therefore, constructing or validating a model for multiple devices requires running experimental tests for each device.

In practice, it is not possible to run experimental measurements in order to collect sufficient data for constructing accurate energy models, as well as to adjust them for all the different mobile devices learners may use. Even for a single device, the number of use cases may be in the order of millions. This is because there are a multitude of possible combinations between device settings users can change (e.g., display brightness, volume level, static/ dynamic network addressing, etc.), device components states (e.g., WiFi OFF, Sleep, Idle, Rx, Tx), application characteristics (e.g., length, computation complexity, etc.), and other environmental factors (e.g., network load, signal strength, etc.).

Palit *et al.* [131], [132] have tried to address this issue by identifying various categories of parameters (i.e., basic, active, passive) among multiple devices, and proposing a methodology for selecting relevant use cases for particular classes of applications. While their method can significantly reduce the testing time for offline energy performance evaluation of applications in a lab-setting environment, this relies on conducting measurements using external equipment. Therefore,

TABLE VI
SUMMARY OF SELECTED MOBILE DEVICE ENERGY MODELLING STUDIES.

Ref.	*Platform* (Device)	Energy Measurement	Modelled Component	Independent Variables	Modelling Approach	Performance
[43]	*Android* (HTC Magic); *Windows Mobile* (HTC Touch, HTC Tytn II)	*HW*: Monsoon Power Monitor @ 5kHz	CPU, Disk, WiFi	System calls; Constant coefficients derived from measurements.	Finite State Machines; Linear regression.	<10% for 50sec interval and <5% for 1min interval, across different applications.
[52]	*Android* (Openmoko Neo FreeRunner)	*HW*: National Instruments PCI-6229 DAQ @ 5kHz	CPU, Audio, Video, SMS, Call, E-mail, Web	Backlit power in Watts; Time; Constant coefficients derived from measurements.	Empirical equations.	n.a.
[117]	*Android* (HTC Nexus One)	*HW*: Arduino @ 140Hz	Screen, CPU	Screen brightness vs. pixels brightness; CPU utilisation; Constant coefficients derived from measurements.	Curve fitting (best-fit polynomial equations).	Screen: R^2 = 0.99; CPU: R^2 = 0.89
[121]	*Symbian* (Nokia N95); *Windows Mobile* (HTC Fuze)	*SW*: Nokia Energy Profler v1.1 @ 4Hz; *HW*: Monsoon Power Monitor @ 5kHz	3G; GSM; WiFi	Size of transfer; Time between successive transfers; Constant coefficients derived from measurements (ramp energy, tail energy, maintenance energy).	Empirical equations.	n.a.
[133]	n.a.	n.a.	WiFi	Theoretical model: running applications, components power states, weight factors indicating the level a component is used by an application; Empirical model: WiFi power states, transfer speed.	Theoretical history based model; Empirical validation.	n.a.
[134]	*Android* (HTC Dream, HTC Magic)	*HW*: Monsoon Power Monitor @ 5kHz	CPU, WiFi, Audio, LCD, GPS, 3G	CPU utilisation, frequency, state; Audio state; WiFi state, number of Rx and Tx packets per second, uplink channel rate, uplink data rate, LCD brightness level; GPS state; 3G state, data rate, downlink/ uplink queue; Constant coefficients derived from measurements; Battery voltage.	Multi-variable regression for HTC Dream offline model.	<10% avg error for 1sec intervals; <2.5% avg error over application lifespan.
[135]	*Linux* (Dell Latitude D600 laptop)	*HW*: Echidna @ 4.7kHz	CPU	CPU frequency & voltage; CPU counters (number of completed burst transactions, number of lines removed from the L2 cache); Time spent in idle state; Temperature.	Regression.	R^2 = 0.96

the method needs to be adapted in order to be used for online energy modelling by adaptive systems and applications such as EAMLSs.

Online energy modelling approaches are more suitable to be used for constructing energy models for multiple devices learners may use, as these eliminate in part the need for having access to the specific devices and to conduct complicated and time consuming measurements. However, these require mobile devices to have built-in power measurement capabilities, as well as to enable access to various information about their state needed in the modelling (e.g., device settings, list of running applications and their calls to access device resources, received network signal strength, etc.). Alternatively, if built-in current measures are not available, energy consumption measures could be derived on longer usage intervals and with smaller accuracy based on battery voltage and temperature measures and knowledge about the battery discharge behaviour [134]. An initial energy model can be constructed for example by embedding training software in the mobile learning application. The software collects energy measurements while setting the device components in different states and running a set of benchmarks. The model can be continuously improved based on historic and current information.

Modelling the power consumption of device components can be done based on utilisation information from the corresponding components' performance counters. While modern CPUs provide a multitude of performance counters to measure a large number of events, only a small number of events can be counted at the same time [135]. Selecting the most important counters can be quite challenging in practice as this requires many identical runs for multiple benchmarks and for multiple settings. CPU performance events were also shown to correlate with the power consumption of device components external to CPU, such as memory and I/O, and thus can be used for energy consumption modelling of these components [136].

By evaluating a number of linear and non-linear regression-based energy models McCullough *et al.* [137] have concluded that while it is possible to estimate the total system power with relatively small errors, estimating the energy consumption of device subsystems such as the CPU is more difficult and prone to high errors due to increased technological complexity and hidden power states not exposed to the OS.

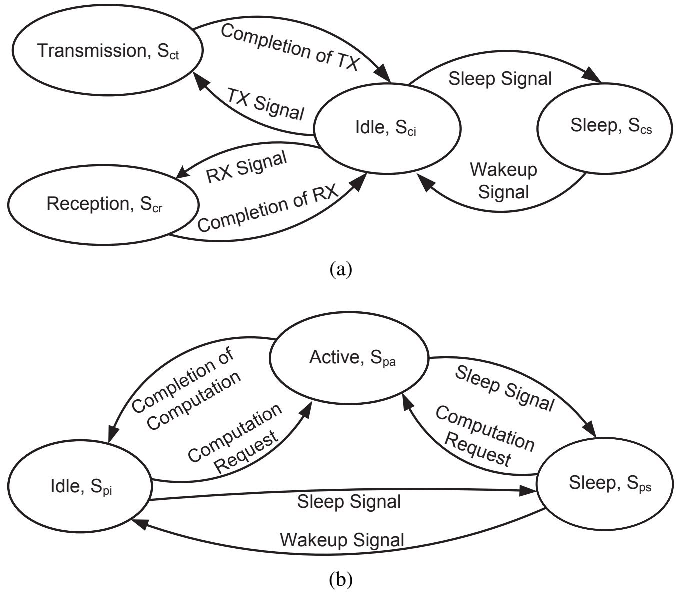


Fig. 9. Modelling of (a) communication and (b) computation components, for a mobile application using Finite State Machines [138].

Pathak *et al.* [43] have further argued that usage-based energy modelling approaches do not provide accurate estimation of the overall device energy consumption, as these do not account for the non-utilisation energy consumption such as the tail energy of the wireless cards. The authors proposed to use system calls via which software applications gain access to hardware resources for fine-grained energy modelling. This approach can account as well for non-utilisation energy since a number of system calls trigger changes in the components' power states, without implying utilisation. The main limitation of this approach is that some device drivers are closed source, and therefore no access to lower level details is provided.

Finite State Machines are frequently used for modelling the power states and state transitions of different mobile device components and of the overall mobile device [43], [138]. Palit *et al.* [138] proposed a model to estimate the energy cost of applications running on a mobile device, which divides the total energy consumed by the system in two components corresponding to computation and communication respectively (see Fig. 9). Each component is modelled as a state-transition diagram. By validating the energy cost in each state using actual measurements, the authors have concluded that due to the energy lost in transition between different states (e.g., idle and sleep states), there is a threshold beneath which no energy saving and possibly even an energy loss is made by changing to the lower power consumption state.

D. User Energy Modelling

Considering the battery properties and the device energy consumption characteristics in the energy modelling can be sufficient to estimate for example the energy required for running a specific mobile learning application or estimating if a learner has sufficient battery energy to complete a specific learning task. However, this offers little insight in the future usage, and the estimation can be seriously impacted by other actions such as for example the learner pausing the mobile learning session in order to answer a phone call and coming back to it afterwards.

Taking into account that nowadays mobile devices are used for conducting a multitude of tasks, and learners can schedule and switch unpredictably between learning tasks and other tasks, predicting when they will be interrupted from a learning task due to low battery power cannot be done without having a good knowledge about their future behaviour.

Usage-related energy modelling however, has been significantly less explored in the literature, mainly due to the difficulties associated with conducting large scale experiments for collecting sufficient data to draw meaningful conclusions.

A summary of research studies that looked at the interaction between mobile users and their devices' energy consumption are presented in Table VII. Looking across different studies, most of these confirm that there is high variability between users' charging patterns, as well as their device usage and energy consumption patterns. However, it is possible to cluster usage characteristics of the same user [139], or users with similar characteristics [140] in order to find meaningful information that can be used in energy modelling and management.

Banerjee *et al.* [141] have assessed battery charge and usage behaviour of different users, using interviews and surveys, as well as trace collection on laptops and mobile phones. Based on findings from the first study, the authors proposed Llama, a system that tracks how much energy is usually used and estimates the remaining energy by the time the device will be recharged, with the goal to use this excess energy for other noncritical applications such as increasing the screen brightness or web prefetching. Although in general the authors received positive feedback during the system validation study, they agreed that not all the users will be happy with such an approach.

Vallina-Rodriguez *et al.* [142] performed a study in order to understand the resource management and battery consumption patterns. The information collected from the mobile devices covers more than 20 parameters related to OS and applications, battery, network, GPS, screen and USB connectivity. The authors have concluded that while the system workload and the resources utilization vary highly among users and contexts, for some users it is still possible to determine strict usage routines as they interact with their devices. Therefore by predicting when some resources are in high demand, improved energy modelling and energy management can be performed.

Contextual information was also investigated by Rahmati *et al.* [143] in order to estimate current and future network conditions and automatically select the most energy efficient network (802.11b or GSM/ EDGE). The authors compared different estimation algorithms that make use of various sources of information such as time, history, cellular tower ID and fingerprint, network conditions, device motion. The use of multiple sources of contextual information can lead to improved estimation performance, while the authors further argue that deploying a context-based interface selection mechanism can lead to significant battery life increase (e.g., up to 35% increase comparing with the case of using the cellular interface only).

TABLE VII
SUMMARY OF SELECTED STUDIES ON MOBILE USERS' ENERGY CONSUMPTION.

Ref.	Goal(s)	Study (Participants; Duration; Devices)	Data Collection	Aspects Analyzed/ *Methods*	Results
[139]	Observe and understand the implications of high-level workload characteristics for smartphones optimisation.	25 users; 6 months ($\sim$53 days logged activity per user on average); Android smartphones.	Log files	Charging, power consumption, and usage patterns. *Clustering*	• Users recharge their phones daily and use them until low battery levels occur. • Differences in usage patterns (e.g., heavy phone users vs. heavy WiFi users). • Idle periods: 89% of the time, and 46% of energy cons. • Most users do not switch between brightness levels, and do not install power management software. • CPU utilisation typically at 100% or below 10%. • Significant CPU utilisation due to OS-level processes. • User activity can be automatically clustered to produce Markov decision processes for individual users.
[140]	Predicting the energy consumption.	20100 users; Blackberry smartphones.	Log files	User type. *Clustering, classification algorithms.*	• Users classified in: opportunistic chargers (63%), light consumers (20%), nighttime chargers (17%). • By classifying the users, energy level can be predicted with 7% error within 1 hour and with 28% within 24 hours.
[141]	Estimate excess energy between recharges. Evaluate Llama, a user and statistics-driven energy saving system.	*Study 1*: 56 users; 15-150 days; laptops. & 10 users; 42-77 days; Windows Mobile phones. *Study 2*: 20 users; 30 days; 10 laptops and 10 phones.	Log files, interviews, survey.	Battery charge usage behaviour. *Probabilistic algorithm (i.e., Histogram of previous battery usage and current capacity used to estimate excess battery.)*	*Study 1*: • Users tend to recharge when there is substantial energy left. • Charges are often driven by context (location and time). • Great variation among users and systems. *Study 2*: • Battery level at charge decreased. • Laptop users did not perceive changes in battery life.
[142]	Study how users interactions with resources affect battery life.	18 users; 2 weeks; Android Smartphones.	Log files	Battery characteristics, usage/ interaction patterns. *Multivariable analysis: Principal Component Analysis (PCA) and Factor Analysis (FA).*	• System workload, resources utilization and energy demands vary broadly among users and contexts. • For some users it is possible to identify strict usage routines as they interact with their devices.
[143] *[144]*	Estimate WiFi conditions without powering up the device.	14 users; 6 months; Windows Mobile phones.	Tower Logger app	Energy consumption. *Algorithms: Naive and simple solutions, Hysteretic, Cell ID, Fingerprinting.*	• Good cellular networks coverage and signal strength exist. • On average users spent 49% of day time on preferred WiFi. • Combining multiple heterogeneous sources of context information improves performance.
[145]	Study the charging habits in order to identify timeslots for intensive operations and better charging.	4035 users; 4 weeks; Android devices.	Over Charged app.	Charging behaviour. *Descriptive Statistics.*	• 65% - lowest average battery level at midnight; • 74% - highest battery level at 5AM; Different charging patterns; • 2 major charging periods (6PM to 8 PM and 1AM to 2AM); • Majority of charging durations are between 0.5 and 2 hours; • 77% of users overcharge the phones for more than 30 min; • AC charging more popular than USB (61% vs. 39%).
[146] *[147]*	Investigate consumer attitudes towards handsets energy consumption and usage behaviour.	*Data logging*: 253 users, mean 50 active days over 4 months (1st year), and 105 users, mean 31 active days over 3 months (2nd year); Nokia Symbian S60 Smartphones. *Questionnaires*: 155 users (1st year) and 150 users (2nd year)	Log files, Survey.	User attitudes; Battery charging and energy consumption patterns. *Descriptive Statistics*	• Users are reasonably good at estimating energy consumption. • 39% of users altered power-saving settings to gain more. • Users are interested in knowing more about energy consumption and to have more accurate battery indications. • Users present significant variation in battery charging behaviour. Two groups: regular and impulsive chargers. • Charging is driven by context and low battery levels, rather than low battery alarms. • Users overcharge the phones, leading to energy wastes. • Battery level has little impact on users decision to launch applications. • Some classes of applications are more often launched.
[148]	Analyze usage patterns.	20 users; 2 months; Android smartphones.	Log files	Usage patterns. *Descriptive Statistics*	• Idle periods account for most time and energy consumption. • Different charging, usage and energy consumption patterns across users.
[149]	Predict device configurations that can optimise energy consumption.	5 users; 1 week; Android smartphones.	Log files	*Machine learning algorithms: Linear Discriminant Analysis (LDA), Linear Logistic Regression (LLR), Neural Networks, K-Nearest Neighbor.*	• Up to 90% successful prediction using neural networks and k-nearest neighbor.

TABLE VIII
APPLICABILITY OF ENERGY MODELLING APPROACHES TO MOBILE LEARNING.

Approach	Applicability	Limitations
General energy modelling	• To enable learner's device, learning content and/ or learner needs-based energy-aware adaptation. • Online energy modelling based on data collected automatically from learners is more suitable for mobile learning.	• Need of good expertise in order to build and implement the energy models with the EAMLS.
Battery modelling	• Needed in order to estimate mobile learners' available battery charge. • Electrical-circuit and mathematical models are more suitable to be integrated on the client side of the EAMLS. • Electrochemical and hybrid models are more suitable to be integrated on the server side of the EAMLS.	• Difficulty to build generic models applicable to the variety of batteries used by mobile learners' devices. • More accurate models are computation intensive; may lead to higher power consumption than saving if implemented on the learner's device. • Learner's usage time on the available battery charge cannot be predicted using battery modelling solely.
Device energy modelling	• To more accurately estimate the learning time, given particular battery charge, device characteristics and application loads. • Building energy models for categories of learners with similar devices. • Online energy modelling approaches are more suitable for mobile learning. • More suitable to be implemented on the server side due to significant data processing.	• Difficulty to build generic energy models applicable to the multitude of devices and platforms used by mobile learners. • Need for continuously update of the models as mobile learners change their devices. • Difficulty to account for the multitude of mobile learning scenarios that use various device components in different states. • Complexity of mobile devices with other applications running along the mobile learning application.
User energy modelling	• To more accurately predict when mobile learners will deplete their battery charge given their different device usage and learning patterns. • To enable personalized energy saving based on the energy needs of individual learners or categories of learners. • Can reuse information already available in the learner profiles. • Can exchange information to improve the learner profiles. • More suitable to be implemented on the server side due to significant data processing required.	• Accurate modelling requires high amounts of contextual data to be collected. • Learners may not be willing to exchange this information. • Privacy and ethical issues have to be addressed. • Added monetary cost and energy consumption due to the data transmission.

E. Applicability to Mobile Learning

Generally speaking energy modelling is necessary in order to estimate learner's available battery charge and to predict their future energy needs. Having a good energy model, enables applying energy adaptation strategies in order to support the learners maximise their learning outcome in low battery power situations.

Battery models can be applied with m-learning systems in order to estimate a learner's available battery charge. To predict their energy needs for conducting specific mobile learning tasks device modelling has also to be addressed. Furthermore, predicting learner's energy needs for conducting mobile learning activities at later times, or in between other non-learning activities user modelling needs also to be applied.

Therefore, device built-in methods for data collection and energy measurement are necessary to enable more accurate energy modelling. Major limitations include the additional energy consumption and monetary cost involved by the data collection, as well as privacy and ethical issues arising from storing and processing the data. Solutions to overcome these limitations have to be identified.

To minimise the impact of the energy modelling on the device energy consumption, approaches that offer a good accuracy while at the same time have a small computation footprint are desired, especially if aiming to do the modelling directly on the mobile device. However, since mobile learning is characterised by highly variable context, empirical models based on experimental measurements only are not suitable as they offer poor performance in real-life scenarios. Adaptive energy modelling solutions are necessary to process the high amount of contextual data being collected during real-life mobile learning scenarios. Doing the energy modelling on the server-side enables minimizing its impact on learner's device energy consumption. At the same time, more accurate but more computation intensive modelling techniques can be deployed, such as for example hybrid electrochemical - electrical circuit - mathematical battery models, or advanced statistics such as classifiers and multi-variable analysis for device and user energy modelling.

In practice however, compromises will have to be made as only limited amount of contextual information could be accessed and/ or send to the server. Furthermore, building generic energy models to account for high variety of learning contexts due to different battery properties, device characteristics and operation modes, learning content types and learner's unpredictable behaviour, is either too difficult or not feasible to be achieved.

Table VIII summarises the applicability to mobile learning as well as the limitations of the main energy modelling approaches.

VII. ENERGY-AWARE ADAPTATION

Energy saving and management with regard to mobile devices has presented much research interest due to the limited energy batteries can provide. Various solutions have been proposed to effectively manage the device battery power, and to reduce the energy consumption of mobile devices, components and applications. Since several different surveys have already addressed this topic, this section starts by pointing the reader to some relevant surveys for more details. The section continues by outlining some energy saving directions with emphasis on their applicability to mobile learning.

A. Related Surveys

Vallina-Rodriguez and Crowcroft [10] have addressed energy management techniques in modern mobile handsets with focus on energy efficient operating systems. The authors presented a number of energy-aware OSs such as EcoSystem, Odyssey ErdOS and CondOS, as well as a number of resource profilers and resource management techniques. Various solutions for optimizing energy consumption of wireless interfaces and protocols, as well as optimization of the device sensors are presented. The authors go further to discuss the use of cloud computing and computation offloading to enable energy saving in mobile handsets. The authors also present experimental results of various studies analysing the energy consumption of mobile devices. Their survey however remains rather descriptive and lacks a clear classification of energy management solutions.

Zhang *et al.* [11] have focused on energy saving techniques for mobile multimedia delivery. The authors group the existing solutions in power aware video coding and video delivery. One important as well as difficult aspect regarding video coding is accurate estimation of codec power consumption based on its computational complexity, in order to enable energy saving. The authors identified several main challenges that come when designing energy efficient mobile multimedia communication devices: 1) real-time multimedia is delay-sensitive and bandwidth-intense, making it also the most power consuming application, 2) the radio frequency environment is changing dynamically over time and space, 3) the diversity of mobile devices and their capabilities, 4) the video quality does not present a linear increase with the increase in complexity, and 5) the battery discharge behaviour is nonlinear. The authors conclude that due to the dynamics involved, enabling power-aware mobile multimedia is extremely challenging, and involves various tradeoffs. The authors also argue that due to limited adaptation to the dynamic wireless link conditions and interaction between layers the traditional layer separated techniques fail to provide the expected QoS, and further go to propose a framework for cross-layer optimization in power aware multimedia applications.

Energy-aware adaptive mobile multimedia was also the focus of another, more recent survey of Kennedy *et al.* [12]. The authors start the survey by identifying major energy consuming components in high-end devices, based on experimental studies conducted for the Google Nexus One device. The presentation of existing energy saving solutions is than centred on the most energy expensive components namely, display, CPU and network interface. With regard to display related solutions, the authors distinguish between general solutions that adapt the entire screen area equally and solutions that divide the screen area in Regions of Interest (RoI) that can be passive (i.e., pre-defined) or active (i.e., change in time based on content). With regard to CPU, the authors distinguish between dynamic hardware resources configuration through voltage/ frequency scaling and coding/ decoding related solutions. The authors put particular emphasis on energy saving solutions addressing the network interfaces, focusing on WiFi and LTE technologies, as well as solutions exploiting multiple wireless interfaces. The WiFi related solutions are further classified in traffic independent (i.e., MAC layer optimization), and traffic dependant for web browsing (i.e., proxy based), video streaming (i.e., traffic reshaping and traffic prediction) and VoIP (i.e., cross-layers) applications. Some cross-layer solutions as well as major global research initiatives and projects on energy optimization are also presented.

Hoque *et al.* [13] have also surveyed various solutions for improving the energy efficiency of wireless multimedia streaming in mobile devices. The authors focus on the wireless communication aspect and categories the existing solutions according to different layers of the Internet protocol stack they utilize. They also group the solutions based on the different traffic scheduling and multimedia content adaptation mechanisms. This categorization may present interest for the reader as many of the solutions presented by the authors are suitable to be integrated with mobile learning systems for delivery of lecture recordings.

Al-Kanj *et al.* [14] have adressed energy-aware content distribution over wireless network in the situation where there is collaboration between multiple closely located mobile terminals. In this situation some devices download the content from the server over long-range more energy-expensive networks, and distribute it to the other devices over short-range more energy-efficient networks. Such solutions could also be applied for mobile learning in order to save the battery energy of multiple mobile learners (i.e., from the same classroom) that want to access the learning content on their personal devices.

B. Characterization of Energy-Saving Solutions

Mobile learning applications have increased in complexity over the recent years. These may combine various types of educational content and media formats such as text, images, audio, video and even games or 3D virtual learning environments. Various adaptive energy saving solutions targeting different components such as wireless interface, display and CPU can be deployed in order to save learners mobile device battery life depending on the content type. Mobile learning applications are not limited to content dissemination only, and can make use of additional device resources such as GPS for location detection and context-based mobile learning adaptation, or video camera for learning centred communication.

1) Content Delivery-related Solutions: These solutions focus on reducing the energy consumption of the device wireless interface(s). Approaches include among others, maintaining the wireless card in a low power state for a longer period of time or using more energy efficient interfaces for part of the communication.

Wireless standards usually include energy saving mechanisms such as the IEEE 802.11 Power Saving Model (PSM) or the LTE Discontinuous Reception (DRX), designed to maintain the network card in low power states while not in use [150]. An efficient and basic power conservation method is to alternate between the operation modes. However, as an amount of energy is spent as well when activating and deactivating the components, additional care should be taken when alternating the operation modes.

These mechanisms exhibit different performance depending on the type of the content delivered and the transmission characteristics. For example, IEEE 802.11 PSM was shown not to be effective enough for the case of real-time multimedia streaming, since WNIC hardly has the chance to go to sleep between active periods due to the constant flow of packets with short intervals in between them [151]. Therefore, a number of studies have proposed to reshape the traffic flow and send the packets in bursts instead of sending them individually, thus allowing the WNIC to sleep for longer between data reception intervals. The major drawback is that traffic burstiness may cause congestion in routers or overflows in transmitter buffers leading to packet losses and a decrease in overall network quality. To avoid the congestions in the network, Korhonen and Wang [151] have proposed to adjust the length of the bursts based on the congestion conditions. The packets from the original stream are rearranged in bursts, each burst containing packets in a decreasing priority order. In this case the receiver can sacrifice some enhancement layer data in order to maintain stable power efficiency.

Other solutions allowing the WNIC to sleep for a longer periods of time, include buffering the incoming data on the mobile device [152], or buffering the data corresponding to several beacons and releasing them at once after the mobile device wakes up several times to check if there are any packets for it [153]. The latter is achieved by introducing an additional buffer to the one already included in the Access Point.

To further reduce the WNIC energy consumption, Anastasi *et al.* [154] proposed to completely switch off the wireless card during long inactivity intervals such as the User Think Times (UTT) and use the IEEE 802.11 PSM during traffic bursts. By integrating simple yet efficient algorithms to detect the beginning of bursts and UTTs, the authors have achieved between 20% and 96% energy saving as compared to using the PSM only.

To maintain the WLAN interface in sleep mode for significant periods of time during the VoIP calls, the GreenCall algorithm [155] uses sleep and wake-up schedules, where the sleep periods are computed based on the maximum delay that a user can tolerate during a conversation.

To reduce the energy consumed by the WLAN while in idle mode waiting for a call, Perrucci *et al.* [156] have proposed to use a second interface with lower energy consumption such as GSM, as a signalling channel to wake up the WLAN interface and run the VoIP service. The authors argue that by sending the WLAN to sleep and using the wake-up signals the energy consumption can be reduced significantly in a VoIP scenario.

Most of the research on WiFi energy management has concentrated on a single mobile device and/ or AP. However, in dense WiFi environments where multiple APs compete for the same resources, a mobile device may have to stay awake for longer, until the corresponding AP gets a chance to transmit the packets to it. For such scenarios, Manweiler and Choudhury [157] have proposed SleepWell, a system that enables energy saving across multiple devices by coordinating the APs to be active/ inactive during different intervals.

Content delivery-related energy saving solutions, are suitable to be considered when deploying energy-aware mobile learning systems and applications, as it is often the case that educational content is retrieved over the wireless network and not stored locally on the device. While these solutions enable significant battery energy saving, additional care needs to be taken not to affect the content reception to a level that negatively impacts the learning experience.

2) Computation-related Solutions: Dynamic Voltage and Frequency Scaling (DVFS), is a commonly used method for reducing the energy consumption of the device CPU, by decreasing the clock frequency, thus enabling a corresponding reduction of the supply voltage. DVFS was shown to offer good power saving for the case of multimedia streaming, due to the fact that the processing power needed to decode a video sequence is highly variable in time' [158]. However this requires an accurate prediction of the following parameters:

- the time required to decode each particular frame when the CPU clock is set at the same voltage/ frequency settings;
- the optimum combination of CPU voltage/ frequency settings to decode each particular frame in the interval corresponding to the video sequence frame rate (e.g., 40ms for a frame rate of 25fps).

An overestimation of this time will lead to unnecessary power consumption, while an underestimation will decrease the video quality.

To avoid predictions and therefore missed deadlines caused by prediction errors, Lu *et al.* [159] have proposed a solution that uses a dynamic online scaling feedback to set the average frame decode rate to the same value as the display refresh rate, thus reducing the power consumed by the CPU to decode the data.

Cao *et al.* [160] have proposed an offline linear programming method to determine the minimum energy consumption required for processing a multimedia task based on knowledge about the complexity and the arrival time of each decoding job. Through simulations, the authors have also shown that their solution can be extended to online multimedia tasks with varying unknown workloads, outperforming other existing online DVFS algorithms, while requiring less than 0.3% more energy to perform the task than indicated by the offline optimal method.

Baker *et al.* [161] have proposed a different approach to enable energy saving through DVFS on CPU, by generating H.264 compressed multimedia streams with prioritised slices (macroblocks). Depending on user selected preference some slices will be ignored by the decoder, reducing the workload and thus the CPU energy consumption through DVFS.

DVFS can also be used for decreasing the memory energy consumption. For example, Amiri *et al.* [162] proposed a transcoding scheme to generate H.264 streams that are tolerant to defective memory cells of the decoding buffer. In this way energy saving is enabled through voltage scaling on the memories. The proposed method has good power saving potential, as memories increase their share in the overall mobile device energy consumption with the shift towards System-on-Chips (SoCs).

DVFS however, was also shown to not have the same energy saving potential on newer CPU and memory architectures, due to technological advances that have resulted in the saturation of clock frequencies, larger static energy consumption, lower dynamic energy consumption range, and more energy efficient idle and sleep states [118].

Apart DVFS, the CPU energy consumption can also be reduced by offloading some of the computations from the device to the cloud, a server or an intermediate proxy node. Such a solution, proposed by Zhao *et al.* [163] was shown to reduce the energy consumed during web browsing by more than 45%, along with reducing the delay by more than 80%. Altamimi *et al.* [164], as opposed have showed that using a Mobile Cloud Computing service to encode videos to a format supported by the mobile device, can save as much as 70% of the energy required to encode the clip locally on the device.

While mobile learning has increased significantly in complexity, and computation-related solutions are suitable to be used for reducing the energy consumption of m-learning systems and applications, various tradeoffs need to be considered. For example, using DVFS or decreasing the content quality to reduce the computation-related energy consumption, should be made within limits that do not negatively impact the learner experience and his/ her learning outcome.

On another side, using computation offloading techniques, should consider the tradeoff between the energy required for local computation and the energy involved by the additional communication, as well as the impact on the learning process, in order to maximise the energy saving while maintaining a good learning experience.

3) Content Display-related Solutions: Various solutions for saving the display energy consumption have been proposed. Pasricha *et al.* [165] have proposed a solution to save power by optimizing the backlight power consumption. In order to reduce the effect on the user perceived quality, the backlight reduction is compensated by changing the luminosity and the contrast of the video at an intermediate proxy node.

Hsiu *et al.* [166] have proposed an algorithm to determine the critical level up to which the backlit can be decreased without significantly affecting the perceived quality of multimedia applications. Their solution uses a dedicated server to compute the critical backlit level for each group of frames in a video by analysing their luminance, and was shown to provide between 19% and 31% energy saving when viewing YouTube videos with different characteristics.

Shim *et al.* [167] made use of the advantage of transflective LCD panels that can operate with or without backlight and allow an image to remain visible even without backlight. They extended the Dynamic Luminance Scaling (DLS) to cope with transflective panels, depending on the battery level and ambient luminance.

Another approach used by Gatti *et al.* [168], involved reducing the display refresh frequency from the native rate, to a value equal with the frame rate of the video that is being played.

While in the case of LCD displays a significant amount of power is consumed by the backlit, newer OLED (Organic Light Emitting Diode) displays that are increasingly used in mobile devices, do not require the backlit since they are self illuminated and their power consumption depends both on the luminosity and of the colour of each pixel being displayed. Solutions that have been proposed to save the energy consumption of OLED displays, include dimming selected areas of the display pixel by pixel [169], or changing the colours of selected areas of the display [170]. Colour transformations however are mostly feasible for GUIs, and not for applications such as image or video viewing, in which case natural colours reproduction are required for providing good quality.

A solution to reduce the OLEDs energy consumption that is suitable to be applied for applications working with natural images was proposed by Shin *et al.* [171]. The solution which consists of scaling down the voltage supply of the display was shown to provide more than 50% energy saving for the case of video playback. As their solution may also incur image degradations for the case of bright images, the authors propose an image compensation solution based on the human perceived colour space.

As the device display is the highest individual energy consumer in many mobile learning scenarios (e.g., viewing a mostly static content that involves very little communication and computation), augmenting mobile learning systems and applications with display-related energy saving solutions can offer the highest or even the only way to significantly increase the learning time in such scenarios.

However, using these solutions needs to also consider various factors that may negatively impact the learning experience (e.g., content characteristics, ambient light), as well as the additional impact of the energy saving strategies taken by the operating system or other energy-saving applications installed on the device.

C. Applicability to Mobile Learning

Depending on their characteristics, different mobile learning systems and applications can use different learning content media types and the learning content can be either retrieved from the server over the wireless network or stored locally on the learner's device. Therefore, a variety of energy adaptation techniques targeting the content-delivery, computation and/ or displaying are suitable to be integrated within EAMLSs, on client or on server side.

Content adaptation techniques such as adapting the encoding characteristics and luminance in case of video lectures, or the colour patterns of static educational content, are usually recommended to be performed on the server side due to the additional processing involved that may lead to more energy consumption than saving in some situations.

Other solutions such as switching between network interfaces, applying DVFS or reducing the screen brightness require a client component as well.

A major limitation of using the various energy adaptation solutions is that they usually save the energy at the expense of impacting the learning experience, through delays, content quality reduction/ change, and/ or changes in the application's

TABLE IX
APPLICABILITY OF ENERGY-AWARE ADAPTATION APPROACHES TO MOBILE LEARNING.

Approach	Applicability	Limitations
Content delivery-related	• Adapting the traffic flow of the educational content delivery on the server side of the EAMLS. • Adapting the quality of the educational content on the server side of the EAMLS in order to decrease the energy consumption of the wireless card(s) in receive mode. • Switching between different network interfaces on the client-side of an EAMLS, in order to choose more energy efficient delivery paths. • Especially suitable for video and audio lectures streaming.	• Delay thresholds maintaining good learning experience need to be defined for traffic adaptation. • Quality thresholds maintaining good learning experience need to be defined for content adaptation. • Additional information and implementation on the client side is required for switching between networks. • Device radio resource management already in place impact energy saving.
Computation-related	• Adapting the content on the server in order to reduce the energy consumption of the CPU, GPU and memory for processing the educational content. • Dynamic voltage and frequency scaling can be used on the client side to reduce the CPU energy consumption. • Techniques to offload computation intensive mobile learning applications such as video encoding, or educational games playback to the EAMLS server can also be used. • Especially suitable for video and audio lectures streaming, educational games.	• Quality thresholds maintaining good learning experience need to be defined for content adaptation. • DVFS optimization required in order not to impact the learning experience due to performance restrictions. • Benefits with computation offloading reduced by the additional communication. • Device computing resource management already in place impact energy saving.
Content display-related	• Adapting the content on the server to reduce the screen energy consumption. • Reducing the screen brightness. • Suitable for video content as well as mostly static text and image-based interfaces.	• Quality and brightness thresholds maintaining good learning experience need to be defined. • Device screen management already in place impact energy saving.

performance or normal behaviour. Therefore, various delay/ quality/ performance thresholds maintaining good learning experience would have to be defined in order to apply the various techniques while minimizing their impact on the learning process.

Furthermore, mobile devices' components usually present various high-power operating states as well as low-power energy saving states. At the same time, various resource management methods are embedded in the mobile operating systems in order to conserve the battery energy by turning the device components to the low power states when not in use.

Therefore, the selected adaptive techniques that are implemented with the adaptive m-learning systems have to complement the existing resource management methods, in order to lead to higher overall energy saving.

Table IX summarises the applicability to mobile learning as well as the limitations of the main energy-aware adaptation approaches.

VIII. DISCUSSION AND CONCLUSIONS

Mobile learning applications and services have been increasingly adopted over the past few years, as mobile devices have improved in functionality and capabilities. The combined increased usage of mobile devices and the increasing complexity of mobile learning applications put significant pressure on the limited battery resources. In this context, this survey argues for the increasing need of energy-awareness in mobile learning applications and systems in order to avoid situations when learners cannot continue their learning activity due to out of power situations.

Starting from the generic architecture of an Adaptive M-learning System, this survey outlines the benefits as well as the possibilities to extend mobile learning systems with additional components to make them energy-aware. There is no simple solution for doing this however, as estimating the learners' available battery energy and predicting when they will run out of battery power requires good knowledge about their device battery state, device energy consumption characteristics as well as their usage patterns. Three important aspects necessary to be considered in order to test and deploy energy-aware mobile learning systems, and applications are treated in this survey: *measurement*, *modelling* and *adaptation*. Since energy modelling appears to be the most challenging part, the survey focuses especially on this part, by presenting various aspects that need to be modelled with regard to battery, device and user.

Although many solutions have been proposed in the literature, there still are many challenges faced when deploying energy-aware mobile learning systems and applications. Accurate modelling implies collecting information about learners and their behaviour, which may actually lead to lower usage due to privacy concerns and issues. Furthermore, careful selection of the energy saving strategies needs to be performed. While ideally maximizing the learning outcome requires both allowing the learners to complete their activity and providing them with a good learning experience, in practice this may turn out to be very difficult to achieve and highly context dependent. Learners' preferences and attitudes to energy saving should also be considered, as not all learners would be equally happy to have the mobile learning system or application automatically taking actions on their device.

There is a multitude of mobile learning contexts characterised by different learners with different learning and energy needs and preferences, different learning content types

TABLE X
SUMMARY OF ENERGY MEASUREMENT, MODELLING AND ADAPTATION APPROACHES MOST SUITABLE FOR CREATING ENERGY-AWARE ADAPTIVE M-LEARNING SYSTEMS (EAMLS).

Most Suitable Approaches	Opportunities	Challenges
Built-in energy measurement	• Mobile devices are increasingly adopting smart batteries, providing information such as battery State-of-Charge, voltage, current draw and temperature. • Can be used to continuously collect measurement data during real-life m-learning scenarios. • Data reporting can be easily integrated with EAMLS. • Availing of history and current energy measurements, more accurate energy models can be built. • Enables evaluating in real-time the performance of the energy saving strategies being applied during real-life m-learning scenarios.	• Targeting learners whose mobile devices do not integrate or provide access to energy measurements. • Minimizing the impact on energy consumption and monetary cost due to monitoring and reporting to the EAMLS server of the energy measurements.
Online server-side energy modelling	• Mobile devices increasingly integrate advanced device logging, monitoring and environment sensing functionalities, enabling to more easily detect the learning context. • Using both history and current data energy models can be continuously updated and improved to better estimate learner's available battery charge and predict their energy needs. • Highly scalable computation resources available through cloud computing enable using more accurate but computation intensive energy modelling techniques. • Enable minimization of additional energy consumption due to energy modelling.	• Finding a good balance between modelling accuracy (i.e., how much and how often input data is collected and reported to the server), and the additional energy consumption and monetary cost due to the monitoring and transmission involved. • Addressing privacy and ethical issues arising with monitoring learner's device and energy usage behaviour.
Server-side energy-aware adaptation	• Big range of adaptive solutions suitable to save the energy consumption of different mobile device components involved in receiving, processing and displaying different types of educational content. • Highly scalable computation resources available through cloud computing for performing the adaptation on the server. • Enable minimization of additional energy consumption due to adaptation.	• Finding a good balance between the amount of energy saved and the impact on the learning experience of the adaptation strategies. • Implementing multiple adaptive energy saving techniques. • Designing strategies to select the most suitable techniques in particular mobile learning contexts.

and particularities, different types of mobile devices with different characteristics, as well as different requirements and limitations in deploying particular m-learning systems or applications. At the same time, from the multitude of energy measurement, modelling and adaptation techniques proposed in the literature, a particular technique or combination or techniques may be more suitable for a particular mobile learning context.

Therefore, it is very difficult to point out and recommend one technique over another without addressing the specific requirements of the particular mobile learning system or application, as well as the compromises that have to be made when deploying and operating it. However, from the multitude of approaches for energy measurement, modelling and adaptation presented in this survey, it can be concluded that automatic online solutions are the most suitable to be integrated with energy-aware adaptive mobile learning systems and applications. A number of opportunities towards using online approaches for client-server m-learning systems, as well as challenges that will have to be overcome are summarised in Table X.

Starting from data collection in general and energy measurement in particular, automatic solutions built within learner's devices are preferable mainly because they relieve the system designer from the tedious task of building and validating energy models a priory in the lab, only to find out later that these models do not offer the expected performance in real mobile learning scenarios. Furthermore, data collected during real-life m-learning scenarios, not only enables more accurate energy modelling, but automatic data collection and learning context detection are increasingly possible as mobile devices integrate more powerful device logging, monitoring and environment sensing functionalities.

The major challenges with automatic data collection and energy measurement appear to be its impact on learner's device energy consumption and induced monetary cost, as well as the privacy and ethical issues arising from collecting, storing and processing this data, especially when the users are young students.

To enable accurate energy modelling a multitude of battery, device and user-related data may be necessary. Recording and transmitting all these data during a mobile learning activity may turn out to have higher impact on energy consumption than performing the actual task in some situations. At the same time sending the data to the server over cellular networks may incur additional costs on the learner's part. Therefore, strategies to minimise these impacts have to be designed such as for example sending the data to the server when learner's device is charging and connected to WiFi network.

Energy modelling and adaptation can also involve significant computation and energy consumption overload. However, thanks to the availability of highly scalable resources through cloud computing, it is more suitable to select server-side energy modelling and adaptation approaches, which enable minimizing their impact on learner's energy consumption.

In case of energy modelling, more accurate but more computation intensive techniques can be deployed, such as for example hybrid electrochemical - electrical circuit - mathematical battery models, or advanced statistics such as classifiers and multi-variable analysis for device and user energy modelling.

In regard to adaptation there is a wide range of particular adaptive techniques that can be implemented on the server side in order to reduce learner's device energy consumption while retrieving, processing and displaying the educational content from the server. However, to account for as many mobile learning situations with different energy saving requirements that may occur for the same m-learning system, and to maximise the energy saving capabilities of the system, multiple techniques may have to be implemented. However, choosing the techniques to be implemented and selecting the most appropriate one(s) in a particular mobile learning context remains challenging and is to be addressed on a case-by-case basis. Furthermore, many adaptive techniques that would be suitable for m-learning systems ranging from traffic shaping to content adaptation, may impact the learning experience through e.g., delays and quality decreases. Therefore, another major challenge will be to find a good balance between energy saving and learning experience, for the ultimate goal of maximising the learning outcomes.

While many questions would arise, and individual decisions to be made from application to application, this survey provides a good starting point for researchers interested in further contributing towards creating energy-aware educational applications and services for mobile learners in particular and mobile users in general.

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