GREEN WIRELESS ENERGY EFFICIENCY IN WIRELESS NETWORKS

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4.1 INTRODUCTION

Wireless networks have become more and more popular because of ease of installation, ease of access, and support of smart terminals and gadgets on the move. Energy-efficient wireless network operation is without doubt of high importance, both for infrastructure and for ad-hoc communication. While for infrastructure networks, economic and ecological considerations are predominant as the networking components are often connected to the power grid, ad-hoc networks mainly rely on limited battery-powered components and, thus, the network's lifetime and availability is challenged. Similarly, the energy

Large-Scale Distributed Systems and Energy Efficiency, First Edition. Edited by Jean-Marc Pierson.

depletion of mobile client devices such as smartphones is a crucial challenge, as they are the user interface to ubiquitous connectivity.

In the overall life cycle of providing *green wireless technology* – from production to operation and, finally, removal – we focus on the operation phase and summarize insights in energy consumption of major technologies. We provide an answer to questions such as how the energy consumption can be characterized, measured, and estimated. Further, we introduce approaches to make wireless networks operate energy efficiently. A strong focus of this chapter is set on the edge of the network, comprising network access points (APs) and mobile user devices. Here, the energy consumption of the wireless communication modules is still considerably high; thus, there is a need for good understanding of energy consumption and novel approaches to increase energy efficiency. In this setting, we not only summarize well-known challenges but also highlight in particular novel approaches, applications of interest, and results for the included wireless technologies and give pointers to related literature.

Our introduction to the topic on energy-efficient wireless networking provides insights in major measurement methodologies and energy-efficient algorithms. We achieve this by making the following contributions:

- First, we summarize major metrics used to describe energy efficiency in wireless networks. Thus, we briefly list generally applicable metrics such as *energy per information bit* and, then, focus on metrics dedicated to wireless networking in Section 4.2.
- To measure and estimate energy consumption, internal software methods as well as external power measurements can be followed. We discuss the advantages and disadvantages of major methodologies and exemplify testbeds in Section 4.3.
- Then, we discuss particularities of most important wireless networking technologies: (i) wireless access networks including 3G/LTE and wireless mesh networks (WMNs) in Section 4.4, (ii) wireless sensor networks (WSNs) in Section 4.5, and (iii) ad-hoc and opportunistic networks in Section 4.6. Besides describing major characteristics of these networks in terms of energy consumption and resulting challenges, we take specific perspectives to approach the discussion of energy efficiency, for example, the quality of experience (QoE) versus energy consumption trade-off for access networks, energy-efficient medium access control (MAC) in WSNs, and methods to establish connections among a group of mobile devices in an energy-efficient and fair way.

This chapter originates from discussions and joint research work of the *Focus Group on Energy-efficient Wireless Networks* of the European Cooperation in Science and Technology (COST) Action IC0804.

4.2 METRICS AND TRADE-OFFS IN WIRELESS NETWORKS

This section introduces the most popular performance metrics for energy efficiency in wireless networks [1, 2] in Section 4.2.1, followed by a brief discussion on energy consumption versus performance trade-offs in these systems in Section 4.2.2.

4.2.1 Metrics

Energy-aware optimization techniques require metrics to evaluate the real energy savings that can be achieved with a certain solution. First, basic energy consumption metrics are introduced, and then metrics capable of measuring the energy efficiency of a system are discussed.

4.2.1.1 Power and Energy Consumption Metrics. The most obvious and simple metric to assess any system's and network's energy footprint is the total **energy consumption** (E) in joule (J), which can be defined as the product of the average power (P) in watt (W) and the time (t), as follows:

$$E(\mathrm{J}) = P(\mathrm{W}) \times t(\mathrm{s}). \tag{4.1}$$

The total energy consumption is mostly used to characterize the energy costs associated with a certain operation, but when there is a need to study a single state, the *average power* (P) can also be used as a standalone metric.

4.2.1.2 Power and Energy Efficiency Metrics. Even though the average power and total energy consumption can describe the energy costs, it is important to correlate the network energy consumption (E) with the other network-level parameters [3]. One of the most important system-level metrics, which can be employed in any network system, is *energy per information bit* (Eb). This metric, expressed in joule per bit, describes the relationship between the total number of bits transmitted (I) and the energy consumed (E):

$$Eb[\mathrm{J/bit}] = \frac{E[\mathrm{J}]}{I[\mathrm{bit}]}. \tag{4.2}$$

While the total energy consumption, the average power, and the energy per information bit metrics can be used in any network system, there are also metrics specially introduced for wireless system. These metrics usually aim to establish a correlation between the energy or power and particular characteristics of the wireless system, such as the number of subscribers or the covered area.

The *power per area unit* metric (Pau) [4] establishes a relationship between the average power used (P) and the size of the covered area (A) and is expressed in watt per meter square:

$$\mathrm{Pau}[\mathrm{W/m^2}] = \frac{P[\mathrm{W}]}{A[\mathrm{m^2}]}. \tag{4.3}$$

The *power per subscriber* (Ps) is a metric used to determine the correlation between the average power used (P) and the number of subscribers present in the network (N)

and is expressed in watt per subscriber:

$$\text{Ps[W/subscriber]} = \frac{P[\text{W}]}{N}. \tag{4.4}$$

The presented system-level metrics can be employed within distinct scenarios and technologies; yet once real equipment is used, the results will be further related with the employed hardware. Apart from other components, the energy consumption of the wireless system is strongly related to the energy used by the antenna core components [2]. The *efficiency of an antenna* (η_{Ant}) is defined as the coefficient between the antenna-radiated power (P_{radiated}) and the power needed to support it during operation (P_{input}):

$$\eta_{\text{Ant}} = \frac{P_{\text{radiated}}[W]}{P_{\text{input}}[W]}. \tag{4.5}$$

Chen et al. [2] have also identified the usage of antenna gain information as an alternative way to depict the antenna's efficiency. The *antenna gain* (Gain_{Ant}) describes the antenna's capability to concentrate or direct the power transmitted in a certain direction. It is represented in dBi (decibel relative to an isotropic radiator) and defined as the ratio between the antenna radiation intensity (U) and the antenna power input (P_{input}):

$$\text{Gain}_{\text{Ant}}[\text{dBi}] = 4\pi \times \frac{U}{P_{\text{input}}}. \tag{4.6}$$

The study of energy consumption behavior at multiple levels, namely, system and component levels, will allow superior energy-aware solutions, ranging from higher (e.g., application) to lower level optimizations (e.g., MAC or PHY layers).

4.2.2 Energy Optimization Trade-Offs

The usage of energy optimization techniques might introduce some performance drawbacks in the network. Chen et al. [5] have studied the most significant trade-offs in green wireless networks. Four main trade-offs were identified, namely, trade-offs related to deployment costs, spectrum efficiency, bandwidth management, and delay. More recently, Zhang et al. [6] have also proposed a new metric to establish the fundamental trade-off between QoE and energy efficiency.

Therefore, six important trade-offs in green wireless networks should be considered as follows:

- *Deployment Efficiency/Energy Efficiency Trade-Off*. Correlating the deployment and operation costs, namely, the capital expenditure (CapEx) and the operational expenditure (OpEx), and its relation with the overall energy required to run the network;
- *Spectrum Efficiency/Energy Efficiency Trade-Off*. Establishing a relationship between spectrum efficiency, usually defined as the system throughput per bandwidth unit, and the overall energy consumption needed;

- *Bandwidth/Power Trade-Off*. Defines the relationship between the available bandwidth and the power needed to perform a transmission;
- *Quality of Service (QoS)/Energy Consumption Trade-Off*. Represents the relation between the network-level performance parameters (e.g., delay and packet loss) and the energy needed to transmit certain data;
- *Quality of Experience (QoE)/Energy Consumption Trade-Off*. Represents the relation between the obtained user-perceived quality (QoE) and the energy consumed to achieved it.

Although the use of these trade-offs is not as simple as the use of the metrics presented previously, it is important to take them into account when proposing novel energy-aware enhancements. By understanding and correlating the energy-aware techniques employed and their multiple impacts on the system, it will be possible to obtain superior energy savings while providing sufficient and establishing better performance trade-offs networking performance.

4.2.3 Summary

This section presented the most relevant metrics and trade-offs to be considered when studying the energy efficiency of a wireless communication system. A brief overview about generic energy metrics (e.g., energy or power consumption) was provided together with some wireless-specific metrics, namely, power per area unit and power per subscriber. The introduced trade-offs showed the importance of establishing a proper relationship between the system optimization goals and the user's requirements, because when saving energy, there is almost always some impact on the performance to be considered. In the next section, energy measurement methodologies are presented, which allow to evaluate real systems along the previously introduced metrics.

4.3 MEASUREMENT METHODOLOGY

The recent growth and heterogeneity of wireless technologies have enabled a high usage of networking devices, ranging from infrastructure nodes to end user devices. While infrastructure nodes of wireless networks are, similar to wired networking equipment, mainly powered by the power grid, user devices in mobile settings such as portable computers and mobile phones, and also wirelessly connected sensors, are primarily battery powered. This particularity of wireless networks determines the focus of this section, which is set on understanding the energy consumption of user devices and WSNs. Yet creating mathematical models to estimate the energy consumption in a wireless communication system might be a complex task; with inaccuracies introduced by the assumptions and simplifications required in this approach, it is important to follow proper methodologies in order to accurately measure the energy consumption of real life systems. Additionally, the data obtained through measurements can also be used to improve simulation environments and to perform more detailed energy consumption pattern estimations.

This section gives a brief overview about the most popular empirical techniques to measure energy consumption. First, relevant energy measurement techniques and testbeds are introduced in Section 4.3.1, followed by a discussion concerning the usage of energy estimation techniques in Section 4.3.2. Section 4.3.3 discusses the benefits and problems of using both energy measurement and estimation techniques through an illustrative example.

4.3.1 Energy Measurement Testbeds

We now describe four measurement methodologies for studying the energy consumption of wireless transmission in different scenarios.

4.3.1.1 Generic Measurement for USB Wireless Interfaces. This first methodology proposes a generic approach that is able to measure energy consumption in any multiple wireless access network such as WiFi, WiMAX, or LTE [7]. In order to fulfill the assessment requirements, two major design requirements are defined:

- *High Precision Measurements*. To guarantee a good accuracy of testbed energy measurements, it is vital to use a measurement hardware capable to support multiple samples per second, because energy in small devices (i.e., network interfaces) tends to have slight variations along the observation time.
- *Independent Network Interface Evaluation*. To better understand how the energy consumption is impacted by the network interface, it is essential to measure exclusively the network interface, namely, by assessing the energy utilization in MAC and PHY layers.

The energy measurement testbed was designed to meet the requirements mentioned earlier and to minimize the changes needed in the network interface hardware. The first option was to use an external Universal Serial Bus (USB) network interface, because it is possible to accurately measure the energy consumed solely by the interface, as desired. One of the main issues already reported in previous energy measurement works is the need to provide a stable and continuous voltage to the system [8, 9]. The impact on the voltage drawn when connecting the USB network interface directly to a user device was noticeable in first tests. To overcome this limitation, the USB network interface was connected to an external alternating current (AC)-powered USB hub, which is able to give stable power to the system. The analysis regarding the voltage drawn when employing the external USB hub has shown that voltage drops are always lower than 1% of the total employed voltage, which is negligible in the overall system analysis.

Figure 4.1a depicts the energy measurement testbed setup. Besides the user device, the measurement configuration includes a controller and a high precision digital multimeter. The digital multimeter is a Rigol DM3061 with a maximum sampling rate of 50 K samples/s and a test resolution of 6 1/2 digits. The multimeter is capable of receiving Standard Commands for Programmable Instruments (SCPI) (defined by IEEE 488.2 [10]) and implements the Universal Serial Bus Test and Measurement Class (USBTMC) specification standard interface. By using SCPI commands and USBTMC,

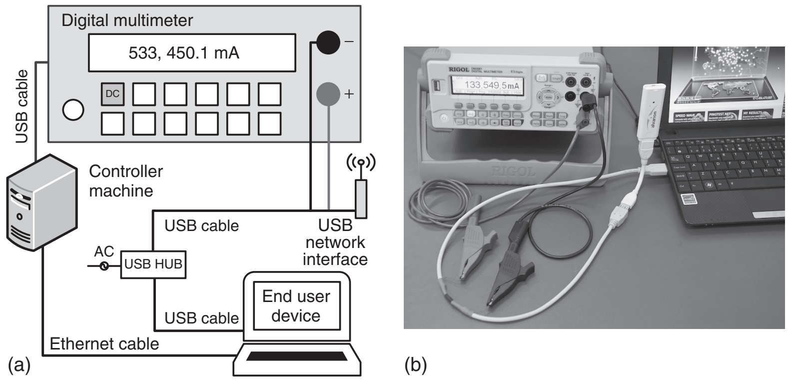

Figure 4.1. Energy measurement setup. Adapted from [7].

the controller is able to control and manage the digital multimeter, which enables accurate and repeatable tests. The controller is also connected to the user device. This entity controls the experiments to be performed in a fast and reliable way and collects all the results from the digital multimeter. As the voltage is stable, all the measurements concerning energy are done by collecting the current values only. The USB cable was intercepted in the common-collector voltage (VCC) cable (i.e., +5 VDC), as illustrated in Figure 4.1b.

In short, the proposed methodology enables the measurement of the energy consumption of a single network interface by employing high precision measurement hardware. By using this methodology, it is possible to study multiple network technologies, which makes it possible to compare and study the behavior of distinct access technologies under different scenarios and conditions. Furthermore, the data collected during the assessments might also be used to support more accurate software-based energy models, namely, for emerging wireless access technologies, as the developed methodology is fully technology independent.

4.3.1.2 Development Boards and Kits. Development equipment allows to isolate the energy consumed for transmission from the consumption of the rest of the system [e.g., central processing unit (CPU) or screen]. Development kits typically expose interfaces to measure the power consumption of, for example, the broadband module or modem under test.

Figure 4.2 shows an example of a measurement setup composed by an Ericsson KRY 901 214/01 development kit provided and a 2G/3G/GPS broadband module (Ericsson F3307). The power consumption is measured using a current probe or measuring the voltage drop over a precision shunt resistor (0.1 Ω). In the example, the voltage drop is measured with a data acquisition unit (National Instruments myDAQ). The development kit is connected to a test computer using a USB cable appearing as a normal interface. The modem can be further operated with AT commands to access the low layer information such as the radio state. This measurement setup presents high accuracy and details

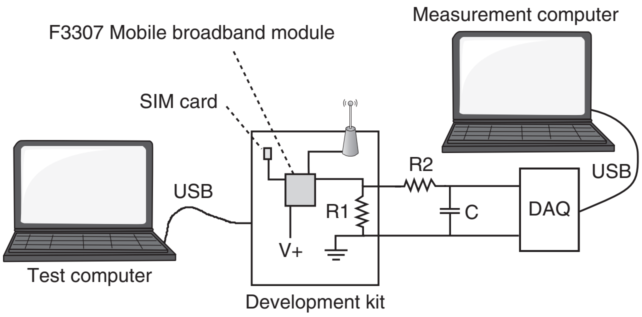

Figure 4.2. A measurement setup based on a development kit.

low layer information, which is useful to understand the impact of the commanding software on the transmission energy (e.g., operating system) [11].

4.3.1.3 Intercepting Battery Terminals. As the software running on the devices drastically impacts the energy consumption, directly measuring the power of the mobile device is a common approach. Measurement platforms for mobile devices typically intercept battery terminals to measure the power consumption. These provide aggregated power measurements of network interfaces and other components (e.g., CPU, screen, or sensors). The devices used to acquire the measurements range from laboratory bench multimeters to USB data acquisition units. A widely used power measurement device is the Monsoon Power Monitor [12]. The following aspects need to be considered when employing this measurement technique:

- *Battery Terminal Interception.* A copper tape (or a similar conductor) is placed between the device terminals (V+ and V−) and the battery terminals. The voltage is directly measured from the battery, whereas a shunt resistor is typically used to measure the current. Mobile devices have battery monitoring terminals (e.g., temperature and a communication line), which need to be connected or the mobile device will not switch on.
- *Shunt Resistor Size.* Adding a shunt resistor introduces additional resistance into the measured circuit. However, if the resistor is too small, the drop in voltage is too small for the input offset voltage of the analog conditioning circuit. This can compromise the measurement accuracy. Typical resistors used for these measurements range from 0.01 to 0.1 Ω with a low tolerance.
- *Power Source.* While the battery discharges, the voltage decreases and the current increases. Both the voltage and the current need to be measured if a battery power source is used. Instead, the voltage can be fixed using an external direct current (DC) power supply allowing only measuring the current.
- *Isolating Transmission Energy.* Ideally, one would like to only measure the transmission energy (i.e., the energy spent by the peripheral hardware for transmission). As the operating system running in mobile devices is typically

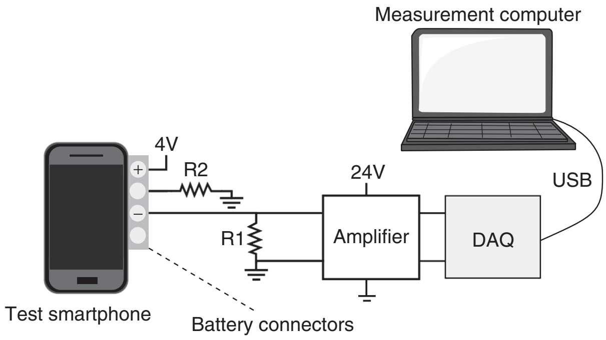

Figure 4.3. The schematic of a mobile device measurement setup that intercepts the battery terminals.

preemptively multitasking, different processes are waking up and consuming resources such as CPU. In order to stabilize the power trace and isolate the transmissions from the rest of the system, the CPU frequency may be fixed and a low priority background process is run in a busy loop [8]. The CPU creates an almost constant power consumption, which enables the isolation of the transmission energy by simply subtracting it. The drawback of this technique is that we cannot distinguish between the CPU load created by the test and the background load.

Figure 4.3 shows an example of a measurement setup used to measure energy consumption in mobile devices. The setup is composed by a low side sensing circuit with a precision shunt resistor (R1 = 0.1 Ω), an isolating amplifier with maximum transmission error of 0.4% (Phoenix Contact MINI MCR-SL-SHUNT-UI), and the data acquisition unit. We added an R2 (33 kΩ) in order to allow the device to switch on.

4.3.1.4 Built-In Sensors and Smart Battery Interfaces. Some vendor-specific development devices are shipped with internal power management integrated circuits that enable power consumption profiling. These allow to separately measure the power consumption of the network interfaces as well as CPU energy consumption. Qualcomm's Trepn Profiler for the Snapdragon processors is an example of such a system [13]. Smart battery interfaces are available in some mobile devices, which provide aggregate current values (e.g., Nokia Energy Profiler [14] or CurrentWidget for Android [15]). The accuracy of these measurements is defined by the battery sensor, which is less than using external physical power measurements [16].

4.3.1.5 Sensors External Measurement Units. Hergenroder et al. [17] proposed an external unit, named Sensor Node Management Device (SNMD), specifically designed to accurately measure the current and voltage of a sensor node with a sampling resolution of up to 20 kHz or even up to 500 kHz in the so-called buffered mode. The SNMD firmware corrects each sampled measurement by an error term, which is obtained in advance. This method reduces the measurement error introduced by the measurement circuit to below 0.5% for any current in the range of 0–100 mA [18], an accuracy range that is definitely sufficient to rely on by any experimental and comparative analyses of sensor network mechanisms. Even though SNMDs are very precise, they represent a high cost hardware-based solution.

4.3.2 Energy Estimation Techniques

While physical power measurements certainly support the evaluation of a system's energy efficiency, performing the measurements is a non-trivial task, which requires some specific knowledge as described in the previous section. Designing and setting up tests, performing the measurements, and analyzing the results is a laborious and time-consuming task. The high cost of the measurement solutions and time limitations (e.g., time to market of applications) stops software developers from investing in these solutions. Thus, applications and system software are often not designed or tested with energy consumption in mind.

Physical power measurements allow device-dependent studies only. As the hardware change between generations can substantially make the energy consumption differ from previous generation devices, the measurements become obsolete quickly. Thus, physical measurements are useful to provide insight and observations, but there is a need for tools and solutions that can complement physical power measurements and enable efficient studies to minimize the energy consumption. This section describes some complementary approaches to physical power measurements for mobile devices and wireless sensor nodes.

4.3.2.1 Measurement-Based Estimation. Energy models abstract the real behavior of the devices by characterizing the mechanisms that consume energy. Some works concentrate on specific mechanisms, whereas others attempt to model the total energy consumption. Here, the focus is on energy models derived from physical measurements used to estimate wireless transmission energy. Yet, theoretical models exist as well [19, 20], which typically investigate the behavior of a specific mechanism of a wireless interface and often suggest guidelines to select parameters for optimizations.

Measurement-based models can be seen as bottom-up approaches, which can be specific to the measured data or generic, depending on the model development approach. The complexity of measurement-based models varies greatly and ranges from simple models characterizing the energy consumption based on some statistical representation of the measurement data (e.g., linear regression) to more complex models employing a finite-state machine (FSM), as described in the following.

Data fitting approaches are often built in two stages. First, the system to be modeled is exercised in a certain manner while collecting physical measurements, and then the collected data is used to create the model. An example is the work by Balasubramanian et al. [21], which models the transmission energy consumption for GSM, 3G, and WiFi. They measure the energy spent to perform bulk data transmissions for different data sizes and build a linear model out of the data. Given the amount of data to be sent in a burst, their model calculates the energy consumed. The data fitting approach is simple, and it results in device- and measurement-specific energy estimation. Yet the proposed model only captures the operation of the system under the conditions that were given during the measurements.

The *finite-state machine (FSM) approach* is a general approach to model energy consumption used to derive the operational states of a system that consume significantly different amounts of power. For example, even if a common wireless interface can be in active or sleep mode, the fact that transmission power substantially increases when transmitting at high data rates can be modeled as an additional state. Power measurements are employed in the modeling phase to select the relevant states, define the transitions between the states, and collect data for the different parameters (e.g., power levels). We illustrate the FSM approach with an example, the EnergyBox [22].

EnergyBox is rooted on wireless interface operation knowledge and measurement data. The tool enables accurate studies of 3G and WiFi transmission energy consumption at the device end. The FSMs built for EnergyBox characterize the 3G network parameters that impact energy consumption and the adaptive power saving mode mechanism specified at the handset driver for WiFi. EnergyBox is focused on studying the impact of the transmission data pattern on energy consumption, thus uses real traffic traces as input. The tool performs trace-based iterative packet-driven simulation: given a packet trace and the configuration parameters, EnergyBox outputs the device states over time. Next, some design decisions are described in the context of EnergyBox.

- *States and Power Values.* In EnergyBox, the states abstract the hardware dependency of measurement-based studies by modeling the mechanisms and interactions that impact the energy consumption. Selecting a reduced number of representative states reduces the model complexity. The FSM states of EnergyBox are derived from the knowledge of the interface operation and a wide range of measurements. The total energy consumption is calculated by associating these states with power levels. Device-specific power-level values are obtained through the measurement platforms. EnergyBox employs fixed power values, which are a convenient simplification in order to feed the model with device-specific measurement data. However, variable power levels are also possible based on some input such as data rate.
- *State Transitions.* State transitions need to model the mechanisms that make a system to change its power consumption. The state transitions are deterministic or stochastic. EnergyBox employs mostly deterministic transitions, which are parameterized allowing the simulation of different interface configurations. Examples of such transitions are the inactivity timeouts used by cellular operators or the adaptive power saving mode timeout to switch between active and sleep states. Stochastic variables can also be used to model the uncertainty of a certain transition, based on the distribution of measurement data, for example.
- *Accuracy Evaluation.* The accuracy of an estimation technique is an important factor to consider, and thus the validation of the model is required. A common approach is to compare the model against physical power measurements. EnergyBox is validated comparing its accuracy against physical power measurements

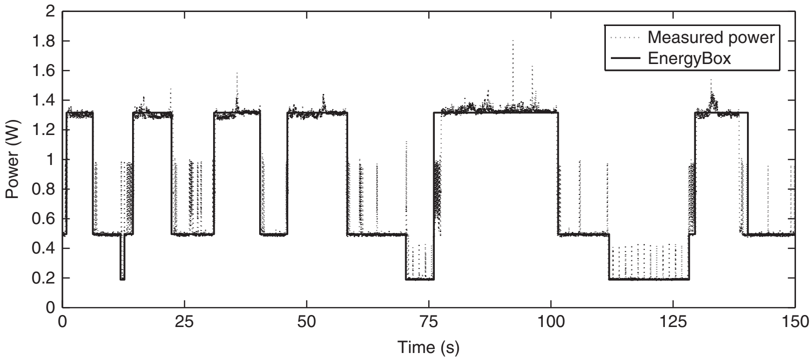

Figure 4.4. EnergyBox compared to physical measurements.

over a set of real application packet traces. Figure 4.4 shows the accuracy of EnergyBox for a sample Web trace sent via 3G. The accuracy in the example is 99% in terms of energy.

Next we detail energy estimation techniques in the context of WSNs and describe the impact of the estimation model on the resulting estimation accuracy.

4.3.2.2 Energy Estimation for Wireless Sensor Networks. The development and operation of energy-efficient WSNs requires to measure or at least to estimate the energy consumption of a sensor node. A simple but expensive approach would be to deploy special measurement devices at each sensor node to measure its energy consumption. This might be too expensive in terms of equipment and deployment costs for large sensor networks. Another approach is to estimate the energy consumption by identifying the states of a sensor node considering the activity of its components. By knowing how long a sensor is in a certain state and what the energy consumption is in each state, for example, by experiments before deployment and operation, it is possible to roughly estimate the energy consumption of a node during its lifetime. This can be done completely by appropriate software recording states and their durations. Simple state-based energy estimation models have already been used in the prominent studies on the common media access control protocols S-MAC [23] and B-MAC [24], yet they have not been evaluated in terms of *accuracy* of their energy estimation model. We discuss now how such software-based energy consumption estimation mechanisms must be designed to achieve the highest accuracy applied to energy-efficient MAC protocols.

Three States Model (TSM). The Three States Model (TSM) is the most frequently used model to date for estimating a node's energy consumption as a function of the three states of the radio transceiver, namely, *receive/idle listening*, *transmit*, and *sleep*, cf. [23–25]. The Contiki OS' energy estimation mechanism models the radio's power consumption using this model, but separately tries to keep track of the CPU power consumption, which can vary depending on the low power mode (LPM) it is currently

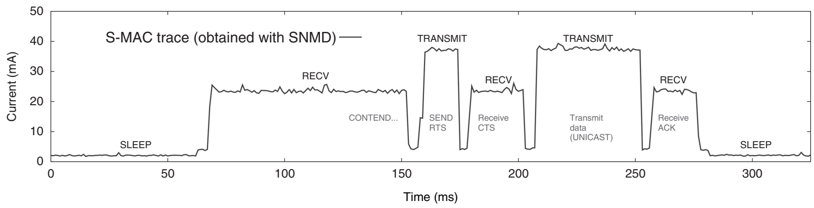

Figure 4.5. Current draw of node B.

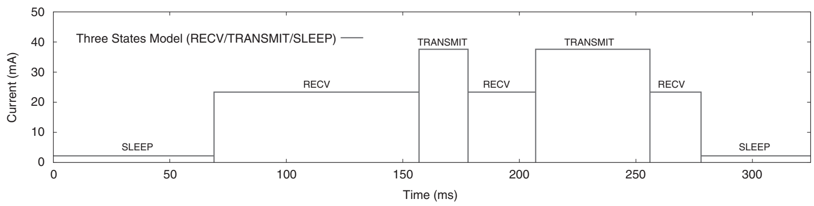

Figure 4.6. Current modeled by the *Three States Model (4.7)*.

operating in. The ScatterWeb[2] OS used in this study put the CPU to LPM as soon as all events have been processed, where the node's current is approximately 1.8 mA, given that the radio is turned off. With the CPU active and the radio off, the node current is roughly 3.5 mA. As energy-efficient MAC protocols generally do not incur intensive computations, we neglected to account for the CPU costs separately and considered the CPU's power consumption to be integrated within the three states of the transceiver.

We, henceforth, employ a model of the energy consumption of major MAC protocol implementations, namely, S-MAC, T-MAC, WiseMAC, and CSMA using the TSM. We let the nodes keep track of the time differences between the transceiver switches, in order to determine how much time has been spent in each state. Figure 4.5 depicts the current draw during the active interval of an S-MAC frame containing an RTS/CTS handshake and a subsequent data packet transmission. Figure 4.6 illustrates how this current draw is approximated by the TSM. The total energy consumed (E) corresponds to the area below the current draw, multiplied by the supply voltage, which is assumed to be constant in the model. Analytically, the TSM can be formulated as equation (4.7). The consumed energy E is calculated as the power level of the node in the receive state P_{rcv} multiplied by the total time spent in this state T_{rcv} and the respective terms for the transmit and sleep states ($P_{\mathrm{slp}}T_{\mathrm{slp}}$ and $P_{\mathrm{tx}}T_{\mathrm{tx}}$). This approach is identical to the one applied in [23–25].

$$E = P_{\mathrm{rcv}}T_{\mathrm{rcv}} + P_{\mathrm{tx}}T_{\mathrm{tx}} + P_{\mathrm{slp}}T_{\mathrm{slp}} = I_{\mathrm{rcv}}V_{\mathrm{rcv}}T_{\mathrm{rcv}} + I_{\mathrm{tx}}V_{\mathrm{tx}}T_{\mathrm{tx}} + I_{\mathrm{slp}}V_{\mathrm{slp}}T_{\mathrm{slp}}. \tag{4.7}$$

Major studies [23–26] calibrate the parameters of their energy model by measuring the currents the nodes draw in the different states and multiplying it with the supply voltage to obtain P_{rcv}, P_{tx}, and P_{slp}. They do so by using either oscilloscopes or high precision multimeters and by measuring the current in each state over a certain timespan. In the

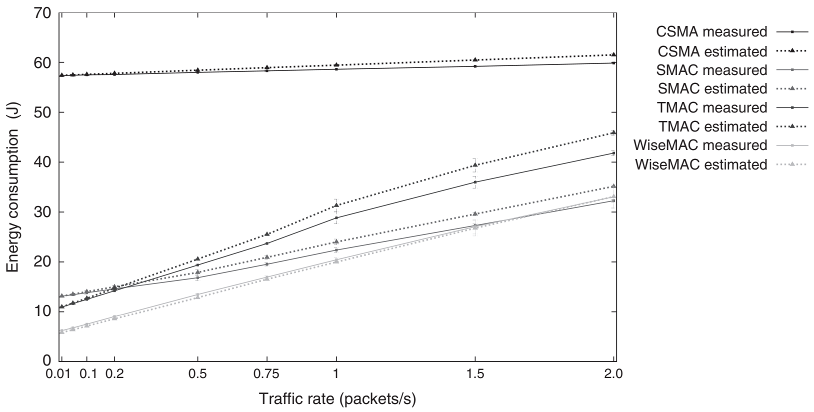

Figure 4.7. Measured versus estimated energy consumption.

first attempt, we pursued exactly the same approach and determined the mean values of I_{rcv}, I_{tx}, and I_{slp} by measuring each state of the *measurement* node using the SNMD for a couple of seconds. The stable mean values were determined to be 23.54, 37.49, and 2.15 mA for I_{rcv}, I_{tx}, and I_{slp}, respectively. We further set the voltage according to the supply voltage of the SNMD to $V_{rcv} = V_{tx} = V_{slp} = 4.06$ V.

Figure 4.7 depicts the mean values of the energy measurements and the estimations for MSB430 sensor nodes being computed with the TSM – using the parameters for P_{rcv}, P_{tx}, and P_{slp} measured in the sample trace. One can clearly see that the estimations fit quite well for low traffic rates but that the gaps between mean estimations and mean measurements become larger with higher rates of packets being sent. For most protocols – especially S-MAC and T-MAC – the energy estimation overestimates the energy consumed by the node with increasing load. This increasing overestimation stems from the fact that the TSM does not account for the transceiver switches. As one can clearly see by comparing Figure 4.5 with Figure 4.6, the current draw decreases to roughly 4 mA when the transceiver is switched to receive or transmit – hence, drawing less current than estimated with the TSM. By defining parameters through example measurement, the impact of the applied traffic load and the frequent transceiver switches as well as the particularities of the MAC protocol are not being taken into account at all. Extrapolating from a short example measurement of a node, hence, leads to suboptimal parameters for the TSM, even when using the same node for parameter calibration and the evaluation of the accuracy.

Parameter Definition through Ordinary Least Squares (OLS). Being able to physically measure the current draw of a sensor node *and*, at the same time, obtain the software-based estimation calculated by the node itself offers the opportunity to relate the estimations to the real-world measurements. Using the plethora of experimental data gained in the experiments (in total over 12 GB of measurement data), we reflect upon a method to determine more resilient parameters for the unknown variables

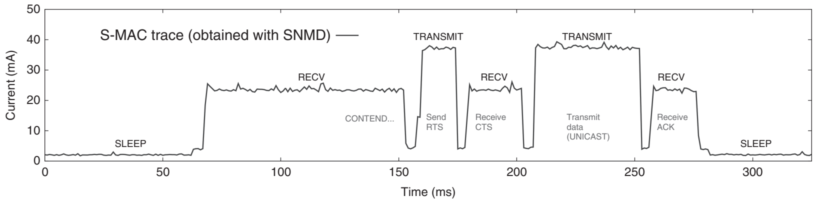

Figure 4.8. Current draw of node B.

P_{rcv}, P_{tx}, and P_{slp} of the TSM. Ideally, the software-based energy estimation running on the node should neither rely on the particularities of a specific MAC protocol nor on the shape or intensity of the traffic. *Ordinary least squares (OLS) regression analysis* yielded the most suitable technique to determine the unknown variables for a linear estimation model with multiple unknown variables. OLS finds the model parameters that minimize the sum of squared errors between the estimations and observations (i.e., the real-world energy measurements captured by the SNMD devices). We formulate a multivariate OLS regression model with explanatory variables T_{rcv}, T_{tx}, and T_{slp}, as well as the physically measured dependent variable E obtained using the SNMD device. The resulting estimation Equation (4.8), hence, simply comprises Equation (4.7) and the error term ε for the residuals. More details can be found in [27].

$$E = P_{\mathrm{rcv}} T_{\mathrm{rcv}} + P_{\mathrm{tx}} T_{\mathrm{tx}} + P_{\mathrm{slp}} T_{\mathrm{slp}} + \varepsilon. \tag{4.8}$$

Estimation Accuracy of the Three States Model. In order to determine the accuracy of the OLS-calibrated model, a cross-validation with totally new experimental data is inevitable to omit overfitting effects, cf. Draper and Smith [28]. The determination of the parameters P_{rcv}, P_{tx}, and P_{slp} using OLS regression is achieved based on a first set of experiment runs, the so-called training set. The estimation accuracy results are then gained with a new set of experimental data, the validation set. Figure 4.10 shows that for each traffic rate, the estimation error using the OLS estimator parameters is 4.2–35.9% lower than the corresponding error when using the model parameters defined through example measurement. Across all measurements, the mean absolute estimation error and standard deviation (denoted as $\mu \pm \sigma$) of the TSM with the parameters defined by example measurement equals 3.77 $\pm$ 3.17%. When determining the parameters by OLS, we obtain 3.00 $\pm$ 2.55% – hence, achieving an overall reduction of the mean absolute error (MEA) by 21% only by altering the calibration technique.

Three States Model with State Transitions (TSMwST). With the mean absolute estimation error still in the range of 3% or more, further means to improve the estimation accuracy are required. As Figure 4.8 exhibits, the current draw temporarily drops to approximately 4 mA during the state switches. These state switches remain unaccounted for in the OLS regression model specified in equation (4.8).

The approach of simply counting the transceiver switches and integrating them into the OLS regression model leads to a significant improvement in the estimation accuracy. The number of transceiver switches (from an arbitrary state) to the receive, transmit, or

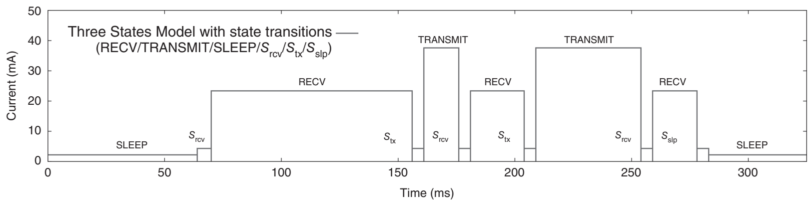

Figure 4.9. Current modeled by the Three States Model with state transitions (4.9).

sleep state was accounted for with the additional regressands s_{rcv}, s_{tx}, and s_{slp}. We refer to this model as *Three States Model with state transitions* (TSMwST) hereafter, as specified in equation (4.9). Figure 4.9 illustrates the model's concept of a node's current draw.

$$E = P_{\text{rcv}} T_{\text{rcv}} + P_{\text{tx}} T_{\text{tx}} + P_{\text{slp}} T_{\text{slp}} + \alpha s_{\text{rcv}} + \beta s_{\text{tx}} + \gamma s_{\text{slp}}. \tag{4.9}$$

According to this enhanced model, the energy consumed by a node is a function of the total time its radio transceiver is in one of the three different states (T_{rcv}, T_{tx}, and T_{slp}) and the three adjustment terms αs_{rcv}, βs_{tx}, and γs_{slp}. The parameters α, β, and γ compensate for the transceiver switches to the states receive, transmit, and sleep.

Estimation Accuracy of the Three States Model with State Transitions. We calibrated the OLS estimators for the parameters of the second model with the training set and examined the resulting estimation accuracy on the validation set. Across all measurements, the MEA and standard deviation (denoted as $\mu \pm \sigma$) of the software-based estimations using the TSMwSM (and the parameters determined by OLS) compared to the physically measured values equals $1.13 \pm 1.15\%$. Comparing this result with the $3.00 \pm 2.55\%$ obtained with the pure TSM (and the parameters determined by OLS), our proposed model enhancement leads to an overall reduction of the MEA by remarkable 62.3%, as also illustrated in Figure 4.10.

Different wireless sensor node instances often exhibit a slightly different behavior with respect to their power consumption levels in the different transceiver states, as quantified for our MSB430 platform and observed in previous studies [25, 29]. We have encountered node pairs of the same node type that differed by more than 4% in their physically measured energy consumption. Hence, even the best *node-generic* software-based energy estimation mechanism can be more than 4%, if its underlying model parameters were not calibrated on a *per-node* basis. Hence, either hardware-dependent deviations have to be tolerated or time-intensive calibration per-node has to be performed, ideally with different MAC protocols and different traffic rates. However, calibrating on a *per-node* basis means that *every single node* needs to be physically measured (e.g., with an SNMD or a high resolution multimeter) ideally with different MAC protocols and different traffic rates. Only this time-intensive calibration leads to the set of *per-node* but *protocol-generic* estimation model parameters to reduce the mean absolute estimation error ($\mu \pm \sigma$) to $1.13 \pm 1.15\%$. To increase the accuracy further, we propose *per-protocol* calibration as an even more accurate estimation approach, which might be useful if researchers know exactly what protocol they intend to use on the MAC layer in advance.

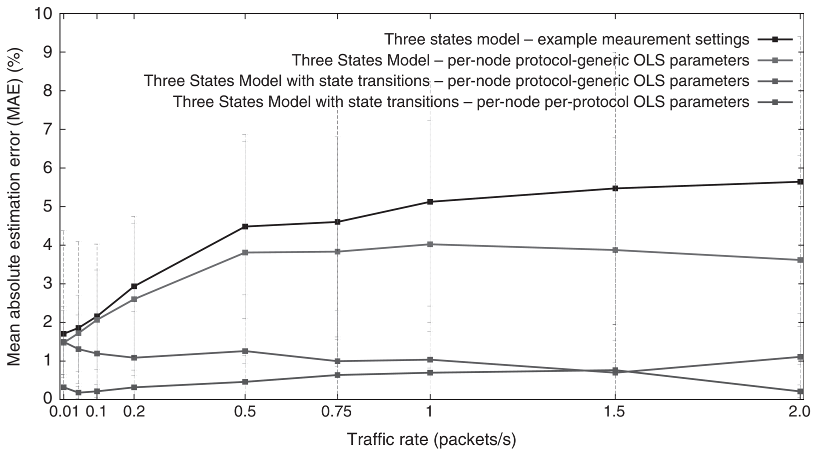

Figure 4.10. Mean absolute estimation error and standard deviation (in %) versus traffic rate (packets per second).

The combined approach of *per-node and per-protocol* calibration obviously leads to the highest accuracy. Across all four protocols and traffic rates, we obtained a mean estimation error and standard deviation ($\mu \pm \sigma$) of only $0.42 \pm 0.72\%$. Figure 4.10 illustrates the different estimation errors when applying the *per-node and protocol-generic* or the *per-node and per-protocol* calibration approach. Yet, the combined calibration approach has multiplicative impact on the overhead before network deployment, as all nodes need to be equipped with tailor-made estimation model parameters for each protocol.

4.3.3 Energy Measurements versus Estimation

Power consumption measurements on mobile handheld devices have trade-offs between intrusiveness and accuracy. For instance, a software tool can obtain measurements without influencing the actual usage behavior of a mobile device; however, it might not obtain accurate measurements. This section provides the comparison between a *physical measurement tool* and a *measurement-based estimation tool* as an illustrative example.

We analyze two tools introduced at the beginning of this section (Monsoon [12] as a hardware tool and PowerTutor [30] as an internal software tool) and compare the pros and cons of each one. During power measurements, choosing the "right" sampling rate is necessary in a way that the tool collects enough data for the purpose, without influencing the behavior of the system [31]. Therefore, the power measurement process needs to minimize the impact on the battery life during the measurement process as the energy consumption is one of the most influential factors on the end-user-perceived quality in the smartphone [32].

The Monsoon power monitor device contains the power monitor hardware and the power tool software, running on Windows XP and Seven, which can provide robust measurements on any device that uses a single lithium (Li) battery. The measurements are obtained and can be saved with a sampling rate of 5 kHz. The tool supplies the power to the device, thus the device battery is bypassed. The Monsoon external power-monitoring device is typically used for ground-truth measurements [33].

PowerTutor is a smartphone application, developed by a collaboration of academic and industrial institutions, which displays the power consumed by a set of system components such as CPU, network interface, display, GPS, and other applications. The aim of its development was to make the power measurements transparent to the app developers as well as to the users, so that they can take appropriate action to minimize their smartphones' power consumption. PowerTutor receives the current values in milliamperes from the driver and then multiplies the value by the voltage that is basically the phone battery (typically 3.7 or 4.5 V depending on the phone type). PowerTutor estimates the energy consumption of applications and services based on the processing times and is only available for specific phone types. Although these software tools provide the overall picture of the power and energy consumption of the applications being running on the smartphone, the interfaces, CPU, display, and o on, they do not provide ground-truth measurements on all type of devices, but only can provide estimations. We modified the PowerTutor in such a way that it writes the obtained measurements directly to the smartphone's internal storage with a sample rate of 1 Hz. This way, we perform statistical tests.

Comparison of Monsoon and PowerTutor. The choice of the power measurement tool depends on the application to be measured, as the sampling rate of the tools need to be kept limited if they are running on the battery-powered devices as a separate application in the background. We describe now measurements of power consumption during video streaming on the mobile terminals with Monsoon Solutions and obtain ground-truth measurements [34, 35]. We conducted further tests to identify a set of differences between PowerTutor and Monsoon. We installed PowerTutor on the HTC G1, as it is recommended particularly for the Google phones, and in parallel, we connected the Monsoon power-monitoring tool directly to the power supply of the smartphone. This way, we were able to conduct simultaneous measurements and observed the differences between the two approaches. We have found slight inconsistencies between the obtained measurements through Monsoon and PowerTutor. We observed that PowerTutor power measurement values can drop down to zero occasionally as depicted in Figure 4.11. On the other hand, the power consumption values obtained via Monsoon are within the robust 1600–2200 mW range as shown in Figure 4.11. Next, we streamed video (with three different bitrates: 150, 300, and 500 kbit/s) to the device with and without the PowerTutor. In both the scenarios, we recorded the power consumption measurements via Monsoon. We conclude that PowerTutor has consumed extra power within the range 23–59 mW. The descriptive statistics are presented in Table 4.1 for both the scenarios, that is, with and without PowerTutor. Monsoon can provide highly accurate power measurements, yet these measurements are highly obtrusive and cannot be used, for example, in user studies. On the other hand, PowerTutor is minimally intrusive and can provide power models based on the device usage, but it relies on power measurements that are not as accurate as Monsoon because of factors such as unavailability of reliable sensors or low sampling rate. Hence, the measurement tool should be carefully chosen depending on the purpose of the study, and the limits should be reported in any discussion of the results.

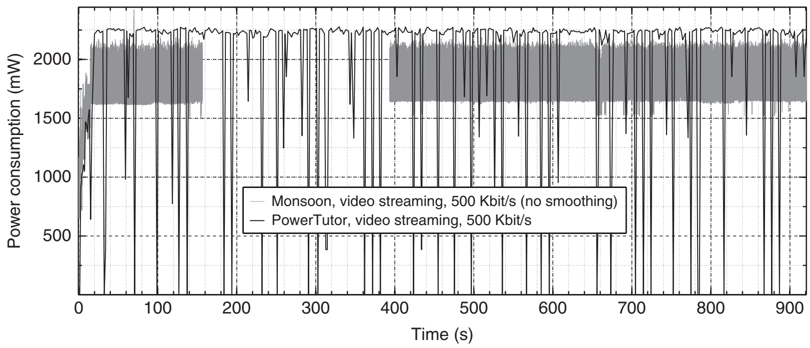

Figure 4.11. Measurements obtained via Monsoon and PowerTutor during video streaming.

TABLE 4.1. Power Measurements Obtained Through Monsoon and PowerTutor in Milliwatts

Rate (kbit/s)	Tool	Max	Min	Standard deviation	Mean	Median	Data Points
			With PowerTutor				
150	Monsoon	2449.3	1351.2	94.0	1786.2	1772.3	4425001
150	PowerTutor	2278.0	0	517.5	2078.8	2227.0	958
300	Monsoon	2404.0	1489.9	94.2	1762.5	1745.0	4375001
300	PowerTutor	2287.0	0	562.3	2047.6	2231.0	453
500	Monsoon	2423.4	1499.1	90.8	1793.6	1776.4	4425001
500	PowerTutor	2278.0	0	649.8	1993.8	2238.0	442
			Without PowerTutor				
150	Monsoon	2198.8	1486.2	110.4	1727.4	1719.6	4425001
300	Monsoon	2170.1	1490.1	107.6	1739.0	1730.0	4425001
500	Monsoon	2201.9	1482.5	99.6	1753.1	1739.7	4425001

4.3.4 Summary

Measuring the energy consumption and deriving the energy efficiency of wireless network components and protocols is a crucial first step toward energy-efficient wireless networking. In this section, we discussed measurements and estimation methodologies based on external and internal measurements. The testbeds presented range from USB interfaces and mobile-battery-powered devices to WSNs. For important sample wireless systems, we detailed the important precautions for measurement and power modeling, such as sampling considerations and achievable accuracy.

The decision between (hardware) power measurement and energy estimation techniques depends on a manifold of considerations. Energy estimation enables simple and fast energy calculations (online and offline) and overcomes some of the major limitations of physical measurements, such as cost, time-intensive setup, and hardware dependency. Moreover, energy estimation techniques provide means to efficiently perform large-scale studies, for example, analyze the energy consumption of a large user trace dataset and can be used in user studies. However, the accuracy of the estimation technique is commonly less when compared to power measurements. This needs to be considered at the time of analyzing the results, and there is a need to consider the energy consumed by the measurement estimation itself. Thus, depending on the requirements of the energy study, either one methodology can followed or different physical measurement methodologies and energy estimation techniques can be used together to complement each other.

4.4 ENERGY EFFICIENCY AND QoE IN WIRELESS ACCESS NETWORKS

The widespread of wireless devices entails an ever-increasing plethora of *wireless access networks* of different kinds. Being wirelessly connected is in the first hand for the benefit of the users. As discussed previously, the convenience comes at the price of limited battery power. In addition, the ever-growing wireless infrastructures consume increasing amounts of energy. Thus, energy saving is of importance for both users and providers, but it may not come at any price: if the *quality of experience* (QoE) gets too low because of energy saving measures, it may entail user churn. For these reasons, energy efficiency must be traded off well against potential quality losses, which is the main point of concern in this section.

Section 4.4.1 provides an overview of recent approaches to increase energy efficiency of mobile long-term evolution (LTE) systems. In particular, several mechanisms that allow an efficient adaptation of the power consumption to the required network resources are summarized. Section 4.4.2 discusses the trade-off between energy consumption, the number of users, and their QoE in a mesh access network. Section 4.4.3 highlights possible energy savings at the user device with a modified resource scheduling. Seen from the perspective of the end user, Section 4.4.4 reveals particular relationships between energy consumption and specific QoE issues for streaming video. A specific-purpose network is targeted in Section 4.4.5. Here, an outlook on environmental access networks is given.

4.4.1 Energy Issues in Cellular Networks

Mobile wireless access networks are increasingly contributing to global energy consumption. Future mobile wireless access, such as LTE networks are no exception. The EARTH (Energy Aware Radio and neTworking tecHnologies) project tackles the important issue of reducing CO_2 emissions by enhancing the energy efficiency of future cellular mobile networks with particular focus on LTE systems. EARTH is a holistic approach to develop a new generation of energy-efficient products, components, deployment strategies, and energy-aware network management solutions in LTE networks. At component level, the various units, including antennas, RF (radio frequency) transceivers, baseband processor, and power amplifiers, are improved to provide envisioned gains for the mobile core and radio access network (RAN) as illustrated in Table 4.2.

Numerical results [42] reveal that for current network design and operation, the power consumption is mostly independent of the traffic load. This highlights the vast potential for energy savings by improving the energy efficiency of cellular networks at low load. Accordingly, techniques and algorithms developed within the EARTH project mainly aim at reducing the power consumption of 4G cellular access networks in low and middle load scenarios. In total, energy savings of 40–60% are possible [43]. Further energy savings can be achieved by combining the proposed methods with other technologies such as DTX, dynamic bandwidth management, and adaptability on system dynamics. However, a well-directed control of the presented mechanisms is required to achieve a reduction of the energy consumption without affecting the user-perceived quality. Controlling the mechanisms is crucial and depends on factors such as network design, user behavior, and technology specifics, both for LTE and for other wireless networks. In the next section, we demonstrated the challenges and potential of such mechanisms for WMNs.

4.4.2 Energy Efficiency and QoE in Wireless Mesh Networks

In the following, we focus on energy efficiency and QoE issues in WMNs. We discuss the trade-off between QoE and energy efficiency in city WMNs as illustrated in Figure 4.12. The evaluation is based on a summary of previous work [44].

4.4.2.1 Evaluation of the Trade-off between QoE and Energy Efficiency in City WMNs. Even though WMN nodes in cites are usually connected to the power grid, network providers still try to minimize the energy consumption and reduce their costs. At the same time, they want to guarantee a good user-perceived quality of the networked services. Accordingly, the QoE of the end user should not be harmed by any reduction of the resources of the WMN. In general, this can be achieved either by controlling the network resources, for example, increasing the number of available mesh gateways, or by controlling the applications, for example, adapting the transmitted content [45]. The implementation of such mechanisms in a wireless mesh environment is rather complicated. On the one hand, fixed bandwidth guarantees are hard to realize because fading or attenuation effects result in a highly variable bandwidth. On the other hand, interference problems may occur when adding more wireless resources which may in the end lead to a decreased network performance.

To demonstrate this challenge, we investigate the trade-off between energy consumption, which depends on the available network resources, the number of supported users, and the perceived application quality. To that end, we conduct measurements in a small wireless mesh network consisting of four mesh nodes, as illustrated in Figure 4.12. The uplink capacity of one relay node to the Internet is regarded as a bottleneck. Hence, adding additional relay nodes (gateways) increases the overall uplink capacity and also the energy consumption. As an application for all users, we consider Web traffic and

TABLE 4.2. Mechanisms Enhancing Energy Efficiency in Cellular Networks

Component	Technology	Technical Approach	Implications and Impact on Energy Efficiency
Antenna [36, 37]	MIMO	• Concurrent transmission on physical layer • Spatial multiplexing	• Higher spectral efficiency • Reduction of error rate/increased capacity • More efficient transmission reduces energy consumption • System supports trade-off between energy efficiency and spectral efficiency
	Beam forming	• Target-oriented antenna arrays	• Spatial selectivity • Interference reduction • Less signal power required
R/F trans-ceiver [36, 38, 39]	Redesign of architecture	• Circuitry and transceiver system level • Power adaptation	• Chips support trade-off between power and performance • Significant reduction of energy consumption for low load situations
Baseband [40]	Micro/pico base stations	• Design of new signal processing algorithms	• Algorithms support trade-off power versus performance • Significant reduce of energy consumption for low load situations
Amplifiers [36, 38, 39]	Operation point adjustments	• Approach specification	• Amplifiers can adapt their operation area • Less power consumption due to more efficient amplifiers
User device [41]	Discontinuous transmission (DTX)	• Deactivation of unused radio components • Micro/short/long timescales	• Less power consumption in idle mode • Significant energy savings in case of low loads • Further savings possible due to not transmitting CRS in short DTX
Mobile core and RAN	Scalability of power consumption	• Bandwidth adaptation • Energy-efficient resource allocation • BS sleep mode	• Improved system efficiency • Improved energy efficiency, in particular for low loads

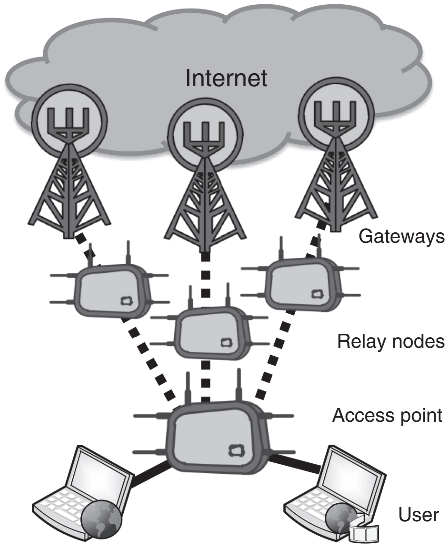

Figure 4.12. City wireless mesh network, multi-hop scenario.

approximate the QoE with the bandwidth/QoE mapping function introduced in [45]:

$$\mathrm{QoE_{web}(bw)} = \max\left\{1, 5 + 1.5 \ln\left(\frac{\mathrm{bw}}{8\ \mathrm{Mbps}}\right)\right\}. \tag{4.10}$$

The QoE of a Web user is supposed to be in logarithmic relation to the available bandwidth and that a bandwidth of at least bw = 8 Mbps is needed to reach a maximal user QoE of $\mathrm{QoE_{web}(bw)} = 5$.

The reference measurements conducted revealed the following issues. First, the power consumption increases linearly with the increasing number of active gateways. Second, the available capacity between the mesh nodes is subject to large variations. An increase of the available resources by increasing the number of gateways from one to three reduced the average available capacity per gateway from 19.15 to 14.58 Mbps. This depends on the placement of the gateway nodes; however, it means that doubling the number of gateways does not necessarily lead to a doubling of the available resources in terms of capacity. In addition, the higher interference leads to higher variations of the available capacity per gateway. In our scenario, the relative gap between the average capacity and the 5% quantile was increased from 14% for the one-gateway case to 42% for the three-gateway case, respectively.

If the available capacity is subject to variations, the resulting QoE will retain this behavior. Hence, we investigate the average QoE and the gap between the average QoE and the 5% quantile of the resulting QoE distribution. Figure 4.13 illustrates the QoE gap for the multi-hop scenario with three gateways. The QoE gap is 0.8186, that is, in 5% of the time, the current opinion score (OS) of a given user can be more than 0.8

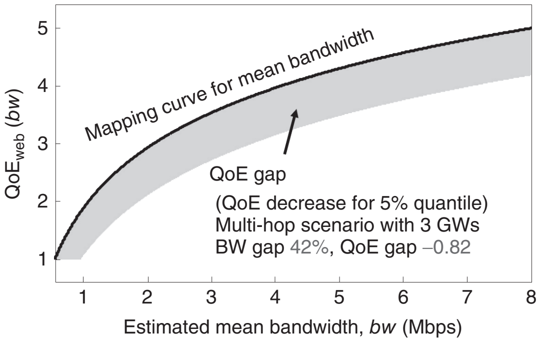

Figure 4.13. Mapping curve mean bandwidth/QoE with QoE gap.

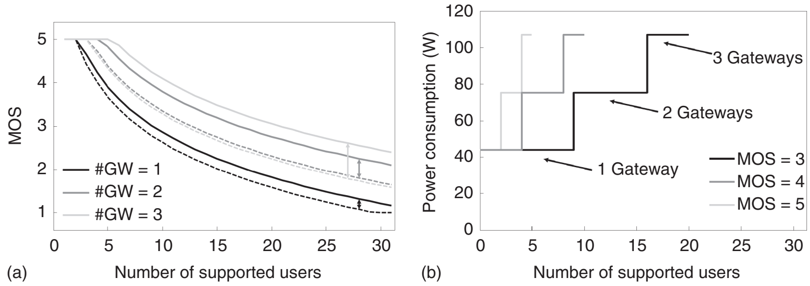

Figure 4.14. Relation between QoE, power consumption, and number of supported users.

worse than the mean opinion score (MOS) of that user. This might be acceptable for an MOS value of 5 and a resulting worst case MOS value of approximately 4.2. However, for an MOS value of 3, this results in a worst case of approximately 2.2, which indicates a higher number of dissatisfied users.

The increased bandwidth fluctuations in multi-gateway scenarios also have a negative impact on the number of supported users with a certain QoE. To study this effect, we first investigate the QoE based on the number of users and the number of used gateways. The results are illustrated in Figure 4.14(a). The bold solid lines represent the case when the average bandwidth in each scenario is regarded, the thin dashed lines represents the 5% percentile case.

As long as the fraction of bandwidth each user obtains is higher than 8 Mbps, the average MOS of the users is 5. For an increasing number of users, the QoE starts to decrease when a certain threshold is reached. From this point, doubling the number of users approximately results in a reduction of the average QoE by 1. Although the decrease can be avoided by adding additional gateways, a lot of resources are wasted because the mentioned interferences lead to a nonlinear relationship between number of gateways and supported users. In particular, this results in a lower minimum quality for three gateways as for two gateways, as illustrated by the 5% quantiles.

Besides the QoE for different numbers of users and gateways, we highlight the number of supported users for a given QoE level and the power consumption of the wireless mesh network. In detail, Figure 4.14(b) illustrates the number of supported users with a certain MOS of 3, 4, or 5 for a given number of gateways and the corresponding power consumption. The power consumption raises almost linearly with the number of gateways and does not depend on the number of users. This is mainly due to the fact that for the access nodes, the energy consumption of the wireless interfaces is negligible compared to the consumption of the overall system. However, the number of users does not increase in the same order of magnitude as the number of gateways. This can be mapped to the following: paying twice the price for power consumption does not necessarily mean to be able to satisfy twice the number of users.

Another important issue besides the application quality is the energy consumption of mobile devices when accessing the network. Current smartphones consume a huge amount of energy while sending and receiving data over the network. Hence, it may be beneficial to reduce the transmission time itself, as investigated in the following.

4.4.3 Reducing Energy Consumption of the End User Device

Huge efforts are currently undertaken to save energy at the mobile end devices. This is reflected by the decreasing power consumption and increasing performance per watt [46] of new devices. Taking the energy consumption profile of smartphones into account, most energy is consumed while sending and receiving data over the network. Thus, mechanisms that reduce the energy consumption of mobile terminals are required. One such a mechanism is DTX, cf. Section 4.4.1. Here, the network determines time intervals where no data is sent to a smartphone and thus allows the smartphone to enter a power saving state while no data is transmitted. This can be combined with data scheduling mechanisms as presented in [47]. The authors propose to adjust resource allocation in multiple user scenarios to avoid long parallel downloads and to allow consecutive short downloads with high data rate [47]. This, however, comes at the cost of additional waiting times before being served. The concept is exemplary illustrated for three users in Figure 4.15. If no additional delays are introduced, the link is utilized similarly for both cases. However, for the second case, the individual downloading durations are reduced.

Without resource scheduling, the available resources are shared fairly among all downloads. As a consequence, the downloading duration per user is increased, because of the reduced resources. On the other hand, a download scheduling on a first come first serve (FCFS) basis might reduce the download duration per task and also might introduce additional waiting times. Hence, the question arises, whether the overall power consumption is reduced compared to the case without scheduling, and whether the overall download duration, which also includes possible waiting times, is increased. We will now study the impact of the scheduling strategy in detail.

4.4.3.1 Evaluation Setup and Performance Metrics. The study is carried out in a WMN. The WMN consists of one wireless AP granting access for the mobile user devices and one mesh node connecting the AP to the WMN's Internet gateway. The

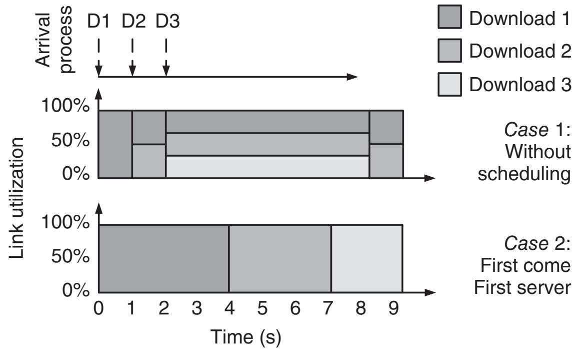

Figure 4.15. Download process with and without a scheduling strategy.

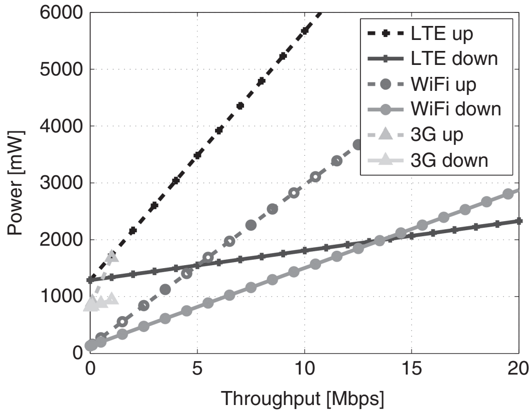

Figure 4.16. Power model for 3G, LTE, and WiFi [48].

mobile users are requesting files with equal or different sizes from a server located in the Internet. On the basis of the order of the requests, a resource algorithm schedules the specific network flows. To determine the energy consumption of the downloads also for other technologies such as LTE, 3G, and WiFi, the model provided by Huang et al. [48] is used.

Figure 4.16 shows the power needed (in mW) depending on the data rate (in Mbps) of the uplink and the downlink for all technologies. A mobile device already consumes a significant amount of energy when 3G or LTE is turned on. In general, LTE provides the highest data rate that is necessary for the emerging high quality applications. Yet it also consumes the most power compared to 3G and WiFi.

4.4.3.2 Performance Results of the Proposed Mechanism. First, we investigate the impact of the FCFS resource allocation algorithm on perceived

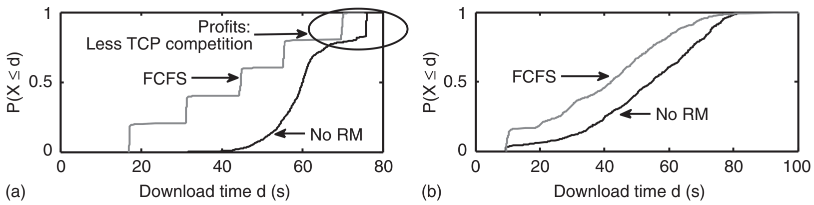

Figure 4.17. CDFs for different download scenarios.

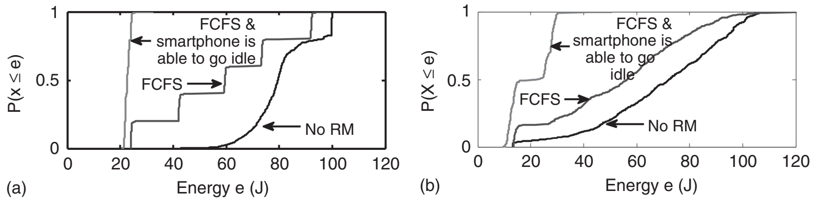

Figure 4.18. Impact if smartphone is able to go idle in transmit pauses in conjunction with FCFS scheduling.

downloading times for two scenarios. We evaluate a scenario with five users that simultaneously try to download the same 5-MB file from a server. Then, we focus on a scenario with a higher statistical variation. The interarrival time for all five download users are distributed exponentially with a mean of 5 s. Further, the users download files with a size of 3 or 6 MB. The available wireless network capacity of the WMN is limited to 3 Mbps. To get statistical significance, the experiments were conducted 100 times. The aggregated results are depicted in Figure 4.17. The results are illustrated as CDF for the download times d. In case of an FCFS scheduling, the download times can be reduced. This is mainly due to less competition between the TCP flows than in the case of "no RM" (no resource management, i.e., without particular scheduling strategy).

A convenient approach for saving energy at the end device is to temporarily suspend their transmissions. Therefore, we consider theoretically how high the savings in energy are if the mobile phone is able to go idle. We compare the results with the energy consumption for terminals that cannot go idle for the cases with and without explicit resource management. The energy consumption per terminal in case of an LTE network are illustrated in Figure 4.18. Again, the results for the static case are depicted in Figure 4.18a, whereas the results for the more varying scenario are illustrated in Figure 4.18b. It can be seen that the FCFS mechanisms with an enabled idle option outperform both the FCFS and the No RM mechanisms. Here, the mobile devices are only activated as long as they are downloading a file. In the lower figure, we can see the effect of different file sizes. The step behavior is the result of energy consumed by the mobile devices for the 3-MB and the 6-MB files.

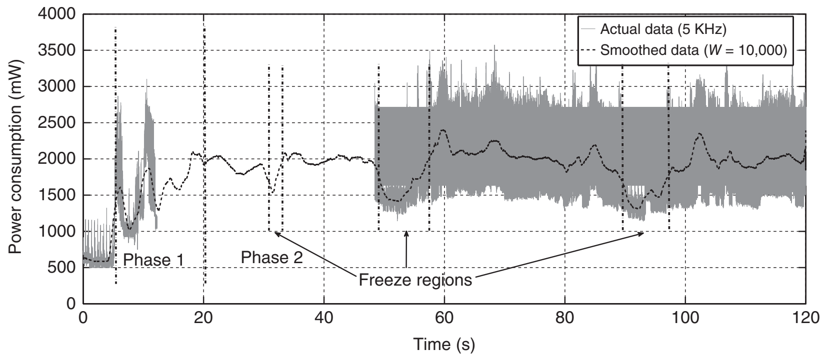

Figure 4.19. Total instantaneous power consumption during video streaming.

As shown in this section, appropriate resource scheduling mechanisms might reduce the energy consumption of end devices by reducing transmission time. The energy saving potential, however, highly depends on the type of application. During a download, the user typically performs other tasks or does not interact with the device at all. As other components such as the device screen do not depend on the download progress, no additional energy is wasted. This may change by taking other applications such as progressive video streaming into account, as discussed in the following.

4.4.4 Energy Measurements Revealing Video QoE Issues

During the playout of a video, the stream often gets interrupted because of starvation of the playback buffer that is caused by bandwidth and delay variations, affecting the BDP (bandwidth–delay product) and RTT (round trip time). Those short or long pauses during the video stream are referred to as *freezes* or *stalling events* that influence the end user perceived QoE. During a stalling event, typically, no data is transmitted, which on the one hand might result in a reduced power consumption. On the other hand, other components such as the screen consume power leading to an intrinsic need to reduce stalling times and therewith the waste of battery power.

In the following, we investigate whether it is possible to identify video stalling based on the energy consumption of the smartphone using anomaly detection techniques [34, 35]. As detailed in Section 4.3.3, power measurements can be conducted using software internal tools such as PowerTutor or external power-monitoring tools such as Monsoon. More details, as well as a comparison of both tools, can be found in [35]. To achieve a good accuracy of the stalling event estimation, a high sampling rate of power measurements is necessary in order to detect anomalies. If the measurement sampling rate is too low, it might miss the anomalies and thus does not identify stalling. However, oversampling might cause unnecessary high energy consumption because of the excessive amount of system calls to fetch the information on the current drain.

The instantaneous total power consumption during video streaming on the smartphone is given in Figure 4.19. The power consumption values are categorized in to two

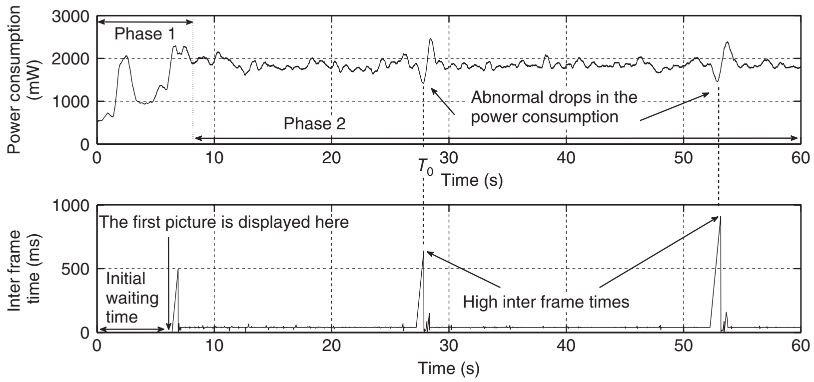

Figure 4.20. Simultaneous interpicture time and power consumption measurements.

parts: Phase 1 and Phase 2. Before Phase 1, the smartphone is in idle state. Phase 1 starts when the user presses the play button and the player requests the video content from the server. Phase 1 duration contains the signaling duration, and it depends on the condition of the link in between the smartphone client and the streaming server. The increases in initial delay extends the duration of Phase 1 and eventually the total energy consumption of the video player. After Phase 1, the instantaneous power consumption values follow a steady-state region in Phase 2, and this second phase continues until the end of the video session. However, in Phase 2, the steady-state behavior of instantaneous power consumption might be impacted by the occasional freezes during the video playout, and we identified these regions as "freeze regions?" We smoothed the high frequency power consumption values obtained via Monsoon with simple moving average (SMA) with varying window sizes (W), where $W = 10,000$ represents a 2 second-long window size. There are two evidences in the power consumption pattern at Phase 2 where the smoothed power consumption values drop down from approximately 2000 to approximately 1500 mW. In parallel, the interpicture times, that is, the time gap in between two consecutively displayed pictures, are obtained via our VLQoE tool [49]. Then, one-to-one mappings between the two parameters (interpicture time and instantaneous power consumption) are obtained using an optimized window size, $W = 7500$ (1.5 s) that yields the highest correlation between those two parameters as shown in Figure 4.20.

The correct choice of internal software-based power measurement tools with minimally obtrusive highly accurate power measurement tool on a mobile device can detect the stalling events through energy measurements. Accordingly, the QoE can be estimated by the device, and appropriate actions to reduce the energy consumption might be performed. The introduced methods have the potential to provide a more energy-efficient QoE monitoring framework that relies on energy measurements instead of a complex instrumentation of network stack and user interfaces.

Until now, we discussed the wireless access networks that are connected to a continuous energy source and the issues related to energy efficiency, and the QoS and QoE for access networks and end device. Next, an outlook on environmental WMNs used to connect weather or climate monitoring stations is given. A main concern these networks face is that they are not connected to the power grid, but are supplied with batteries and have no stable energy supply.

4.4.5 Energy Issues in Environmental WMNs

While environmental WMNs take advantage of wireless communications, they face the challenge of energy supply. In environmental monitoring, in particular, the mesh nodes generally cannot count on energy supplies close by. Thus, they need to be equipped with batteries and will be able to communicate only as long as there is enough charge left. Self-sufficient energy supply means leverage local energy sourcing, for example, through the use of solar panels or windmills. It, furthermore, implies the need to carefully handle power consumption and resource allocation such that communication outages owing to discharged batteries are avoided [50, 51]. The latter has shown to be a QoE issue that is taken very seriously by users [32]. Countermeasures have been proposed, such as a context-aware energy management system for network nodes that are energy self-sufficient [52], a battery-aware scheme for energy-efficient coverage and routing [53], and an energy model for network coding-enabled WMNs based on IEEE 802.11 [54]. In [55], an investigation of the energy consumption behavior from the perspective of a wireless network interface in an ad-hoc networking environment is detailed.

The challenges stated in the works above have recently been studied in an environmental mesh network deployed in the Valais region of the Swiss Alps for hydrometeorological monitoring [56]. The environmental conditions are challenging and changing, comprising highly varying sunlight conditions and lots of snow throughout the year. This A^4-Mesh network [57] provides researchers quasi-permanent near-real-time remote control of sensors and access to (quite large volumes of) sensor data. Thus, data loss should be avoided by all means. Figure 4.21 shows the network setup, with the distance of each wireless link and the locations of the connected environmental monitoring stations. Energy measurements, in particular, load of the mesh node and charge of the battery (both in Ah), were taken over two periods of several weeks each, one in summer and the other in winter.

Figure 4.22 displays the daily battery load (charge) together with daily usage (discharge) for an arbitrary week in summer and winter. The measurements concern a central node in the wireless mesh network, node 8, and node 3, which is at the edge of the network and acts as gateway for some specific sensors, cf. Figure 4.21. In both the figures, at first sight, it seems that there is lacking data for the battery charge. As the battery day load denotes the battery charging by the solar panel module, we can expect activity only when the panel actually generates charge, which explains the lack of recorded data at the beginning and end of each day when sunlight stops hitting the panel. The case is more extreme in winter because of the shorter period of daytime. Moreover, it is interesting to note that the battery day load registers large differences from one day to the next, indicating that depending on weather conditions, the amount of sunlight reaching the panel varies considerably. Although sunny days can be used to bring back the battery to full charge and compensate for periods (days) with poor sunlight, one should always consider daylight statistics of potential deployment locations.

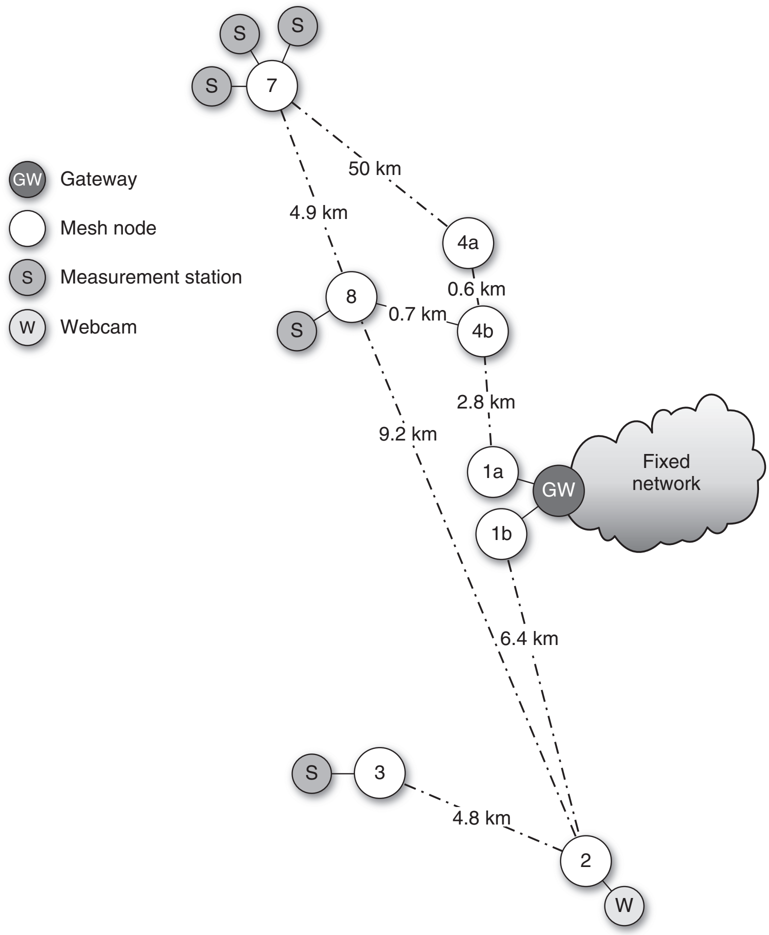

Figure 4.21. Wireless mesh network deployed for support to environmental research.

Comparing the energy usage of the two mesh nodes shows that the central node 8 needs more energy (~17 Ah in a day) compared to what node 3 consumes (~12 Ah in a day). The measured data indisputably points out that the mesh node 8 is involved in more intensive internode communication using in that way more energy. The impact of the length of the communication link on the required transmit power should also not be neglected, mainly because of higher per-link transmission power. Hence, the design of a wireless mesh network relying on solar energy for its sustainable operation should take into account the role of each individual node in the overall mesh network as well as the node's location, which affects communication distances, and also the amount of usable sunlight in the region.

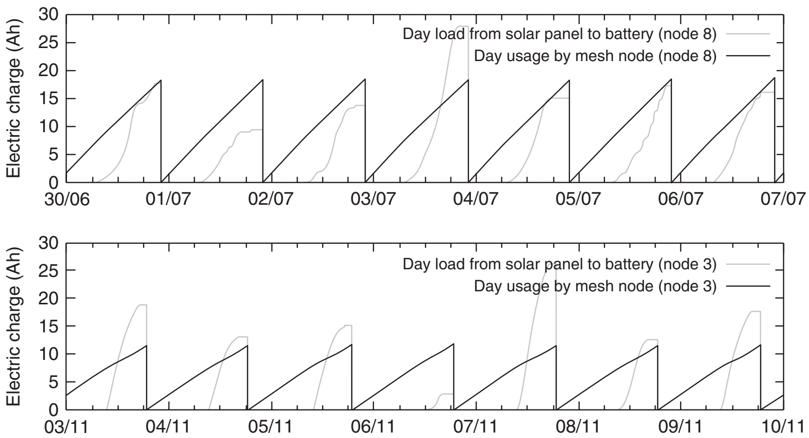

Figure 4.22. Battery day load (in Ah) along with the mesh node day usage (in Ah): measurements are taken at the mesh node 8 and 3 from our real-world wireless mesh network, for a period of 1 week in summer/winter.

4.4.6 Summary

This section discussed the trade-off between QoS and QoE as well as the energy efficiency of access network structures and user devices, starting with summarizing ideas and mechanisms to scale cellular network resources better to the number of users. We found that the power consumption of 4G (LTE) cellular access networks for low and middle load scenarios can be reduced by deploying energy-efficient technologies resulting in energy savings of 40–60%.

We demonstrated the trade-off between QoE and energy consumption of a WMN for an exemplary use case, web browsing. The results illustrate the relationship between the number of customers, their QoE, and the energy consumption of the access network and reveal possible energy savings. Beside energy consumption of the access network, energy savings at the mobile devices is also an important issue. Therefore, resource scheduling mechanisms are candidate technologies for reducing the energy consumption of data transmissions by reducing the download times. In combination with techniques such as discontinuous transmission, which allows to deactivate unused radio components on different timescales, energy consumption for occurring waiting times can be significantly reduced. This, however, changes for applications such as progressive video streaming. Here, the components such as CPU and screen might remain active regardless of the state of the video playback, for example, stalled or smooth playout [58].

Last but not least, environmental wireless access networks that are not connected to the power grid have been discussed. In such a scenario, access nodes are equipped with batteries and solar panels to allow energy harvesting. This type of access network requires a much more sophisticated network design to provide sufficient resources for the supported networking services. Accordingly, various parameters such as length of the communication links, role of the individual nodes, their locations, as well as the amount of usable sunlight have to be taken into account.

4.5 ENERGY-EFFICIENT MEDIUM ACCESS IN WIRELESS SENSOR NETWORKS

Energy efficiency is of highest concern in WSNs. Developed protocols have considered energy efficiency from the beginning, because usually sensor nodes are battery powered and are expected to have long lifetime. Mechanisms developed in WSNs have thus influenced protocols and mechanisms in other (wireless) network environments. The MAC layer is the most important one concerning energy efficiency, because it depends mainly on the MAC protocol when a sensor's transceiver can go to sleep state. The transceiver is the component of a sensor consuming most of its energy, and putting a transceiver into sleep state is by far more effective than adjusting the transmit power.

Many energy-efficient MAC protocols for WSNs have been developed. However, most of those protocols and mechanisms trade energy efficiency for network performance (delay, throughput) and are not able to support varying traffic patterns. This section presents work on energy-efficient WSN MAC protocols (cf. Section 4.5.1), in particular, MaxMAC, which is able to adapt to varying traffic patterns. Measurement in real WSN testbeds demonstrates that it is possible to design both energy-efficient and traffic-adaptive MAC protocols for WSNs (cf. Section 4.5.2).

4.5.1 MaxMAC – An Energy-Efficient MAC Protocol

MaxMAC is an energy-efficient MAC approach, which takes advantage of the substantial work carried out on energy-efficient MAC (E^2-MAC) protocols in the past decade, especially the asynchronous contention-based protocols B-MAC [24], WiseMAC [59], and X-MAC [26].

4.5.1.1 Preamble Sampling. With preamble sampling (also referred to as *low power listening*) introduced in B-MAC and WiseMAC, nodes keep their radios off for most of the time and only wake up for brief periodic duty cycles to poll the channel for a preamble signal once every *Base Interval T* (cf. Figure 4.23). ContikiMAC [60] also applies the WiseMAC preamble minimization to reduce the transmission overhead.

The preamble sampling technique of WiseMAC is already quite efficient in avoiding costly overhearing. However, with sparse traffic, chances are high that the wake-ups of nontargeted receivers do not coincide with those of the targeted receivers. However, with higher traffic and transmissions of queued packet trains, overhearing of preambles and frames can also become an increasing source of energy waste. MaxMAC minimizes overhearing by enriching preambles with target ID information, as illustrated in Figure 4.23. Target nodes turn their radio transceivers on and sense the carrier for *their particular preamble* to receive preamble and frame. Nontarget nodes turn their radios on, extract the target information in the ongoing preamble transmission, notice that they are not targeted, and immediately turn the radio off again. This concept has been applied in X-MAC [26], where nodes send preamble strobes in between which receiver nodes can

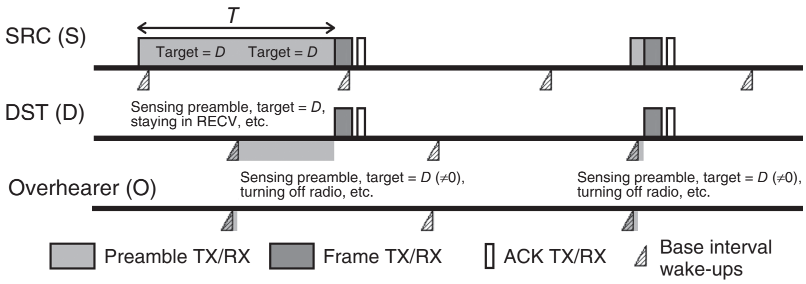

Figure 4.23. Preamble sampling with embedded target address in MaxMAC.

signal reception readiness with the so-called *Early-ACK*. MaxMAC is the first protocol that merges this concept of integrating a target address identifier into the preamble in order to reduce overhearing with the highly efficient preamble minimization technique of WiseMAC.

4.5.1.2 Run-Time Traffic-Adaptation Mechanisms. In contrast to most of today's E^2-MAC protocols, which operate with rather static parameter settings, MaxMAC introduces traffic-adaptation features to instantly react to changing load conditions by altering its behavior at run-time. Similarly as in dynamic frequency/voltage scaling, where the CPU reacts to higher computation load with an increase of the frequency/voltage, a traffic-adaptive E^2-MAC protocol should react to changing load by correspondingly tuning the radio: turning it on more frequently when more traffic has to be handled, keeping it permanently on during load peaks, and turning it off again when the load level permits it.

With E^2-MAC protocols alternating between statically configured sleep in each interval, given that no traffic-adaptation mechanisms are integrated. Latency typically increases sharply, as forwarding nodes need to buffer incoming frames and wait for the next wake-up of their intermediate gateway node, which often sums up to several seconds in multi-hop scenarios. In MaxMAC, nodes change their state and, hence, their behavior, and allocate the so-called *extra wake-ups* when the rate of incoming packets reaches predefined threshold values and release them when the traffic rate drops below these thresholds again, falling back to their initial channel sampling behavior.

Figure 4.24 illustrates the state-based adaptivity mechanism with a source node (SRC) sending packets to a receiver node (DST) with increasing rate. Nodes operate in the *base interval* state per default, polling the channel periodically each base interval T. They alter their state (and behavior) by switching to states S_1 and S_2 when the corresponding thresholds T_1 and T_2 are reached. Thresholds T_1 and T_2 are set to 2 and 6 packets/s in Figure 4.24 but only serve to illustrate the basic concept. Each node keeps estimating the rate of incoming packets, using a sliding window of 1 s (cf. rate estimation graph of DST in Figure 4.24). In case of increasing load, it schedules extra wake-ups in between each base interval, effectively doubling the amount of duty cycles over time. The receiver node DST communicates its increased wake-up frequency in the ACK. SRC receives this announcement and marks the increased wake-up frequency of node DST in

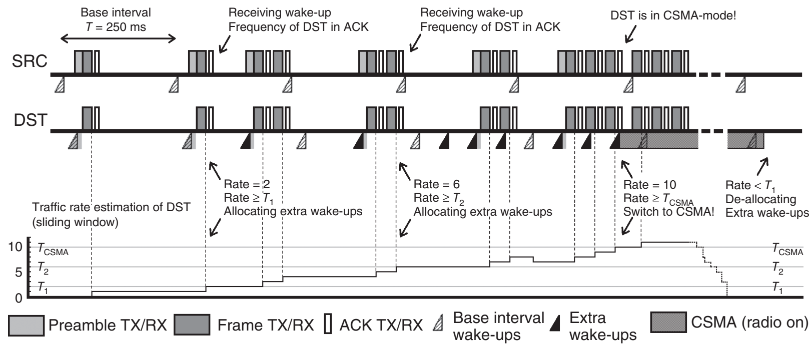

Figure 4.24. Rate estimation, extra wake-ups, and CSMA mode in MaxMAC.

its schedule offset table. With the notification sent by DST in the ACK, DST promises to remain in the new state and keep its increased wake-up frequency for a predefined timespan S1_LEASE. For each state in MaxMAC, the LEASE timespans (S1_LEASE, S2_LEASE, CSMA_LEASE) define how long a node promises to remain in the new state when announcing the state change in the ACK. LEASE timespans can be extended in any new ACK transmission. By remaining in a higher state for at least the LEASE duration, fast oscillation between the different states can be mitigated.

With the rate of incoming packets reaching the threshold T_2, DST changes to state S_2, doubles the frequency of wake-ups again, and announces its state change in the ACK (cf. Figure 4.24). As soon as these timespans expire, nodes having received prior state change announcements will assume that the corresponding node has fallen back to its default behavior, polling the channel with the base interval T, which prevents them from transmitting when the target is not awake.

Most E^2-MAC protocols have been designed under the assumption of sparse low rate traffic and, hence, take into account a severe degradation of the maximum throughput compared to non-duty-cycled MACs. They only reach a fraction of that of CSMA. MaxMAC has been specifically designed to achieve a throughput similar as CSMA in situations of increased network activity, which can be seen as best case for the class of contention-based random-access MAC protocols. While the allocation of extra wake-ups helps to achieve a somewhat increased throughput and reduces the latency, the characteristics of CSMA can still not be reached. MaxMAC thus carries the concept of changing the behavior one step further: when the rate of incoming packets reaches a further threshold T_{CSMA} (with $T_{CSMA} > T_2 > T_1$), MaxMAC switches to energy-unconstrained CSMA and announces this state change to the sender node (and potentially overhearing nodes) in the ACK. Figure 4.24 illustrates node DST measuring the rate of incoming packets to reach $T_{CSMA} = 10$ packets/s in the right part of the figure. DST, hence, switches to the CSMA state, announcing the state change to SRC in the ACK and promising to remain in the CSMA state for at least the predefined timespan CSMA_LEASE. Within this timespan, SRC can transmit packets without having to wait for a wake-up of DST, as it knows that DST keeps its transceiver on for at least the timespan CSMA_LEASE. With

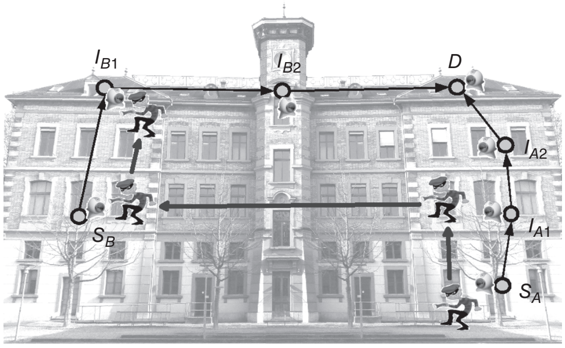

Figure 4.25. Intruder breaking into offices of nodes S_A, I_{A1}, S_B, I_{B1}.

CSMA_LEASE expiring, all nodes having received the prior state change announcement of DST assume that DST has fallen back to the base interval state, which prevents them from transmitting at times when DST is asleep.

4.5.2 Real-World Testbed Experiments with MaxMAC

Our real-world testbed evaluation scenario is inspired by recent work on artificial-intelligence and neural-network-based intrusion detection and office monitoring systems. Figure 4.25 illustrates our application-oriented scenario: the figure displays the testbed with the V-shaped network topology. The nodes in the testbed network are assumed to be part of a distributed office monitoring and intrusion detection system. Each node is assumed to generate sensing information originating from a small CMOS camera and an infrared sensor. On the basis of its sensor values and prior calibration, it detects anomalous behavior as proposed in [61]. The sink node D is again located in the top right corner and is assumed to be connected to the Internet to contact the facility management staff. The events we emulate are described in the following.

All nodes except for the sink are generating *status* messages each 20 s to inform the sink about their alive status (background traffic). In each experiment run, the initial idle period lasts for 100 s. At $t = 100$ s after experiment start, an intruder enters the building in the ground floor and enters the office of node S_A, as displayed in Figure 4.25. Node S_A notices the intruder and generates an image, which is split into 100 packets and sent toward the sink. The node is configured to send two packets per second, hence, the process takes roughly 50 s. The intruder moves up the stairs into the first floor, where he breaks into the office of node I_{A1}, exactly 40 s after visiting the first office. Node I_{A1} notices the intruder and also sends an image toward the sin. After another 40 s, the intruder breaks into the room of node S_B located on the same floor, where the same procedure is triggered. Again, 40 s later, the intruder breaks into the room of node I_{B1} located in the second floor triggering image sending. Finally, the intruder leaves the building. Every node, after transmitting its image data, falls back to its default behavior, generating status messages every 20 s and sending them toward the sink.

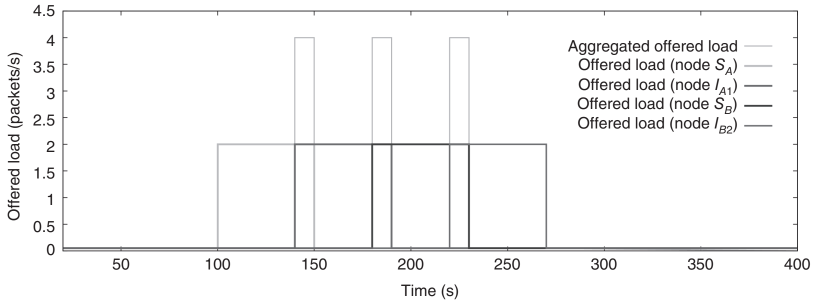

Figure 4.26. Offered load from nodes S_A, I_{A1}, S_B, and I_{B1}.

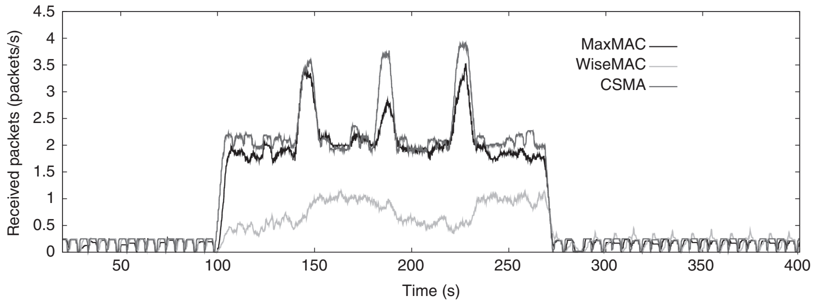

Figure 4.27. Packet reception rate at sink node D.

Figure 4.26 illustrates the shape of the offered load generated by the four sensor nodes in the different rooms of the building over experiment time. Each node starts transmitting its series of packets when the intruder is in its office. There are overlaps of duration of 10 s where two nodes are concurrently attempting to send their packets toward the sink, as illustrated in the aggregated offered load curve.

Figure 4.27 depicts the rate of received packets by the sink node D. The rates were calculated using a central moving average filter of 1 s and computing the average across the results of the 20 experiment runs. In general, WiseMAC obviously manages well to deliver its periodic *alive* status messages to the sink. However, it suffers from major packet loss when the nodes have to transmit the 100 payload messages at a rate of 2 packets/s. With the wake-up interval $T = 500$ ms, each node only wakes up twice per second. As packets have to be forwarded across multiple hops, the rather limited channel contention mechanism and the hidden node problem lead to high packet losses. These are most likely caused by collisions and buffer overflows after failed transmission attempts. The rate of successfully delivered packets from the nodes S_A, I_{A1}, S_B, and I_{B1} during the image transmission period does not exceed 1 packet/s on an average, with the major share of packets being lost. After the triggered events, the periodic *alive* status packets sent for every 20 s are again received at the sink without major losses.

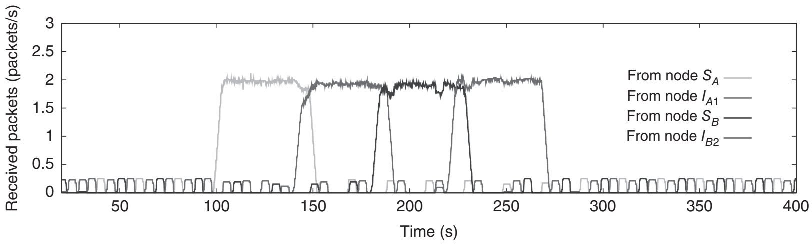

Figure 4.28. CSMA: packet reception rate from nodes S_A, I_{A1},S_B and I_{B1}.

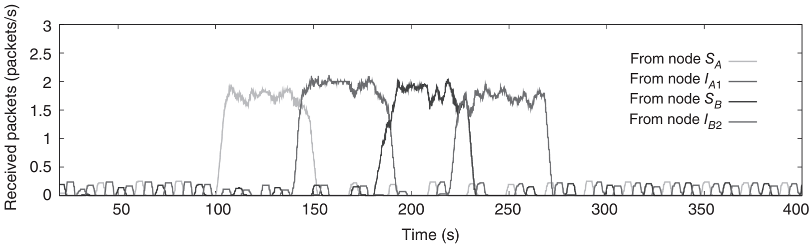

Figure 4.29. MaxMAC: packet reception rate from nodes S_A, I_{A1},S_B, and I_{B1}.

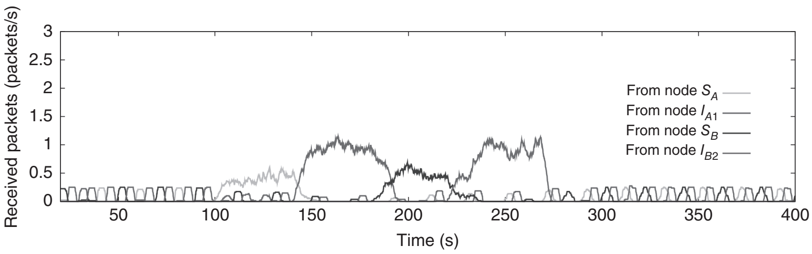

Figure 4.30. WiseMAC: packet reception rate from nodes S_A, I_{A1},S_B, and I_{B1}.

In contrast to WiseMAC, CSMA and MaxMAC succeed in delivering the periodic *alive* status messages, and also the major share of the 100 packets which are triggered by the intruder. The small time periods where two nodes are delivering their series of packets at the same time is managed best by CSMA. MaxMAC's rate of received packets reaches a slightly lower maximum throughput and also tends to drop some packets when only one event is being handled.

Figures 4.28–4.30 depict the share of packets from each originating node S_A, I_{A1},S_B, and I_{B1} coming in at the sink node D. Figure 4.28 conveys the superior performance of CSMA with respect to the achieved packet delivery ratio (PDR) (96%). MaxMAC is able to deliver the major portion of packets (89%) but suffers some losses during the

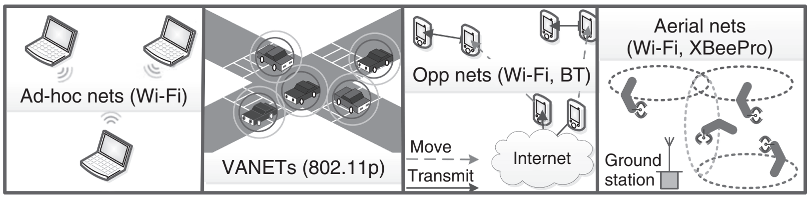

Figure 4.31. Ad-hoc and opportunistic networks and typical technologies.

load peaks, cf. Figure 4.29. WiseMAC suffers heavily from congestion during the load peaks. The rate of 2 packets/s across a couple of hops is not manageable by the protocol and results in buffer overflows and collisions. Nevertheless, it succeeds equally well as MaxMAC or CSMA in delivering the major portion of the periodic *alive* messages.

4.5.3 Summary

This section described the state of the art of energy-efficient and adaptive MAC protocols for WSNs. We have discussed MaxMAC as adaptive and energy-efficient MAC protocol and applied it in a real office scenario testbed for intrusion detection. The results show that it is possible to combine energy-efficient and traffic-adaptive protocol operation.

4.6 ENERGY-EFFICIENT CONNECTIVITY IN AD-HOC AND OPPORTUNISTIC NETWORKS

In today's world of information exchange anywhere at any time, heterogeneous infrastructure networks based on a manifold of radio technologies are available. Yet, the ever-increasing need for bandwidth and connectivity asks for the integration of alternative networking technologies in addition to traditional, infrastructure-based ones. Such need is stated by large amounts of traffic because of, for example, multimedia services leveraged by the evolution of smartphones and other smart devices. As a consequence of these demands, offloading the infrastructure by alternative technologies is considered. Additionally, connectivity is still a problem in rural regions of developing countries and when infrastructure networks are destroyed during natural or man-made disasters. Here, ad-hoc and opportunistic networks establish connectivity provided by equal peers, that is, mainly mobile devices. Figure 4.31 visualizes major types of infrastructureless networks that have been introduced in the past. Starting with general ad-hoc networks mainly based on WiFi and concerned with establishing connectivity and efficient routing in the early years, different use cases demanded special solutions. For example, the IEEE 802.11p amendment has been adopted for vehicular ad-hoc networks (VANETs). Other new approaches originating from early ad-hoc networking research are opportunistic networks leveraging Bluetooth- or WiFi-based networking options for device-to-device communication. Recently, aerial networks have been introduced, which establish ad-hoc network connections between flying unmanned aerial vehicles (UAVs) (flying robots), for example, supported by WiFi ad-hoc and long range technologies for control traffic such as XBeePro.

As end user devices are in these settings often concerned with providing network functions such as relaying of packets and network maintenance, energy-efficient operation of these devices is required to assure a sufficiently long lifetime of the network. Thus, we will ask the question whether the networking technologies are mature enough to cope with this problem and discuss the trade-offs that have to be considered to achieve energy-efficient connection provisioning. Thus, we introduce major technologies, their energy footprint, and methods to increase energy efficiency, as well as typical application fields of ad-hoc (cf. Section 4.6.1) and opportunistic networks (cf. Section 4.6.2).

4.6.1 Ad-Hoc Networking

The original appeal of ad-hoc networking is due to the lack of reliance on an infrastructure, for example, in times of disasters, and the self-organizing nature of the network in a distributed fashion. Research in the area during the past 15 years has, therefore, attempted to show the viability of the ideas in terms of connectivity and message delivery ratio as a function of network capacity (node density and sparseness as a function of mobility). Less research has targeted the important question of energy consumption in ad-hoc networks. One major technology used is WiFi IEEE 802.11a/g/n – operating in infrastructure and ad-hoc mode. Civil use cases of ad-hoc networking based on 802.11 are VANETs, and recently aerial networks of micro UAVs.

A major insight from early studies [62–65] is that ad-hoc networking protocols should target the reduction of energy consumption by avoiding staying too long in an idle listening mode. For example, studies on Symbian and Android phones (N97 and Magic 1, respectively) show that the base consumption for staying connected in the ad-hoc mode of WiFi is considerably high, for example, 0.7 W on the Nokia N97. This is on a par with the amount of energy consumed by the screen. A similar finding is presented in [66], where Nexus One phones are analyzed with respect to their energy consumption during scanning and service set identifier (SSID) beaconing in ad-hoc mode. While the scanning operation is the least energy consuming network operation (4.8% in 24 h), beaconing causes draining of the battery within less than a day.

Another way to save energy is to reduce the number of transmissions and use a way of overhearing communication by many, for example, by using broadcasting or multicasting. The work of Asplund and Nadjm-Tehrani [62] introduces a manycast algorithm termed *Random Walk Gossip* (RWG), which keeps the number of active transmissions to a minimum, thereby saving energy. This protocol was successfully implemented on real devices as well as studied on simulation platforms [63–65]. Implementations of the protocol run on smart phones using the Android as well as Symbian phone platforms.

A major drawback of real implementations of these concepts is that they have to be ported multiple times to new emerging platforms and adapted because of the new energy footprints of networking operations. For example, while it was possible to operate in true WiFi ad-hoc mode with former mobile phones, recent (unrooted and not jail-broken) smartphones do not support this mode any more. We discuss new modes of spontaneous connection establishment in Section 4.6.2. In the following, we summarize major concerns of energy-efficient ad-hoc networking in the use cases disaster and rescue missions.

4.6.1.1 Use Case Establishing Connectivity after Disasters and in Res-cue Missions.

In disaster scenarios, the major concern is to establish a robust network that maintains connectivity for the time necessary to sufficiently carry out the disaster relief task. Thus, prolonging the network lifetime is a major concern, in particular, in the likely case that some or all ad-hoc nodes are running on batteries.

To study such a situation, a simple model of device energy depletion, including both the idle listening footprint and cost of transmissions on the ad-hoc 802.11 interface, has been added to the NS3 simulator as described by Raciti et al. [67]. In the context of a disaster scenario, it is shown that the lifetime of the network can be extended by 14% with no major loss of performance if each node uses the knowledge about own current energy levels and a local estimation of the normality (or hostility) of the behavior in the nearest environment. This work is based on plugging a module into NS3 whose calibration is based on the actual energy measurements obtained in a small-scale testbed emulating device transmissions [68].

In addition to mobile devices such as notebooks and mobile phones, modern search and rescue missions commence the inclusion of battery-powered micro UAVs. This allows, first, to gather image data of an area and, second, to establish an aerial multi-hop network to transmit over wider distances. These networks are sparse but can make use of sending aerial vehicles to certain waypoints to establish and improve connectivity. Yet this comes at a cost in terms of battery depletion of the vehicles when moving.For example, the battery of small airplanes (wingspan of 80 cm and battery capacity of 2100 mAh) and quadrocopters (frame of 64×64 cm and battery capacity of 3300 mAh) used in the testbed described in [69] allows flight autonomy in the range of 30 and 20 min, respectively (at speeds of about 10 and 5 m/s, respectively). Thus, moving the vehicle away from its original, mission-driven pathway to improve connectivity likely reduces the lifetime of the vehicle significantly and has to be performed carefully.

These sample use cases show that energy efficiency is and remains an important topic for ad-hoc networks, which establish connectivity when infrastructure networks are not available or not reliable. Yet, in particular, mobile devices can further act as clients of infrastructure networks and provide additional device-to-device communication to offload the infrastructure and to enhance the connectivity range of infrastructures. This is done by leveraging technologies providing device-to-device links and device mobility, which creates new “opportunities” for connectivity as we discuss next.

4.6.2 Opportunistic and Delay-Tolerant Networking

Delay-tolerant networks (DTNs) are networks where end-to-end connectivity cannot be assumed resulting in nontraditional delays for services. Opportunistic networks are DTNs that make use of mobility to establish connections when devices come into transmission range of one another [70]. Here, mobile devices store data locally, carry them while moving, and forward the data through wireless transmission. Mobile devices are – as in ad-hoc networks – themselves the relays in the network but, different to MANETs, are extremely mobile, and dissemination is more based on flooding than on setting up deterministic routes.

In this setting, the energy consumption of mobile devices, mainly smartphones, is crucial for the operation of an opportunistic network. The wireless networks primarily

TABLE 4.3. Power and Energy Consumption of Wireless Technologies Measured on the Samsung Galaxy Nexus Smartphone [71].

Technology	Operation	Power/Energy Average	Standard Deviation
Bluetooth	Discoverable	2.59 mW	0.56 mW
Bluetooth	Discovery	2027.38 mJ	146.7 mJ
Bluetooth	Connect slave (master)	1998.11 (944.81) mJ	157.77 (77.95) mJ
Bluetooth	Connected slave (master)	58.49 (28.53) mW	3.29 (0.05) mW
WiFi Direct	Turn on	633.31 mJ	115.59 mJ
WiFi Direct	Discovery	340.89 mW	4.02 mW
WiFi Direct	Connect station (AP)	3523.78 (1654.50) mJ	714.44 (395.25) mJ
WiFi Direct	Connected station (AP)	49.75 (231.92) mW	3.9 (9.14) mW
WLAN-Opp	WiFi scan	697.47 mJ	115.07 mJ
WLAN-Opp	WiFi AP turn on	754.03 mJ	257.30 mJ
WLAN-Opp	WiFi AP on	210.97 mW	11.72 mW
WLAN-Opp	Associate station (AP)	3194.32 (2626.86) mJ	722.81 (366.25) mJ
WLAN-Opp	Associated station (AP)	60.79 (210.97) mW	9.74 (11.72) mW

in use are Bluetooth and WiFi – here, not in ad-hoc mode, as this is not available for most off-the-shelf smartphones (unless rooted or jail-broken), but using a kind of soft AP mode. Example technologies are WiFi Direct and WLAN-Opp [66]. Table 4.3 summarizes the energy consumption of a typical smartphone, the Samsung Galaxy Nexus, as measured by the Monsoon Power Monitor [12].

One major observation [71] is that the average power consumption for discovery is least for Bluetooth, and it depends on the duty cycle interval. Bluetooth is 2.5–3 times more efficient than WLAN-Opp, which is twice as efficient as WiFi Direct. The efficiency of Bluetooth originates from its ability to operate while the phone is in sleep mode. Yet, the low energy consumption of Bluetooth comes with the disadvantage of a very short transmission range, which is a major drawback for opportunistic connectivity: Bluetooth supports a transmission range of few tens of centimeters while WiFi allows a range of few hundreds of meters on smartphones.

An additional important observation is that the different roles of the devices (access point or station, master or slave) result in a different energy consumption for each of the technologies. In a group of devices, thus, static role assignment leads to unequal and unfair energy depletion of some devices. To overcome this phenomenon, a *fair role-switching scheme* has been developed for WLAN-Opp based on estimating the remaining contact duration of peers as a function of the elapsed contact time [71]. In this way, an equal depletion of devices can be achieved without switching too often.

These insights for discovery and solutions for fair connectivity provisioning in opportunistic are generally valid. In the following, we take the specific perspective of opportunistic networking used to connect so far disconnected regions.

4.6.2.1 Use Case Opportunistic Networking to Connect Disconnected Regions. Despite the constantly rising numbers of mobile device usage and the increased mobile Internet access, still only 28% of the households in developing countries can access the Internet (2013 report of the ITU [72]). Here, opportunistic networks can contribute to share access to the Internet by using mobile devices as relays and data carriers. Mobile devices can establish contacts to other mobile devices to forward data until, finally, one device with Internet access (via 3G, e.g.) transfers the data to the Internet. Alternatively, mobile devices may act as carriers from one stationary hub (access point with storage capacity) to another, for example, from a city hub with Internet access to a village hub without. In both cases, mobile devices rely on battery power and if communication modules are always on, this will drain the battery. A way to overcome this problem is to switch communication modules off when not needed and on when contact opportunities exist.

In case of device-to-device communication, this requires an aligning of the wake-up schedules of the devices as proposed in [73]. In this approach, the wake-up cycles depend on predicted future contacts, while energy consumption and communication performance are analytically balanced. The approach is studied and proven successful by applying it to major contact traces. Yet, this is not deterministic and the delivery ratio of information can be significantly impaired by the prediction error. Similarly, in [74], the device discovery duration and interval are configured based on contact characteristics, for example, originating from past observations. Thus, the energy efficiency of discovery can be increased as long as the actual contact characteristics correspond to the distributions used for estimation. Once the peers are discovered, the role switching scheme described previously [71] provides fairness and flexibility by adapting role switching depending on the elapsed contact time for device-to-device communication.

In the case of stationary hubs, mobile devices act as ferrying stations and just transmit to hubs, when in range. As devices are data carriers, the mobility flows of humans determine connectivity and transmission options and the overall capacity of this opportunistic network [75]. Here, it is crucial to switch on communication modules for discovery and connection establishment only when in proximity of a hub (access point). Providing efficient estimation methods for wake-ups is a major concern here.

4.6.3 Summary

In ad-hoc and opportunistic networks, the nodes providing connectivity are often battery powered. Thus, it is of importance to reduce the time the devices stay in power-hungry networking states in order to prolong the devices' lifetime. One option is to switch the communication modules on only for a limited time and apply a batch communication style and to apply overhearing of communications. Another option arises from the way today's smartphones can be spontaneously connected. As 802.11 ad-hoc is disabled for normal operation mode of smartphones and Bluetooth only provides very limited ranges, WiFi adaptations are in use, such as WiFi Direct and WLAN-Opp. These technologies leverage a soft AP mode that allows clients to connect to. In such a setting, however, the devices are not equal and consume different amounts of energy depending on their role. Consequently, in addition to decreasing the energy consumption of the individual device, fair role-switching strategies may be employed. In a different setting, in case mobility can be controlled to achieve better connectivity as for battery-driven (aerial) robot networks, energy moves even more to the center of investigation as energy required for movement is orders of magnitude higher than energy consumed for networking.

It is worth noting that the research results in this field are often derived from simulations of larger groups of entities, yet based on realistic energy and mobility models. The manifold of devices and embedded computers and modules around requires, so far, ever new calibrations of the energy model along new arising technologies. Thus, there is a need for methodological improvement to overcome this situation by providing sustainable, modular energy models for ad-hoc and opportunistic node classes.

4.7 SUMMARY AND CONCLUSIONS

Wireless networks face particular challenges related to energy consumption, yet, also provide specific options for energy-efficient networking. First, in wireless communications, the signal propagation, as well as the range of a wireless link and its quality depends on the antenna profile and its power characteristics. Then, nodes and devices connect and disconnect frequently and increase network dynamics and, thus, lead to varying needs for connectivity. Finally, mobile nodes and devices are in the focus of energy efficiency research, which are battery powered and the battery is a limited resource. On the one hand, the user device is the final edge of an access network, where the user is exposed to an eventual degradation of the quality of experience because of energy saving for the sake of the battery lifetime. On the other hand, mobile nodes and devices can provide network resources themselves in ad-hoc and opportunistic networks.

In this wide field, we gave an introduction to wireless energy efficiency metrics and discussed measurement methodologies followed in recent wireless networking research with a strong focus on the battery-powered mobile device. The two principal methods, namely, external measurements and internal software-based estimation, can provide valid insights in the energy consumption of wireless network operations. In particular for wider field studies, software-based estimation is a feasible choice. Yet, the variety of devices makes it impractical to refer to a single energy device depletion model leading to inaccurate estimation. Thus, to retrieve accurate energy consumption values, external measurements are preferable.

Concerning energy efficiency, we discussed challenges in access, wireless sensor, and ad-hoc and opportunistic networks. Hereby, we put a focus on the trade-off between quality of experience and energy consumption in access networks and discussed an example mesh network in nature environments that is challenged by varying charging and discharging in the field. WSNs require means to adapt to changing situations to operate efficiently, as has been exemplified by an adaptive MAC method. Finally, providing connectivity by battery-powered devices is a major concern in ad-hoc and opportunistic networks. Energy-efficient operation targets the reduction of energy consumption by, for example, introducing duty cycling to communication, and also fairness in resource provisioning. To do so, estimates about future connectivity demands are leveraged.

We conclude that adaptive wireless network solutions outperform static approaches in access, sensor, and ad-hoc and opportunistic networks in terms of energy efficiency.

The smartness of the algorithms described in this chapter stems from a good understanding of the energy consumption of the networking operations and context information, which can be used for optimization.

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