Energy Efficiency Analysis and Optimization on Mobile Video Wireless Delivery

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ENERGY EFFICIENCY ANALYSIS AND OPTIMIZATION ON MOBILE VIDEO

WIRELESS DELIVERY

by

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Micro-electronic industry has been boosting the capability of wireless mobile devices on full-scale. However, battery, as the only power source of most mobile devices, is experiencing a relatively slow development. Therefore, how to optimally utilize the limited battery energy on mobile devices under a predefined performance requirement becomes a critical issue. On the other hand, it is still unclear that how the battery capacity consumption is allocated on different working pattern of a specific video codec under various tempo-spatial scales and parameters, which has posed a design challenge on power management on multimedia communication system. Furthermore, an optimization method is needed to be proposed and experimentally tested to achieve the tradeoff between the computational complexity and the distortion of multimedia delivery in order to discover the relationship and interaction between computational parameters of multimedia communication and battery capacity consumption. From point of view of battery-aware system design and optimization, batteries discharging characteristics and a precise model under different thermal condition still need an exhaustive investigation. In this paper, we proposed a dynamic frequency scaling algorithm to optimize the energy efficiency on each sensor node under the different ambient thermal condition. A new battery model with thermal parameter is proposed
and analyzed in order to predict the scheduling of dynamic frequency scaling. Experiment results indicate the efficiency and effectiveness of the proposed optimization framework, and the insight of the relationship between scheduling of dynamic frequency scaling and battery discharging curves under different environmental temperature.
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Chapter 1. Introduction to Energy-Aware Mobile Multimedia Computing

1.1 Background

In recent years, mobile multimedia becomes feasible and popular due to the rapid advances of semiconductor and portable device technology. Technology advances in video compression and transmission over wireless communication networks have enabled mobile multimedia on portable wireless devices, such as cellular phones, laptop computers connected to WLANs, and cameras in surveillance and environmental tracking systems. Video coding and streaming are also envisioned in an increasing number of applications in the areas of battlefield intelligence, reconnaissance, public security, and telemedicine. Present 3G and emerging 4G wireless systems, and IEEE 802.11 WLAN/WMAN have dramatically increased the transmission bandwidth, and generated a great amount of users on video streaming applications.

Although wireless video communications is highly desirable, a primary limitation in wireless systems is the basic design architecture that most mobile devices are typically powered by batteries with limited energy capacity. This limitation is of fundamental importance due to the high energy consumption rate in encoding and transmitting video bit streams during multimedia communications. Moreover, due to the relatively slow development on battery technologies, energy stored in battery fitted in the limited size of mobile devices cannot catch up with the power
consumption of the super multimedia processor continuously developed in the pattern of Moore's law. Thus, the gap between power consumption of mobile multimedia application and the limited power source is becoming widened. A lot of work and research has been focused on energy-aware mobile multimedia communication and green computing of multimedia coding processes.

Basically, there are three main directions of dealing with this problem. The first direction is to engage in the hardware architecture improvement to optimize the energy efficiency, which mainly depends on the technique and new design on micro-electronics. Secondly, the nonlinear characteristics of different types of battery, such as battery current effect, have been analyzed and adopted to achieve higher battery utilization. Piles of battery cells are operated to provide energy according to a dynamic sequence or pattern, which is called power management and scheduling. The third main direction looks into series of procedures applied in the multimedia communication and wisely select complexity control parameters in each procedure to secure the delivered quality and minimize the energy consumption at the same time. It has been shown that achieving a satisfactory user experience needs a systematic consideration of both video source adaptation and network transmission adaptation, indicating that the core of mobile multimedia system design is how to achieve an ideal energy allocation balance between computation and communication. In other words, it depends on how to jointly select those computational complexity control parameters during video coding and transmission according to the real-time status and constraints, such as the video content characteristics, available network resources, underlying
network conditions, battery capacity conditions and distortion requirement.

1.2 Energy-Aware Wireless Video Communication

Figure 1.1 A conceptual power-aware mobile multimedia system

A conceptual power-aware mobile multimedia system is illustrated in Figure 1.1. At the transmitter, different video source adaptation methods, such as typical prediction and quantization, scalable video coding [1], transcoding [2], object-based video coding [3], and summarization [4], may provide different video compression rate based on the video content to match the receiver capability. Then, the compressed data packets are transmitted over wireless links. To combat the lossy nature of a wireless channel, adaptive modulation and channel coding schemes as well as transmitter power at the physical layer can be adjusted based on the channel state information (CSI). Mobile multimedia receiver devices demodulate the received bit stream, perform error detection and correction, decode the received bit stream and display reconstructed video clips. Mobile receiver devices may interact with the transmitter devices to adaptively adjust the compression rate to provide differentiated
services following the interactive activities of end users. Note that mobile multimedia devices are powered by battery, which is not an ideal energy source, since it tends to provide less energy at higher discharging currents. To minimize the total consumed battery energy for delivering a video clip with satisfied quality, joint rate-distortion-complexity optimization to prolong the battery operating time is necessary.

1.2.1 Power Management in Mobile Devices

Since the battery technology cannot satisfy the growing power demand of mobile multimedia devices, power management technology is needed to increase system power efficiency. However, efficient use of the limited battery energy is one of the major challenges in designing mobile multimedia communication devices with limited battery energy supply. This is because 1) real-time multimedia is bandwidth-intense and delay-sensitive, and battery may need to continuously discharge, 2) wireless channel dynamically varies over time and space due to fast and large-scale channel variations, 3) different mobile devices have different limited processing power levels, limited memory and display capabilities, and limited battery energy supply due to the size and weight constraints, 4) video quality does not increase linearly as the complexity increases, and 5) battery discharge behaviors are nonlinear. Since the performance of each part in the mobile multimedia device is dynamic and heterogeneous, all these innate conflicts induce the major research challenges in designing these mobile multimedia devices. Therefore, how and when to apply particular power reduction technique is a challenging problem. However, there
is not yet a systematic method for the power management of mobile devices in real-time multimedia applications.

1.2.1.1 Dynamic Voltage and Frequency Scaling

The multimedia content is time-varying as well as delay sensitive. As a result, to maintain a dynamic balance between the operating level of the processor and the QoS of multimedia application is challenging. In [5], an offline linear programming method has been proposed to determine the minimum energy consumption for processing multimedia tasks under stringent delay deadlines. In [6], an optimal frequency was assigned by a buffer-controlled DVS framework to optimally schedule active and passive states for a video decoding system. The work in [7] uses the workload of a video application to determine the frequency and voltage of a processor for playing streaming video with less power consumption while minimizing data losses. The proposed DVS algorithm has been implemented on PXA270 processor with Linux 2.6 kernel. In [8], both CPU and multimedia accelerator have been considered to reduce the power consumption of handhold systems. In [9], based on the statistical analysis of more than 600 processor load trace files, a novel interval-based DVS scheme has been proposed to handle the non-stationary behavior by using an efficient online change detector and important parameters, and thereby the penalty incurred by DVS can be efficiently controlled.

1.2.1.2 Maximizing Available Battery Capacity

Due to the nonlinear battery effects, the actual battery capacity of a full charged battery is always less than its theoretical capacity. Battery capacity decreases as the discharging current increases, and will recover the decreased capacity when the
battery has been rested or discharged at a low current rate. Therefore, useable battery capacity is significantly affected by the discharge current shape. As a result, a minimum-power-consumption policy does not necessarily result in the longest battery operating time. Battery-aware scheduling schemes attempt to tailor the current of a device to match the optimal discharge rate of the battery. However, for the run-time and delay sensitive multimedia application, how to achieve the best tradeoff between the discharge current shape and video quality is extremely challenging.

1.2.1.3 Power-Aware Transmission and Buffer Management

Wireless network interface cards (NIC) have multiple operation modes such as sleep, idle, transmit, and receive. Each mode has different power consumption. Thus, significant energy saving can be achieved by switching the operation mode from idle to sleep or even off during idle periods. However, an extra amount of power consumption is spent to activate or deactivate the electronic components for mode transition. For multimedia applications, how to optimally set the transition point of the NIC is a crucial problem. Bursty traffic could combine the short idle intervals into longer ones to reduce the number of mode transition [10][11]. Consequently, power consumption on mode transition is reduced. In [12], the minimum buffer size on the receiver side was determined to achieve the maximum energy saving under three cases: single-task, multiple subtasks, and multi-task. In [13], a power saving approach using a realistic network framework in the presence of noise has been analyzed. The transcoded video is buffered by proxy middleware buffers, and then the buffered video is transferred in bursts over a given time. Thus, the NIC modes are alternatively
switched between active and idle to save power. In [14], a power-aware transmission scheme can switch off the card while frames are being played back until a low-threshold level is reached in the client buffer. In [15], the video data is queued in a buffer and sent by bursts at a longer interval. Consequently, much energy on transmission can be saved.

1.2.2 Power Consumption Tradeoff between Computation and Communication

The total power consumed by a mobile device is mainly composed of the power to code the source at the application layer and the power to transmit the coded bits at the physical layer. A high compression ratio will increase the encoding computational complexity and require more computational power. For desired compression introduced distortion, the computational power is a decreasing function of the coded bit rate. On the other hand, to maintain the desired bit error rate, adequate transmission power is needed. Therefore, the total power consumption on coding and transmitting video frame $k$ is a convex function of the transmission rate, which can be denoted as:

$$P_{total}^k = P_C^k(R) + P_T^k(R)$$

Where $P_C^k$ is the consumed power in coding the $k$th frame. $P_T^k$ is the consumed power in transmitting the coded bits at transmission rate $R$.

Overall, all practical communication networks have limited bandwidth and are lossy by nature. Furthermore, wireless channel conditions and multimedia content characteristics may change continuously, requiring constant value updates of source
and channel parameters. In addition, multimedia streaming applications typically have different quality of service (QoS) requirements with respect to packed loss probability and delay constraints. Therefore, the total power consumption of mobile multimedia devices can be minimized by taking advantage of the specific characteristics of video source and jointly adapting video source coding, transmission power, and modulation and coding schemes.

Generally, to minimize the total power $P_{tot}$, the source coding parameters $S$, channel (transmission) parameters $C$, network interface card (NIC) setting $N$, and decoder parameters (e.g., error concealment strategy) $Q$ have to be jointly considered to satisfy distortion and delay constraints. The goal of power consumption tradeoff between computation and communication is to minimize the total consumed power. The problem can be stated as:

$$
\min P_{tot}(S, C, N, Q) \\
\text{s.t. } \begin{cases} 
D_{tot}(S, C, N, Q) \leq D_0 \\
T_{tot}(S, C, N, Q) \leq T_0 \\
T_{tot}(S, C, N, Q) \leq C_0
\end{cases}
$$

where $D_0$ is the maximum distortion to ensure the satisfied video quality. $T_0$ is the end-to-end delay constraint imposed by the given video application. $C_0$ is the maximum computational complexity that the mobile multimedia device can provide. The selection of $S$, $C$, $N$, and $Q$ will affect the end-to-end distortion $D_{tot}$, delay $D_{tot}$, and computational complexity $C_{tot}$.

To solve the problem above, we need to understand 1) how source adaptation at a video codec affects the computational complexity and the achieved video quality; 2) how transmission adaptation affects the power consumption on transmission and the
obtained video quality.

1.3 Power-Aware Video Coding

Video coding achieves high compression efficiency, and enables high resolution videos to be played by mobile multimedia devices. However, the high coding efficiency of video coding is achieved at the cost of high computational complexity. As a result, a significant burden is put on the processor, which is challenging for mobile multimedia devices with limited processing capabilities and battery energy.

1.3.1 Estimation of Codec Power Consumption by Its Predictable Computational Complexity

The video encoding and decoding flexibility provides a variety of multimedia implementation platforms, and enables significant tradeoff between video coding quality and computational complexity. In order to optimally select the optimal operating point of a multimedia application for a specific system, the rate distortion and the complexity characteristics of the operational video coders should be accurately modeled. For example, the computational complexity of an H.264/AVC baseline decoder is mainly determined by two major components: time complexity and space (or storage) complexity. The computational complexity of each module can be found in [16]. A tool for the complexity analysis of reference description has been proposed in [17]. In [18], a generic rate-distortion-complexity model has been proposed to generate digital item adaptation descriptions for image and video decoding algorithms running on various hardware architectures. The model can estimate average decoding complexities as well as the transmission bit-rate and
content characteristics. As a result, the receiver can negotiate with the media server/proxy to have a desired complexity level based on their resource constraints. Operational source statistics and off-line or online training is based to estimate algorithm and system parameters. An analytical rate-distortion-complexity modeling framework for wavelet-based video coders has been proposed in [19].

### 1.3.2 Computational Complexity Reduction by Approximation and the Corresponding Challenges

The computational complexity can be scalable in various aspects. Based on the observations: 1) not every round of local refinement of fast motion search algorithms can achieve equally good sum of absolute difference operations; 2) motion estimation of smaller block modes is often redundant. A joint rate-distortion-complexity optimization framework has been proposed to balance the coding efficiency and the complexity cost of the H.264 encoder in [20]. The method can cutoff the complexity-inefficient motion search rounds, skip redundant motion search of small block modes, and terminate motion search at the optimal rate-distortion-complexity points. In [21], scalable memory complexity reduction has been considered via recompressing I- and P- frames prior to motion-compensated prediction. A simple rate-distortion-complexity adaptation mechanism for wavelet-based video decoding based on the number of decoded non-zero coefficients used prior to the inverse discrete wavelet transform has been proposed in [22].

In addition, the right chose of set of encoder parameters results in efficiently coded video. However, joint rate-distortion-complexity analysis of H.264 is complex
due to the large number of possible combinations of encoding parameters. As a result, exhaustive search techniques is infeasible in encoder parameter selection. Several heuristic algorithms have proposed to reduce the computational complexity in video coding. In [23], a subset of coding parameter choices are selected and algorithmic simplifications are enforced, and then the effect of each parameter choice and simplification on both performance and complexity reduction is quantified. Rate-distortion-complexity optimization of integer motion estimation in H.264 has been discussed in [24]. In [25], the computational complexity and distortion are estimated based on the encoding time and mean squared error measurement. Furthermore, the generalized Breiman, Friedman, Olshen, and Stone (GBFOS) algorithm has been used to efficiently obtain parameter settings so that obtained Distortion-Complexity points are close to optimal. In [26], a non-heuristic non-probabilistic approach based on non-additive measure quantitatively captures the dynamic interdependency among system parameters under uncertainties, which is a possible method to effectively and efficiently optimize codec parameters.

Furthermore, the quality performance does not increase linearly as the complexity increases. There is a saturation point of quality improvement. Beyond that point, significant computational effort may get little performance improvement, which makes joint rate-distortion-complexity analysis significantly challenging. Moreover, the video content and their characteristics can be very different sequence by sequence, or even frame by frame. The video content can be slow motion such as head-and-shoulder video, fast motion such as sport videos, or global motion. A video
frame may contain a simple scene with a few object motions or a complex scene with many object motions.

The goal of power-aware codec design is to optimally select codec modes to minimize the power consumption on computation with the desired visual quality and delay constraints. However, joint rate-distortion complexity optimization makes our optimization framework even more challenging as the state space increases significantly if more options are considered in the optimization. In that sense, designing deterministic power-aware codec algorithms are extremely challenging. Therefore, various heuristic approaches have been proposed to design power-aware codec. Selection of different video compression algorithms will bring about different levels of video quality and power consumption. Content-aware algorithms can reduce the power consumption with the lossless user perception, while lossy fast algorithms can adaptively tradeoff the user perception with power consumption. Consequently, power-aware codec can dynamically select video compression algorithms to reduce power consumption based on user satisfaction, video content characteristics, as well as battery states. In [27], a configurable video coding system is proposed, which uses an exhaustive search and the Lagrangian multiplier method to optimize the performance and computational complexity. Power-aware concepts and considerations of specific conditions such as different battery status, signal content, user preferences, and operating environments have been proposed. The proposed system can dynamically set the codec mode based on different battery situations to prolong the battery operating time. In [28], an embedded compression algorithm and
VLSI architecture with multiple modes for a power-aware motion estimation has been presented, which reduces external access caused by video content, and further reduces the power consumption of the codec. The architecture adaptively performs graceful tradeoffs between power consumption and compression quality. The methodology of power-aware motion estimation has also been addressed in literature. In [29], hardware-oriented algorithms and corresponding parallel architectures of integer ME and fractional ME have been proposed to achieve memory access power reduction and provide power scalability and hardware efficiency, respectively.

1.3.3 Scalable Video Coding

Scalable Video Coding (SVC) provides the capability to easily and rapidly fit a compressed bit stream with the bit rate of various transmission channels and with the display capabilities and computational resource constraints of various receivers. This is achieved by structuring the data of compressed video bit streams into layers. The base layer bit streams correspond to the minimum quality, frame rate, and resolution, which provides basic video quality and must be transferred, and determines the minimum power needed to drive the codec. The enhancement layer bit streams represent the same video at gradually increased quality and/or increased resolution, and/or increased frame rate, which provides a flexible coding structure for temporal, spatial, and quality scalability. Properly enabling the enhancement layer is able to balance the video quantity and computational complexity so as to provide a power-aware feature for codec design.

For mobile devices, throughput variations and varying delay depend on the
current reception conditions, and need to be considered. Scalability of a video bit stream provides various media bit rates to match device capability without the need of transcoding or re-encoding. Video scalable coding can intelligently thin a scalable bit-stream. Bit rate scalable media may combine with unequal error protection, selective retransmission, or hierarchical modulation schemes to strongly protect the important part of the scalable media for overcoming worst-case error scenarios and give less protection to the enhancement layer in order to overcome the most typical error situations. Thus, video quality may gracefully degrade to adapt the channel conditions. In [30], a video bit rate adaptation method relying on a scalable representation drastically reduces computational requirement in network element.

1.4 Power-Aware Video Delivery

Transmitting video over wireless channel faces a unique challenge. Due to the shadowing and multipath effects, wireless channel gain varies over time, and thus signal transmission is significantly unreliable. Therefore, constant power cannot lead to the best performance. Although the reliability of signal transmission can be increased by increasing the transmitter power, most of mobile multimedia devices are powered by battery with limited power source, making it an unpractical solution. How to achieve satisfied QoS over a fading channel with the minimum power consumption is critical for mobile multimedia device design. In this section, we examine and review the most popular techniques for power-aware video delivery in mobile multimedia applications, i.e., joint source-channel coding and power adaptation, and cross-layer design and optimization. We present a general framework that takes into
account multiple factors, including source coding, channel resource allocation, and error concealment, for the design of power-aware wireless video delivery systems.

1.4.1 General Framework

Since video encoding and data transmission are the two dominant power-consuming operations in wireless video communication, we focus on how to jointly optimize source coding parameters $S$ (e.g., prediction mode and quantization step size) and channel parameters $C$ (e.g., channel codes, modulation modes, transmission power levels, or data rates) in a power-aware video communication system to achieve a targeted video quality or energy usage. Moreover, the delay performance is more crucial than the computational complexity in real-time video delivery. Therefore, from the equation in section 1.2.2, the problem of power-aware wireless video delivery can be formally stated as

\[
\min_{\{S,C\}} E_{\text{tot}} \\
\text{s.t.} \quad \begin{cases} D_{\text{tot}}(S,C) \leq D_0 \\
T_{\text{tot}}(S,C) \leq T_0 \end{cases}
\]

where $E_{\text{tot}}$ is the total energy consumption, $T_0$ is the end-to-end delay constraint imposed by the application, and $D_0$ is the end-to-end distortion constraint. For video delivery over a lossy channel, the distortion at the receiver is a random variable from the point of view of sender. Thus, the expected end-to-end distortion (averaged over the probability of loss) is usually used to characterize the received video quality, and guide the source coding and transmission strategies at the sender.

The expected end-to-end distortion $E[D]$, the end-to-end delay $T_{\text{tot}}$, and the total energy $E_{\text{tot}}$ in are all affected by parameters $S$ and $C$. We use $D_{\text{tot}}(S,C)$, $T_{\text{tot}}(S,C)$,
and $E_{tot}(S,C)$ to explicitly indicate these dependencies. The expected distortion for the $k$th packet can be written as

$$E[D_k] = (1 - p_k)E[D^r_k] + p_kE[D^l_k]$$

where $p_k$ is the probability of loss for the $k$th packet, $E[D^r_k]$ is the expected distortion if the packet is received correctly, which accounts for the distortion due to source coding as well as error propagation caused by interframe coding. $E[D^l_k]$ is the expected distortion if the packet is lost, which accounts for the distortion due to concealment. The probability of packet loss $p_k$ depends on the channel state information (CSI), transmitter power, modulation and channel coding used. Given transmission rate $R$, the transmission delay needed to send a packet of $L$ bits is $T = \frac{L}{R}$. The energy needed to transmit the packet with transmission power $P$ is given by $E = \frac{PL}{R}$.

### 1.4.2 Joint Source-Channel Coding and Power Adaptation

In the literature, joint source-channel coding and power adaptation is a critical technique to achieve power-aware video delivery. In this section, we consider several examples to show how the source coding and channel parameters including the transmission power can be jointly selected to achieve energy efficient video coding and transmission.

A joint source-channel coding and power adaptation system is a scheme, where source coding parameters at the encoder and channel parameters at the transmitter are jointly selected by the controller based on the source content, the error concealment strategy and the available CSI. In power aware wireless video delivery systems,
transmitter power adaptation and channel coding are two powerful techniques to overcome bit errors caused by unreliable wireless network links. Taking advantage of the specific characteristics of video source and jointly adapting video source coding decisions with transmission power, modulation and coding schemes can achieve substantial energy efficiency compared with nonadaptive transmission schemes. The authors in [31] proposed a framework where source coding, channel coding, and transmission power adaptation are jointly designed to optimize video quality given constraints on the total transmission energy and delay for each video frame. In addition to the used rate-compatible punctured convolutional (RCPC) codes, transmission power of each packet is also adapted to decrease the loss probabilities of packets. The work in [32] jointly considered optimal mode and quantizer selection with transmission power allocation.

To illustrate the performance gain of joint adaptation of the source coding and transmission parameters in power-aware mobile video systems, we present some experimental results, which are discussed in detail. In the experiment, a joint source coding and transmission power allocation (JSCPA) approach is compared with an independent source coding and power allocation (ISCPA) approach in which $S$ and $C$ are independently adapted. It is important to note that both approaches use the same transmission energy and delay/frame. In addition, the generalized skip option is used by the JSCPA approach to improve efficiency. The idea is that if the concealment of a certain packet results in sufficient quality, then the algorithm can intentionally not transmit this packet in order to allocate additional resources to packets that are more
difficult to conceal. Due to the independent operation between the video encoder and the transmitter in the ISCPA approach, the relative importance of each packet, i.e., their contribution to the total distortion is unknown to the transmitter. Therefore, the transmitter treats each packet equally and adapts the power in order to maintain a constant probability of packet loss. The JSCPA on the other hand is able to adapt the power/packet and, thus, the probability of loss, based on the relative importance of each packet. For example, more power can be allocated to packets that are difficult to conceal.

To sum up, power-aware joint source channel coding usually should implement the following three tasks: 1) finding an optimal power adaptation scheme and bit allocation between source coding and channel coding for given channel loss characteristics; 2) optimizing the source coding to reduce the computational complexity and achieve the target source rate, and 3) Optimizing the channel coding to achieve the required robustness. Although, these three tasks are separately mentioned, they are essentially correlated. Properly choosing the mode and coding rate of codec, channel coding schemes, and transmission power can reduce the total power of the system.

1.4.3 Power-Aware Cross-Layer Design and Optimization

Due to limited adaptation to dynamic wireless link conditions and interaction between layers, traditional layer-separated protocols and solutions fail to provide QoS for mobile multimedia applications. Therefore, more efficient adaptation requires cross-layer design, not only from the video applications’ side, but also from the
network protocol’s side. Cross-layer design for power-aware multimedia is aimed to improve the overall performance and energy efficiency of the system by jointly considering the video encoder and multiple protocol layers. A cross-layer controller is designed at the sender (the source node) to provide the following functionalities: 1) interact with each layer and obtain the corresponding managerial information, such as the expected video distortion from the encoder and the network conditions from lower layers; 2) perform optimization and determine the corresponding optimal values of control variables residing in various layers. The control variables may include, but not limited to, source coding parameters $S$ at the application layer and channel parameters $C$ at the lower layers which include the sending rate at the transport layer, transmission path at the network layer, retransmission limit and channel coding at the data link layer, and modulation and transmitter power at the physical layer. In this cross-layer framework, network conditions, such as CSI, packet loss rate, network throughput, network congestion status, etc., are all assumed to be available to the controller. How to timely acquire and deliver these network condition informations to the controller still remains a challenging task.

Power-aware cross-layer design and optimization for mobile multimedia has received a lot of research efforts. Various design techniques and optimization methods have been developed. First, almost all the work of joint source-channel coding and power adaptation where video source coding and communication applied decisions have been jointly considered. Besides source coding adaptation, other video source adaptation techniques can also be considered in power-aware cross-layer optimization,
such as scalable video stream extraction [1], transcoding [2], object-based video coding [3], and summarization [33]. Cross-layer optimization for resource allocation and scheduling is another interesting research topic in power-aware mobile multimedia. Plenty of research has focused on multi-user wireless video streaming systems [34] where the assignments of the transmission power as well as other network resources among multiple users were discussed.

1.5 Challenges and Research Directions

Based on the above discussion, there has been a dramatic advance in the research and development of mobile multimedia systems. However, due to the limited energy supply in mobile device batteries, unfriendly wireless network conditions, and stringent QoS requirement, current research on mobile multimedia still faces several major challenges. In this section, we will list these challenges and point out the corresponding future research directions.

Power management in mobile devices: Efficient use of the limited battery energy is challenging due to 1) nonlinear discharge behavior of battery; 2) high QoS requirement of real-time multimedia applications; 3) dynamic wireless network conditions, and 4) interactive activities of mobile end-users. Therefore, developing efficient methods for scheduling battery discharge under different battery capacity status and different workload is imperative to prolong the battery operating time.

Rate-distortion-complexity analysis of video Codecs: Joint rate-distortion-complexity analysis for advanced video codecs, such as H.264 codec, is complex due to the large number of possible combinations of encoding parameters.
It becomes more challenging due to the facts: 1) the quality performance does not increase linearly as the complexity increases, and 2) different videos with different contents and characteristics have different rate-distortion-complexity results. Therefore, developing efficient, accurate and content-aware rate-distortion-complexity analysis models for different video codecs is another challenging research task.

Computational complexity: Many source parameters (e.g., prediction mode, quantization step size, and summary choice) and channel parameters (e.g., transmitter power level, modulation, channel coding, and scheduling) could be considered as the control variables for the optimization of mobile multimedia systems. In order to achieve the global optimality, we need to consider control variables and the interactions among them as much as possible. Moreover, the size of the state space of an optimization problem normally increases exponentially with the number increasing of the selected control variables and their operating points. Therefore, to make the best trade-off between the system performance and the computational complexity, how to reduce the computational complexity and how to determine the suitable control variables and their operating points still remain challenging.

Network Information Feedback and Cross-Layer Signaling: To perform the best adaptation of control variables to the underlying network conditions, power-aware cross-layer optimization for mobile multimedia requires both accurate and timely feedback of network status information (e.g., CSI and availability information of network resources), as well as more effective communications between network
layers. However, in the literature, perfect channel state information is usually assumed available at the controller, which is not real in practice. Therefore, how to manage the cost of acquiring and transmitting the necessary network conditions and how to design cost-effective and time-efficient cross-layer signaling architectures are still the challenging issues.
Chapter 2. Problem Statement

2.1 Literature Review

Mobile multimedia on portable wireless devices, such as cellular phones, laptop computers connected to WLANs, and cameras in surveillance and environmental tracking systems has been greatly enhanced by the network infrastructure upgrade and development in video communication technology over wireless network. Although wireless video communication is highly desirable, a primary limitation in wireless systems is the basic design architecture that most mobile devices are typically powered by batteries with limited capacity. Many researches have been engaged in the improvement of battery performance, but, due to the technical difficulties and financial issue, it is still counterproductive to rely on the battery improvement to narrow the gap between high energy consumption of multimedia processing and the limited battery capacity. From the perspective of battery-aware design and power management, how to wisely perform the energy allocation is a critical issue to guarantee a required service quality.

On the other hand, Due to the deploy range, common application and requirement of wireless mobile network, most of the mobile devices need to be used in an outdoor circumstance in a dramatically ranged area and that makes it necessary to take many natural factors in to account. Temperature as one of the most critical effectors will dramatically influence the performance of battery. Moreover, the specialty and changing of thermal parameter also varies according to time (year, season, day and hours), geographic characteristics (altitude and latitude) and local climate. Although,
many researchers have been engaged in the improvement on the computational complexity of working load and customize the working schedule for a specific wireless sensor network, it is still necessary to fundamentally consider battery discharging characteristic and customize wireless sensor network under different circumstantial conditions. An accurate battery model, which can capture complicated and dynamic battery circuit features, nonlinear capacity effects and thermal influence, is also very crucial for circuit simulation, battery performance prediction, optimization and battery maintenance.

In literature, complexity control parameters in those steps of a generic video encoder was investigated in [35]. However, video transmission was not considered in that work. Although energy efficiency of both video coding and transmission were studied in [36][37][38], only power was considered by defining the mathematic relationship between coding parameters and power consumption instead of battery capacity consumption which is significant in revealing the battery working manner in multimedia delivery. Currently, no dedicated analytical framework or experimental analysis on battery capacity consumption under the context of H.264 codec has been performed. In the literature of low level optimization like power management and DVFS, battery discharging characteristics are not jointly addressed with dynamic voltage scaling in [39], and [40] presents an optimization based on task in real-time instead of dynamic discharging of battery power source. [40] gives a solution under the constraint of QoS, however, battery energy consumption needs to be analyzed. Although [41] provide a dynamic frequency scaling to maximize the working load
which can be achieved by a given type of battery, it still cannot predefine the scheduling of frequency scaling points in the battery working time line which dramatically increases the computational complexity in calculating and monitoring the dynamic changes of battery discharging voltage.

In literature [42], different types of battery models were introduced. Generally speaking, existing battery models can be divided into three categories: physical models, analytical models, and circuit-based models. In physical models, differential equations are used to capture the complex electrical-chemical process inside the battery [43]. Therefore, physical models can provide an accurate and generic battery model solution which can be used to indicate battery behaviors. However, this type of model require intensive computational complexity by solving the interdependent partial differential equations. Moreover, due to the lack of battery model parameters such as specific battery structure and chemical composition, physical models are relatively difficult to be configured and used [42], [44], [45]. Analytical models were developed to reduce the computational complexity, where an equivalent mathematical representation is used to approximate the battery performance [46][67]. Although analytical models are accurate and simple enough for practical power management, they ignore the circuit features such as voltage and internal resistance, making them infeasible for circuit simulation and multi-cell battery pack design. Circuit-based models bases on the circuit analysis point of view to emulate battery nonlinear circuit behaviors by using capacitors, resistors, voltage and current resources. Circuit-based models can capture the complicated battery properties, which can be easily
implemented in electronic design automation (EDA) tools at different levels of abstraction \[48][49]. In order to estimate the impact of nonlinear behaviors and improve the accuracy of prediction on remaining capacity during battery charging and discharging processes, [50] proposes an improved circuit-based battery model to capture the battery circuit features and nonlinear battery capacity effects, especially recovery effect. Although this model can accurately capture the battery performance both at constant and variable loads, it still does not consider the influence of thermal parameter which is the main factor in determine the capacity loss of battery.

2.2 Research Focus and Contribution

In order to analyze energy consumption in a wireless video system, we set up a battery capacity measurement testbed for multimedia delivery application based on H.264 codec, which will footprint the battery capacity consumption in video coding and transmission. Based on the profiles from measurements, complexity control parameters in both coding and transmission processes will be jointly selected by applying proposed optimization algorithm in order to minimize the battery capacity consumption under a certain constraint of expected received end-to-end distortion. The contribution of this work is to reveal the relationship between multimedia communication parameters and battery capacity consumption under a required video communication distortion. By analyzing the measurement result, we can also establish an overall conclusion to provide an efficient optimization guideline in future real-time optimization system and application which does not have sufficient resource for complex computation. This battery capacity footprinting and optimization analyzing
method can also be applied on multimedia application on different hardware platform. Once the corresponding relationship is established and analyzed, future real-time multimedia communication optimization, on this specific platform, can be achieve by referring to the conclusion of those previous experimental results.

In this paper, we also develop a systematic optimization framework for battery-aware energy efficiency optimization for wireless sensor node under a given thermal parameter. We proposed a new circuit-based battery model which incorporates the effect of thermal parameters, and based on this model, we proposed an algorithm to come up with a dynamic frequency scaling scheduling for a certain battery type and hardware platform of sensor node. The main achievement of this work is to provide a new way to customize the optimization on battery energy efficiency toward specific local environments where the wireless sensor network is applied and minimize the computational complexity in calculating the dynamic frequency scaling scheduling.

2.3 Problem Description

In order to evaluate and optimize the battery energy efficiency on wireless sensor node platform, it is necessary to analyze parameters resides in some of the main components during constant working processes of a sensor node. Mode or changes of those parameters will result in significant different performance on working efficiency and battery usage. For a specific sensor node, two sets of parameters mainly determine the overall computational complexity and energy efficiency. One is the set of parameters of physical level which represent the characteristics of hardware
platform and architecture, such as predefined CPU core structure and scalability, I/O and interface mechanism, memory distribution, range and sampling rate of sensors on the node. Let \( H = [h_1, h_2, \ldots, h_y, \tau] \) be the set of control parameters to determine the computational complexity and energy consumption condition of those hardware modules. \( \tau \) is the ambient temperature of the platform which do not affect the energy efficiency performance too much. The other set of parameters are from system level which control the coding and executional behavior and exclusively customized by high level embedded operating system and programs run under it. This type of parameters vary according to different operating systems and tasks engaged by the sensor node. Let \( C = [c_1, c_2, \ldots, c_z] \) represents the set of control parameters to determine the computational complexity and energy consumption condition from operating system and instruction execution. For a wireless sensor node, by adjusting parameters set \( H \) to achieve the tradeoff between computational complexity and end to end distortion of wireless transmission, a certain level of QoS can be attained. For a specific type of battery, there are also a set of parameters to represent the characteristics and chemical physics of battery itself, such as nominal capacity, rated voltage, internal resistance and discharging cut-off voltage. Here we use \( B = [\beta_1, \beta_2, \ldots, \beta_x, \tau] \) to represent all the parameters which will affect the battery performance, where \( \beta \) series denote the parameters of battery itself and \( \tau \) is the thermal parameter which will dramatically influence the battery capacity loss. The objective of the proposed framework is to determine a scheduling \( S \) of dynamic frequency scaling for a given program execution running on a specific sensor node.
platform which can maximizes the working load $W$ of a continuous task under a certain type of battery power source with a limited capacity. This problem can be described as

$$\max W_{B,H,C}(S)$$

subject to:

$$S = f(t)$$
$$\tau = \Gamma(t)$$

$$B = (\beta_1, \beta_2, \ldots, \beta_x, \tau)$$
$$H = (h_1, h_2, \ldots, h_y, \tau)$$
$$C = (c_1, c_2, \ldots, c_z)$$

where thermal parameter $\tau$ and scheduling $S$ are continuous functions of time.

### 2.4 Problem Statement

Figure 2.1 Wireless Video Delivery Scheme

Figure 2.2 Block diagram of a typical video encoder. For INTRA MB or frames, motion estimation and compensation are not needed
Because this paper mainly focus on genetic optimization framework on energy efficiency optimization by solving relationship between dynamic frequency scaling and battery condition. For the purpose of introducing the algorithm of optimization in detail, in this paper, we consider a common wireless sensor network application on wireless video communication system as a way to demonstrate our idea. First of all, we have to consider all the parameters in coding and transmission steps to set up the relation to total energy consumption. Figure 2.1 show two key steps to accomplish video delivery. Major modules in a typical video encoding system, showed in Figure 2.2, include motion estimation (ME) and compensation, DCT, quantization, entropy encoding of the quantized DCT coefficients, inverse quantization, inverse DCT, picture reconstruction, and interpolation. Computational complexity and power consumption of these modules have been evaluated in [28][35][51]. In video transmission step, energy efficiency is influenced by both transmission scheme and power control technology adopted by transmitter on wireless devices. In general, the battery capacity consumed in transmitting data not only depends on wireless channel conditions, such as the instantaneous channel fading factor and channel noise power density, but also on transmission parameters, such as frequency bandwidth, desirable packet error rate (PER), and modulation and coding schemes. Because the energy efficiency analysis of system level parameters in coding and transmission processes has been investigated in [52] and [53], here we set those parameters as constant value for a given QoS and distortion requirement. We select quantization step size $q$, search range $r$, number of reference frames $n$ and adaptive modulation and coding (AMC)
mode $AMC_{mode}$ as main system level parameters to control the computational complexity and energy consumption of video delivery task on wireless mobile device, more detail is discussed in section 3. Under this scenario the overall work load achieved can be measured by calculating how many video frames can be delivered (coded and transmitted). Once the hardware platform is fixed, the characteristics of electronics are decided as well, we extract the relation between discharging current and supplying voltage under a scaled frequency to represent the physical level specification. Most of the practical CPUs provide discrete frequency options from the highest frequency of $f_1$ to lowest frequency $f_n$. And a CPU frequency scheduling can be determined by indicating time points at which to change frequency option from the current value to another. In order to define those crucial scheduling to avoid the real time computational complexity, a battery model with thermal parameter is necessary to be constructed. $B_{Model}^{r_i}$ represents a model which incorporates parameters of battery itself and thermal parameter. We suppose the temperature condition $r_i$ of each sensor node stays constant and belong to a set of thermal values from $r_1$ to $r_m$ with the same interval. So the objective of the paper can be simplified and restate as to find a series of time points for dynamic frequency scaling in order to maximize the total delivered video frames with the constraints of distortion and a given type of battery with limited capacity under a specific thermal parameter. The problem can be formulated as
\[
\max_{\tau_i \in (\tau_1, \tau_2, \ldots, \tau_m)} N_{B, I, c, \tau_i}(t_{f_1}, t_{f_2}, \ldots, t_{f_n})
\]

\[
\begin{align*}
F &= (f_1, f_2, \ldots, f_n) \\
B_{Model}^{\tau_i} &= (\beta_1, \beta_2, \ldots, \beta_k, \tau_i) \\
I_j &= I(f_j, v_{Battery}) \\
C &= (q, n, r, \text{AMC}_\text{mode})
\end{align*}
\]
Chapter 3. Battery Capacity Footprinting and Distortion Analysis for Wireless Multimedia Communication

3.1 Battery Capacity Consumption Profiling

3.1.1 Battery Capacity Consumption on encoding

Video compression is a basic technology that enables the storage and transmission of a large amount of digital video data. Many standard video encoder systems employ a hybrid coding architecture based on DCT and Motion Estimation Compensation (ME/MC) scheme. Experiments have shown that PRECODING [35] (including DCT, inverse DCT, quantization, inverse quantization, and reconstruction) takes a large proportion of CPU occupancy and consumes more than 50% of the total energy consumption at encoder. Therefore, it is reasonable to adopt the quantization step size $q$, which is the key parameter in PRECODING process, as one of the optimal complexity control parameters. On the other hand, from the perspective of inter coding, maximal search range $r$ and number of previous frames used for inter motion search (number of reference frames $n$) also play very important roles in controlling the computational complexity during coding process. As a result, we select these three coding parameters as the control parameters in coding.
In this work, we have established a testbed with the considerations of high-resolution battery measurements. Figure 3.1 shows the hardware measurement system which is Imote2 wireless sensor node connected with Arbin Battery Testing System. The H.264 video codec runs on a Linux-based Imote2 wireless sensor node with a PXA271 XScale processor. In order to get a more standard result, we set the CPU as a constant frequency (the frequency of Performance Mode of Imote2), that means no dynamic voltage or frequency scaling is applied. A PC terminal receives and records two kinds of data from the Arbin battery testing equipment: the current value and the battery capacity consumption. Meanwhile, during the coding process, Imote2 records and transmits the related key information to the PC terminal, such as coded frame bits $F_k$ and frame coding time $t_k$ (the time elapse to code the $k$th frame). H.264 codec is stored in the flash memory of Imote2 under different codec configuration. The three coding control parameters, $q$, $r$ and $n$, can be adjusted by
modifying the baseline configuration file every time before running the codec.

Figure 3.2 Codec running flow-process diagram
Figure 3.3 Measurement result of the first 50 frames Forman video clip when $q = 24$, $r = 4$, $n = 3$.
H.264 codec is stored in the flash memory of Imote2. Figure 3.2 shows the flow-process diagram of how a codec runs during the measurement. Five seconds after the measurement begins, the battery system board starts to power Imote2 and activates the bootloader in ROM, then the linux kernel begins loading. Before the codec begins to run, the system rests for 10 seconds to initialize the time base and set the starting point as $t_0$ to start the codec. During the video coding process, when compression of the $k$th video frame is finished, the codec will output the processing time $t_k$ of that frame and the size $F_k$ of coded frame bits. Once the control parameters are fixed, we can establish a relationship between $t_k$ and the total battery capacity usage started from the beginning of the test at the time point $t_0$ to $t_k$. Figure 3.3 shows the measurement result of a 50-frame video clip ``Foreman'', in which $q$, $r$ and $n$ respectively equals to 24, 4 and 3. In general, the coding battery capacity consumption profile of each frame is a set of data based on the three coding control parameters and content of the $k$th frame, and it can be denoted as

$$C^k_e = C_k - C_{k-1} = C_e(q, r, n, k)$$
Figure 3.4 Measurement result of coding 50-frames Foreman video clip with 416MHz frequency
Figure 3.5 Measurement result of coding 50-frames Foreman video clip with 104MHz, 208MHz, and 416MHz under their highest voltage level of 4.2V and lowest working voltage level of 3.2V, 3.3V and 3.4V respectively (3 AAA standard batteries are used as the power source).

Under this platform, we launch a series of tests under different configuration of frequency scaling and supplying voltages. Figure 3.4 is the measurement result and its details by selecting CPU frequency as 416M to encode the first 50 frames of Foreman video clip in QCIF format. From figure 3.5 we can observe in columns that higher frequency result in less energy consumption, and that means based on Imote2 platform, higher frequency has a better energy efficiency. We can also observe that in rows frequency is the dominate effector to determine the execution performance (task finish time) and energy consumption, that means if the frequency is fixed,
performance and energy consumption is less likely to be effected by adjusting supplying voltage. As a result, higher frequency is a more optimal option to maximize the working performance, so it is resalable to choose a high CPU frequency scaling as long as the battery is capable to supply the minimal working voltage of this value of frequency.

3.1.2 Energy Consumption on Transmission

Table 3.1 Parameters of different AMC schemes

<table>
<thead>
<tr>
<th>Mod Scheme</th>
<th>$\delta$(dB)</th>
<th>$\lambda$(dB$^{-1}$)</th>
<th>CodeRate(bits/symbol)</th>
<th>AMC index</th>
</tr>
</thead>
<tbody>
<tr>
<td>BPSK</td>
<td>2.3</td>
<td>0.640</td>
<td>0.5</td>
<td>1</td>
</tr>
<tr>
<td>BPSK</td>
<td>6.1</td>
<td>0.417</td>
<td>0.75</td>
<td>2</td>
</tr>
<tr>
<td>QPSK</td>
<td>5.3</td>
<td>0.461</td>
<td>1</td>
<td>3</td>
</tr>
<tr>
<td>QPSK</td>
<td>9.3</td>
<td>0.444</td>
<td>1.5</td>
<td>4</td>
</tr>
<tr>
<td>16-QAM</td>
<td>10.9</td>
<td>0.375</td>
<td>2</td>
<td>5</td>
</tr>
<tr>
<td>16-QAM</td>
<td>15.1</td>
<td>0.352</td>
<td>3</td>
<td>6</td>
</tr>
<tr>
<td>64-QAM</td>
<td>18.2</td>
<td>0.625</td>
<td>4</td>
<td>7</td>
</tr>
<tr>
<td>64-QAM</td>
<td>21.2</td>
<td>0.419</td>
<td>4.5</td>
<td>8</td>
</tr>
</tbody>
</table>

The energy used to transmit a frame depends on the number of bits of coded frame and the current wireless channel capacity. Usually, the number of bits per coded frame is decided by the video content and the three coding parameters adopted in coding that frame. The transmission rate of a wireless channel depends on the current channel quality and the adaptive modulation and coding (AMC) scheme. Different AMC schemes will result in different transmission rates and spectrum efficiency.
Table 3.1 shows the sigmoid parameters \((\lambda, \delta)\) for the 8 AMC schemes in modeling packet transmissions over an 802.11a WLAN network. Let \(W\) be the wireless channel bandwidth, and \(K_i\) be the transmission rate of AMC scheme \(i\) which can be calculated from table 3.1 by applying the method introduced in [54]. Then, the transmission rate of the \(i\)th AMC scheme is \(K_i \cdot W\). Denote \(F_k\) to represent the number of coded bits of the \(k\)th frame and it is determined by the corresponding measurement. \(P\) be the transmission power. Battery capacity consumption of one frame can be derived if operating voltage of hardware platform \(V\) is known, therefore,

\[
C^k_t = \sum_{k=1}^{n} P \cdot \frac{F_k}{K_i \cdot W} \cdot \frac{1}{V}
\]

Because \(F_k\) depends on the coding process, so it is determined by the previous three coding control parameters as well. In general, the battery capacity consumed on delivering the \(k\)th frame is a function of the frame number, the AMC scheme \(i\), and coding control parameters, which is

\[
C^k_t = C_t(q, r, n, i, k)
\]

The total battery capacity consumption in delivering one frame is the sum of the capacity usage in both coding process and transmission process.

\[
C^k_{tot} = C^k_c + C^k_t
\]

Figure 3.1 and 3.2 show the battery capacity consumption profile of the 25th frame based on control parameter vectors \((q, p)\) and \((r, n)\). Figure 3.1 shows that AMC scheme does not have an obvious contribution as quantization step does on battery capacity consumption. In figure 3.2, the maximal search range can change the battery capacity consumption more efficiently than number of reference frames.
Figure 3.1 Battery capacity consumption profile of the 25th frame under control parameters of q and i \((s = 4, n = 1)\)

Figure 3.2 Battery capacity consumption profile of the 25th frame under control parameters of s and r \((q = 21, i = 1)\)
3.2 Expected End-To-End Distortion Profiling

In this work, the received video quality is evaluated as the expected end-to-end distortion by using the ROPE (Recursive Optimal per-Pixel Estimate) method. Therefore, given the dependency introduced by the error concealment scheme, the expected distortion of slice/packet $\pi_i$ can be calculated as

$$E[D_i] = (1 - p_i)E[D_i^R] + p_i(1 - p_{i-1})E[D_i^{LR}] + p_ip_{i-1}E[D_i^{LL}]$$

where $p_i$ is the loss probability of packet $\pi_i$, $E[D_i^R]$ is the expected distortion of packet $\pi_i$ if received, and $E[D_i^{LR}]$ and $E[D_i^{LL}]$ are respectively the expected distortion of the lost packet $\pi_i$ after concealment when packet $\pi_{i-1}$ is received or lost. The expected distortion of the whole video frame, denoted by $E[D]$, can be written as

$$E[D] = \sum_{i=1}^{I} E[D_i]$$

Generally speaking, multiple modulation and coding schemes are available to achieve a good tradeoff between the transmission rate and the packet error rate. The error probability of a packet of $L$ bytes, under a given AMC scheme $i$, is a function of the bit error probability $p_{b,i}$, which can be express as $p_{p,i}(L) = 1 - (1 - p_{b,i})^{8L}$. Moreover, $p_{b,i}$ can be approximated with sigmoid functions in [55] and [56] as

$$p_{b,i}(L) = \frac{1}{1 + e^{A(x-\delta)}}$$

where $x$ is the Signal-to-Interference-Noise-Ratio (SINR). From this equation above and table 3.1, it can be observed that $p_{p,i}$ depends on the AMC scheme $i$, and so does the overall distortion, since the end-to-end distortion is the function of $p_{p,i}$. Once the packet error probability is calculated, the expected end-to-end distortion will be
calculated. In other words, the set of coding control parameters need to be considered as other effective system parameters to reduce the total video distortion. Based on the statistic evaluation that SINR does not change frequently on a common communication scenario, we set $x$ as a reasonable constant in our later experiments. Therefore, the expected frame distortion associated with AMC scheme $i$ and coding control parameters can be denoted as

$$E[D]_k = D(q, r, n, i, k)$$

Figure 3.3 Received end-to-end distortion profile of the 25th frame under control parameters of $q$ and $i$ ($s = 4, n = 1$)
Figure 3.4 Received end-to-end distortion profile of the 25th frame under control parameters of $s$ and $r$ ($q = 21$, $i = 1$)

Figures 3.3 and 3.4 show the received end-to-end distortion profile of the 25th frame based on control parameter vector $(q, i)$ and $(r, n)$. Figure 3.3 shows that AMC scheme and quantization step jointly affect the distortion of the one video frame. From figure 3.4, we notice that the distortion can be affected by adjusting the number of reference frames. Meanwhile, max search range does not have appreciable influence on distortion.

### 3.3 Energy Efficiency Analysis under Constraint of Distortion

In this section, we are going to analyze the energy efficiency performance under
constraint of distortion, and see what set of control parameters can result in the minimal battery energy consumption for a given distortion level.

Since we have established the two profiles on battery capacity consumption and received end-to-end distortion, and both of the profiles are based on three coding parameters and one transmission parameter. Coding parameters can be adjusted by setting configuration file of encoder. And in the streaming system, intermediate buffer between video coder and network subsystem takes charge of adjusting the transmission parameter at frame level. For simplicity, we establish a four dimension vector \((q,i,r,n)\) to stand for all the combination of possible control parameters. Let \(Q\) be the total options of \(QP\), \(I\) the total optional AMC schemes, \(R\) the total optional max search range and \(N\) the total optional number of reference frame. So every video frame has \(Q \cdot I \cdot R \cdot N\) options of this vector, and all the options form a possible set \(\Psi\).

Therefore, the task is to find the best control vector toward each frame to minimize the battery capacity consumed on delivering each frame under the constraint of expected received frame distortion. By applying our measurement hardware platform, we can derive received frame distortion profile and frame coding battery capacity consumption profile from the experiments of measurement. If we set the received frame distortion constraint as a certain level, every control vector result in the distortion smaller than this constraint is representing a qualified options and all of these qualified control vectors form a selected set \(\Omega\). By referring to the battery capacity consumption profile of a given frame, we can select the best control vector which has the minimized battery capacity consumption while satisfies the received
frame distortion constraint. The algorithm of this optimization framework is described in Table 3.2.

<table>
<thead>
<tr>
<th>Table 3.2 Algorithm of battery capacity optimization framework</th>
</tr>
</thead>
<tbody>
<tr>
<td>For each frame n=1,2,…</td>
</tr>
<tr>
<td>Distortion profile $P_d$</td>
</tr>
<tr>
<td>Coding battery capacity consumption profile $P_c^c$</td>
</tr>
<tr>
<td>Transmission battery capacity consumption profile $P_c^t$</td>
</tr>
<tr>
<td>Battery capacity consumption profile $P_c = P_c^c + P_c^t$</td>
</tr>
<tr>
<td>For each Control Vector $(q, i, r, n) \in \text{Possible Set } \Psi$</td>
</tr>
<tr>
<td>If $P_d(q, i, r, n) &lt; D_{\text{max}}$</td>
</tr>
<tr>
<td>Add this Control Vector into Selected Set $\Omega$</td>
</tr>
<tr>
<td>Next Control Vector $(q, i, r, n)$</td>
</tr>
<tr>
<td>For each Control Vector $(q, i, r, n) \in \text{Selected Set } \Omega$</td>
</tr>
<tr>
<td>If Control Vector $(q, i, r, n)$ has the minimized $P_c$</td>
</tr>
<tr>
<td>Label this $(q, i, r, n)$ as the optimal Control Vector</td>
</tr>
<tr>
<td>Next Control Vector $(q, i, r, n)$</td>
</tr>
<tr>
<td>Next n</td>
</tr>
</tbody>
</table>

**3.4 Experimental Data and Analysis**

We have conducted experiments to evaluate the performance of the proposed framework. The testbed is in charge of monitoring and recording all the desired battery operation data. The first 50 frames of each video sequence is encoded with the H.264 codec (JVT reference software, JM 16.2 [57]). We chose the quantization step
size ($q$), max search range ($r$), number of reference frames ($n$) and AMC schemes ($i$) as the tunable source coding and transmission parameters. The permissible QP $q$ values are $[9,12,15,\ldots,36]$, the values of $r$ are $[4,8,12,\ldots,42]$, and the values of $n$ are $[1,3,9,\ldots,15]$. According to Table 3.1, the permissible AMC schemes index $i$ are $[1,2,3,\ldots,8]$. The optimization framework proposed in this paper was firstly tested by three experiments under different distortion constraints. In the first experiment, we took the first 50 frames of the “Foreman” video clip and set the average frame distortion constraint at 36$dB$ of PSNR. And the other two were executed under the average frame distortion constraint of 42$dB$ and 47$dB$.

Table 3.3 Optimized control vectors corresponding to the first 15 frames under frame distortion constraints of 36$dB$, 42$dB$ and 47$dB$:

<table>
<thead>
<tr>
<th>Frame Number</th>
<th>36dB ($q,i,r,n$)</th>
<th>42dB ($q,i,r,n$)</th>
<th>47dB ($q,i,r,n$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>(30,6,4,1)</td>
<td>(24,6,4,1)</td>
<td>(15,3,4,1)</td>
</tr>
<tr>
<td>2</td>
<td>(33,8,4,1)</td>
<td>(18,6,4,1)</td>
<td>(18,3,4,1)</td>
</tr>
<tr>
<td>3</td>
<td>(33,6,4,1)</td>
<td>(24,5,4,1)</td>
<td>(21,3,4,1)</td>
</tr>
<tr>
<td>4</td>
<td>(30,6,4,1)</td>
<td>(24,5,4,1)</td>
<td>(21,3,4,1)</td>
</tr>
<tr>
<td>5</td>
<td>(30,6,4,1)</td>
<td>(24,5,4,1)</td>
<td>(21,3,4,1)</td>
</tr>
<tr>
<td>6</td>
<td>(27,6,4,1)</td>
<td>(24,3,4,1)</td>
<td>(21,3,4,1)</td>
</tr>
<tr>
<td>7</td>
<td>(33,6,4,1)</td>
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<td>8</td>
<td>(33,6,4,1)</td>
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<td>(21,3,4,1)</td>
</tr>
<tr>
<td></td>
<td>(33,6,4,1)</td>
<td>(27,3,4,1)</td>
<td>(21,3,4,1)</td>
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<tr>
<td>9</td>
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<td>(21,3,4,1)</td>
</tr>
<tr>
<td>12</td>
<td>(33,6,4,1)</td>
<td>(27,3,4,1)</td>
<td>(21,3,4,1)</td>
</tr>
<tr>
<td>13</td>
<td>(33,6,4,1)</td>
<td>(27,3,4,1)</td>
<td>(21,3,4,1)</td>
</tr>
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<td>(27,3,4,1)</td>
<td>(21,3,4,1)</td>
</tr>
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<td>15</td>
<td>(33,7,4,1)</td>
<td>(27,3,4,1)</td>
<td>(21,3,4,1)</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
</tr>
</tbody>
</table>

Table 3.3 lists experiment results of the first 15 control vectors corresponding to the first 50 frames of the tested video clip after applying the optimization framework under those three constraints. Every vector which consists of 4 parameters in the figure represents one optimal control set according to frame number which satisfies the frame distortion constraint. All the optimal control vectors of these 50 frames have formed an optimal solution for this video clip. Figure 3.5 is showing changing of all the four optimal parameters of the first 50 frames of the tested video clip under the constraint of 42dB of PSNR. Figure 3.6 represents how much battery capacity can be saved for delivering a given number of video frames under different dimensions of control vectors. From the figure, we observe that the gain on battery capacity consumption increases linearly with the total number of video frames and the optimization that involves more control parameters can result in better energy efficiency. Thus, the proposed optimization framework can save a considerable amount of battery capacity by adopting more control parameter in the optimization.
framework when it is applied to the cases of long-duration video deliveries.

Figure 3.5 Optimized control vectors corresponding to the first 50 frames under frame distortion constraints of 42dB of PSNR
Figure 3.6 Comparison of battery capacity saving in delivering 50, 500, 5000 and 50000 frames under different dimensions of control vector

According to the additional experiments we tested under the other values of PSNR constraints, we observed that different parameters choices in optimal results follow a predictable changing pattern: The overall value of quantization step tends to decrease as required PSNR increases, but the detail value for each frame is slightly effected by the current frame content. Max search range and number of reference frames grows according to the increase of PSNR requirement, but former is more effective than the later in controlling the battery capacity consumption. Transmission parameter AMC tends to decrease as the required PSNR increases, but it also slightly fluctuates due to different frame content. Without losing generality, we also executed the same measurement on other platform with different hardware architecture.
Although the battery capacity consumption behavior change at a scaling pattern, the relationship between adjusting direction of these parameters and optimal result remained the same as the analyzed conclusion above. The proposed optimization method can be generally repeated on different kind of mobile hardware, the corresponding battery capacity footprinting can be generated, and related parameters changing pattern can also be discovery to provide parameter management guideline for future realtime application on multimedia optimization.
Chapter 4. Battery Modeling for Energy-Aware System Design

4.1 Introduction and Background

In the modern electronic world, hardware and software applications are developing at a tremendous speed. Mobile devices as the biggest category in both academic researches and daily usage are becoming the hottest topic in the recent years. Variety of new technologies are merging every day and got upgraded and improved continuously. New generation of wireless communication networking, sensitive big touch screen user interfaces and optical/magnetic storage drives are all carrying a significant energy cost. However, the development of the battery, probably the single energy source of most mobile devices, is developing at a relevant slow speed and this gap between demand and supply is enlarged at time goes by[58].

For most of the mobile devices, one battery fully charge takes several hours to finished and can only standby for one day or two. As one of the important part of a mobile system, except for optimization on higher application layer parameters, many researches has be initiated by dealing with the parameters reside in battery itself. Many new types of battery has be developed like Nickel-zinc battery, lithium battery and Lithium ion polymer battery. On the other hand, based on the point of cross layer optimization on energy efficiency, many parameters through every level of application system are jointly considered to figure out an overall optimal solution. A series of mathematical battery charging and discharging which can capture the nonlinear characteristics of different types of batteries are need to be developed. However,
Accurate low-level models [43][59][60] is constructed with series of differential equations which capture the chemical reaction of a battery. But this model is very complicated to solve, and the parameters in this model need a long time to be calculated. As a result, some simplified and efficient battery models are proposed aim at solving real-time application and optimization with a less computational complexity.

4.2 Battery Discharging Characteristics

Battery has its special discharging behavior, so it is crucial to take account all those factors that affect the battery capacity discharging performance for system design and optimization.

A typical battery consists of electrodes at end which are anode and cathode, and they are connected by electrolyte. Electrons will be transferred from anode to cathode when a load is connected to the ends of a battery. In the meantime, the chemical material stored in battery has reaction to convert chemical energy to electrical energy. The output voltage of a battery drops in the process of discharging and stops working when the output voltage decreases below a cutoff voltage. This cutoff voltage is predefined by the type and capacity of the battery.

The energy store in battery cell is measured by battery capacity. Full capacity is the total capacity left in a fully charged battery at the beginning of discharge cycle. And theoretical capacity is the maximum capacity that can be used according to the total chemical material stored in the battery. And standard capacity is the total capacity that can be discharged from a battery under a standard condition(standard
load, air pressure and temperature).

Battery as an electrochemical energy supplying system is affected by variety of factors and parameters like temperature, charge-recharge cycle number and load condition. The following are listing three main factor on battery performance.

**4.2.1 Discharging Rate**

Before charging a fully charged battery, maximum amount of active species are concentrating on the surface of electrode. Current will start to flow across the external circuit when a load is connected to the battery. The diffusion process in the bulk of the electrolyte will replenish active species and make the active chemical species decrease. A relatively high discharging rate will generate a high concentration gradient and as a result a low concentration of active species at the electrode surface. When the output voltage drops below the cutoff value due to the falling of concentration of active species, the chemical reaction is not able to effective enough to generate current. What is notable is that at this point the overall capacity in the battery is not totally depleted. It is just coming to a balance between the speed of chemical reaction and current output demand (diffusion rates). When the load is disconnected for a while or long enough, the concentration gradient will flattens again and reach the equilibrium. That means the battery stopped working due to the voltage dropping under cutoff value can start to work again for a relative short period of time after sufficient time of “rest”.

The characteristic described above is called battery recovery effect. Many applications and optimizations have been using this trait for the purpose of maximum
usage of battery. For example, Multi-cell battery and its management have come with the idea of using portion of batteries of a battery pack while resting other batteries for their capacity recovery. How to wisely manage all those batteries becomes the crucial problem to solve.

On the other hand, mobile devices used for video coding are mostly driven by battery. Once the battery becomes fully discharged, a battery-powered portable electronic system goes off-line. Available battery capacity has a nonlinear relationship with its discharging current due to the battery current effect. That means a battery tends to provide more energy at a lower discharge current. Figure 4.1 shows a typical battery discharging process. In this case we use 26650P 2.6Ah lithium-iron battery, and discharge it with constant currents of 1A and 0.25A under the temperature of 20°C. We can observe from the figure that battery has a nonlinear decrease of voltage after it starts to discharge and the voltage drops very fast when it is near the limit of its capacity. Because a relatively low discharging current can make the battery work like an ideal energy source, a lower discharging rate can discharge more capacity from the battery. From figure 4.1, discharging curve of 0.24A can deplete more capacity then the discharging curve of 1A. State of charge (SOC) is the equivalent of a fuel gauge for the battery. (SOC is a number from 0 to 1. 0 represent no capacity discharged form the battery while 1 represent the battery is fully discharged)
Figure 4.1 26650P 2.6Ah lithium-iron battery discharging curve with discharging rate of 1A and 0.5A

4.2.2 Thermal Effect

Temperature is another important parameter which can dramatically affect the battery discharging behavior. When temperature drops below $25^\circ C$, Chemical activity in battery gradually stats to deactivate and internal resistance increase. As a result the full charge capacity is reduced. When temperature increases, internal resistance decreases which increases the full charge capacity and voltage.

We initiated multiple battery discharging tests under a discharging rate of 1.6A under ambient temperature from $-20^\circ C \sim 60^\circ C$ by using Arbin Battery Testing System. The battery we used is the Heter lithium battery 26650, detail of the battery
parameters are listed in table 4.1.

Table 4.1 Heter lithium battery 26650(LiFePO4) description

<table>
<thead>
<tr>
<th>NO.</th>
<th>Item</th>
<th>Parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Nominal Capacity</td>
<td>3200mAh (0.5C)</td>
</tr>
<tr>
<td>2</td>
<td>Minimal Capacity</td>
<td>3150mAh (0.5C)</td>
</tr>
<tr>
<td>3</td>
<td>Rated Voltage</td>
<td>3.3V</td>
</tr>
<tr>
<td>4</td>
<td>Internal Resistance</td>
<td>≤ 30mΩ</td>
</tr>
<tr>
<td>5</td>
<td>Charge Voltage</td>
<td>3.65V</td>
</tr>
<tr>
<td>6</td>
<td>Charge Mode</td>
<td>CC/CV</td>
</tr>
</tbody>
</table>
| 7   | Charge Time                 | Standard Charge Method: 6.0h (for ref.)  
|    |                             | Quick Charge Method: 2.5h (for ref.)     |
| 8   | Max. Continuous Discharge Current | 3C             |
| 9   | Discharge Cut-off Voltage   | 2.5V                  |
| 10  | Working Temperature         | Charge: 0°C ~ 55°C  
|    |                             | Discharge: −20°C ~ 60°C |
| 11  | Storage Temperature         | −20°C ~ 45°C          |
| 12  | Storage Humidity            | < 85%                 |
| 13  | Cell Weight                 | 90g(approx.)          |
| 14  | Size                        | D*H(26*65mm)          |

The rough test result after data transformation is list below:
Figure 4.2 Heter battery 26650 charging and discharging performance (CCCV charging and 1.6A discharging)

Figure 4.3 Total Capacity Loss under different ambient temperature
Key data is derived from testing data. In Figure 4.2, a fact is observed that at high temperature ambient environment, battery tends to discharge more capacity which excesses its standard capacity value from its specification. Secondly, the relation between the temperature and loss capacity has a non-linear relationship. In Figure 4.3, as temperature goes up, the performance of battery goes up stably, but when temperature drop down, especially below $0^\circ C$, the battery performance goes down rapidly. That means when temperature goes below $0^\circ C$, tested battery will lost almost half of its total capacity. In Figure 4.4, higher temperature can make a constant current discharging run for a longer time before the voltage drops under cutoff voltage. The operating time will dramatically drop when the temperature keeps dropping under $0^\circ C$. 

Figure 4.4 Total operating time during discharging phase

[Graph showing the relationship between temperature and operating time]
4.2.3 Battery Capacity Fading

For most of the current lithium-ion battery on the market, large capacity is the biggest feature and advantage. However, the total usable capacity of a battery tends to gradually decrease with increasing cycles of charging and discharging. This capacity fading is mainly because of active chemical material dissolution, passive film formation and electrolyte decomposition. As a result, the internal resistance of battery will increase and affect battery performance eventually.

One of the solution for minimizing lithium-ion battery capacity fading it to deeply discharge the battery before charge it. This will prevent recharging battery when it still has a relatively high open circuit voltage. It is batter to start to recharge battery when the battery output voltage drops below the cutoff voltage value.

4.3 Categories of Battery Models

In recent years, many applicable battery models with acceptable computational complexity have been developed and those models can capture most of the battery charging or discharging information and trait. In literature [58], the author classifies those current models in to four categories:

1) Physical Models: Simulating physical and chemical processes happed in battery.

2) Empirical Models: Consist of ad hoc equations describing battery behavior with parameters fitted to match experimental data.

3) Abstract Models: View and formulate battery as an electrical circuits, discrete-time equivalents or stochastic process models.
4) Mixed Models: Combining mathematic representation of physical and chemical process and fitted parameters for empirical models.

General battery model can be evaluated according to the following criteria:

1) Accuracy: How good the model can represent the practical testing of the battery charging or discharging characteristics and how accurate the model can capture the crucial trait of a battery charging or discharging curve.

2) Building Computational Complexity: To what degree the model uses computational complexity to calculate the parameters in this model. This is crucial for testing and parameters fitting system without sufficient hardware or software resource.

3) Simulation Computational Complexity: To what degree the model uses computational complexity to simulate the model to predict the battery charging or discharging performance. This is crucial for application without sufficient hardware or software resource.

Table 4.1 lists a number of representative models for battery and provides related information.

<table>
<thead>
<tr>
<th>Model</th>
<th>Temperature effect</th>
<th>Capacity fading</th>
<th>Accuracy</th>
<th>Computational complexity</th>
<th>Configuration effort</th>
<th>Analytical insight</th>
<th>Application</th>
</tr>
</thead>
<tbody>
<tr>
<td>Physical</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Lithium-Polymer-insertion cell</td>
<td>Yes</td>
<td>Yes; support for Arrhenius temperature dependence and cycle</td>
<td>Very high</td>
<td>High</td>
<td>Very high (&gt;50 parameters)</td>
<td>Low</td>
<td></td>
</tr>
<tr>
<td></td>
<td>aging</td>
<td>No</td>
<td>Medium</td>
<td>Low</td>
<td>Low(2 parameters)</td>
<td>Low</td>
<td></td>
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</tr>
<tr>
<td><strong>Empirical</strong></td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Peukert's law</td>
<td>Yes; needs</td>
<td>No</td>
<td>Medium</td>
<td>Low</td>
<td>Low(2 parameters)</td>
<td>Low</td>
<td></td>
</tr>
<tr>
<td></td>
<td>recalibration for each temperature</td>
<td></td>
<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td>Battery</td>
<td>Yes; needs</td>
<td>No</td>
<td>Medium</td>
<td>Low</td>
<td>Low(2 parameters)</td>
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<tr>
<td>efficiency</td>
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<td>Weibull fit</td>
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<td>Medium</td>
<td>Low</td>
<td>Low(3 parameters)</td>
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<tr>
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<td></td>
</tr>
<tr>
<td>Electrical-</td>
<td>Yes</td>
<td>Yes</td>
<td>Medium</td>
<td>Medium (12% error predicting cell voltage and thermal characteristics, 5% error predicting cycle aging)</td>
<td>Medium (&gt;15 parameters)</td>
<td>Medium</td>
<td></td>
</tr>
<tr>
<td>circuit</td>
<td></td>
<td></td>
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<tr>
<td></td>
<td>Yes</td>
<td>No</td>
<td>Medium</td>
<td>Medium</td>
<td>High (&gt;30 parameters)</td>
<td>Medium</td>
<td></td>
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<tr>
<td>Discrete-time</td>
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<td>No</td>
<td>Medium</td>
<td>Medium</td>
<td>Medium (&gt;15 parameters)</td>
<td>Medium</td>
<td></td>
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<td></td>
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<tr>
<td>Stochastic</td>
<td>No</td>
<td>No</td>
<td>Medium</td>
<td>Low</td>
<td>Low(2 parameters)</td>
<td>Medium</td>
<td></td>
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<td></td>
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</tbody>
</table>

- Design of interleaved dual-battery power supply; load splitting for maximum lifetime of multibattery systems
- Thermostatic charge method: high
- Dynamic Power management: multibattery discharge
- Shaping load pattern
### 4.3.1 Physical Models

Physical models have the most accurate performance and can be used on application needs high standard and strict requirement. This type of model is based on the physical and chemical processes to give an accurate mathematic expression of battery charging and discharging behavior. However, it is the most complex model which needs huge amount of computational recourse to calculate the model and its parameters. As a result, this large computational cost prevents its practical application on daily usage, especially on mobile device which has limited computational ability.

An isothermal electrochemical model that describes the charging and discharging characteristic of lithium/polymer/insertion battery is proposed in [43][61]. A group of differential equations are used to express the model by applying concentrated solution theory. This set of equations is representing functions of time and expressing variety
of battery values. However, based on knowledge of structure, physical processes, chemical composition, battery type, temperature and other factors, it takes more than 50 parameters to simulate a given lithium-ion battery. Moreover, complex numerical system is needed to solve the interdependent partial differential equations of battery model. That means several hours or even days are needed to simulate profiles of each battery load.

4.3.2 Empirical Models

The most remarkable advantage of empirical models is the simplicity in term of computation, but they are relatively less accurate. So this model always goes with some sort of tradeoff between the performance level and capability of computation.

4.3.2.1 Peukert’s Low Model

After a series of practical test, a set of equations are calculated according to the curves derived from testing result. Those key parameters in each equations are decided by applying data fitting in order to match the empirical testing data. Peukert’s law expresses a power law relationship which can be applied in an ideal battery with capacity $C$ discharged at a constant current. In this case, battery lifetime can be given by $C = LI, C = LI^\alpha$. So the rate dependence can be provided by this exponent. In addition, the parameter $\alpha$ needs to be fitted according to empirical tests and experiments. However, because data fitting is always rely on the validity of testing results and number of repeated tests, it is hard to secure an accurate parameter through a limited times of empirical practices[62].

The main disadvantage of applying Peukert’s law is making the model no longer
applicable when battery discharging in a inconstant current under a varying load over a course of time. In a system with continuous changing load, a proximate evaluation is needed to come up with a rough optimal solution if Peukert’s law model is used.

4.3.2.2 Battery Efficiency Model

A battery efficiency model is proposed in [63]. The ratio of actual capacity to theoretical capacity defined as battery efficiency is analyzed as a linear quadratic function of the load current. The bounds are derived from the actual different current distribution power consumption with the identical discharging current and show that those bounds depend on the maximum and minimum values of the current. Within all the distribution share the same mean, a fixed discharging current will make the battery run the longest time, and a uniformly distributed current will make the battery run the shortest time.

The advantage of this model is the ability to handle changing discharging current with varying load. Many application have been using this model to maximize the lifetime of battery pack and multi-cell battery system[64], minimize the discharging delay in interleaved dual-battery system design[65] and arrange task scheduling for real-time embedded system[66].

4.3.2.3 Weibull Fit Model

A statistical way of modeling lithium-oxyhalide battery is used in [67]. This method records battery voltage changes at different stages of discharging process under a constant load and temperature. Weibull model is used to present the discharging curve. This model contains three coefficients to these voltage changes to build a voltage as a function of discharged capacity. Those coefficients are estimated
under different combination of discharging current, load and temperature and modeled the variation of coefficients as a quadratic surface. Battery lifetime is a function of load and temperature.

4.3.3 Abstract Models

Different from describing the physical and chemical processes in battery and fitting curves from empirical experimental result, abstract models attempt to provide an equivalent form of representation for a specific type of battery. This model does not have too many parameters to be calculated as physical model, but a lookup table it needed to be predefined and require effort to configure. Moreover, abstract models provide an acceptable accuracy and need lower computational complexity. However, due to the lack of analytical expressions with adjustable parameters, it has a limited utility and flexibility for applications require real-time calculation and prediction.

When compatible models of system components like circuit models and VHSIC Hardware Description Language (VHDL) models are available to simulate the whole system in a single continuous-time or discrete-time environment, electrical-circuit and discrete-time models become especially useful.

4.3.3.1 Electrical-Circuit Models

PSpice circuits consisting of linear passive elements, voltage source, and lookup tables for modeling nickel-metal-hydride and lithium-ion batteries are proposed in [67][68] respectively. [69] provides a similar electrical-circuit model of a nickel-cadmium battery be assemble a set of mathematical equations capture the battery processes. [68] models the capacity fading with a capacitor $C_{CAP}$ which has a
linear decrease with the number of cycles. Discharging current $I$ minus rate-dependence offset flows across the capacitance. The voltage of $C_{CAP}$ can be view as an indicator of delivered capacity to full charge capacity. This state of charge can be converted through a lookup table into a voltage $V_{COMP}$.

A resistor-capacitor circuit with temperature-dependent sources, $V_{AMBIENT} \propto T$ and $E_{RISE} \propto I^2 R_{cell}$, is used to model the temperature effect. $T$ is the ambient temperature and $R_{cell}$ is battery internal resistance. Effect of the state of charging, temperature and battery internal resistance are used to calculate the battery output voltage by consider as a main loop. When the simulation times are faster than physical models, continuous time electrical-circuit models take long time to build. Considerable effort is need to build the lookup table when there is not too many circuit parameters in model in [68].

4.3.3.2 Discrete-Time Model

[70] provides an approximation of continuous-time model and turn it into a discrete-time model. Battery voltage dependence on the first-order effects like charge state, discharge rate, and discharge frequency and second-order effects of temperature and internal resistance are incorporated in this modeling method. Characteristics of DC-DC converter is modeled by a lookup table. Discrete-time model can predicts lifetime of different types of battery under constant and time-varying discharging rate. This mode is widely used in many applications on energy efficiency optimization, dynamic power management and scheduling of management for multi-cell battery pack.
4.3.3.3 Stochastic Model

[71] provides a battery model represents a function of charge recovery as a decreasing exponential function of SOC (State of Charge) and charged capacity. In this model, pulsed discharging pattern is used to present load of each battery. This model also uses transient stochastic process to represent the discharging process and effect of recovery.

Because stochastic model can obtain capacity gain for different types of stochastic loads analytically without simulation, this model is mainly used in pulsed discharging representation. [71] also introduced multiple analytical results about distributing the load between two batteries of a set of battery pack. However, the disadvantage of this model is limitation that the mode is only focus on charging recovery and lack of the ability to reveal other battery nonlinearities. [72] provide a lookup table to proposed an abstract model by incorporating rate dependence. This mode is relative fast and able to give a prediction which matches the Dualfoil predictions.

4.3.4 Mixed Models

In some of the case for applications and optimization, a combination of high-level modeling of battery for which experimental data determines the parameters with analytical expressions based on physical and chemical processes. In literature [73], a high-level analytical model which can capture the battery by using two constants parameters, $\alpha$ and $\beta$, derived from the battery lifetime for a series of constant discharging current experiments is developed. Parameter $\alpha$ is the measurement of
theoretical capacity of battery and the active charging carriers are replenished at rate of $\beta$ at the electrode surface.

By applying Faraday’s law and Fick’s laws [74] for electrochemical processed of reaction and concentration behavior during one-dimensional diffusion respectively in an electrochemical battery, the following equation can be obtained by being associated with load current $I$, battery lifetime $L$, and other battery parameters:

$$\alpha = \int_{0}^{L} i(\tau) d\tau + \lim_{\epsilon \to 0^+} 2 \sum_{m=1}^{\infty} \int_{0}^{L-\epsilon} i(\tau) e^{-\beta^2 m^2 (L-\tau)} d\tau$$

The total consumed capacity during time $(0, L)$ is presented in the first term, and the total capacity that was unable to use at the electrode surface at the moment of stop of battery due to the cutoff voltage is presented in the second term. $L$ is the total battery lifetime. The total capacity unable to use models the effect of the concentration gradient that builds up as the flow of active species across the electrolyte falls behind the rate at which capacity is discharged at the electrode surface.

According to tests and experiments, the battery lifetime predicted by this mode is very close to the Dualfoil simulation results and experimental measurement. Simulation time of this model can be moderated. In addition, model accuracy and speed can be trade off by reducing the number of terms in the summation and approximating the continuous-time load waveform $i(t)$ to an $N$-step staircase, where $N = 1$ represents an extreme case of a constant load approximation. However, this model is not able to give information for other parameters like effect of temperature and capacity fading on the discharging characteristics. Although this model has higher
computational complexity than stochastic model, less configuration effort is required and more analytical dimensions can be offered.

In [75], a high level battery model to estimate the remaining capacity which takes into account both the temperature effect and capacity fading successive cycles under a constant discharging current. Battery terminal voltage is expressed as a function of time by using the Arrhenius dependence on temperature of cell kinetics and transport phenomena. By this way, an expression for the major properties of the active chemical material is derived as a function of temperature. Moreover another expression for film thickness is also derived as a function of temperature, discharge rate, and number of cycles. In this mode, SOC (state of charge) is defined as remaining capacity/full charge capacity and SOH (state of health) as full charge capacity/full design capacity.

Dualfoil simulations are matched well by these capacity ratios, and this model can effectively characterize the temperature effect and cycle aging on the battery SOC. However, comparing to the model in [73], this model involves more expressions for remaining capacity and require configuration of more than 15 different parameters to set up the equivalent battery. The main disadvantage of this model is the applicable limitation of optimizing portable systems with highly variable loads due to the constant-load assumption when building this model.

4.4 Application of Battery Model

Battery models are mainly use to assist system design to optimize the battery performance according to management algorithms and policies. Battery discharging managements include battery discharging control under performance constraints,
optimized charging processes design, and battery customization for a given application under volume and weight constraints.

### 4.4.1 Battery-Aware Power Design

Nowadays, complementary metal oxide semiconductor logic are widely used in digital integrated circuits in most mobile devices. Supply voltage $V_{dd}$, threshold voltage $V_{th}$ and other characteristics of CMOS transistors are all affecting the total energy assumption during the switching in these circuits.

For the purpose of minimizing the battery discharged capacity and delay, [65] apply the efficiency model to compute the optimal $V_{dd}$. Battery discharging is defined as a ratio between the actual energy drawn from the battery and the total energy stored in a fully charged battery. In a typical CMOS circuit, delay is proportional to $V_{dd}/(V_{dd} - V_{th})^\alpha$, where $1 \leq \alpha \leq 2$.

An interleaved power supply system is also proposed in this method for the purpose of discharging a part of batteries with different discharging current and characteristics. If the total energy is fixed, an optimal distributed active material weight between the two batteries that maximizes system lifetime is established. The most efficient battery will be chosen according to the load value compared to the threshold. For example, a hspice simulations using random current distributions show that a dual-battery system offers an improvement of 25% in power supply over a single optimal battery [65].

### 4.4.2 Scheduling for Embedded System

[76] provide an algorithm of battery-aware scheduling for real-time embedded
systems to supply different voltages. The purpose of this algorithm is to minimize the mean value of discharging current in order to maximize the overall battery life. The total power provided from the battery is derived as a cost function to be optimized.

An initial applicable schedule with a set of algorithms is obtained by using a global shifting transformation to reduce the peak power consumption. In this application, the authors execute local transformations with iteratively sequencing and shifting tasks involved, starting at points along the hyper-period with the highest power consumption, to reduce the overall cost function. In addition, voltage clock scaling is also performed for processing elements which distributes the total available slack time among the tasks to support variable levels of voltage. Total energy consumption is minimized by choosing the speed and voltage reduction ratios.

An analytical model of battery is applied to develop a cost function of $\sigma(t)$ of a battery as a function for the time-varying load $i(t)$. The actual charge loast to the load $l(t)$ and the temporarily unavailable charge $u(t)$ are added together and can be express as the cost function. The optimization can be expressed as a task-scheduling problem which has a set of adjustable parameters like start times $t_k$, voltage-frequency combinations $V_k$ and $\phi_k$ for each of a set of $N$ tasks for minimization of the cost function of a chosen schedule. The constrains involved in this problem is list as below:

1) Task dependencies must be maintained by the scheduling

2) The total time used in each task must not exceed a deadline $B$

3) The battery needs to be prevented from failure before the end of operation
The objective of early task scheduling methods is to minimize the charge lost to the load and energy consumed during a specific task, however the author of this new method propose that the charge lost can be presented as a lower bound on $\sigma$. If the difficulty of deriving an accurate solution to the task-scheduling problem is given, a heuristics for the general case stating from initial solutions corresponding to the minimum-charge is proposed and can be solved for the general case. Heuristics used in this application are generated from the provable properties of the cost function. This application on load profile is improved later by inserting rest periods, voltage up/down scaling, and task sequencing.

### 4.4.3 Multi-Cell Battery System

Multiple batteries as a pack of energy resource is widely used in many hardware devices like laptops, tablets and other mobile equipment. The traditional way of discharging batteries in sequence has been using for long time, but more optimization can be done in this area. New discharging methods are now developing to improve the battery performance in both experimental and analytical level.

#### 4.4.3.1 Experimental Work

A discrete-time model is used in [70] to simulate the following techniques:

1) Sequentially discharge each battery in the pack until it reaches its cutoff voltage

2) Static switch the battery to be discharged in a predefined duration in round-robin schedule

3) Dynamically switch the healthiest battery to be discharged at a moment
while other batteries rest

For the purpose of comparison, a monolithic equivalent of the multi-cell battery system is simulated. Based on the result, battery lifetime follows the relation monolithic ≥ dynamic switching ≥ static switching ≥ sequential discharge. In addition, when frequency increases in static switching, the simulation result of lifetime of battery can be approximated by the analysis of a monolithic battery. [70] also incorporates an algorithm of fast switching between batteries to implement a virtual parallel discharging pattern of multi-cell battery pack. A nonlinear optimization to distribute the load current over a group of batteries is proposed to maximize the system lifetime. The current-allocation scheme was regarded as a moderate improvement compared to early equally distributed load scheme.

[77] achieved the virtual parallel scheme in which multi-cells in battery pack are connected in series and combined output voltage down-converted. Experimental tests showed the improved result in system lifetime for high current loads.

4.4.3.2 Analytical Work

[71] implements the experimental data from load balancing in computer systems to dynamically split the load between two cells of a multi-cell battery pack. A delay-free method was first considered to provide charge unites to battery load once this is in need. The discharge profile can be optimized to maximize battery lifetime by adjusting the delay introduced by delayed approach. The authors also prove that a “best of two” approach is better than the round-robin and random scheduling approaches by using a stochastic cell model. Although the delayed approach has a
similar mechanism as dynamic switching, buffers in delayed approach has requests when no cell is being used. The main idea of this algorithm is to use each battery cell multiple times with interval of resting for battery cell recovery.

The total battery capacity discharged when using delayed approach is hypothetically equals the theoretical capacity of the battery. However, it is unrealistic for most mobile devices to implement an infinite buffer to hold the requests of load for charge units. Moreover, some application like video streaming and displaying consume battery capacity in a matter of constant current. On the other hand, for application has an appreciable background discharge cannot be applied to stochastic model.

A high-level battery model [73] is used to achieve an upper bound on the lifetime of a multi-cell battery pack under a fixed discharging current. Experimental result shows the insight as following:

1) Sequential discharging has no improvement comparing to an equivalent monolithic battery discharged under the same load.

2) Simultaneously discharging has a performance no better than an equivalent monolithic battery discharged under the same load.

3) Switching with a fixed frequency with constant load has a similar performance as an equivalent monolithic battery at high frequencies with constant load.

Analytical results show the parallel discharging performs is as good as a monolithic battery, and the same performance can only be achieved asymptotically by
switching techniques. As long as simultaneous discharge of multiple batteries is feasible to apply, parallel discharge is a better option for cases in complex switching mechanism.

4.4.4 Battery-Aware Dynamic Power Management

The main improvement for applying DPM policies is to minimize the average energy consumption of a system by switching to low-power modes like standby, sleep, and off if the operating system remains idle after a certain time period decided by predefined time-out interval. The time out interval is decided according to the overhead caused by the mode transition and energy savings resulting from the transition. However, the SOC of battery is not considered by DPM policies in determining when to start change mode.

[78] provides a closed-loop DPM policy which can analyze battery-state information from a discrete-time battery model in order to change the overall state of system. A simple scheme for switching between a “fine” and a lower-power “raw” play mode on a typical MP3 player is implemented according to if the battery output voltage is higher or lower than the predefined threshold. A significant increase in battery life is revealed with an acceptable sacrifice of penalty.
Chapter 5. Proposed Battery Model

5.1 Related Work

Battery as the most common energy storage has been widely used on variety of platforms. Although other type of energy storage component like supercapacitor can be found in application such as power harvesting system, battery is still extensively used and sharing the biggest market on various devices such as wireless sensor node, cell phone, laptop, electric vehicle and energy storage system. From the perspective of energy efficiency optimization and power management, an accurate battery model, which can reveal the dynamic battery circuit features and nonlinear capacity effects during phases of charging and discharging, is very crucial for simulation of complicated circuit, battery pack analysis with multiple cells, battery performance prediction and optimization by applying dynamic voltage and frequency scaling (DVFS).

![Figure 5.1 Existing circuit-based battery model](image)

Figure 5.1 Existing circuit-based battery model
Table 5.1 Summery of Notations

<table>
<thead>
<tr>
<th>Notation</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$V^o$</td>
<td>Open-circuit voltage</td>
</tr>
<tr>
<td>$V_i^C$</td>
<td>Output voltage</td>
</tr>
<tr>
<td>$V^F$</td>
<td>Cutoff voltage of the single-cell battery</td>
</tr>
<tr>
<td>$R^T$</td>
<td>Self-discharge resistance</td>
</tr>
<tr>
<td>$R$</td>
<td>Internal resistance</td>
</tr>
<tr>
<td>$R^S$</td>
<td>Short-transient resistance</td>
</tr>
<tr>
<td>$R^L$</td>
<td>Long-transient resistance</td>
</tr>
<tr>
<td>$C^S$</td>
<td>Short-transient capacitance</td>
</tr>
<tr>
<td>$C^L$</td>
<td>Long-transient capacitance</td>
</tr>
<tr>
<td>$\varphi$</td>
<td>SOC (State of charge)</td>
</tr>
<tr>
<td>$\alpha^f$</td>
<td>Full capacity of a single cell</td>
</tr>
<tr>
<td>$\alpha^A$</td>
<td>Consumed capacity of a single-cell battery</td>
</tr>
<tr>
<td>$I^C$</td>
<td>Discharge current rate</td>
</tr>
<tr>
<td>$\mu$</td>
<td>Recoverable capacity</td>
</tr>
</tbody>
</table>

Figure 5.1 is capturing the existing model of circuit-based battery[79]. The voltage controlled voltage source is used to represent the State of Charge (SOC) and open-circuit voltage. A summary of notations is listed in table 5.1. The current controlled current source is used to represent battery capacity and SOC. The RC network emulates the transient voltage response. All model parameters including open-circuit voltage, resistors, and capacitors can be approximated by mathematic
equations listed as follows:

\[
\begin{align*}
\alpha^A(t^C, t_s, t_e) &= I^C(t_e - t_s) \\
\phi^C &= 1 - \frac{\alpha^A}{c_I} \\
V^0 &= a_1 e^{a_2 \phi^C} + a_3 \phi^C - a_4 \phi^C^2 + a_5 \phi^C^3 + a_6 \\
R(\phi^C) &= b_1 e^{b_2 \phi^C} + b_3 \phi^C - b_4 \phi^C^2 + b_5 \phi^C^3 + b_6 \\
R^S(\phi^C) &= d_1 e^{-d_2 \phi^C} + d_3 \\
C^S(\phi^C) &= f_1 e^{-f_2 \phi^C} + f_3 \\
R^L(\phi^C) &= g_1 e^{-g_2 \phi^C} + g_3 \\
C^L(\phi^C) &= l_1 e^{-l_2 \phi^C} + l_3
\end{align*}
\]

Where, \( \alpha^A \) is the accumulated capacity during time period \([t_s, t_e]\) at rate of \( I_C \); 
\( R, V^0, c_I, \) and \( \phi^C \) are battery internal resistance, open-circuit voltage, battery full capacity, and SOC respectively; \( R^S, \) \( R^L, \) \( C^S, \) and \( C^L \) are resistances and capacitors to capture the transient response of battery voltage. \( a_1 \sim a_6, b_1 \sim b_6, d_1 \sim d_6, f_1 \sim f_6, g_1 \sim g_6, l_1 \sim l_6 \) are coefficients of the model.

Although the circuit-based model can accurately capture the dynamic circuit characteristics of a battery such as nonlinear open-circuit voltage, cycle number, and self-discharging, the original circuit-based model uses constant capacitor to model battery capacity which limits the ability to capture and model the battery recovery effect during relaxing process. Moreover, the accuracy of this model is very sensitive to the load variation rate, making it unable to handle dynamic battery load. [80] proposes an improved circuit-based battery model to capture the battery circuit features and nonlinear battery capacity effects, especially recovery effect. Although this model can accurately capture the battery performance both at constant and variable loads, it still does not consider the influence of thermal parameter which is the main factor in the dramatic capacity loss of battery. In our experiment tests,
5.2 Proposed Battery Model with Thermal Parameter

5.2.1 Proposed Battery Model

We proposed a new battery model which can not only capture the battery circuit features and nonlinear battery capacity effects, but also incorporate ambient thermal parameter in order to predict the capacity lost due to the temperature changes.

\[
\alpha^A(I^C, t_s, t_e, \beta, L, T) = I^C[(t_e - t_s) + 2\sum_{i=1}^{m} \frac{e^{-\beta^2i^2(L-t_e)} - e^{-\beta^2i^2(L-t_s)}}{\beta^2i^2}) \cdot g(T)]
\]

\[
g(T) = t_1e^{t_2T} + t_3
\]

\[
\varphi^C = 1 - \frac{\alpha^A}{c_f}
\]

\[
V^{\text{open}}(\varphi^C) = a_1e^{a_2\varphi^C} + a_3\varphi^C + a_4\varphi^C_2 + a_5\varphi^C_3 + a_6\varphi^C_4 + a_7
\]

\[
R(\varphi^C) = b_1e^{b_2\varphi^C} + b_3\varphi^C - b_4\varphi^C_2 + b_5\varphi^C_3 + b_6\varphi^C_4 + b_7
\]

\[
R^S(\varphi^C) = d_1e^{-d_2\varphi^C} + d_3
\]

\[
C^S(\varphi^C) = f_1e^{-f_2\varphi^C} + f_3
\]

\[
R^L(\varphi^C) = g_1e^{-g_2\varphi^C} + g_3
\]

\[
C^L(\varphi^C) = l_1e^{-l_2\varphi^C} + l_3
\]

\[
V^C(\varphi^C) = V^{\text{open}}(\varphi^C) - R(\varphi^C)I^C - \frac{R^S(\varphi^C)}{R^S(\varphi^C) \cdot C^S(\varphi^C) \cdot j\omega + 1} I^C - \frac{R^L(\varphi^C)}{R^S(\varphi^C) \cdot C^S(\varphi^C) \cdot j\omega + 1} I^C
\]

The proposed battery model can be denoted as equation above. Where, \(\beta\) is a constant related to the diffusion rate within a specific battery. The larger the \(\beta\), the faster the diffusion rate is. \(L\) is the total operating time of the battery. \(T\) is the thermal parameter in term of temperature in Celsius degree. \(m\) determines the computational complexity and accuracy of the model. \(t_1, t_2\) and \(t_3\) are parameters fitted to model

regular lithium-ion battery lose more than half of its capacity in the temperature of 0°C, that means, in some extreme cases, thermal parameter is the primary factor to determine the battery performance.
\( g(T) \). \( V^{\text{open}}(\phi^C) \) is the open-circuit voltage. \( V^C(\phi^C) \) denotes battery output voltage. \( \omega \) means the current variation rate. In this proposed model, the consumed capacity dissipated during the load period \([t_s, t_e]\) at the discharge current \( I_C \) under temperature of \( T \) can be written as:

\[
\begin{align*}
\alpha^A(I^C, t_s, t_e, \beta, L, T) &= I^C(t_e - t_s) + C^{\text{loss}}_{\text{total}} \\
C^{\text{loss}}_{\text{total}} &= 2I^C g(T) \sum_{i=1}^{m} \frac{e^{-\beta^2 i^2 (L-t_s)} - e^{-\beta^2 i^2 (L-t_e)}}{\beta^2 i^2}
\end{align*}
\]

where the first term \( I^C(t_e - t_s) \) is the consumed capacity by the load \( I^C \) during the load period \([t_s, t_e]\). The second term \( 2I^C g(T) \sum_{i=1}^{m} \frac{e^{-\beta^2 i^2 (L-t_s)} - e^{-\beta^2 i^2 (L-t_e)}}{\beta^2 i^2} \) is the total amount of discharging loss due to the current effect and thermal parameter, which is the maximum recoverable battery capacity at \( t_e \). Coefficient \( g(T) \) is a function of temperature which captures the dynamic of capacity loss due to thermal effect.

### 5.2.2 Discharging Tests and Data Collection

In the test and data collection, we used Heter lithium battery 26650(LiFePO4) with 3200mAh capacity. The model in HTCF26650-3200-3.3. The battery is undergoing series of discharging tests under a discharging rate of 0.32A, 0.64A, 0.96A, 1.6A and 2.24A under ambient temperature from -20°C~60°C. Discharged capacity of each scenario is showed in the Figure 5.2 and the Battery capacity loss is listed in Figure 5.3.
Figure 5.2 Discharging capacity with rate of different discharging rate under ambient temperature from -20°C~60°C

In Figure 5.2, a fact is observed that at high temperature ambient environment, battery tends to discharge more capacity which even can excesses its standard capacity value from its specification. Secondly, the relation between the temperature and loss capacity has a non-linear relationship. Moreover, as temperature goes up, the performance of battery goes up stably, but when temperature drop down, especially below 0 degree, the battery performance goes down rapidly.
Figure 5.3 Capacity loss with different discharging rate under ambient temperature from -20°C~60°C

Compare with low discharging rate, discharging process with higher discharging rate loss will lose relatively more capacity, Figure 5.3 is showing the comparison of discharging performance among 0.32A, 0.64A, 0.96A, 1.6A and 2.24A. The capacity loss lower than 0 means the battery discharged more than the standard specification of 3.2Ah. It can also be observe that as the discharging current increases the capacity loss will also increase. Moreover, as temperature goes down, the capacity loss increases as well. Compare with capacity loss due to the discharging rate, the temperature have more effect on the loss of capacity. On the other hand, the relation between the temperature and loss capacity has a non-linear relationship. As temperature goes up, the performance of battery goes up stably, but when temperature drop down, especially below 0 degree, the battery performance goes down rapidly.
5.2.3 Model Validation

The proposed model have been validated under different discharging rate and ambient temperature by using Heter 26650(LiFePO4) lithium-ion battery with standard capacity of 3200mAh, rated voltage of 3.3V and discharge cut-off voltage of 2.5V. All parameters of the proposed battery model, as shown in Table 5.2, can be calculated by applying the standard least-square estimator in [49]. For the purpose of comparison, the experimental data is collected by Arbin Battery Testing Instrument of BT2000. The battery is first charged to its full capacity through CCCV(Constant Current Constant Voltage) and rested for 30 minutes, then battery will be charged under different conditional profiles on discharging rate and ambient temperature.

Table 5.2 Battery model parameters

|   | $a_1$ | $a_2$ | $a_3$ | $a_4$ | $b_1$ | $b_2$ | $b_3$ | $b_4$ | $b_5$ | $b_6$ | $b_7$ | $d_1$ | $d_2$ | $f_1$ | $f_2$ | $f_3$ | $g_1$ | $g_2$ | $g_3$ | $l_1$ | $l_2$ | $l_3$ | $t_1$ | $t_1$ | $\beta$ |
| $a_5$ | -0.3 | -10 | -0.376 | -4.107 | 2.249 | 3.244 | -6 | -155.07 | -0.0218 | 0.0618 | 0.0858 | 0.03842 | 0.03 | 752.9 | 13.51 | 703.6 | 6.603 | -155.2 | 0.011 | -29.14 | 0.3208 | -6056 | 4475 | -0.0537 | -0.0537 | 0.1350 | 0.1350 |

Figure 5.4, 5.5, 5.6, 5.7 and 5.8 are showing performance of the proposed model on thermal effect under the discharging rate of 2.24A, 1.6A, 0.96A, 0.64A and 0.32A
from temperature of $-20^\circ C$ to $60^\circ C$. The evaluation is measured by capacity loss due to temperature. Table 5.3 is showing the statistic result for model performance evaluation in term of simulated capacity loss under different temperature from $-20^\circ C$ to $60^\circ C$.

Figure 5.4 Comparison of the testing data and proposed model under the discharging rate of 2.24A

Figure 5.5 Comparison of the testing data and proposed model under the discharging rate of 1.6A
Figure 5.6 Comparison of the testing data and proposed model under the discharging rate of 0.96A

Figure 5.7 Comparison of the testing data and proposed model under the discharging rate of 0.64A
Figure 5.8 Comparison of the testing data and proposed model under the discharging rate of 0.32A

Table 5.3 Statistic result of model performance evaluation

<table>
<thead>
<tr>
<th>Discharging Rate (A)</th>
<th>Variance (Ah^2)</th>
<th>Standard Deviation (Ah)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2.24</td>
<td>1.348</td>
<td>0.3671</td>
</tr>
<tr>
<td>1.6</td>
<td>0.0075</td>
<td>0.0865</td>
</tr>
<tr>
<td>0.96</td>
<td>0.1428</td>
<td>0.3779</td>
</tr>
<tr>
<td>0.64</td>
<td>0.3400</td>
<td>0.5831</td>
</tr>
<tr>
<td>0.32</td>
<td>0.6468</td>
<td>0.8042</td>
</tr>
</tbody>
</table>

Figure 5.9 shows the battery performance at multiple discharging rate of 0.1563C, 0.3125C and 0.625C under the same thermal parameter of 20℃. We can observe that the SOC drops from 1 towards 0 as the battery output voltage decreasing in the
discharging process. The fact that available capacity can be used varies with discharging rate reflects the current effect. The simulated proposed model can capture the feature of experimental curves of testing results. Figure 5.10 is presenting tests when battery is discharged as a constant current rate of 0.5C under different ambient thermal parameters from –20°C to 20°C. First of all, We can detect that battery tends to discharge more capacity as the temperature of ambient environment rise. Secondly, the temperature and capacity loss has a non-linear relationship which means the performance of battery can be slightly improve when temperature goes up but dramatically decrease when temperature goes down. When temperature goes under 0°C the battery is losing almost half of its original capacity. The proposed model can also represent the thermal effect on battery performance. We can derive that the proposed model generates voltage response less than 36mv. Therefore we can conclude that the simulation results of the proposed battery model matches well with the experimental result. We can also conclude that both the increasing of discharging rate and decreasing of thermal parameter can cause capacity loss, and in the typical outdoor environment condition with a temperature range of 20–30°C, thermal parameter contribute more significant influence on the total capacity loss.
Figure 5.9 Multiple discharging rates under constant temperature

Figure 5.10 Constant discharging rate under different temperatures
Chapter 6. Battery-Aware Optimization on Video Delivery

6.1 Optimization Framework

For a given sensor node under a specific circumstance, we come up with an optimization algorithm to offer methods to predefine a scheduling to adjust CPU operating frequency based on the battery model of certain battery type. As we discussed in chapter 3, in order to perform an efficient coding process, we need to assign a higher priority to the relatively high frequency of the given CPU scaling options. In another word, the dynamic frequency scaling operator need to fallow a scheduling which automatically applies a priority oriented policy to execute the tasks in frame coding and transmission. However, considering the battery discharging characteristic discussed in chapter 4, the battery-driven system can no longer supply a specific frequency when its output voltage value drop below a certain threshold which is the minimal voltage needed to drive this frequency. Once this happens, the whole system is in a hazard state of being down and CPU stops executing instruction. The optimization framework we are proposing here is to make the CPU keep working at different frequency as operating time goes by and provide a predefined optimal scheduling for dynamic frequency scaling based on the battery model. In this way, the operating hardware platform does not have to sense the battery current state which makes this algorithm be able to run on variety of cheap sensor nodes which lack the ability and function to monitor its energy resource. The optimal scheduling for CPU frequency scaling is achieved by considering CPU specification and model of battery
which is using as the energy recourse. From the highest frequency to the lowest, an array of time points can be calculated by recording each time when frequency switch down from its current working frequency to the next level of working frequency then the processor can go on operating at a lower speed. This time points array can be used as frequency scaling profile to guide frequency scaling of CPU operator, in this way the coding process can work to achieve the maximal workload and battery can deplete more energy than the case without CPU frequency scaling.

Table 6.1 shows the flow-process diagram of deriving optimal frequency scheduling on a 8 frequency options scalable CPU hardware case. In this case, the CPU can be scaled from the highest frequency of $f_1$ to the lowest frequency of $f_8$. According to each CPU frequency, an average working current $I_i$ can be calculated. $C_{full}$ is the full capacity of the battery in use. Parameters of battery model can be derived once the battery worked as power source is decided. The array of time points which is going to be used as the CPU frequency scaling profile can be built by calculating how much SOC can be used under a different level of frequency and its minimal supplying voltage $V_{min}$. Each time points designate the time to scale frequency from current value to the next highest value and the last time point, $t_8$ in this example, it the time when system shuts down the platform.

**Table 6.1 Optimization algorithm for 8 frequency options scaling CPU**

Initiate:

$$f_{CPU} = (f_1, f_2, f_3, f_4, f_5, f_6, f_7, f_8); \ (f_1 > f_2 > \ldots > f_8)$$

$$V_{output} = F(SOC); \ (Battery \ Model)$$
\[ t_0 = 0; \ SOC_0 = 1; \]

Scheduling Building:

For \( j=1:1:8 \)

\[ \SOC_j = F^{-1}(V_j^{min}) \]

\[ t_j = \frac{\SOC_{j-1} - \SOC_j}{I_j} C_{full} + t_{t-1} \]

recode array[j] = \( t_j \)

Next \( j \)

\[ 6.2 \text{ Experimental Result} \]

We have conducted experiments on four video sequences (Carphone, Foreman, Coastguard, Mobile) with varied contents in QCIF format. An Imote2 wireless sensor node with PXA271 Xscale processor is used in experiments. Arbin Battery testing instrument is used for monitoring and recoding all the battery data in its discharging process. The frame of each video sequence is encoded according to H.264 codec (JVT reference software, JM 16.2 [57]). The permissible QP value, is set as \( q=24 \), frame rate is set as 30, number of previous frames used for inter motion search is \( n=3 \), search range is set as \( r=16 \). All video frames expect the first one are coded as inter frames. To reduce error propagation due to packet loss, ten random Microblocks were inserted into each frame. The video frames are packetized such that each packet/slice contains one row of MBs, which enables a good balance between error robustness and compression efficiency. AMC is set as \( i=3 \) which is QPSK. In the experiment, Imote2 with Linux embedded system allow user to adjust 3 levels of CPU frequencies which are 416MHz, 208MHz and 104MHz with the respective minimal supplying voltage of
3.5V, 3.4V and 3.3V. Figure 6.1 shows the CPU dynamic scaling specifics under architecture of Imote2 sensor node. A battery with output voltage of 4.5V and capacity of 3.6Ah (LiFeS\textsubscript{2}) is used for the testing. Sensor node is set in an isolated chamber of Espec Temperature Benchtop to keep it in a constant temperature. In the experiment under the temperature of 20°C, optimization algorithm provide two frequency scaling time points which are at $8.5360 \times 10^3$ and $8.7120 \times 10^3$. Optimized discharging curve by applying scaling is presenting in figure 6.2 and the two frequency scaling points are marked by arrows. We also run the same task with the identical parameter setting without CPU frequency scaling. Although the low frequency option can enable CPU to run a longer operating time, it does not do much work due to its low efficiency. And high frequency option has a higher processing efficiency but stops working quickly because of the dramatic voltage dropping down. The total frame number achieved by this algorithm is 2036. The improvement of the proposed optimization algorithm against the other three CPU frequency (416MHz, 208MHz and 104MHz) without scaling are 6.23%, 23.33% and 40.16%.

Figure 6.1 Scaling specifics of Imote2 with PXA271 XScale processor
Figure 6.2 Battery voltage curve after applying optimization algorithm
Chapter 7. Summary and Conclusions

7.1 Summary

Micro-electronic industry has been boosting the capability of wireless mobile devices on full-scale. However, battery, as the only power source of most mobile devices, is experiencing a relatively slow development. Therefore, how to optimally utilize the limited battery energy on mobile devices under a predefined performance requirement becomes a critical issue. On the other hand, it is still unclear that how the battery capacity consumption is allocated on different working pattern of a specific video codec under various tempo-spatial scales and parameters, which has posed a design challenge on power management on multimedia communication system. Furthermore, an optimization method is needed to be proposed and experimentally tested to achieve the tradeoff between the computational complexity and the distortion of multimedia delivery in order to discover the relationship and interaction between computational parameters of multimedia communication and battery capacity consumption. In this paper, we set up a measurement system to reveal the battery capacity consumption behavior and its footprinting in a video delivery system using H.264 codec. A systematic optimization framework which jointly considers the coding parameters and transmission parameters is proposed to achieve the tradeoff between battery capacity consumption and quality of services (QoS).

For the purpose of energy efficiency optimization, battery as the only power source of most mobile devices need profound analysis and optimization. Therefore, how to optimally utilize the limited battery energy under a certain ambient
environment and predefined quality of services (QoS) becomes a critical issue. Most of the solutions currently provided aim at the minimization of energy usage under a given task scheduling by adjusting parameters reside in hardware architecture and high level coding execution. However, the battery discharging characteristics and a precise model under different thermal condition still need an exhaustive investigation.

In this paper, we proposed a dynamic frequency scaling algorithm to optimize the energy efficiency on each sensor node under the different ambient thermal condition. A new battery model with thermal parameter is proposed and analyzed in order to predict the scheduling of dynamic frequency scaling. Experiment results indicate the efficiency and effectiveness of the proposed optimization framework, and the insight of the relationship between scheduling of dynamic frequency scaling and battery discharging curves under different environmental temperature.

### 7.2 Conclusion

In this work, we built testbed to measure the battery capacity consumption in multimedia communication and provided an analysis of the proposed optimization framework for wireless video communication systems powered by battery. Based on optimization, the video coding and transmission are jointly optimized to minimize the battery capacity under the required constraint of expected received frame distortion. Experimental results of optimized solutions revealed the relationship between the adjustment of important parameters in both video coding and transmission and the corresponding battery capacity consumption under a given distortion constraint, and this provides an optimal adjusting direction which can be applied in realtime.
multimedia optimization system without recalculating all the options for coding and transmitting each video frame. The battery capacity consumption footprinting carried out in this work also provides design insights for battery resource allocation in future mobile multimedia systems.

In addition, we have developed a systematic optimization framework for wireless video delivery system powered by battery under different ambient temperature. Energy consumption by signal processing and transmission is analyzed and a new battery model with thermal parameter is proposed in order to redefine the optimal schedule of CPU frequency scaling. Experimental results verified the efficiency and effectiveness of the proposed optimization framework. The experiments and optimization on dynamic frequency scaling carried out in this work provides design insights for resource allocation in future mobile communication and network.
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