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Sizing and Exploiting Energy Storage in Intermittently-Powered Systems

by

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Abstract

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A growing number of autonomous sensor nodes are expected to be deployed in the Internet of Things. Energy harvesting has gained increasing attention for powering these nodes due to its features of long lifetime and energy independence. However, energy harvesting sources manifest intrinsic temporal and spatial variability, which conflicts with the requirement of stable power supply for conventional electronic designs. Energy-driven computing has recently developed to adapt system architecture to only ambient energy sources, with various specifications, such as prolonging active time, increasing energy efficiency, and ensuring forward execution, for different scenarios. While energy storage and energy harvester are critical components in terms of application performance and device dimensions, considerations on how to size energy storage and energy harvester have not been fully studied.

This thesis presents a study on the sizing issue of energy storage and energy harvester in deploying self-powered computing devices. A sizing method is proposed with respect to real-world energy conditions. A configurable system model is built to represent a typical execution process in energy harvesting computing. Based on this model, the sizing method is implemented. This sizing method suggests an efficient range of energy harvester sizes that balance average application performance and harvester dimensions. In this range of harvester sizes, results show that properly sizing energy storage leads to an execution speedup by 5.7-22.2% under real-world deployment. Furthermore, exploration extends to the sizing effect of energy storage on a recent-published power adaptation method for storage-less energy-driven computing.

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Chapter 1

Introduction

The promising expansion of the Internet of Things (IoT) has drawn research interests on new design paradigms for deploying tens of billions of electronic devices over a wide geographical range and probably in hard-to-reach places [1, 2]. Such a scenario generates considerations on how to enable the devices in networks to operate independently and effectively and how to construct a long-life, maintenance-free, environmentally friendly, and low-cost IoT.

1.1 Energy Harvesting Computing

1.1.1 Energy Harvesting and Energy-Neutral Computing

One of the most significant concerns in deploying IoT devices is how to power numerous low-power devices (tens of billions expected [1, 3, 4]). Traditional wired electricity limits flexibility of deployment and involve expensive wiring costs [5]. Primary batteries (i.e. non-rechargeable batteries) cannot support such a large number of devices, since the widespread use of primary batteries will cause heavy battery replacement work due to the limited battery lifetime as well as pollution issues. Therefore, it is necessary to find an alternative powering solution.

A potential powering solution is to employ energy harvesting techniques. Energy harvesting denotes scavenging energy from environmental sources (e.g. solar irradiation, wind flow, radio frequency (RF) signals, and kinetic energy) [6]. Devices powered by energy harvesters get rid of wires and surpass the lifetime limit of primary batteries, enabling a scalable IoT. However, the power generated by energy harvesters in real-world deployment is variable, uncontrollable, and intermittent, and hence, hinders forward execution if directly connected (without energy buffering) to loads [7].

Initially, large energy storage, in forms of rechargeable batteries or supercapacitors, is allocated with energy harvesters to buffer the temporal variations of energy sources and provide reliable power supply. Energy-neutral (EN) computing was derived from such a method of power buffering [8]. EN computing aims to sustain systems over a long period (e.g. a few days [9] or a year [10]) by adapting system run-time schedules (e.g. duty cycles [9–11] or task schedules [12, 13]) according to the available energy amount.

Rechargeable batteries (also known as secondary batteries) and supercapacitors are two main choices of energy storage in EN computing. Rechargeable batteries are historically used as energy storage in energy harvesting embedded systems because of their high energy density [14] and stable discharging profile [8]. However, due to electrolyte deterioration, the limited charge-discharge cycles of rechargeable batteries constrain the operating lifetime, causing heavy battery replacement work as well as environmental issues as primary batteries [15]. To alleviate the problems of batteries, supercapacitors are then explored in research. Although the energy density of supercapacitors is several orders of magnitude lower than the energy density of batteries [16], supercapacitors outperform rechargeable batteries in terms of lifetime (e.g. 10-20 years for supercapacitors and 3-5 years for rechargeable batteries [17]). However, to achieve a comparable energy capacity to batteries, supercapacitors should be designed to tens of farads or one hundred farads [18, 19]; supercapacitors in such a scale occupy large volume in small IoT devices.

1.1.2 Storage-Less Energy Harvesting Computing

To circumvent the maintenance, pollution, and volume problems in rechargeable batteries and supercapacitors, a recent research trend of energy harvesting sensor nodes switches towards eliminating the demand for energy storage and adopting only a minimum amount of energy storage (denoted as storage-less, where energy storage is only enough for ensuring the most energy-expensive atomic[1] operation of systems), typically in the form of a capacitor. However, given a negligible amount of energy storage, it becomes a major research concern that how to guarantee forward execution and functionality of energy harvesting sensor nodes .

Avoiding large energy storage makes IoT devices long-life, maintenance-free, environmentally friendly, and compact (small in dimensions). However, in energy harvesting sensor nodes, replacing batteries and supercapacitors with small capacitors considerably limits the buffering capacity for varying harvested power, and hence, the variable power is directly given to the load. This violates the demand for stable power supply

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[1]In this context, an operation is atomic if it should be completed in one consecutive period without power interrupts; otherwise, if interrupted, it should be re-executed from the beginning. Example atomic operations in IoT devices can be peripheral operations and nonvolatile memory read/write operations.

in conventional computing architecture and causes program execution to be frequently stranded in the same portion of code due to recurring power outages.

However, ensuring and improving local processing ability of sensor nodes is crucial for the following reasons. First, sensor nodes should be able to process sensing data on-site and transmit only the useful information, such that the network traffic volume and energy consumption is reduced [4]. Second, advanced communications techniques (such as scheduling, routing, coding, decoding) require local computing ability to ensure timeliness and efficiency in networking [20]. Third, IoT objects are also expected to be able to trigger actions in reaction to the physical reality by either receiving commands from other nodes and servers or making a decision based on locally acquired data [21].

In order to adapt conventional computing architecture to energy harvesting power supply without large energy storage, many methodologies for storage-less energy harvesting computing have emerged in the past few years, with considerations on forward execution, computation correctness, and improving execution speed. Recently, there are two research topics in storage-less energy harvesting computing: intermittent computing (IC) and power-neutral (PN) computing. A summary of this research trend in energy harvesting computing is shown in Figure 1.1.
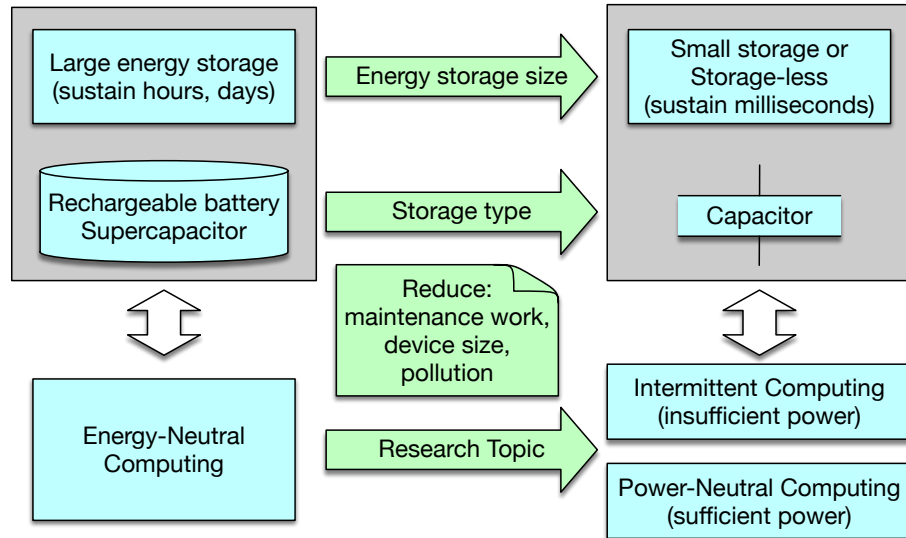
FIGURE 1.1: Research trend in energy harvesting computing: towards minimising energy storage.

Intermittent computing aims to maintain system volatile state after power outages with low time and energy overheads, so as to ensure forward execution and computation correctness of applications [22]. Approaches in intermittent computing fundamentally diverge due to different design goals and can be classified into five categories: checkpointing, reactive, harvest-store-use, task-based, and non-volatile processors. Each of

these approaches has one or a few advantages on reducing the number of system snapshots during a power cycle, reducing the size of system snapshots, minimising hardware dependency, etc [23].

PN computing aims to make more progress from available power by matching system power consumption with power harvested instantaneously. PN computing dynamically adapts system performance, typically by scaling CPU clock frequency, to match the instantaneous system power consumption with the instantaneous harvested power [24, 25]. By such performance adaptation, PN systems immediately consume excessive harvested power, prolong system active time when the harvested power drops, and reduce the frequency of system state saving and restoring operations.

1.1.3   Application Suitability of Storage-less Energy Harvesting Computing

An inherent limitation of storage-less energy harvesting computing is that the systems can only execute when there is available power, as opposed to EN computing where the EN systems can still executes with buffered energy if ambient power is not available. This limitation thereby requires that *application operation periods and power availability should be compatible in time*. While there are various needs of application operation periods for various applications scenarios, the power availability is constrained and determined by the availability of the target energy source in the deployed environment. The applications of storage-less energy harvesting computing should be adapted or selected to suit the power availability. Under this consideration, there are two typical categories of application scenarios according to recent publications.

- **Category 1: Applications with flexible time requirements.**

  Applications with flexible requirements on operating periods tolerate the intermittency of energy harvesting sources. In such applications, energy-harvesting devices are allowed to wait for power-available periods to execute.

  Use case 1: Kitchen event detection

  The application aims to capture kitchen events (e.g. dishwasher working, fan on, refrigerator cooling) to record equipment usage. As such events usually last for from tens of seconds to a few hours, the device does not need to operate immediately after the event occurs or disappears. An implementation of this application is shown by Maeng et al. [26]. The device iterates the following tasks in turn during power-available periods: sampling acoustic information from microphone input, classifying kitchen events with a pre-trained model, and transmitting the results in Bluetooth Low-Energy (BLE) packets to an always-on server. The device harvests RF energy from a dedicated RFID reader, and the packets are transmitted every a few seconds as reported. A specification for this application

is to complete program iterations as frequently as possible so as to improve the accuracy of event records.

Use case 2: Temperature monitor for air conditioning

The application aims to monitor indoor temperature for air conditioning. As the temperature does not usually change over a few minutes, the temperature monitor does not need to wake up frequently or periodically. An implementation of this application is shown by Colin et al. [27]. During power-available periods, the device samples temperature by an external analog sensor. If the temperature is detected to be out of a pre-defined range, the device send a BLE packet to alarm the server. The device is also powered by a dedicated RFID reader. Similar to use case 1, the device is expected to maximise sampling frequency in order to capture out-of-range temperature as soon as possible.

- **Category 2: Application activity in correlation with available power.**

  In such applications, the application operations correlates with power-available periods. This correlation is typically linked by an event with harvestable power. When the event occurs, the device is activated by harvesting the power of the event at the same time to start operating. Therefore, the application operation periods and the power availability are inherently simultaneous in such applications.

Use case 3: Bicycle trip counter

The bicycle trip counter aims to calculate cycling speed and traveled distance. The wheel rotation brings energy for the device to sense the cycling speed; the device does not need to operate without cycle movement. The trip counter is designed as a nail-sized chip installed on the frame of a bicycle, with a magnet on the wheel for gaining energy [28]. Every wheel rotation activates the trip counter to calculate the current speed and log traveled distance. After collecting enough energy over a few cycling rounds, the trip counter transmits the logged information. This application is also expected to complete computing tasks faster and report results as frequently as possible.

Use case 4: Power meter

The power meter measures the power flow of a main load wire. The AC power in the wire can be harvested by a coil to activate the power meter. A design is shown in Monjolo [29], where the power meter transmits a plain packet to a server once it collects a preset amount of energy. The server then calculates the elapsed time between the recent two packets to estimate the main load power.

As shown in the above use cases, a common application specification of storage-less energy harvesting computing is to do as much 'work' as possible under the same energy conditions, e.g. completing program iterations as frequently as possible, because the energy cannot be saved for later use. Other 'work' could include improving sensing accuracy or processing offloaded tasks received from other devices. To summarise the application suitability of storage-less energy harvesting computing, a diagram is shown in Figure 1.2. An example unsuitable application can be a periodic sensing task without periodically available power or the period of the energy source does not match the sensing period (left bottom circle in Figure 1.2).
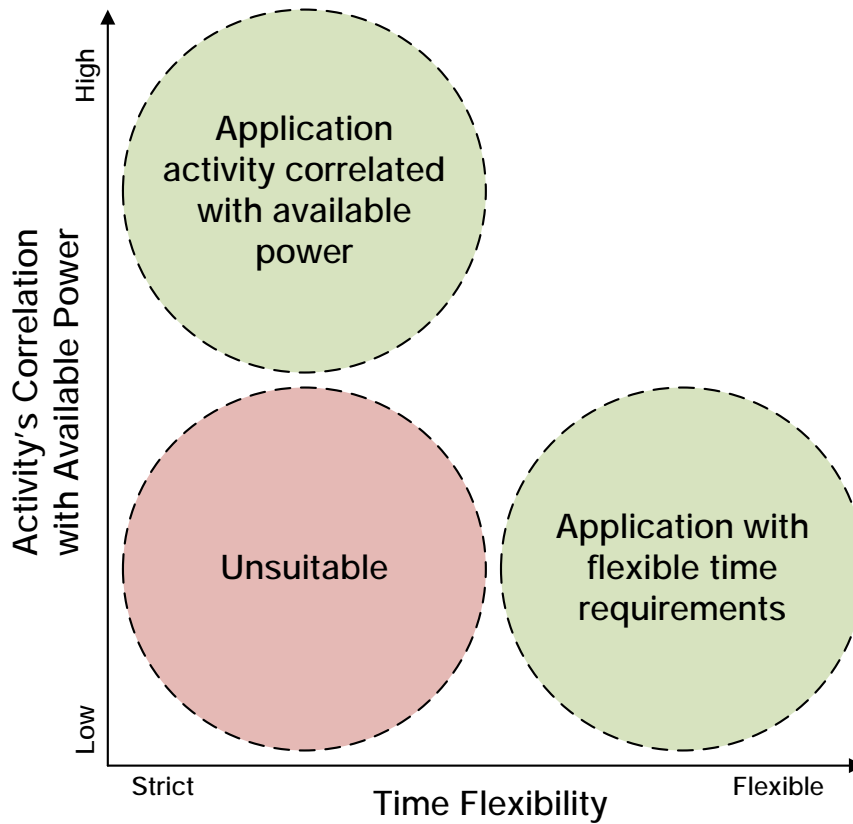
FIGURE 1.2: Application Suitability of Storage-less Energy Harvesting Computing.

1.2   Research Justification

Self-powered devices solely rely on energy harvesters to power themselves. Energy harvesting power supply varies over time due to uncontrollable environmental conditions. Due to the lifespan, pollution, dimension problems of batteries and supercapacitors, there is a demand for adapting computing architecture to energy harvesting supply with small storage, e.g. a capacitor. Various approaches in intermittent computing and PN computing emerge to enable and improve energy harvesting computing in the scenario of minimised storage in order to reduce dimensions and cost as well as to

increase lifespan of IoT devices. However, a larger storage than the minimum one can reduce the frequency of power outages and increase flexibility in power management, which may benefit the application throughput. Hence, there is a trade-off in sizing energy storage. Apart from energy storage, the size of energy harvesters should also be considered based on a set of factors, such as system power consumption, performance requirements, energy utilization, device dimensions, and cost. A gap of study exists in how to determine the size of energy storage and energy harvesters. The research gap is further described as listed below:

1. A variety of methods in intermittent computing have been proposed to overcome power outages during execution, ensuring forward execution [22], memory consistency [30], peripheral re-configuration [31], etc. Such approaches usually adopt only a minimum amount of energy storage which only allow systems to complete state saving and restoring operations before and after power outages. However, provisioning a certain amount of storage reduces the overhead of intermittent operations. This effect is especially noticeable in reactive intermittent systems (Section 2.4.2), where the energy and time overheads of saving and restoring operations are proportional to the frequency of power outages. On the other hand, increasing energy storage also increases the system leakage power and affects the reactivity (the energy and the charging time to activate devices) of intermittently-powered systems [27, 32]. The trade-off of scaling energy storage in intermittent computing systems should be fully studied.

2. The size of energy harvesters significantly determines the amount of harvested power. Undersized energy harvesters constrain available power, affecting the maximum performance of devices; oversized energy harvesters provides redundant energy, which cannot be consumed on useful work and is wasted in circuitry or never harvested, affecting the utilization of energy harvesters and unnecessarily increasing device costs. Besides, the size of energy harvesters contributes to a large part in device dimensions, which may violate the size constraint of autonomous devices [10]. Therefore, there is a trade-off between under-provisioning and over-provisioning energy harvesters in energy harvesting devices, and this trade-off should be thoroughly studied.

3. Current power management techniques in energy harvesting computing rely on the feedback of the dynamic detection of available energy in energy storage, whether in EN systems [9, 13] or in PN systems [24, 25]. Scaling the capacity of energy storage may change the responsiveness of such energy detection, and consequently, have an impact on performance adaptation and system application throughput. This impact exhibits more significant in PN computing than in EN computing as the allocated energy storage in PN systems is minimised and energy detection is more acute.

1.3   Research Questions

Based on the research justification, three research questions are listed below:

1. What is the effect of energy storage capacity on the forward progress of intermittent-powered systems?

   The amount of forward progress directly determines application performance, e.g. program iteration rate or task completion time. Most intermittent-powered systems minimise energy storage capacity so as to minimise device dimensions and interruption periods [33–37]. However, increasing energy storage capacity can also benefit forward progress. Our goal is to explore and quantify the relationship between energy storage capacity and forward progress and to analyse the reasons behind this relationship.

2. How can developers size energy storage in intermittently-powered systems to trade off forward progress against device dimensions and interruption periods?

   Based on the knowledge of sizing effect on forward progress, this question encompass more design factors in sizing energy storage when deploying intermittently-powered systems. A simulation tool of intermittently-powered systems should be provided, where users can define energy source conditions and energy harvester sizes. The tool should be able to output the physical size of energy storage and interruption periods in certain metrics. An appropriate size of energy storage can be suggested by this tool with a cost function to trade off multiple factors.

3. How can intermittent-powered systems exploit energy storage so as to perform atomic operations and cope with capacitor degradation?

   Atomic operations in intermittent-powered systems denote operations that should be completed in one continuous period. If an atomic operation is interrupted by a power failure, it should be re-executed rather than resumed. Current approaches handle atomic operations by accumulating energy to a predefined voltage threshold; after reaching that threshold, the system starts execution and re-executes the atomic section if the power fails. However, this threshold is typically set high enough for all atomic operations in a program, so the systems usually wait for a long charging period which wastes energy and impedes response time. Also, when capacitor degrades, the predefined threshold may not provide enough energy for the same operations, so that the system cannot make forward progress. A new method of utilizing energy storage to solve these two problems is necessary.

1.4   Contributions

The contributions done to the address the research questions in this thesis are:

1. Exploration and analysis of the energy storage sizing effect on reactive intermittent computing system, where we quantify and explain the relationship between energy storage capacity and forward progress.

2. A method and a simulation tool for sizing energy storage in deploying intermittent-powered systems, where forward progress, dimensions, and interruption periods are traded off in a cost function.

3. An online task profiling and voltage threshold adaptation approach for efficiently performing atomic operations and coping with capacitor degradation.

Chapter 2

Energy Harvesting Computing

The emerging of energy harvesters provides diversified prospects for design paradigms of energy harvesting sensor nodes in IoT applications [21]. This chapter first provides a review on various energy harvesting sources and corresponding energy harvesters in Section 2.1, followed by energy storage techniques that used in energy harvesting computing in Section 2.2. Energy-neutral computing, an early paradigm in energy harvesting computing, is reviewed in Section 2.3. Finally, two recent research topics towards storage-less energy harvesting computing, i.e. intermittent computing and power-neutral computing, are reviewed in Section 2.4 and Section 2.5 respectively with an illustration of proposed methodologies.

2.1   Energy Harvesting Techniques

For all kinds of energy harvesters, although there is only one basic concept — to extract energy from ambient sources, various energy sources and harvesters lead to miscellaneous output characteristics in the amount and wave forms of harvested power, voltage, and current. To select a energy harvester for powering sensor nodes, one important concern is whether the supply power level matches the consumption of the load [38]. For one certain type of energy harvesters, the amount of energy harvesting supply can be scaled within an extent by the amount of energy sources or scaling the energy harvesters. The amount of energy sources is determined by the deploying environment, which cannot be controlled by the harvesting devices, but the size of energy harvesters can be decided at design-time with considerations on systems requirements, such as energy utilization, form factors, performance, etc.

In order to appropriately size and designate energy harvesters for sensor nodes, the power features of different energy harvesters are widely considered by researchers and

engineers [39]. A classification of common energy harvesting sources and correspond-
ing energy harvesters used in IoT is presented in Table 2.1. The voltage and current
features of different energy harvesters largely differ from each other, due to the intrin-
sic differences in temporal distributions of the available amount of different energy
sources and the physical principles of power conversion. The following part of this
section introduces each kind of energy sources and energy harvesting techniques listed
in Table 2.1.

Energy source	Energy harvester
Light (solar, artificial)	Photovoltaic cells
Radio waves	Radio frequency harvester (antenna)
Flow (air, liquid)	Wind turbine, hydrogenerator
Mechanical (vibrations, pressure, stress-strain)	Electromagnetic, electrostatic, piezoelectric harvester
Heat	Theomo electric generator

TABLE 2.1: Classification of energy sources and energy harvesters in IoT.

2.1.1 Light Energy Harvesting

Due to the abundant energy amount of light, whether from outdoor sunlight or indoor
artificial light, light energy becomes a feasible source to powering sensor nodes and
is historically treated as a substitute for battery supplies [40, 41]. Light energy can be
converted to DC power by photovoltaic (PV) cells, which consist of semiconducting
materials, e.g. silicon. When PV cells absorb light, electrons are excited by the photo-
voltaic effect, producing an electric potential by the separation of electrons and holes.

Given a fixed intensity of light, the output current from PV cells manifests an inverse
relationship with the output voltage, as there is a semiconducting bypass within the
PV cells. Although the power conversion efficiency may vary among different PV cell
techniques (such as monocrystalline, polycrystalline, thin film), the curve shapes of
current-voltage relationships are similar. Obviously, higher irradiance leads to higher
current output when the output voltage is fixed, because there is more intensive light
sources provided. More importantly, the output feature of PV cells can be summarised
like "an inverse semiconductor" —— when the terminal voltage is low, the output
current is almost constant and close to short-circuit current; when the terminal voltage

gets close to open-circuit voltage, the output current significantly decreases and finally terminates at the open-circuit voltage.

Typical current-voltage curves of PV cells are shown in Figure 2.1, with an example of a monocrystalline cell given five values of illumination intensity from 200 W/m^2 to 1000 W/m^2. When the voltage is under 15V, the PV cell is similar to a current generator (so when the voltage increases, the power increases almost linearly). When the output voltage increases above 15V, the output current drops significantly and reaches zero at around 22V. According to this phenomenon, there is a voltage point where the cell produces the maximum power, which is named Maximum Power Point (MPP) as indicated by black dots in Figure 2.1.

● **Maximum Power Point**
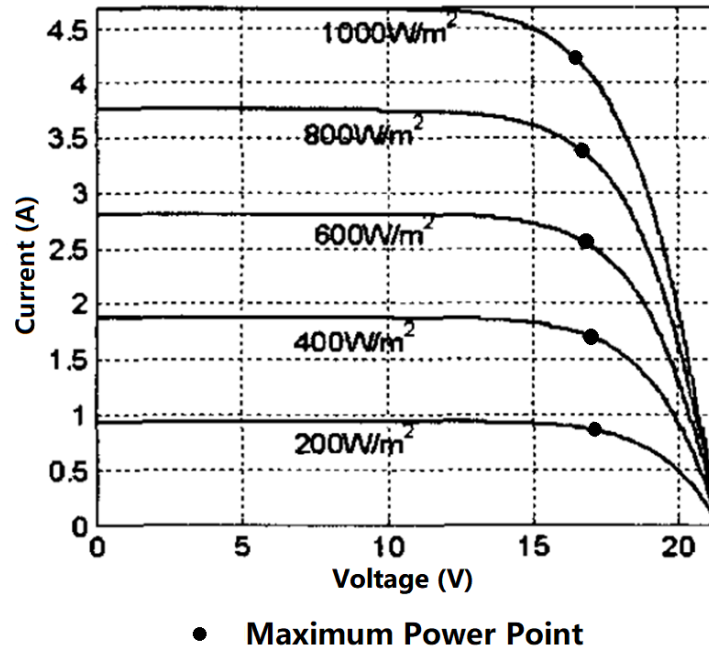
FIGURE 2.1: Typical current-voltage curve of a solar module (monocrystalline, adapted from [42])

In order to extract as much power as possible out of PV panels, most energy harvesting systems with PV modules adopts maximum power point tracking (MPPT) techniques [43–45]. MPPT is achieved by dynamically controlling the output voltage of PV cells around the maximum power point (MPP).

Outdoor sunlight and indoor artificial light are two main sources for light energy harvesting. The illumination intensity of direct sunlight on the earth's surface is typically $1000\ W/m^2$ [46], while the typical indoor illumination intensity is $10\ W/m^2$ [38]. Due to this large difference in the power density of these two circumstances, PV modules are more prospective in outdoor applications for harvesting solar energy. Conversion efficiency of PV cells is typically 15% to 25% in outdoor conditions [47].

Solar energy is an uncontrollable but partially predictable source [10, 48]. Solar irradiance demonstrates daily and annual periodicity due to the regularity of celestial movements, as well as irregular variations due to cloud movements, air mass, etc. A 3-year trace of diurnal global horizontal solar energy available measured in Los Angeles from 2012 to 2014 is presented in Figure 2.2, and an example of daily dynamics of global horizontal solar irradiance of the same location is presented in Figure 2.3. As shown in both figures, the predictability is reflected from the roughly annual and daily periodicity, and the uncontrollability and randomness relates to the irregular variations, which include both daily variations in an annual scale and variations over a few seconds and minutes on a daily scale.
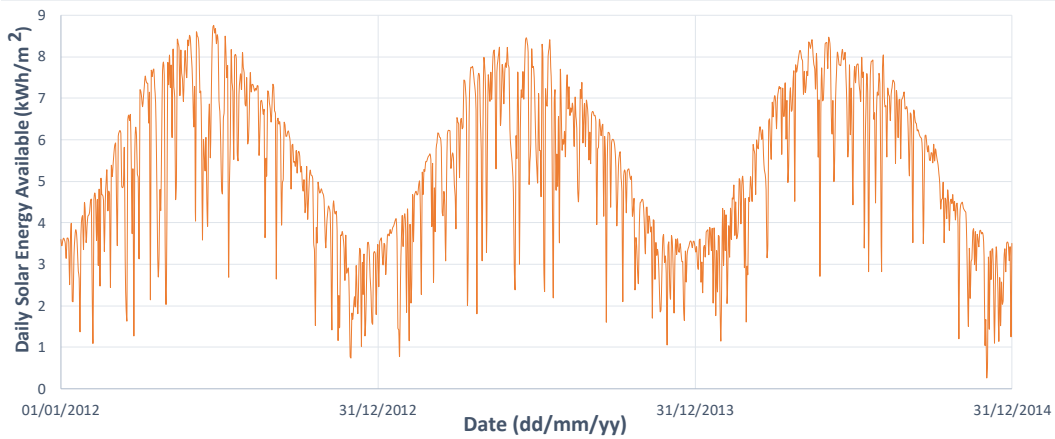
FIGURE 2.2: Daily global horizontal solar energy available in Los Angeles 2012-2014 [49].
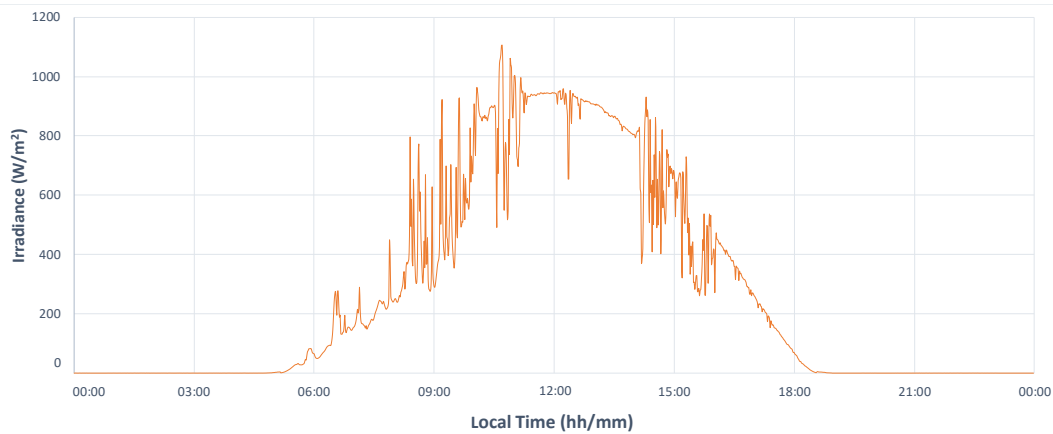
FIGURE 2.3: One-day dynamics of global horizontal solar irradiance in Los Angeles 29 April 2016 [50].

In order to make full use of solar energy, substantial efforts have been made to develop and improve energy harvesting sensor nodes with solar panels [40, 41]. Generally, solar energy harvesting approaches adopt large energy storage, e.g. a rechargeable battery, to smooth out the daily and annual variations. Examples of solar-powered sensor nodes are presented in [9, 40, 51], and a comprehensive review on solar-powered sensor nodes is published in [8].

2.1.2 Radio Frequency Energy Harvesting

Radio Frequency (RF) energy exists in time-varying electromagnetic fields, which widely spread in our environment now due to the propagation of wireless networks, such as Wi-Fi and cellular phone signals [52]. When radio waves pass through an antenna, due to electromagnetic induction, AC voltage is generated. This AC voltage can be rectified and regulated to DC power for sensor nodes. The received RF power is reciprocal to the square of distance from the source to the destination. The maximum conversion efficiency from RF waves to DC power is typically 50-75% given a transmission distance of 100 metres [38].

Due to the widespread deployment of telecommunication networks, RF energy harvesting becomes available in a wide range of locations, both outdoors and indoors. Compared to light energy harvesting, RF harvesting shows its strength in indoor applications as there is often low or no light intensity inside buildings.

A basic and common example of RF harvesting is RF Identification (RFID). In a passive RFID application, an RFID reader transmits RF signals to an RFID tag for asking its tag information. The tag absorbs the signals and energy through its antenna, and then responds the reader with its information. Up to now, Wireless Identification and Sensing Platform (WISP) [53, 54] is presented to show the possibility of the integration of RF energy harvesting in IoT applications.

2.1.3 Flow Energy Harvesting

Flow-based energy harvesting utilizes turbines and rotors to collect the kinetic energy in air flow or liquid flow. Air flow is converted by wind turbines and liquid flow is converted by hydrogenerators. Wind turbines and hydrogenerators are normally in different mechanical structures (shapes), but the fundamental principles of them are the same.

Wind turbines are manufactured in a wide spectrum in terms of dimensions, from a large-scale wind farm (arrays of large turbines) to a portable micro wind turbine. Micro wind turbines are suitable for battery charging and powering autonomous electronic devices.

A raw voltage output trace of a micro wind turbine given a blast of wind is presented in Figure 2.4. Given a constant blow, a wind turbine should produce a sinusoidal voltage signal. Its voltage output vibrates from the positive domain to the negative domain with time, so a rectifier is normally required in order to utilize this AC power for DC load.
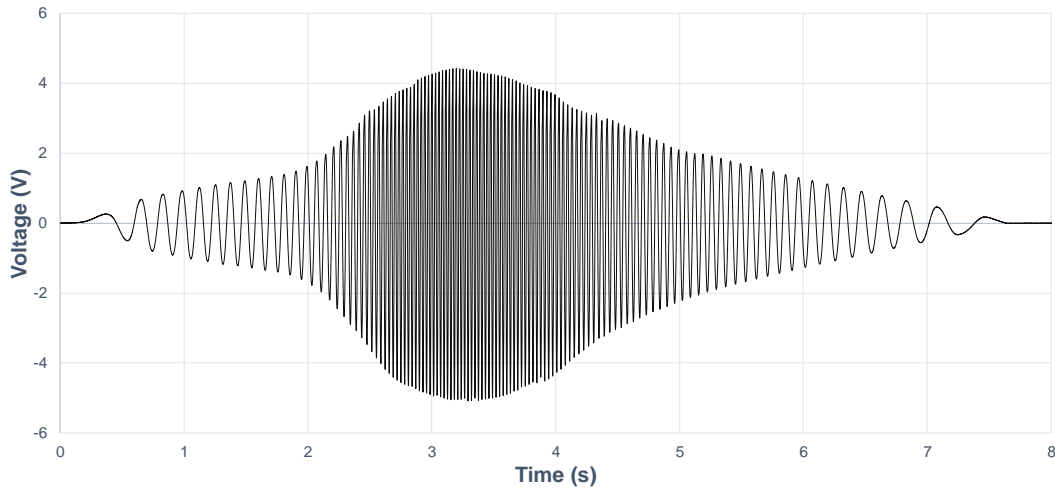
FIGURE 2.4: Dynamics of a micro wind harvester (reproduced from [24]).

Similar to solar energy, wind energy is uncontrollable but partially predictable. Sharma et al. [55] introduce a system that achieves available wind energy predictions based on downloaded weather forecast information within recent 3 days. Also, Cammarano et al. [56] present a wind and solar energy predicting method which dynamically adjusts its time horizon of prediction in order to achieve higher accuracy than its prior methods.

Hydrogenerators harness the energy in moving liquids, such as water or a mix of different liquids. Traditionally, hydrogenerators are used for generating large-scale electricity from rivers and streams. However, since the possible underwater applications in IoT, hydrogenerators can be a suitable alternative for powering sensor nodes. For example, Morais et al. [57] incorporate a small-sized hydrogenerator as a part of energy harvesting supply for sensor nodes.

2.2   Energy Storage for Sensor Nodes

Energy harvesting supply is variable and intermittent over time, causing disparity between power supply and power consumption. In order to deliver stable power output from a varying source, a critical component in an energy harvesting power unit is energy storage, which buffers the harvested energy and powers the load when needed. Besides its ability to buffer energy and its effect on overall efficiency, energy storage has a dominant effect on the size, cost, and lifetime of sensor nodes [14]. Therefore, how to design energy storage is a critical concern in deploying energy harvesting sensor nodes.

Technologies of energy storage used in sensor nodes are generally divided into two categories: rechargeable batteries and capacitors, which are different from each other in

terms of energy density, power density, lifetime, discharging features, leakage, etc. In general, batteries have higher energy density (containing more energy with the same volume/weight), lower leakage, and a more stable discharging curve (a stable voltage output while discharging), while capacitors have higher power density (higher limits for charging/discharging current), and longer lifetime in terms of charge-discharge cycles [14, 40]. The choice of these two forms of energy storage depends on application requirements. These two technologies and their implementations will be briefly reviewed in the following subsections.

2.2.1 Rechargeable Batteries

Batteries are more energy-dense than capacitors and manifest a stable voltage output when discharging. Rechargeable batteries have been widely adopted in mobile devices. Rechargeable batteries are generally made in the following techniques: Sealed Lead Acid (SLA), Nickel Cadmium (NiCd), Nickel Metal Hydride (NiMH), Lithium Ion (Li-ion), and Lithium ion Polymer (Li-Po). Due to the similar techniques and features of Li-ion and Li-Po batteries, Li-ion will be used to represent Li-ion and Li-Po batteries in this subsection. SLA and NiCd batteries are less likely to be implemented in energy harvesting sensor nodes [14, 40]. SLA batteries suffer from low energy density and are normally bulky and heavy, which is unfavorable for sensor nodes. NiCd batteries involve memory effect, i.e. decrease of energy capacity after repeated partially discharging and recharging, which is a common situation in energy harvesting implementations.

Compared to SLA and NiCd batteries, NiMH and Li-ion batteries show a strength in energy density in both weight and volume, and hence, are more suitable for energy harvesting applications [14, 40, 58, 59]. A comparison of two commercial NiMH and Li-ion batteries is listed in Table 2.2 with a variety of perspectives and features. Li-ion batteries are typical lighter than NiMH batteries, with weight energy density 2-3x and volume energy density 1-2x to NiMH batteries. Also, Li-ion batteries significantly outperform NiNH batteries in terms of charging efficiency and self-discharge rate. However, Li-ion batteries are normally more expensive than NiMH batteries, and require more complicated pulse charging circuits [40]. NiMH batteries also provide a relatively constant voltage supply during discharging [9].

NiMH and Li-ion batteries have been widely implemented in energy harvesting sensor nodes. Heliomote [40] uses two NiMH batteries in series to match the charging voltage (2.2-2.8V) with the MPP of the solar panel. HydroSolar [58] also adopts two NiMH batteries to avoid the Li-ion charging hardware. Jiang et al. [18] design a hybrid storage system including a lithium based rechargeable battery as the secondary buffer, due to its high efficiency and charge density.

	NiMH (Panasonic BK150AA)	Li-ion (EEMB LIR14500)
Nominal voltage	1.2 V	3.7 V
Charge capacity	1500 mAh	750 mAh
Energy capacity	1.80 Wh	2.775 Wh
Weight	26 g	20 g
Dimensions	⌀14.5mm × 50.5mm	⌀14.1mm × 48.5mm
Weight energy density	69 Wh/Kg	139 Wh/Kg
Volume energy density	216 Wh/L	366 Wh/L
Operating temperature	-20°C to 65°C	-20°C to 60°C
Charging cycles (until 80% capacity)	>500	>300
Reference price	£2.91	£3.25
Charging efficiency [59]	66%	99.9%
Self-discharge [59]	30% per month	10% per month
Charging Method [59]	Trickle	Pulse

TABLE 2.2: Comparison between commercial NiMH and Li-ion rechargeable batteries.

Despite the high energy density and stable discharging voltage, batteries still show a typical drawback at short lifetime (less than 5 years [17]), which involves manual replacement of batteries or devices after the battery lifetime expires. Also, batteries raise environmental concerns due to the heavy metals and toxic chemicals within. If not properly charged, Li-ion batteries can cause safety issues, i.e. explosion and fire, which are problematic when deployed in distant and wild places. In addition, rechargeable batteries are susceptible to temperature. Most batteries only exhibit their rated characteristics around 20°C, and lose their efficiency and capacity when operating at extreme temperatures (around their rated limits) [59].

2.2.2   Capacitors

Due to the lifetime limits and pollution issues of batteries, capacitors, typically supercapacitors, are considered as an alternative to replace rechargeable batteries as energy storage. Supercapacitor (also known as ultracapacitors or electrostatic double-layer capacitors) are capacitors with higher energy density than electrolytic capacitors. Unlike conventional capacitors, where charges are stored and separated by solid dielectric, supercapacitors maintain charges based on double-layer or pseudo-capacitive charging phenomena [60]. Supercapacitors are still much less energy-dense than batteries, but act as a transition from capacitors to batteries.

Compared to rechargeable batteries, supercapacitors exhibit strengths in a large number of charge/discharge cycles, long lifetime (20 years), high charge/discharge efficiency (98%). The self-discharge rate of supercapacitors is higher than batteries, with 5.9-11% of maximum capacity per day [61, 62], but this leakage is insignificant compared to the small capacity and the total energy gained per day. The main constraint

of supercapacitors is still the low energy density, which results in large storage dimensions if the aim were to achieve a comparable capacity with batteries. In order to maintain the same form factors of sensor nodes, designers have to adapt system architecture to a small storage (compared to batteries).

Prometheus [18] introduces supercapacitors into energy storage for sensor nodes whereby two 22F supercapacitors are used in combine with a Li-Po battery. AmbiMax [63] also proposes a hybrid storage design similar to Prometheus, but with two more 10F supercapacitors for wind energy harvesters. To achieve longer lifetime than battery-based sensor nodes, Everlast [19] demonstrates the feasibility of replacing batteries with supercapacitors in energy harvesting sensor nodes, designing a power system that adopts a 100F supercapacitor as the only energy reservoir.

However, farad-level supercapacitors occupy a significant part of device volume. The advent of energy-driven computing [64] introduces the application and design scenario where execution happens only if there is energy available. Within this scenario, energy storage using millifarad-level supercapacitors are investigated in energy harvesting sensing applications [54, 65]. Furthermore, intermittent computing, which will be illustrated in the next section, enables computation given intermittent power, making progress with electrolytic capacitors or even without dedicated storage (only microfarad-level parasitic capacitance).

2.2.3 Discussion

To summarise, due to the requirements on lifetime, environmental-friendliness, and form factors in energy harvesting sensor nodes, the energy storage designs have transformed from batteries to supercapacitors, and eventually eliminated the need for dedicated storage.

Batteries have been the preferable choice for buffering harvested energy and powering sensor nodes because they make sensor nodes easy to program and operate reliably until the battery lifetime expires. However, the environmental issues and short lifetime of batteries limit the deployment of ubiquitous sensors. Supercapacitors avoid the problems of batteries and have been used to replace batteries, but the low energy density of supercapacitors also makes sensor nodes bulky and heavy in order to achieve sufficient capacity for uninterrupted operations. Recent development of intermittent computing enables forward execution over power outages and encourages storage-less designs in energy harvesting sensor nodes.

Although the minimum need for storage capacity to operate sensor nodes decreases with the evolution of computing techniques, decreased storage does limit the flexibility of energy usage. A storage-less system has to consume the incoming power immediately, otherwise the energy is wasted. This fact consequently restricts the application

scenarios of storage-less systems to energy-driven applications, where execution needs to run only when there is available energy sources to harvest. However, energy-driven applications do not cover all the demands in IoT, so simply reducing the storage need is not always desirable. A wider spectrum of storage designs should be explored to suit and optimise for different application scenarios.

2.3 Energy-Neutral Computing

Energy-neutral (EN) computing aims to operate sensor nodes with at least a certain performance level over a period of time. Energy-neutrality can be described as the following equation:

$$E_{min} \leq E_{t_0} + \int_{t_0}^{t_0+\Delta t} [P_h(t) - P_c(t)]dt \leq E_{max} \tag{2.1}$$

where $P_h(t)$ and $P_c(t)$ are the harvested and consumed power at time t, t_0 is the time when EN computing is meant to start, Δt is the length of period during which EN conditions are achieved, E_{t_0} is the initial available energy in energy storage at time t_0, E_{min} is the minimum amount of stored energy below which the system cannot sustain (typically due to insufficient supply voltage), and E_{max} is the maximum capacity of energy storage beyond which the harvested energy is wasted. $P_c(t)$ includes the power consumption of the whole system, such as the MCU, peripherals, power conversion circuit, and the power leakage of energy storage. $P_h(t)$ is the harvested power after conversion.

EN devices are typically powered by solar cells [66], and Δt is typically 24 hours or one year to suit the period of the solar energy source. In order to achieve energy neutrality over such a long term, sufficient amount of energy storage, typically in the form of rechargeable batteries, is required to smooth out the large temporal variations of harvested power. The capacity of the energy storage is determined by how long the system tries to maintain a stable performance as larger energy storage tolerates more energy differences. In general, the length of Δt and the difference between P_h and P_c determine how much storage is required, and on the other hand, the capacity of energy storage limits how long Δt can be.

In order to ensure that the system works uninterruptedly by managing the stored energy (the middle term in Equation 2.1) between E_{min} and E_{max}, EN computing dynamically adapts system performance and power consumption over the period Δt. Typical adapting techniques include adjusting workload duty cycles and participation in network activity [64].

Kansal et al. [9] illustrate a preliminary power management algorithm by which the incoming energy is estimated by an Exponentially Weighted Moving Average (EWMA) of the past recorded slots of harvested energy, and the system tries to exploit the harvested energy by scaling its duty cycles. Vigorito et al. [67] introduce a Linear-Quadratic Tracking (LQT) approach to scale duty cycles based on the current battery level, and as evaluated in its datasets, mean duty cycle is improved by 6-32% and duty-cycle variation is reduced by 6-69% compared to [9], which means the system works with a more a stable performance. In [11], a Proportional-Integral-Derivative (PID) controller is used for monitoring and stabilizing the voltage of a supercapacitor-based energy storage, and hence, the storage level of this system. While these approaches achieve satisfactory energy neutrality for the magnitude of hours, they all show a latency when responding to the harvested power, and high variance of duty cycles when adapting to a new power trace. Additionally, approaches in [67] and [9] rely on an accurate estimating algorithm to detect the remaining battery energy, which is vulnerable to deployed time and temperature.

In [68], a prediction algorithm for solar energy named Weather-Conditioned Moving Average (WCMA) is presented, in which both the current and the past weather data are taken into account to achieve higher accuracy than EWMA methods. It is reported by the authors that the average prediction error is improved from 28.6% in EWMA to 9.8% in WCMA over a test duration of 45 days, but it is unclear in the article that how to harness this prediction to improve the system performance. Similarly, weather forecast is adopted in [55], by which the authors build a model to approximate the available solar and wind energy. Although these two methods based on weather data provide high prediction accuracy, the network overheads for receiving these data are not presented, and how to fully utilize this daily prediction is still a problem.

Different from the aforementioned daily EN operations, a long-term annual power management based on duty-cycling is presented in [10] to achieve annual energy neutrality. The authors use an adjustment factor, which is dynamically calculated from the historical windows, to modify the design-time energy prediction model to a more realistic model, and determine its performance level accordingly. However, this algorithm is only tested in simulation instead of practical experiments. Moreover, for such a long-term EN operation, a large battery is required, but the battery deterioration is ignored in their analysis.

In [12], a task scheduling algorithm for optimising the performance of an energy harvesting system (typically based on PV harvesters) is exhibited. Given a predicted power trace, storage bounds, energy consumption of tasks and quality of tasks, the proposed scheduling algorithm is proved to be able to find the optimal scheduling in a pseudo-polynomial time which leads to the maximum sensing quality. While this algorithm provides an ideal solution for power management, it requires that the energy source should be predictable with high accuracy, and the energy cost and quality

of each task should be defined at design time. The first requirement almost constrains this algorithm within the cooperation of solar energy. The second requirement is hard to achieve since a) in practice the energy consumption of tasks may change due to temperature and dynamic data amount [69] and b) the energy cost of a system includes many elements other than the energy consumption of computing tasks.

EN computing efficiently utilizes energy and maintains system performance, ensure reliability and periodic task execution despite variable harvesting power input. However, in almost all energy neutral approaches reviewed above, a large energy storage, i.e. a rechargeable battery, is in need in order to buffer temporal energy variations. The usage of batteries poses sustainability challenges due to the limited lifetime and pollution issues. Recent research develops intermittent computing and power-neutral computing, which minimise the need for energy storage. The next two sections (Section 2.4 and Section 2.5) review the methodologies of these two research topics.

2.4 Intermittent Computing

Energy harvesting provides an autonomous power supply for wireless sensor nodes as an alternative of battery power. However, with small storage, energy harvesting systems inevitably suffer from frequent power outages, which affect forward execution of programs. Intermittent computing (IC, also known as transient computing) aims to maintain forward execution and computation correctness through power failures [22]. Intermittent execution spans its execution and intermittently computes over power outages, while conventional execution restarts after power interrupts. A typical characteristic of an IC system is that it starts executing whenever there is power available and suspends during power outages; after power recovery, it can continue its prior task correctly instead of restarting from the beginning of a program.

Due to different design considerations, the methodologies in IC varies in a wide spectrum [23]. These methodologies include saving snapshots of system state to non-volatile memory (NVM), breaking down execution into small tasks, hardware circuits for suspend and restore operations, etc. The existing IC approaches can be classified into four types: checkpointing, reactive IC, task-based IC, and non-volatile processors (NVP). The following part of this section explains the each methodology one by one, as well as their works and current research progress.

2.4.1 Checkpointing IC

Checkpointing IC inserts checkpoints into code at compile time. When a checkpoint is called, the system checks the current available energy amount. If this amount is less

than a predefined threshold, which indicates the available energy may not be enough to sustain execution, a snapshot saving function is called at this checkpoint. To save a snapshot of the system computing state, the system copy current stacks and heaps, local and global variables, general registers, the stack pointer, and the program counter, into the NVM. A checkpointing system continuously operates until it encounters power outages, where the supply voltage is less than the minimum operating voltage of the systems. After the supply voltage recovers, the system restore its state from the last checkpoint, and hence, continue its execution from that checkpoint.

Mementos [22] first provides a checkpointing solution in which checkpoints are planned at compile time. Mementos includes three strategies of placing checkpoints, which are placing at every loop, placing at every function call, and an auxiliary timer delay to determine the minimum cycle between two adjacent checkpoints. Additionally, programmers can also insert or delete checkpoints manually as a custom option. Two NVM blocks are used and snapshots are saved to the two blocks alternately, so there is always at least one available and complete snapshot even if the energy is depleted during saving a new snapshot. One significant shortcoming of Mementos is the instrumenting strategy: with the different sizes of loops and functions, the granularity of checkpoints can be either too small, which introduces high run-time overheads, or too large, which leads to non-termination where the execution can never get to the next checkpoint. It is a concern in Mementos that how to set the voltage threshold which triggers saving snapshot. Setting this too high leads to redundant snapshots, while setting this too low leads to the failure of saving snapshots and cannot guarantee forward progress.

HarvOS [70] is proposed to improve the strategies of inserting checkpoints in Mementos. HarvOS analyses the control-flow graph of a program and splits it into sub-graphs with a checkpoint inserted for each sub-graph. To reduce the number of checkpoints compared to Mementos, the size of sub-graphs is set close to the worst-case number of useful cycles the MCU can execute until the next checkpoint. To reduce the size of snapshots, the RAM usage in each sub-graph is analysed and the checkpoint is placed at the point with the least RAM usage. HarvOS claims to reduce 68% checkpoints on average compared to Mementos.

Chinchilla [71] proposes a checkpointing tool which automatically overprovisions checkpoints at compile time and adaptively eliminates unnecessary checkpoints at run time. Compared to Mementos and HarvOS, Chinchilla relieves the programming efforts on manually inserting checkpoints while still achieves an efficient number of checkpoints at run time.

An advantage of the checkpointing method is the size of a specific snapshot can be estimated from the program execution flow to find a smaller snapshot [70]. However,

there are still two significant challenges remaining unsolved in checkpointing methods: idempotency violation and non-termination.

An execution is idempotent if it can be repeated while maintaining the same result [30]. Non-idempotent actions include I/O operations and NVM writes, which are fairly common in IC applications. Repeating non-idempotent actions can leads to undesired results, so these non-idempotent actions should be executed only once. Checkpointing systems repeat executing the code between two adjacent checkpoints, and hence, cause non-idempotency. Current compile-time checkpointing methods as listed above are not able to ensure idempotency.

Non-termination in checkpointing systems exhibits when the energy consumption of execution between two checkpoints is too much that the system energy buffer and harvested supply cannot sustain. Non-termination typically happens when the instrumentation strategy of checkpoints ignores the size of the energy buffer, as in Mementos. HarvOS and Chinchilla manage to mitigate non-termination, but they cannot eliminate this problem as they cannot dynamically insert checkpoints at run time according to varying environmental sources.

2.4.2 Reactive IC

Instead of instrumenting checkpoints at compile time, reactive IC does not set predefined checkpoints but save snapshots at run time when the supply voltage is detected to be lower than a threshold that indicates an imminent power failure. Therefore, the snapshot saving operations is only invoked when there is an indication of an imminent power outage, i.e. a low supply voltage. Also, after saving a snapshot, a reactive IC system suspends its execution and enter a low-power mode, rather than continues execution until a power outage as checkpointing systems do. When the voltage supply recovers above a restore threshold, the system either restores the last snapshot if the system reboots, or just continues execution if the system comes back from the low-power mode.

Hibernus [72] saves only one snapshot before a power interruption and then enter the sleep mode. Two fixed voltage thresholds, V_H and V_R, are predefined for hibernation (save a snapshot and sleep) and restoring a snapshot. An on-chip voltage comparator and an on-chip voltage reference generator are used for monitoring the supply voltage and triggering hibernation when the supply voltage drops to V_H or restoration when the supply voltage recovers to V_R. A voltage trace is shown in Figure 2.5 to explain Hibernus behaviours, and this trace is representative for a reactive IC system behaviours. To adapt thresholds to variable energy sources, Hibernus++ [73] implements dynamic self-calibration for suspend and restore thresholds by executing a hibernation test. By using adaptive thresholds instead of fixed thresholds as in Hibernus,

Hibernus++ makes itself compatible with a variety of energy sources. Compared to Hibernus, Hibernus++ improves application execution time by reducing the overheads of suspend and restore operations.
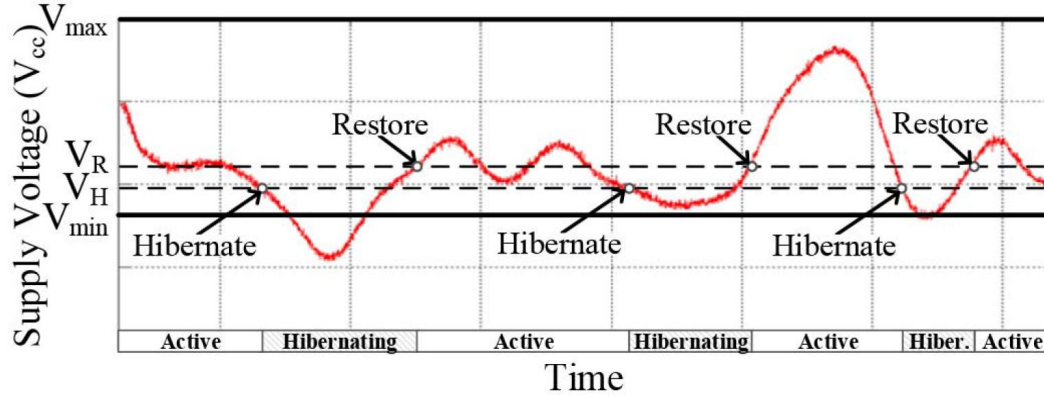

FIGURE 2.5: Voltage trace with hibernation and restoration points in Hibernus (taken from [72]).

Quickrecall [74] is a similar approach to Hibernus except replacing RAM with NVM, so that all the run-time volatile data become non-volatile and only registers are necessary to be saved in a snapshot. An external voltage comparator detects a triggering voltage V_{trig} to back up only peripherals and registers. Compared to the voltage thresholds in Mementos and Hibernus, V_{trig} in Quickrecall is lower since the reduced energy and time overheads for saving and restoring a snapshot. However, using NVM as RAM may lead to the higher cost of NVM accesses. A comparison between Hibernus and Quickrecall is presented in [75], showing that Quickrecall performs worse when the frequency of power interrupts is low as the NVM consumes more than volatile RAM, and performs better when the frequency of power interrupts is high as the overheads of saving snapshots are much lower.

Reactive IC methods only save snapshots when power failure is imminent, and hence, reduce the number of snapshots compared to checkpointing methods. Also, reactive IC avoids code re-execution by suspending execution after saving a snapshot, and hence, ensures idempotency.

The RAM usage varies at run time, so the size of snapshots in reactive IC also varies throughout code execution. To circumvent this issue, Hibernus saves the entire RAM in each snapshot while Quickrecall does not use RAM at all. Comparing Hibernus to checkpointing methods, the overheads of saving snapshots in Hibernus is larger as checkpointing methods can avoid saving large snapshots by analysing the program. Such high saving overheads becomes significant when the frequency of power outages increases. Increasing the size of energy storage in reactive IC should be helpful to mitigate frequent snapshot taking because the increased energy storage can filter the variations of supply voltage and avoid frequent voltage drops.

2.4.3   Harvest-Store-Use IC

Harvest-store-use IC systems perform a complete task in one consecutive period when
the harvested energy in energy storage is enough. A complete task typically includes
sensing, processing, and transmitting actions. In order to sustain a successful task ex-
ecution, the required capacity of energy storage is larger than the minimum required
storage in other IC methodologies. Harvest-store-use systems need to calibrate the en-
ergy consumption of the task at design time and set an energy threshold to trigger
execution based on that energy consumption. When the threshold is reached, which
means there is enough energy for a task, the system performs one task and sleeps until
the next threshold trigger. As shown in Figure 2.6, the behaviours of the amount of
stored energy can be seen as alternating in turn between two states: the collecting state
and the executing state.
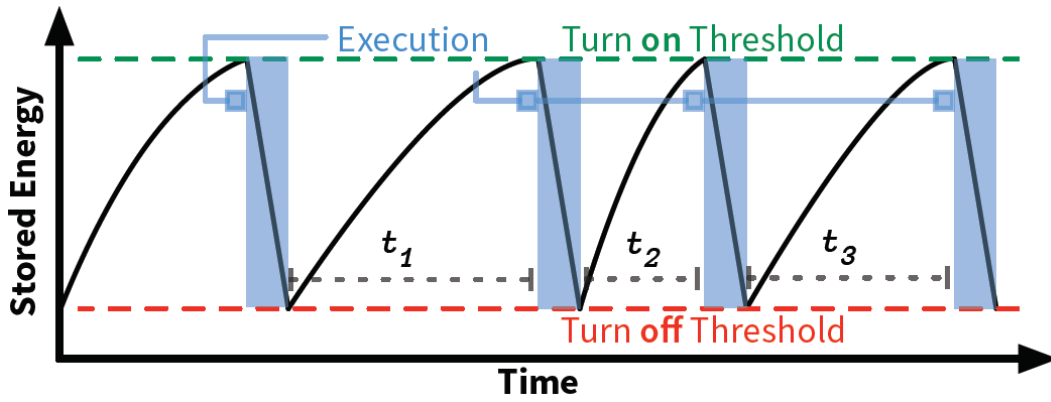
FIGURE 2.6: Harvest-Store-Use execution (taken from [76]).

Monjolo [29] is an early design following the harvest-store-use pattern. Monjolo presents
a home power meter, whereby a current transformer is installed around the main power
cable and provides the energy for this metering system. When the energy stored in a
500μF capacitor reaches a predefined amount, the system transmits a data packet. An-
other wireless receiver keeps collecting these packets and approximates the power of
the main cable based on the receiving frequency of packets. Such a system contains
little sensing and processing work on the transmitting node, and instead, it treats the
intensity of energy sources as the sensing data, and processes this translation of data
on the receiving node which is powered stably.

WISPCam [54] is a wireless camera that obtains energy from an RF harvester. The
harvested energy is stored in a 6mF supercapacitor and the data (photos) are saved in
NVM. Once the energy is sufficient for taking one photo, the system starts execution
and depletes the energy for taking a picture and data transmission.

Similarly, Dynamic Energy Burst Scaling (DEBS) [65] also wakes up and executes tasks
when there is enough energy in the 80μF capacitor. The major difference between DEBS
and the above two approaches is DEBS can adjust the energy thresholds dynamically

for a set of different tasks and generates energy bursts according to which task is in need.

Harvest-store-use paradigms are suitable for occasions where the harvested power is too weak to support the power consumption of any normal execution (other IC methodologies may quickly deplete energy storage and make little progress). Also, harvest-store-use methods circumvent the idempotency issues by complete tasks in one burst. However, this pattern is task-based, which means its operation is limited to one or several fixed energy-defined tasks and also relies on high-quality design-time profiling of tasks.

2.4.4 Task-based IC

Task-based IC decomposes a program into a series of atomic tasks, which only deliver non-volatile results after all operations in a task are completed [30]. Task-based IC is achieved by programming and execution models, which aim to ensure NVM consistency and idempotency. In such models, accesses to NVM and I/O operations are carefully managed to prevent idempotent violations. To ensure idempotency, the program control flow is divided by task boundaries, and the communication between tasks is enabled by reading or writing NVM data on those boundaries. To avoid non-termination, the maximum size of one task is limited by the capacity of energy storage. Therefore, task-based IC can be seen as a rigorously-organized and fine-grained check-pointing method, which eliminates the the non-termination and idempotency problems in checkpointing IC. Task-based systems feature with fast suspend and restore operations because only the runtime and the current task should be versioned and restored through power outages [23].

DINO [30] proposes the first task-based IC programming and execution model, illustrating the task-based idea and providing a basic groundwork. DINO implements the programming and execution model on the LLVM compiler for C code, with program libraries and compiler passes. Chain [77] improves DINO data flows with "Channels", which is dedicated to manage non-volatile data, guaranteeing the correctness on applications with both idempotent and non-idempotent code. Alpaca [78] introduces data privatization which reduces memory usage compared to Chain.

A main drawback of DINO, Chain, and Alpaca is they require great programming efforts for programmers to understand the implemented libraries and redesign a program according to the task-based concept. A recent work, CleanCut [79], proposes an auxiliary tool to check and automatically decompose the non-terminating tasks (the energy consumption of which exceeds the capacity of system energy storage).

Also, like checkpointing IC, task-based IC inevitably involves re-execution. Alpaca, the state-of-the-art task-based approach, reports a run time overhead of 1.3-3.6x compared to plain C code given constant power supply.

2.4.5   Non-Volatile Processors

Non-Volatile Processors (NVPs) incorporate automatic backup and restore hardware within the chips. A comparison of memory architecture between traditional processors and NVPs is shown in Figure 2.7. The traditional volatile elements are replaced with non-volatile elements to achieve efficient backup and restore operations with a faster speed and lower energy consumption than the conventional memory architecture. To be specific, the registers and cache are equipped with built-in additional non-volatile backup and restore circuits, so that when the supply power is going to disappear, the computing state can be saved locally just beside the elements, rather than being copied out into an external NVM. It is reported that the backup and restore speed of NVPs can be 2-4× magnitudes faster than the state-of-the-art NVM based commercial processors [80].
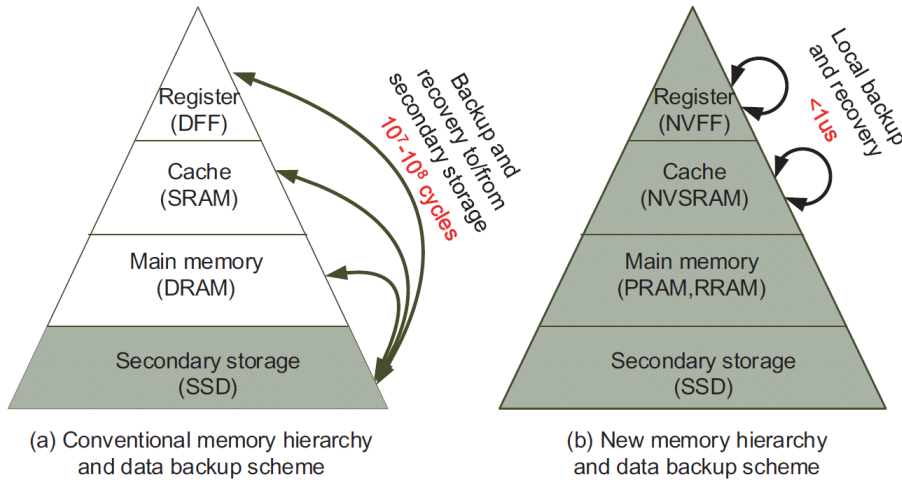
FIGURE 2.7:   Memory architectures of traditional processors and NVPs (taken from [80]).

Wang et al. [81] present a preliminary NVP with $3\mu s$ backup time and $7\mu s$ restore time, which enables the processor to operate safely under a 20 kHz square wave of power. As a comparison, the existing MCUs in TI MSP430 family can only achieve $212\mu s$ and $310\mu s$ for saving and restoring states respectively. Su et al. [82] extend the backup and restore time overheads to a system level, presenting a NVP with $46\mu s$ system-level wake-up time and $14\mu s$ system-level sleep time. Liu et al. [31] integrate a NVP into a system-on-chip with independent backup and restore circuits for peripherals.

NVP-based research follows with the development of NVP hardware. Ma et al. [83] examine the performance and energy consumption of several types of NVPs with different ambient sources, providing a guideline for NVPs selection. The concept of "Incidental Computing" based on NVPs is proposed in [84] to improve the forward progress under unstable power supply, and also provides an evaluation of performance on NVPs. Essentially, it pays more attention to processing forward data in need than the buffered historical data from recovery, but an incidental recomputing on the historical data is performed when there is abundant energy. It is reported that this approach outperforms the existing save-and-use computing scheme by 2.2-5$\times$ in the simulation with respect to an image processing speed, and also the forward progress is improved by 4.28$\times$ on average over a basic NVP.

NVPs perform well in terms of the response to power intermittency, but the research on how to deliver better forward progress with NVPs is limited. Dynamic Voltage and Frequency Scaling (DVFS) can be a potentially applicable solution [85]. In a traditional NVP, the small buffering capacitor tends to be either charged to be full or depleted rapidly and frequently [86]. This behaviour accounts for a large part of backup and recovery overheads, so power management based on NVP is in need.

2.5 Power-Neutral Computing

While IC aims to ensure forward execution despite frequent power outages, energy harvesters may also generate more power than systems can consume when ambient sources are sufficient. Such excessive energy is wasted if not stored for later usage or consumed immediately.

2.5.1 Principles of Operations

Power-neutral (PN) computing aims to manage power without additional storage or with only a very limited amount of storage which can only sustain its system for milliseconds. In principle, power-neutral computing is a special case of energy neutral computing when Δt in Equation 2.1 is equal (or close) to zero. Technically, PN computing scales the instantaneous system power consumption to match the instantaneous harvested power with theoretically zero storage (in other words, energy neutrality is met instantaneously). PN operations can be translated into the following expressions:

$$P_h(t) = P_c(t) \tag{2.2}$$

$$where \quad t \in \{t|V_{cc}(t) \geq V_{min}\} \tag{2.3}$$

where V_{cc} is the input voltage of the computing load, and V_{min} is the minimum voltage required for the system to operate. Equation 2.2 describes the methodology of power neutrality (dynamic and instantaneous power adaptation). Equation 2.3 limits the requirement for power neutrality that the system should be powered and active to make reactions of performance scaling. This requirement may change according to different system designs, but for contemporary computing and sensing loads, this is determined by the supply voltage.

Given a very limited amount of storage and a range of scalable performance and power consumption, PN computing scales down performance if P_h is lower than P_c, such that V_{cc} remains stable, which extends execution time and avoids suspend and restore operations. On the other hand, PN computing scales up performance if P_h is higher than P_c, such that the excessive harvested energy is immediately consumed on useful work rather than wasted.

In practice, however, there does not exist a system that can adjust its power consumption instantaneously to the harvested power without any overheads. Any performance scaling costs a small amount of time and energy overheads, which a system cannot afford without any energy storage. Therefore, a minimum storage is still required, normally in the form of decoupling or parasitic capacitance, to provide a small but sufficient amount of energy for scaling performance and adapting power consumption.

In order to achieve power neutrality, a system has to adapt its performance and hence power consumption. Performance scaling can be achieved by hardware controlling, such as Dynamic Frequency Scaling (DFS) [24], Dynamic Voltage and Frequency Scaling (DVFS) [25], or switching on/off load elements [25, 87] (also known as Dynamic Power Management, DPM [88] or hot-plugging). Apart from these achieved methods, duty-cycle scaling and task scheduling are also choices for changing performance and consumption, though they have not been implemented in current research yet.

2.5.2   Recent Approaches

The concept of PN computing is proposed in [24] and implemented on a Texas Instrument MSP430FR5739 MCU without an external energy buffer. As shown in Figure 2.8, the executing load is directly connected to a regulated energy harvesting source. The control scheme in [24] utilizes DFS with a voltage feedback. Specifically, two voltage thresholds, V_{dec} and V_{inc}, are set for detecting voltage variance caused by power inequality and then scaling performance accordingly. In order to respond fast to power difference, the capacitance is reduced to $19\mu F$, which is only the parasitic and on-board decoupling capacitance. When $P_h(t) > P_c(t)$ and the operating voltage V_{cc} increases rapidly due to the small capacitance and reaches V_{inc}, the MCU increases its operating frequency resulting in faster computing speed and higher power consumption, and

also increases the thresholds between which the new voltage value is contained; and vice versa, a reverse procedure is executed for $P_h(t) < P_c(t)$. In a word, this control scheme is trying to make the operating voltage stable around a desired value so that $P_h(t)$ equals $P_c(t)$ approximately.
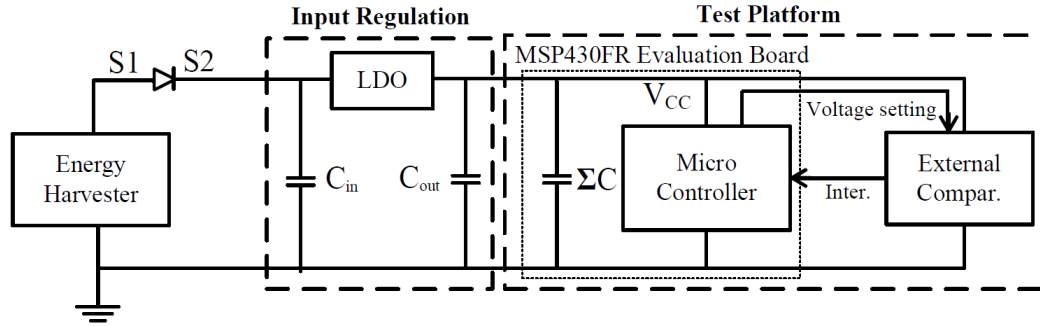

FIGURE 2.8: Architecture of an example power neutral system based on TI MSP430FR platform (taken from [24]).

A similar control scheme is adopted in [25] where the platform is an MP-SoC adopting DVFS and DPM, which leads to higher performance, higher power consumption, and more operating points than the MCU in [24]. A 47mF supercapacitor is used for safely overcoming performance switching where the power consumption of the board is normally above 2W. As an illustration for how to scale performance by DVFS and DPM, Figure 2.9 presents an example application profile of 'power consumption vs performance' when DVFS and DPM applied on a heterogeneous multi-processor system-on-chip (MP-SoC) platform. The SoC used in this platform is the Samsung Exynos5422 big.LITTLE SoC with four 'big' high-performance A15 cores and four 'LITTLE' low-power A7 cores. In this case, the performance refers to the speed of executing this application for one time and is proportional to the operating frequency under a certain core configuration. As shown in the figure, each performance level (a pair of frequency and core status, also named as an operating point) requires a certain power consumption. At run-time, the system dynamically switch its performance among these operating points so as to timely match $P_c(t)$ with $P_h(t)$.

There are three advantages in this kind of PN control scheme. First, the voltage is stabilized so it can offset ephemeral power drops which cause insufficient voltage supply and power failures, and therefore the lifetime increases (e.g. reported by 4-88% in [24]). Second, as power neutral computing eliminates many elements that required in EN systems, such as large energy storage, power converters and MPPT units, the size and cost of devices is reduced and the number of power consumption components also decreases. Third, if powered by a solar panel and the operating voltage range encompasses the MPP of the given solar panel, the system embraces an intrinsic MPPT characteristic as it can stabilize the voltage around a target value.
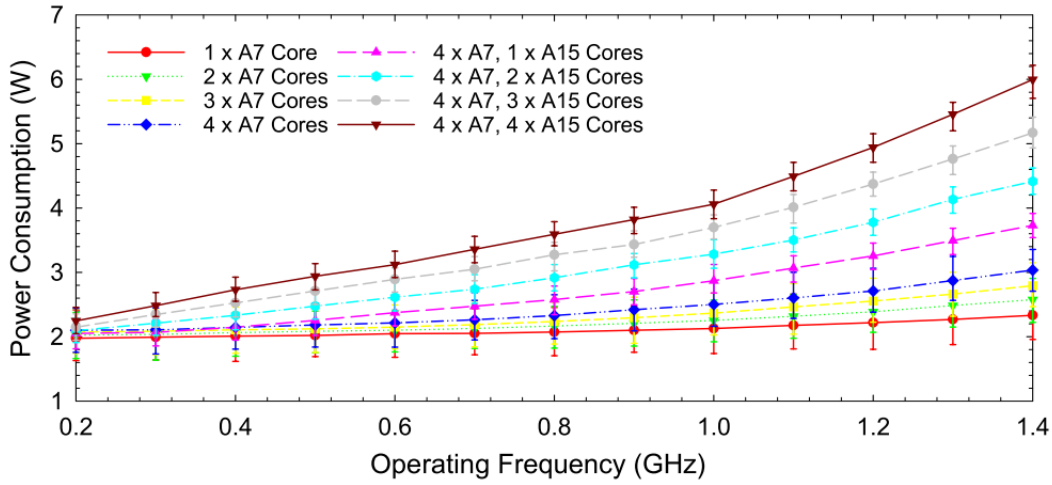
FIGURE 2.9: Board power consumption of ODROID XU4 vs operating frequency and
core configurations, running CPU intensive application Raytrace (taken from [25]).

Similarly, Wang et al. [87] propose a storage-less and converter-less approach which
can be classified as a power neutral system. In this design, a 47μF bulk capacitor is
equipped with a 3.29mW non-volatile MCU and up to 16.5mW peripherals. This ca-
pacitor is also small enough compared to the 19μF capacitance operating with an up
to 3 mW MCU in [24]. An external MPPT controlling element dynamically adjusts the
power duty-cycle for the non-volatile load in order to match the harvested current and
the consumed current, and hence power neutrality is met.

One disadvantage of power neutral computing is that it has to passively scale its power
consumption as well as its performance, causing large variations in performance. How-
ever, this might not be good in terms of the overall forward progress. In the next chap-
ter, a preliminary analyse is explained about how the forward progress is improved
when the capacitor size is increased, while not violating the merits of PN computing.

2.6   Summary

This chapter introduces a background of energy harvesting techniques, summarises
the evolution of energy storage used in energy harvesting computing, and reviews the
existing methodologies of battery-less energy harvesting computing.

EN computing emphasizes the continuous activity of devices over a long-term dura-
tion (e.g. several days, one year) by buffering harvested energy in large energy storage
and adapting energy consumption "reluctantly". However, large energy buffers, usu-
ally in the form of batteries or large supercapacitors, are demanded for EN operations,
whereas such large energy storage limits device lifespans, increases the cost, mass, di-
mensions of devices, and bring pollution and maintenance issues. This contradicts the
design requirements of ubiquitous sensor deployments.

To circumvent the limitations in EN computing, intermittent computing is recently developed. Intermittent computing continues computation after the supply fails rather than restarts from the beginning of programs. Hence, intermittent computing devices can achieve forward execution despite frequent power failures with only minimum storage (e.g. a decoupling capacitor) to secure successful saving and restoring operations of computing states between volatile and non-volatile components. Based on intermittent computing, PN computing introduces run-time performance adaptation to match power consumption with harvested power, such that the number of saving and restoring operations can be reduced and application execution speed is increased.

However, with minimised storage, an intermittent computing device has to frequently wake up, execute shortly, and halt when the harvested power is less than the load power consumption, consuming much energy in managing system states. As for PN computing, volatile power from environment results in significant performance variations, which then cause performance loss. The remaining part of this thesis reports a study on how to mitigate these two problems and improve system execution speed by adding a small amount of energy storage without significantly affect device dimensions.

Chapter 3

Sizing Effect: Exploring the Effect of Energy Storage Sizing on Intermittent Computing System Performance

3.1 Motivation

3.2 Reactive ICS Modelling

3.2.1 Operating Modes of Reactive ICS

3.2.2 Formulating Forward Progress

3.3 Exploration of Energy Storage Sizing

3.3.1 Model Configuration

3.3.1.1 Energy Storage

3.3.1.2 Intermittent Computing Load

3.3.2 Sizing Energy Storage to Improve Forward Progress

3.3.2.1 Impact of Supply Current

3.3.2.2 Impact of Volatile State Size

3.4 Experimental Validation

Chapter 4

Sizing Approach: Energy Storage Sizing Approach for Deploying Intermittent Computing Systems

4.1 Motivation

4.2 Energy Storage Sizing Approach

4.2.1 Input

4.2.2 System Model

4.2.2.1 Energy Source

4.2.2.2 Energy Harvester

4.2.2.3 Energy Storage

4.2.2.4 Intermittent Computing Load

4.2.3 Trade-off

4.3 Sizing under Real-World Energy Conditions

4.3.1 Model Configuration

4.3.2 Sizing the Energy Harvester

4.3.3 Sizing the Energy Storage

4.3.4 Interruption Period

Chapter 5

Exploit the Size: Efficient Atomic Operations with Capacitor Anti-Degradation

5.1   Motivation

5.2   Background

5.2.1   Atomic Tasks Handling in Intermittent Systems

5.2.2   Capacitor Degradation

5.3   Online Task Profiling and Threshold Adaptation

5.3.1   System Architecture

5.3.2   Software Routine

5.3.3   Online Task Profiling

5.3.4   Voltage Threshold Adaptation

5.3.5   Task Overhead Models

5.3.5.1   Constant Model

5.3.5.2   Linear Model

5.4   Implementation

5.4.1   Hardware

Chapter 6

Conclusions and Future Work

6.1 Conclusions

Intermittent computing enables continuity of computation on energy harvesting sensor nodes despite frequent power failures by managing system volatile and non-volatile states. With a goal of minimising device dimensions and cost, intermittent computing systems only adopt energy storage (e.g. a decoupling capacitor) at the minimum requirement of ensuring computing correctness. However, given power production is less than power consumption, such systems have to frequently wake up, execute shortly, and halt, wasting energy on state managing operations. A method of sizing energy storage and energy harvester for intermittent computing devices under real-world deployment is proposed. This sizing method provides a suggestion on how to balance performance and dimensions in sizing energy harvester. In a suggested range of energy harvester sizes, increasing storage from 20μF to 80μF and improve 5.7-22.2% on application execution speed under real-world energy source conditions while not affect device dimensions.

A power-neutral system has to match the power consumption with the available power instantaneously through DVFS since it has almost no energy storage. However, this affects the overall performance, since a system performing DVFS can obtain more computation when operating within a constrained range of frequency instead of scaling frequency according to the harvested power. Based on this, a study on the effect of energy storage capacity on the performance of power-neutral systems is proposed. In this study, the analysis shows that with the increase in capacitance, the system is able to operate within a more stable range of frequency, and hence more forward progress achieved given the same power input and within the same time. It is reported in the simulation that when properly selecting the size of the capacitor, the forward progress can be improved by 14.6% given a sinusoidal power input.
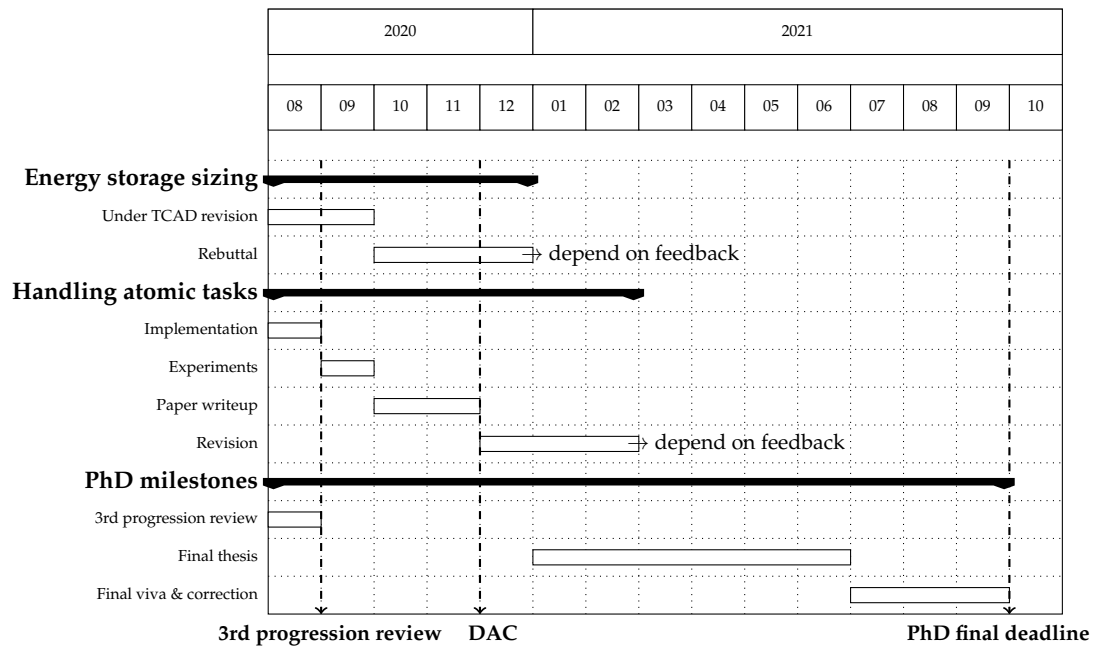
6.2 Future Work

FIGURE 6.1: A gantt chart.

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