2

Energy Sources

2.1 Introduction

There are many different types of energy sources available for harvesting in wireless communications. Depending on their characteristics, they can be categorized as follows:

- *Uncontrollable and unpredictable*: These energy sources cannot be controlled to generate the amount of energy required at a specific time in a specific location. Also, they do not follow commonly used predictive models or implementation of such predictive models is too complicated for relevant applications. An example of such an energy source is mechanical vibration. A piezoelectric or electrostatic energy harvester can convert the vibrational energy into electricity but it may be hard to predict when or where the vibration will occur and it is even harder to generate it intentionally (Mitcheson et al. 2008).
- *Uncontrollable but predictable*: These energy sources cannot be controlled to generate the energy when and where it is needed. However, their generation follows certain patterns that have been well studied and are relatively predictable with acceptable errors. For example, solar energy is mainly determined by solar activities and weather conditions. It is hard to control the movement of the sun or the weather to achieve the level of solar energy desired but solar energy has strong diurnal and seasonal cycles that can be predicted (Bergozini et al. 2010). This prediction can be further improved by incorporating weather data in the forecast.
- *Controllable and partially predictable*: These energy sources can be controlled to produce the amount of energy required at a specific time in a specific location by the wireless device. In other words, these energy sources are controlled by the communications system. Wireless power is a good example of energy sources in this category. In wireless powered communications systems, a radio frequency (RF) signal can be sent by the power transmitter to the remote wireless device for electricity. Also, in an indoor environment, the indoor light can be controlled for the wireless device to harvest its energy using a photovoltaic cell (Wang et al. 2010). These energy sources are only partially predictable, because their behaviors are not fully deterministic. For example, channel fading may change the received wireless power randomly. Obstacles in the room may change the illumination too.

Figure 2.1 shows some commonly used energy sources in energy harvesting wireless communications. They have different characteristics. For example, the solar energy can

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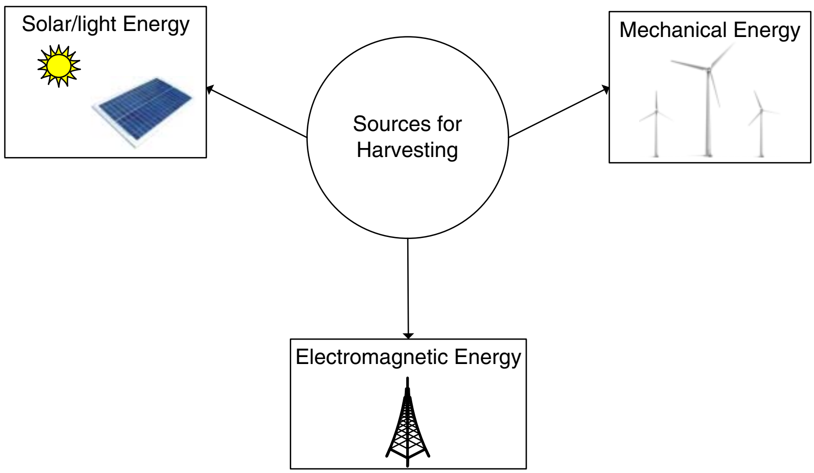

Figure 2.1 Some commonly used energy sources for energy harvesting wireless communications.

only be used when or where it is sunny. The wind energy can only be used when or where it is windy. The electromagnetic energy can only be used when radio transmissions are not blocked. Hence, not all the energy sources can be used in all wireless communications systems due to size, mobility or power limitations of the wireless device. It is important to choose the appropriate source for harvesting in the designs of energy harvesting wireless communications systems. In the next section, we will discuss some of these energy sources, their characteristics, and their applications.

2.2 Types of Sources

In this section, we briefly discuss some commonly used energy sources in energy harvesting wireless communications. These sources can be mainly divided into three categories: mechanical energy, solar/light energy, and electromagnetic energy. All of them need to be converted into electricity using transducers.

2.2.1 Mechanical Energy

Mechanical energy is commonly available in our daily life. Many devices can be used to convert vibration, motion, stress, pressure or strain into electricity. Their main principle is the conversion of mechanical energy from the displacement and oscillation of a spring-mounted mass component into electricity. Based on the randomness of the mechanical energy source, they can be categorized into three types: random vibration energy; steady flow energy; and intermittent motion energy.

The random vibration energy is often seen in built environments, such as bridges, buildings and train tracks (Roundy et al. 2003). They follow certain amplitudes and frequencies but may be random due to the random occurrence of events. The vibration energy can be extracted from these sources but the amount of energy extracted depends on the amplitude and frequency of vibration. In some cases, the presence of the energy harvesting device may also affect the vibration due to the harvester's own weight, as vibration is normally generated by the movement of a mass on a supporting frame and the harvester could add weight to the mass.

The steady flow energy comes from fluid flow, such as air or water, through pipes, or the continuous motion around a shaft, etc. Wind power is one of the most important examples of this energy. It uses the wind turbine to convert the air flow energy into electricity. Another example is the use of blood flow in vessels and breathing in human subjects to generate energy for body sensors that can monitor human body temperature or blood pressure (Mitcheson et al. 2008). The air flow and the blood flow are relatively stable so that the energy harvested from these flows is more deterministic.

The intermittent motion energy falls between vibration and flow. These energy sources come from cyclical motion in the natural environment but the energy can only be harvested during a short period of the cycle. For example, a sensor monitoring the surface of a road can harvest energy from vehicles passing over it but this energy is only available periodically. Also, energy can be harvested from human walking through shoes but only when the foot steps on the ground.

These three types of mechanical energy have different levels of randomness, leading to different levels of predictability. Based on the transduction method, the mechanical energy sources can also be categorized into three types: electromagnetic; electrostatic; and piezoelectric.

In the electromagnetic method, a magnet is used with a metal coil based on the law of induction. This method produces electricity by moving the coil through the magnetic field created by the stationary magnet (Moghe et al. 2009). When the coil moves or the distance between the magnet and the coil changes due to mechanical motion or vibration, an alternating current (AC) will be generated in the coil, which can be used to power up the wireless devices. This motion can be either controllable or uncontrollable. The advantage of this method is that no contact between coil and magnet is required and the electricity generated can be used directly. However, it is hard to integrate the electromagnetic device with the sensor circuit due to its size.

In the electrostatic method, the mechanical motion or vibration is used to change the distance between two electrodes of a capacitor against an electrical field (He et al. 2009). This will change the capacitance of a variable capacitor. The variable capacitor is made of two plates, one fixed and one moving. It needs to be initially charged. When vibration or motion separates the two plates, the vibration or motion is transformed into electricity due to the capacitance change, as the voltage across the capacitor will also change to generate a current in the circuit for use. This method allows the integration of the harvesting device into the sensor circuit.

In the piezoelectric method, a layer of piezoelectric material is used on top of the wireless device so that mechanical strain on the surface of the wireless device will be converted into electricity (Mitcheson et al. 2008). It uses a cantilever structure with a mass attached to a piezoelectric beam that has contacts on both sides of the piezoelectric material. The strain creates charge separation across the device to generate a voltage proportional to the stress applied. In some cases, the amount of energy harvested from this method is small and therefore, it may need to be combined with other methods. Also, the piezoelectric materials are breakable.

Different motion, vibration and strain sources have different power densities. For example, for a wind turbine operating at a wind speed between 2 m/s and 9 m/s, it can generate a power of about 100 mW (Ramasur and Hancke 2012). The blood flow can generate a power of 1 μW, while the running shoes can generate a power of several milliwatts (Paradiso and Starner 2005; Mitcheson et al. 2008). Finger typing can generate a power of 7 mW, while lower limb movement could generate a power of 67 W (Mitcheson et al. 2008). Also, these energy sources have different applications. For example, for a wireless sensor, it is unlikely to use a wind turbine or any harvesters based on the electromagnetic method due to their bulky sizes. On the other hand, the piezoelectric method is well suited for the sensor networks due to their size but only for low-power applications due to the limited power.

2.2.2 Solar/Light Energy

Light is perhaps one of the most commonly used sources of energy for harvesting. The photons from the light source can be converted into electricity using photovoltaic cells. The photovoltaic cell has two types of semiconductor materials and their area of contact forms a PN junction. When the photons arrive from the light source, the photovoltaic cell will release electrons to produce electricity.

For outdoor applications, solar energy is a very reliable source for self-powered devices. It has been used in many wireless networks to replace batteries by providing an almost unlimited energy supply (Sitka et al. 2004). In most of these applications, a solar panel is used to convert the radiation from the sun into electricity. This method has been well established with relatively low cost and high efficiency over a wide range of wavelengths. Also, the energy level provided by a solar panel is very close to the nominal energy required by wireless devices. Specifically, the solar power density is around 1370 W/m^2 when it arrives at the Earth and after attenuation and conversion, the available power density is still around 2 W/m^2. However, one main disadvantage of solar energy is its heavy reliance on the weather, time, and the operating environment. For example, in the evenings when the sun goes down, there is hardly any solar energy to harvest. Also, for indoor applications, solar energy may not be available. In this case, it must be complemented by other energy sources. In general, solar energy is uncontrollable but can be predicted in standard conditions. In most cases, it can provide more power than any other energy sources and thus is suitable for power-consuming energy-harvesting communications applications.

For indoor applications, illumination from indoor lights is another source of energy. Its radiation is typically at the level of 1 W/m^2 and given an efficiency of 15%, the converted electricity could be at the level of 0.15 W/m^2. Typical values range between 10 $\mu W/cm^2$ and 100 $\mu W/cm^2$ (Wang et al. 2010). This is much smaller than the power density of the Sun. Indoor light is relatively controllable compared with the Sun but still varies depending on obstacles, distances, and operations.

Another type of energy that also uses the thermal effect is thermal energy (Leonov 2013). It uses the thermoelectric effect by converting the temperature difference between two metals or semiconductors of different materials into electricity. This is also called the Seebeck effect. Such temperature difference naturally occurs in human bodies or in certain machines. The amount of power converted depends on the thermoelectric properties of the materials and the temperature difference but in general is on the order of 10 $\mu W/cm^2$ to 1 mW/cm^2 (Leonov 2013). This is suitable for wearable sensors, such as fitness bands and smart watches.

2.2.3 Electromagnetic Energy

The electromagnetic energy in this subsection mainly refers to RF energy. The advantage of RF energy over solar energy is that it can work under most conditions: indoor or outdoor, day or evening, sunny or cloudy. It can be as controllable as the light illumination but can also be as unpredictable as vibration. RF energy sources can be divided into two main categories: near field; and far field (Lu et al. 2015). The near field applications include magnetic resonance or inductive coupling. They are often used to charge devices in a wireless way over a very short distance. Due to the short distance, their efficiency can be higher than 80% but this efficiency decreases quickly with distance. This method is completely controllable and predictable. However, for wireless communications systems, this short distance may not be realistic. Hence, energy harvesting wireless communications often use the far field method that can harvest energy over a distance of more than 10 m.

The sources of RF energy in the far field method can be from the ambient environment, such as radiations from the cellular base station, TV transmitter or WiFi router. It can also be from dedicated power transmitters. One unique advantage of RF energy is that most wireless systems are implemented using radio waves too and hence, information delivery can be combined with energy transfer in the same system and sometimes by the same signal.

The level of power from a global system for mobile communications (GSM) base station is around -40 dBm/cm^2. Studies show that other ambient sources, such as TV, third generation (3G) and WiFi produce even weaker power. For example, a 3G base station generates a power density of around -50 dBm/cm^2, while WiFi signals provide a power density of around -70 dBm/cm^2 (Pinuela et al. 2013). Hence, although there are many different ambient RF energy sources, in general their power densities are very low, as their power densities decay quickly with distance. Consequently, these ambient RF sources can only be used for low-power applications, such as radio frequency identification (RFID) or sensor networks, or the wireless device must be very close to the sources. To harvest enough energy for more power-consuming wireless operations, either a large antenna or a wide-band antenna need to be used. Alternatively, dedicated sources of RF energy are required, as in wireless powered communications systems, at additional cost.

There are other types of energy available for harvesting. For example, the pyroelectric effect of materials can be used to generate electricity. Biomedical substances can be used to generate biochemical energy. Acoustic waves can be converted into electricity using transducers or resonators too. Alternatively, all the above energy sources can be combined. Table 2.1 gives an overview of the amount of energy available from different sources.

2.3 Predictive Models of Sources

The amount of energy from most energy sources varies with time. This time-variance leads to uncertainty in the energy supply for wireless communications. Thus, it is very useful to have accurate models that describe this energy uncertainty, because wireless communications systems can use these models to make critical decisions on the usage of energy.

Table 2.1 Typical amount of energy from different sources.

Source	**Typical amount of energy**
Solar	100 mW/cm^2 (sunny)
Indoor light	$0.01 \sim 0.1$ mW/cm^2
Wind	0.38 mW/cm^3 (at 5 m/s)
Piezoelectric	$0.2 \sim 0.4$ mW/cm^3
Electrostatic	$0.05 \sim 0.1$ mW/cm^3
Ambient RF	0.2 nW/cm^2 $\sim$ 1μW/cm^2

In this section, we will discuss some important modeling studies on the amount of energy provided by various sources. The data used to derive these models were collected by using a certain measuring equipment or energy harvester. Thus, there is a conversion loss from the available energy at the source as the input of the equipment to the measured or harvested energy as the output of the equipment. Nevertheless, since the same equipment or energy harvester is used to collect all data, this conversion loss can be considered as constant so that the behaviors of the data before collection and after collection are approximately the same to justify the usefulness of the derived models. In the next chapter, we will discuss models that describe the conversion loss or the efficiency of the energy harvester. Using the energy source model here and the energy harvester model in the next chapter, one can predict how much energy is available for wireless communications. We will also discuss models of the harvested power directly in the next chapter. In the following, we will focus on the solar energy models and the ambient RF energy models, as they are the two most widely used energy sources in wireless communications systems.

2.3.1 Solar Energy Modeling

As discussed before, solar energy is not controllable but due to its clear diurnal and seasonal patterns, it is predictable. However, its prediction is highly dependent on the weather conditions.

The simplest model for solar energy prediction is the exponentially weighted moving average (EWMA) model (Cox 1961; Kansal et al. 2007). It divides the data at different time slots on different days into a matrix, where the columns of the matrix could represent different time slots on the same day while the rows of the matrix could represent different days. It uses a weighting factor of ρ to predict the solar energy in the next time slot by linearly combining the current measurement and the previously predicted solar energy. The weighting factor decreases with time to lay a higher emphasis on the measurements taken at a time closer to the time to be predicted. Mathematically, the EWMA predictor is given by

$$\hat{E}(t+1) = \rho E(t) + (1-\rho)\hat{E}(t) \tag{2.1}$$

where $\hat{E}(t+1)$ is the predicted value in the next time slot $t+1$, $E(t)$ is the measurement in the current time slot t, and $\hat{E}(t)$ is the predicted value in the current time slot t.

The exponential weighting can be seen by replacing $\hat{E}(t)$ with $\rho E(t-1) + (1-\rho)\hat{E}(t-1)$ to give

$$\hat{E}(t+1) = \rho E(t) + (1-\rho)\rho E(t-1) + (1-\rho)^2 \hat{E}(t-1) \tag{2.2}$$

where the predicted value at time slot $t-1$ has a smaller weighting factor of $(1-\rho)^2$ since $0 < \rho < 1$. Using (2.1) in solar energy prediction, one has

$$\hat{E}_t(d+1) = \rho E_t(d) + (1-\rho)\hat{E}_t(d) \tag{2.3}$$

where d represents the day, t represents the time slot on that day, $\hat{E}_t(d+1)$ is the predicted value at time t on the $(d+1)$th day, $E_t(d)$ is the measured value at time slot t on the dth day, and $\hat{E}_t(d)$ is the predicted value at time slot t on the dth day. If a matrix is used, $E_t(d)$ is the element on the dth row and tth column of the measurement matrix. From (2.3), the prediction for each time slot is calculated by taking into account the predicted and measured values at the same time slot on the previous day.

The EWMA model works well when the weather condition is stable over a few days or does not change at all. However, if the weather does change, its accuracy will decrease. For example, if the weather keeps switching between sunny and cloudy on different days, using the predicted and measured values on the current day will not help the prediction for the next day much. In this case, the weather conditioned moving average (WCMA) model can be used (Piorno et al. 2009). The WCMA model again divides data into a matrix with rows representing days and columns representing time slots. However, unlike EWMA, it uses the average of the measured values on a few previous days, not just one previous day. Specifically, one has

$$\hat{E}_{t+1}(d) = \rho E_t(d) + (1-\rho)\frac{\sum_{i=1}^{D} E_{t+1}(i)}{D} \tag{2.4}$$

where $\hat{E}_{t+1}(d)$ is the value predicted for the next time slot $t+1$ on the dth day, $E_t(d)$ is the measured value at the current time slot t on the dth day, D is the number of previous days used, and $E_{t+1}(i)$ is the measured value at time slot $t+1$ on the ith day, $i = 1, 2, \cdots, D$. This model can improve the accuracy over the EWMA model by using an average of the values at the same time slots on previous days instead of one single predicted value on the previous day. However, if there is a cloudy day followed by many sunny days or vice versa, this method will cause errors. To reduce the error, the measurements in the previous time slots on the same day can also be used, to replace a single measurement at the current time slot on the same day assuming that the weather conditions are at least stable for the whole day. In this case, the WCMA model can be modified as

$$\hat{E}_{t+1}(d) = \rho E_t(d) + (1-\rho)G(K, d, t)\frac{\sum_{i=1}^{D} E_{t+1}(i)}{D} \tag{2.5}$$

where

$$G(K, d, t) = \frac{\mathbf{V} \cdot \mathbf{P}}{\mathbf{1} \cdot \mathbf{P}} \tag{2.6}$$

K is the number of time slots in the past on the same day, $\mathbf{V}$ is a $K \times 1$ vector with the kth element being $v_k = \frac{E_{t-k+1}(d)}{1/D \sum_{i=1}^{D} E_{t-k+1}(i)}$, $\mathbf{P}$ is a $K \times 1$ vector with the kth element being $p_k = \frac{k-1}{K}$, $\cdot$ is the dot product of two vectors, and $k = 1, 2, \cdots, K$. One sees that there is an additional weighting factor $G(K, d, t)$ to consider the variance over different time slots.

Another simple predictor uses a 2-D linear filter. In this case, the predicted value is calculated as

$$\hat{E}_{t+1}(d) = a_1 E_{t+1}(d-1) + a_2 E_t(d) + a_3 E_t(d-1) \tag{2.7}$$

where the parameters of a_1, a_2 and a_3 can be optimized using training data. There are other more complicated models, such as adaptive management or neural networks. They are not discussed here. In general, WCMA is better than EWMA. A detailed comparison of these models can be found in Bergozini et al. (2010).

2.3.2 Ambient RF Energy Modeling

Another widely used energy source is the ambient RF energy. Example measurements of such ambient RF energy at different time instants in different frequencies are shown in Figure 2.2. This plot shows the measurements taken from the GSM uplink from 880 to 915 MHz in the UK (Azmat et al. 2016). One can see that the input power of the energy harvester or the available power from this band changes with both time and frequency. It is close to zero in many cases but at certain time instants and frequencies, it could be as large as a few milliwatts. Thus, if a wireless device harvests energy from this band, it will be useful to have some model that describes the change of power at different time instants and frequencies so that the device knows when and where to harvest. To simplify the problem, a wide-band harvester can also be used so that all input power at different frequencies can be collected. In this case, all the components at different frequencies will be added to give a simpler measurement plot similar to Figure 2.3, where the measurements become a function of time only. Figure 2.3 measures the power in

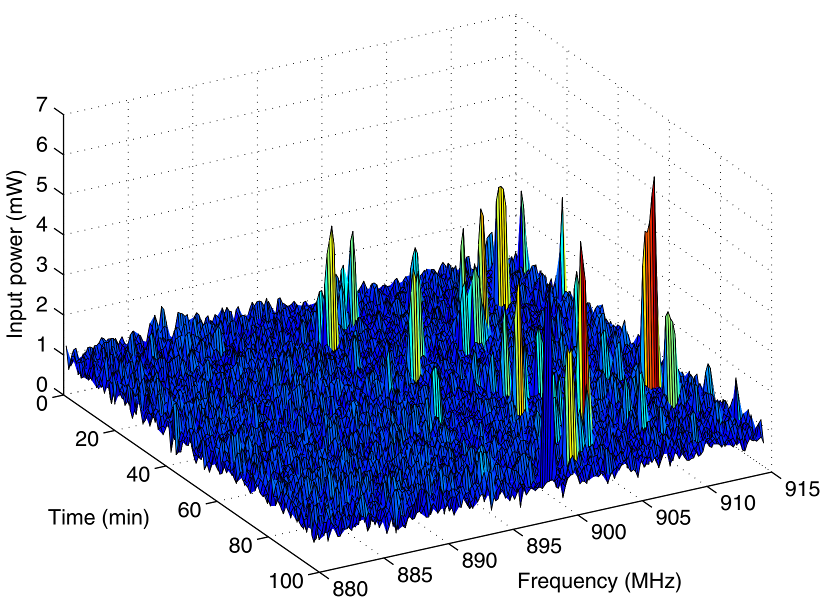

Figure 2.2 Example measurements of ambient RF energy at different time instants and frequencies in the GSM band from 880 to 915 MHz.

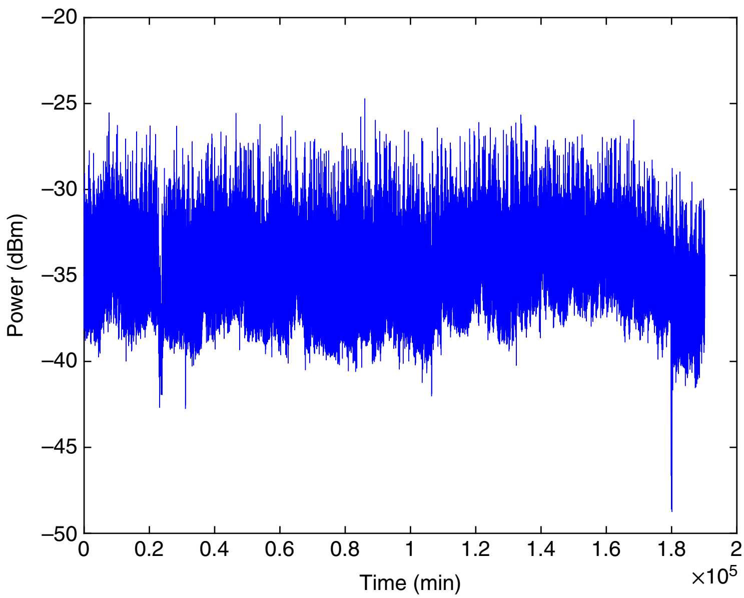

Figure 2.3 Time series of measured power in the 3G band from 1805 to 1880 MHz in the UK.

the 3G downlink from 1805 to 1880 MHz for four months in the UK. There are certain patterns embedded in the data that can be extracted.

Using these measurements and time series analysis methods, the relationship between the available ambient power and the time variable can be modeled. For example, machine learning algorithms can be used. The linear regression method states that the available power can be modeled as

$$\hat{E}(t) = \sum_{i=1}^{I} a_i E_i(t) + a_0 \tag{2.8}$$

where $a_1, \cdots, a_I$ are the parameters to be obtained via training, a_0 represents some random error or disturbance, and $E_i(t)$ are the features used. For polynomial regression, the available power can be predicted as

$$\hat{E}(t) = \sum_{i=1}^{I} a_i [E(t)]^i + a_0 \tag{2.9}$$

to a power of order I. There are other machine learning algorithms, such as support vector regression and random forest. All of them split the data into two parts, one part for training to obtain the optimal parameters and the other part for testing to calculate the prediction error. Define the normalized root mean squared error (NRMSE) as $NRMSE = \frac{\sqrt{\frac{1}{I}\sum_{t=1}^{I}(E(t)-\hat{E}(t))^2}}{\frac{1}{I}\sum_{i=1}^{I}E(t)}$. Figure 2.4 compares the prediction errors of different machine learning algorithms. In this case, the power measurements at different minutes are combined into hours and the combined hourly data are used to predict the RF energy in the next hours. One sees that the random forest algorithm has the highest

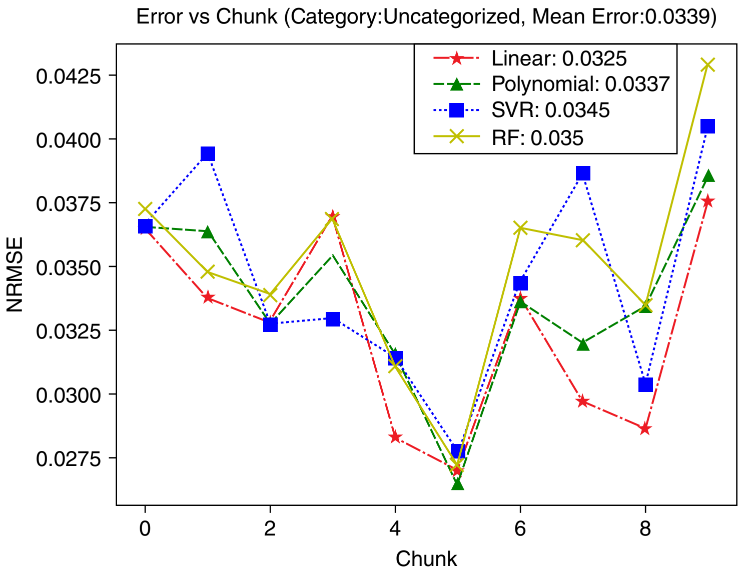

Figure 2.4 Comparison of prediction errors for different machine learning algorithms.

error, while the linear regression has the lowest error, in most cases. The average error is 0.0339, or about 3% error.

The predicted energy can be used to control the wireless device so that it knows when it should start to harvest the energy, as most energy harvesters have an activation energy below which they cannot operate and hence it is only meaningful to harvest energy above the activation level. Thus, there may be two types of errors. If the predicted energy is too high but the actual energy is below the activation level, the energy harvester will start but harvest no energy. Hence, it will waste existing energy. If the predicted energy is too low but the actual energy is above the activation level, the energy harvester will miss an energy opportunity. Figure 2.5 describes this situation, where over-estimation leads to wasted existing energy while under-estimation leads to missed energy. The error rate is 0.108 so that the total efficiency using linear regression is around 89.2%.

In addition to regression methods, the wavelets method can also be used to model the available ambient RF energy (Chen and Oh 2016). For example, the Daubechies D-2n wavelet can be used. For a time series $\mathbf{E}$ of length N, the level 1 Daubechies D-2n transform is given by

$$\mathbf{E} \rightarrow [\mathbf{m}^{(1)}|\mathbf{k}^{(1)}] \tag{2.10}$$

where $\mathbf{E} = [E(1)\ E(2)\ \cdots E(N)]$ is the time series, $\mathbf{m}^{(1)} = [m_1^{(1)}\ m_2^{(1)}\ \cdots m_{N/2}^{(1)}]$ is the first trend sub-signal whose ith element is given by $m_i^{(1)} = \mathbf{E} \cdot \mathbf{V}_\mathbf{i}^{(1)}$, $\mathbf{k}^{(1)} = [k_1^{(1)}\ k_2^{(1)}\ \cdots k_{N/2}^{(1)}]$ is the first fluctuation sub-signal whose jth element is given by $k_j^{(1)} = \mathbf{E} \cdot \mathbf{U}_\mathbf{j}^{(1)}$, $\mathbf{V}_\mathbf{i}^{(1)}$ is the level 1 scaling signal and $\mathbf{U}_\mathbf{j}^{(1)}$ is the level 1 wavelet that will be explained later. In practice, multiple levels are often used in order to obtain as many details about the time series as possible. Thus, $\mathbf{m}^{(1)}$ can be used as if it were the signal to obtain level 2 decomposition as

$$\mathbf{m}^{(1)} \rightarrow [\mathbf{m}^{(2)}|\mathbf{k}^{(2)}] \tag{2.11}$$

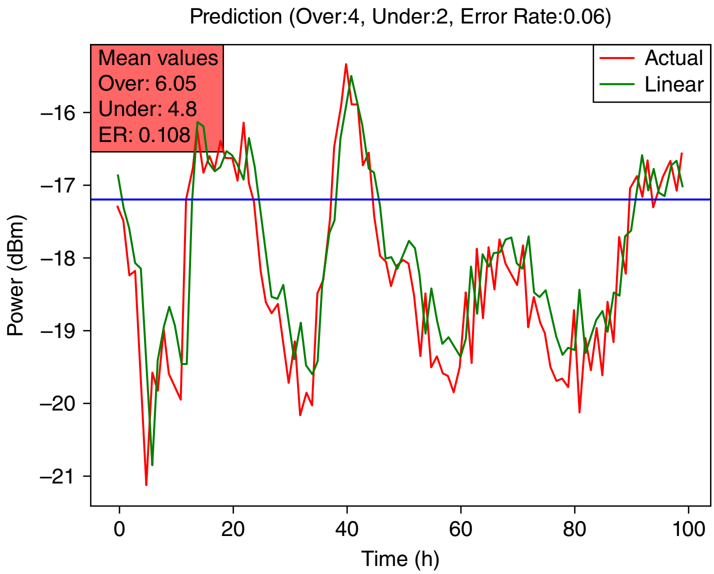

Figure 2.5 Effect of prediction error on wasted and missed energy using linear regression.

where $\mathbf{m}^{(2)}$ is the level 2 trend sub-signal (or low-frequency component) and $\mathbf{k}^{(2)}$ is the level 2 fluctuation sub-signal (or high-frequency component). They are defined in a similar way to $\mathbf{m}^{(1)}$ and $\mathbf{k}^{(1)}$, except that their lengths are $N/4$ now. Thus, one has

$$\mathbf{E} \rightarrow [\mathbf{m}^{(2)} | \mathbf{k}^{(2)} | \mathbf{k}^{(1)}]. \tag{2.12}$$

This process can continue until L levels are used. A level selection at this point is necessary to decide how many high-frequency components should be included to reconstruct the signal with the low-frequency component. Once this is decided, if two levels are selected, the reconstructed signal would be

$$\hat{\mathbf{E}} = \sum_{i=1}^{N/4} m_i^{(2)} \mathbf{V}_\mathbf{i}^{(2)} + \sum_{j=1}^{N/4} k_j^{(2)} \mathbf{U}_\mathbf{j}^{(2)} + \sum_{j=1}^{N/2} k_j^{(1)} \mathbf{U}_\mathbf{j}^{(1)} \tag{2.13}$$

and so on. There will be some difference between the original signal and the reconstructed signal. The choice of levels actually determines the amount of this difference. An important observation here is that, using these reconstruction equations, one can have an analytical relationship between the power measurement and the time. Thus, they provide a statistical model between the measured energy and the time.

The scaling signal and the wavelet are explained as follows. Specifically, one has $\mathbf{V}_\mathbf{i}^{(\mathbf{l})} = \sum_{k=1}^{2n} c_k V_{2i-2+k}^{(l-1)}$ and $\mathbf{U}_\mathbf{j}^{(\mathbf{l})} = \sum_{k=1}^{2n} d_k V_{2j-2+k}^{(l-1)}$, where $l = 1, 2, \cdots, L$ so that they can be iteratively derived with the initial conditions being the natural basis of V_i^0 whose ith element is 1 and all the other elements are zero, and c_k and d_k are the scaling and wavelet coefficients, respectively, and are constants that are predefined. Figure 2.6 compares the measured energy and the predicted energy using the Daubechies D-2n wavelet with vanishing moments $n = 10$. One can see that the predicted value can track the actual measurement very well. Other wavelets methods can also be used to model or predict the ambient RF energy.

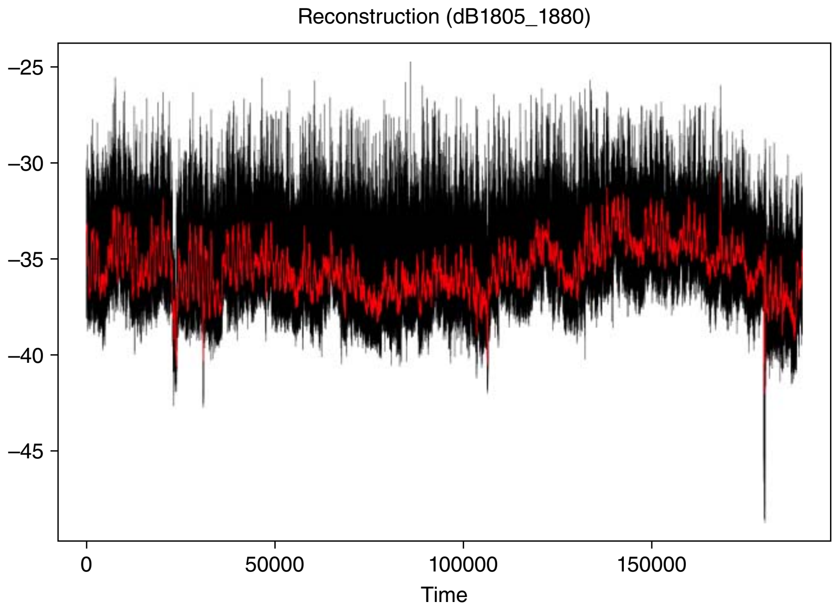

Figure 2.6 Comparison of predicted and measured power using the wavelets method for the band from 1805 to 1880 MHz in the UK (black outside represents measured power and light grey inside represents predicted power).

2.4 Summary

In this chapter, we have discussed different sources of energy available for harvesting to be used in wireless communications systems. This is the start of all energy harvesting wireless communications systems.

First, it has been shown that different sources have different characteristics and hence they can only be used for certain applications. For example, for mobile applications, solar energy may not be convenient due to the bulky size of a solar panel. However, for fixed nodes, such as a wireless sensor network access point, solar energy may be a good choice by providing adequate energy. On the other hand, RF energy may be convenient for radio communications systems due to its excellent integration with the RF circuits. However, it may not provide enough energy for operations.

Secondly, different types of energy are generated based on different principles. Some of them are green and renewable and hence they can be used for green communications. Others may not be green or renewable and are only used for convenience. It is important to consider the different amount of energy available from different sources so that the right source can be chosen for the considered application.

Thirdly, in many cases, the energy source is not controllable but predictable due to certain patterns or behaviors. The prediction models of the energy sources are useful in offline system planning or online real-time adaptation. Different methods can be used to model the available energy at the source. Since the measured energy is a time series, many time series analysis methods, such as regression and wavelets, can be used.

This chapter has discussed the energy source. In the next chapter, we will discuss the energy harvester, which acts as a transducer between different types of sources and electricity. It is also an interface between the natural environment and the communication circuit in the wireless device.