A Unified Stochastic Model for Energy Management in Solar-Powered Embedded Systems

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Abstract—Energy harvesting from environments such as solar energy are promising solutions to tackle energy sustainability in embedded systems. However, uncertainties in energy availability, non-ideal characteristics of harvesting circuits, energy storage (battery or supercapacitor), and application demand dynamics add more complexity in the system. We present a unified model based on discrete-time Finite State Markov Chain to capture the dynamicity and variations in both the energy supply from solar irradiance and the energy demand from the application. In this paper, we exploit the temporal and spatial characteristics of solar energy and propose a deterministic profile with stochastic process to reflect the fluctuation due to unexpected weather condition. Optimal policy to maximize expected total QoS is derived from the presented model using a probabilistic dynamic programming approach. Compared to a state-of-the-art deterministic energy management framework, our proposed approach outperforms in term of QoS and energy sustainability (with less shutdown time) of the system.

I. INTRODUCTION

To achieve energy sustainability in embedded systems, energy harvesting technology is emerging as a promising solution. However, design and operation of such systems have faced various challenges. Renewable energy sources such as solar energy often exhibit both temporal and spatial variations, which cause uncertainty in energy availability. Furthermore, an energy harvesting system requires dedicated components including harvesters (e.g., solar panel), MPPT circuits, and energy storage (supercapacitor or rechargeable battery). Energy harvesting/storage management schemes need to account for energy efficiency and the significant loss in energy harvesting storage and circuitry [10]. On the other hand, there is also variation in energy consumption (or load) due to the unpredictable behavior of physical phenomenon applications are monitoring or interacting with. For example, in smart camera systems or sensor platforms for monitoring smart spaces, energy management tools should account for more computation and data processing/transfer in case of event processing (vs. monitoring). In this paper, we present a unified model to enable the orchestration and tight integration between energy harvesting/storage management and energy consumption management in solar-powered systems.

The proposed unified model is based on discrete-time Finite State Markov Chain and captures the dynamicity and variations in both the energy supply from solar irradiance and the energy demand from the applications. System states enclose the energy harvesting rate (Energy Harvesting process), the energy status of the system (Energy Storage process), and the energy consumption required to meet the current application QoS (Application process). In Energy Harvesting process, we consider patterns in solar energy and propose a model based on a deterministic profile integrated with a stochastic process to characterize the energy harvesting rate in the system. The model is a multi-layer parameterized Markovian model capturing the dynamics of solar energy behavior due to weather changes. In the Energy Storage process, we consider the non-linear leakage in the supercapacitor as well as the varying efficiency of DC-DC converters. For Application process, we determine various states of application in response to physical phenomenon (e.g., event monitoring vs. event processing), the transition probabilities among states, and model the energy consumption in system depending on the current state and the desired application QoS. Our proposed unified model enables to fuse and capture the variations in solar energy and application QoS together with complex characteristics of energy harvesting circuitry and storage.

Based on our proposed stochastic model, we develop a dynamic-programming-based algorithm to find an optimal policy in order to stochastically maximize expected performance, measured by reward associated with application QoS levels and states. We apply our model and optimal policy on a solar-powered smart camera system (cameras with built-in embedded processors for image processing). Compared to deterministic methods [12] using prediction of solar energy, our proposed method quickly responds to variation in energy availability more effectively and provides a higher QoS with significantly shorter shutdown time.

II. RELATED WORK

There are several related works in harvesting-aware communication systems, wireless sensor networks, and body area networks [1-3]. In these work, the harvesting process is modeled as a fully random process or a stationary Markov Chain for a short period of time. Furthermore, the model of the energy storage and underlying hardware components are too simplistic or simply neglected. There are approaches for energy management in harvesting systems that do not rely on stochastic models but prediction of harvesting in the future [16]. Deterministic approaches [4-8, 12] that are based on long-term harvesting prediction will suffer from misplanning because of prediction inaccuracy, either resulting in system shutdown or energy harvesting under-utilization. Instantaneous approaches which rely on near future prediction

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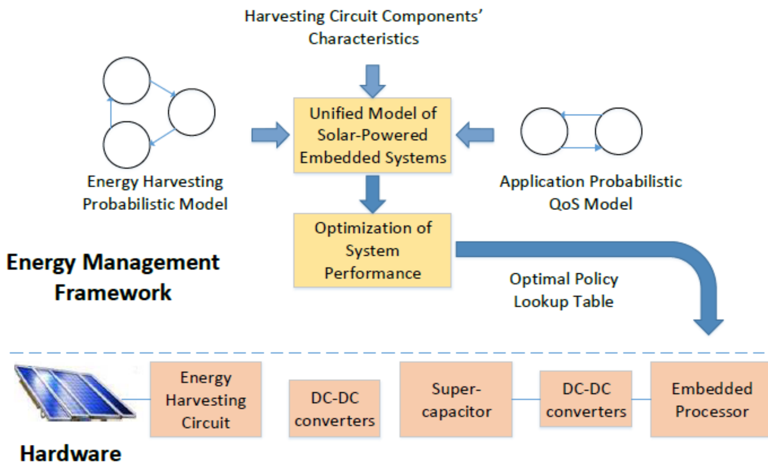


Fig. 1. Overview of Energy Management Framework for Solar-Powered Supercapacitor-based Embedded Systems

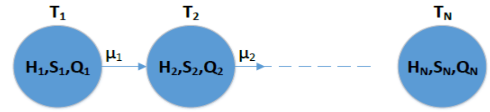


Fig. 2. System State Evolution in a harvesting period

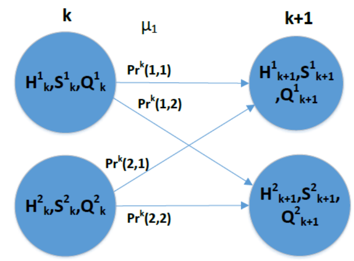


Fig. 3. An example of non-stationary Markov Chain with System States and Transition Edges

[9] often involve optimization techniques at runtime with high overhead [10]. Such runtime techniques might not obtain optimal result due to its local optimization nature.

III. Overview of Proposed Energy Management Framework

Fig. 1 shows the overview of a solar-powered embedded system with proposed energy management middleware framework which is a software component running on top of the processor. As illustrated in the lower half of Fig. 1, the embedded system is powered by solar energy harvested through a solar panel. An energy harvesting circuit controls the operation of the solar panel and maximizes its efficiency by setting the optimal solar panel operating voltage according to MPPT methods [13]. The generated energy is stored in a supercapacitor and its terminal voltage varies according to its energy storage status. To avoid degrading solar panel efficiency, a DC-DC converter isolates solar panel from the supercapacitor. Similarly, another DC-DC converter is used to match supercapacitor voltage with the required operating voltage of the embedded system's processor. Since terminal voltage of the supercapacitor changes according to its energy storage status, the efficiency of DC-DC converters can vary widely.

The upper half of Fig. 1 shows the main components of our proposed energy management framework. A unified model for solar-powered embedded systems is built from a probabilistic model for energy harvesting, a probabilistic model for application state, and a model for the harvesting circuit and energy storage. The probabilistic models for energy harvesting and application state capture the variations of physical environment which the embedded system interacts with through a set of Finite State Markov Chains, enabling a complete cyber physical model and closed loop control. It also models the non-ideal behaviors of hardware components such as DC-DC converters and supercapacitor.

The proposed system performance optimization algorithm is based on Markov Decision Process. The goal is to maximize the expected performance in the next harvesting period (which is a day for solar-powered systems) given the dynamics of harvesting, application, and characteristics of circuit and energy storage. The system performs actions subject to available QoS levels and application state. Each completed action earns a reward, representing system performance. The output of the optimization algorithm is an optimal policy lookup table which guides the system to take the right action once the actual harvesting state, application state, and energy storage state are detected at runtime. As opposed to deterministic approaches [12], our framework does not assume that energy harvesting availability or application state is known a priori. The best action is selected at every control time unit to quickly adapt to variations in harvesting and application state. The optimal policy guarantees to maximize the expected total system performance in the long run.

IV. A Unified Model for Solar-Powered Embedded Systems

The proposed model is a Finite State Markov Chain defining system states and transition probabilities among states. Each system state contains information about the current states of harvesting process, application process, and energy storage. Formally, we define a system state as a tri-tuple $<H_k,S_k,Q_k>$ where H_k is the harvesting state, S_k is the energy storage state of supercapacitor, and Q_k is the application state at time k. Harvesting period is divided into N equal time epochs. The duration of each time epoch (T) is small enough for the system state to be stable. Therefore, it depends on the time granularity of harvesting process, application process, and energy storage which altogether determine how often the system should react. After each duration T, the system may evolve in to a new system state and a new action must be taken to respond to system state changes. System state evolves over time as illustrated in Fig. 2.

The transition probability from state $<H_k,S_k,Q_k>$ to $<H_{k+1},S_{k+1},Q_{k+1}>$ is

$$Pr_{<H_k,S_k,Q_k><H_{k+1},S_{k+1},Q_{k+1}>}(\mu_k) = \tag{1}$$
$$Pr\{S_{k+1} \mid H_k, S_k, Q_k, \mu_k\} \times Pr\{H_{k+1} \mid H_k\} \times Pr\{Q_{k+1} \mid Q_k\}$$

The harvesting process and the application process evolve independently. However, the evolution of energy storage process depends not only on the other two processes but also on the energy storage characteristics, converter efficiency, and the action taken at each time unit *T*. It is reflected in the transition probabilities. This model is a non-homogeneous Markov Chain as the state transition probability is a function of time index *k*. Fig. 3 shows an example of system states at time *k* moving to other states at time *k+1* with different probabilities, assuming there are two possible system states.

A. Harvesting Process

The solar irradiance profile is composed of a deterministic profile with fluctuations due to weather as illustrated in Fig. 4. The deterministic profile is based on astronomical model (for e.g., [14]) considering solar panel efficiency, orientation, longitude, latitude, air/pollution attenuation level, daily shadow effects from static objects such as building, trees, and under typical weather condition and temperature. This deterministic profile is represented as $\{I_1, I_2, \ldots I_N\}$ where I_k is the typical solar irradiance at time index *k*.

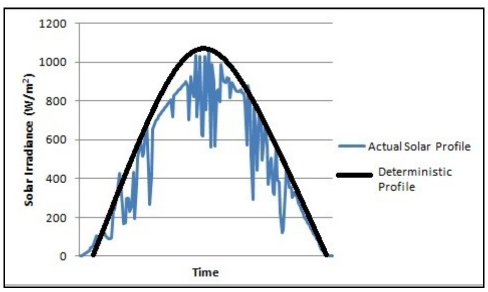


Fig. 4. Solar Profile combined of a deterministic curve and fluctuations

The dynamic fluctuations in the harvesting profile is captured by a weather process which models weather condition such as sunny, cloudy, and rainy. This weather process is denoted as $\{W_k\}$. Each weather state is associated with an attenuation level ($A(W_k)$). The Markov Chain model for the weather process (see Fig. 5) is non-stationary as the transition probability $Pr^k\{W_{k+1} \mid W_k\}$ can change over time. It is possible to have multiple such Markov Chains, e.g., one for normal days and one for rainy days. Selection of the right Markov Chain on a given day is based on weather forecast or another stochastic process. These Markov Chains for the weather process can be trained and built from the harvesting history at a location and be updated each day [1].

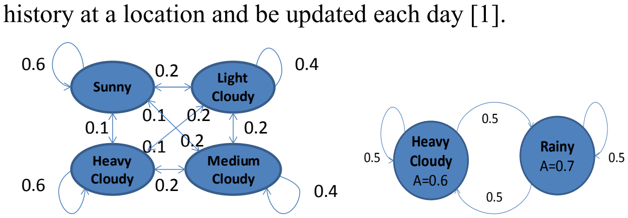


Fig. 5. Weather Process Markov Chains

Given a weather state at time *k*, the harvesting irradiance is computed as

$$H_k = I_k \times (1 - A(W_k)) \tag{2}$$

Given the solar irradiance H_k, the output voltage and current of the solar panel at its maximum power point can be obtained either by profiling the solar panel operation or through an analytical model [14].

B. Application and Action Processes

Application state changes in response to physical world. For example, states of a smart camera system can be regular monitoring vs. event processing. The actions (tasks to perform) are different in each state. For example, low resolution images can be accepted in monitoring state while higher resolution images are more desirable after an event such as motion is detected. In event processing state, the application may need to perform more computation such as face detection or object contour detection. The QoS levels and energy consumption in each mode are therefore different.

The application process has a stochastic nature because it is hard to predict the arrival time and duration of events. Therefore, we use a Finite State Markov Chain model to capture the application process which is denoted as $\{Q_k\}$. This model captures the correlation over time that is typical of the physical event dynamics. Fig. 6 shows an example of such model where the system has two states: event monitoring and event processing. The transition edges from one state to another state are associated with probabilities of event occurrence leading to application state changes.

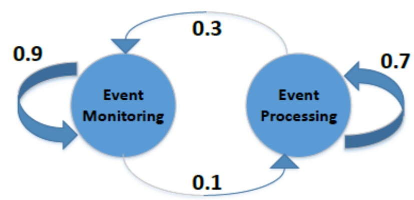


Fig. 6. Application Process Markov Chain

In each application state *i*, we assume the system have a list of available *QoS* levels $\{QoS_{i1}, QoS_{i2}, \ldots QoS_{iM(i)}\}$. Each *QoS* level represents a different set of actions to take in response to physical environment in the current state *i*. Furthermore, each QoS_{ij} level is associated with a required operating voltage and current $V_{load}(QoS_{ij})$, $I_{load}(QoS_{ij})$ of the embedded processor, and a reward $R(QoS_{ij})$. We assume higher QoS level has higher energy consumption and higher reward as it improves the application accuracy or quality.

Action process is denoted as $\{\mu_k\}$ where $\mu_k \in 0 \cup \{QoS_{i1}, \ldots QoS_{iM}\}$ given $Q_k = i$, where *0* represent the possibility of shutdown due to energy outage or as a controller decision. Action is decided by the embedded processor at each time epoch. Action can be any of the QoS levels in the current application state, provided that the system has sufficient energy storage to supply the action's energy demand. By completing an action, the system gains a reward associated with that action.

C. Energy Storage Process

In case of battery-less system, the energy storage is a (an array of) supercapacitor(s). Given the nominal capacity C, the maximum energy that can be stored in a supercapacitor is

$$E_{\max} = \frac{1}{2} C V_{\max}^{\ 2} \quad (3)$$

where V_{max} is the maximum rating voltage of the supercapacitor. We choose to represent energy storage process of the supercapacitor by its voltage as it has direct relation with its energy as shown in (3). Let S_k be the voltage of the supercapacitor at time index k. S_k is updated in each epoch according to its current value, harvesting process, application process, and actions taken. In addition, S_k is affected by the supercapacitor leakage and converter losses as explained below.

1) Supercapacitor leakage: The advantages of supercapacitors as compared to batteries are higher power density and no aging effect. However, supercapacitors have a non-ideal behavior which is leakage that grows exponentially with its voltage. The leakage of the supercapacitor can be approximated using empirical constants α and β [11].

$$P_{leakage} = \alpha e^{\beta V} \quad (4)$$

2) DC-DC converter efficiency: Because the voltage of the supercapacitor varies widely according to its energy, the circuit needs DC-DC converters to match the supercapacitor voltage with the required output voltage and current. These converters for charging and discharging could work in either buck mode or boost mode, i.e. reducing or increasing the voltage output of the supercapacitor to match with an optimal voltage for MPPT of the solar panel or a required operating voltage of the embedded processor.

$$g_{charge}(H_k,S_k) = f_{charge}(S_k,\ V_{solar}(H_k),\ I_{solar}(H_k)) \quad (5)$$

$$g_{discharge}(S_k,\mu_k) = f_{discharge}(S_k, V_{load}(\mu_k),\ I_{load}(\mu_k)) \quad (6)$$

The power loss due to a converter is a function of input voltage, output voltage, and output current. In case of charging, it is a function of S_k, V_{solar}, and I_{solar} as in (5). In case of discharging, the power loss is a function of S_k, V_{load} and I_{load} as in (6). The loss due to a converter is significant, ranging from 20% to 80% [10]. The larger the gap between input and output voltage of a converter, the higher the loss is.

3) Energy storage update and quantization: Formally, the next state S_{k+1} is computed according to (7-9) below.

$$P_k = V_{solar}(H_k) \times I_{solar}(H_k) - V_{load}(\mu_k) \times I_{load}(\mu_k) - P_{leakage}(S_k) \quad (7)$$
$$- g_{charge}(H_k, S_k) - g_{discharge}(S_k, \mu_k)$$

$$E_{k+1} = \frac{1}{2} C S_k^{\ 2} + P_k T \quad (8)$$

$$S_{k+1} = \sqrt{\frac{2E_{k+1}}{C}} \quad (9)$$

To evaluate exactly the next system state and transition probability, there is a large amount of information to keep track of. Therefore we propose to quantize the energy storage state of the supercapacitor, i.e. its voltage to enable a Finite-State Markov Chain representation.

The supercapacitor voltage range $[0..V_{max}]$ is partitioned into K non-overlapping intervals using K-1 thresholds $\{0, v_1, v_2, .., v_{K-1}, V_{max}\}$. The voltage range $[v_i,v_{i+1})$ is denoted as *intv(i)*. Steady state probability of energy storage state i is

$$\pi_i = \int_{\tau_i}^{\tau_{i+1}} f(s)ds \quad (10)$$

where $f(s)$ is the probability density function of supercapacitor voltage. The transition probability that system is moving from state $<H_k,E_k,Q_k>$ at time k to state $<H_{k+1},E_{k+1},Q_{k+1}>$ at time $k+1$, given the action μ_k is in (11). Numerical computation of this double integral is time consuming. Therefore, we use Monte Carlo integration method to obtain the state transition probability matrix.

$$Pr_{<H_k,S_k,Q_k><H_{k+1},S_{k+1},Q_{k+1}>}(\mu_k) = Pr\{H_{k+1} \mid H_k\} \times Pr\{Q_{k+1} \mid Q_k\}$$
$$\times \frac{\int_{\mathrm{int}v(H_k)} f_S(s) \int_{\mathrm{int}v(H_{k+1})} f_S(S_{k+1} \mid H_k, S_k, Q_k, \mu_k) ds ds}{\int_{\mathrm{int}v(H_k)} f_s(s)ds} \quad (11)$$

V. Optimal Policy to Maximize Expected System Performance

In the previous section, we presented the unified Markov Chain model for solar-powered embedded systems. In this section, we discuss an optimization framework based on dynamic programming to maximize expected rewards.

Each time epoch, the system needs to make a decision of which action to take. The actions are possible QoS levels in the current application state. The selected action dictates the embedded processor to perform certain tasks. The cost is the corresponding energy consumption of the action that changes the energy storage state of the system. In return, the system gains an accumulated reward over the harvesting period. Since a current action can change the energy storage, a smart decision making process is required to avoid energy outage. The goal of the optimization is to maximize the expected reward associated with actions taken in each time epoch in the next harvesting period N.

$$Maximize \sum_N E\{R(\mu_k)\} \quad (12)$$

A. Optimal Policy

The optimization problem can be solved using a back-ward probabilistic dynamic programming for finite horizon [15]. The result is a policy that maps a system state to an action that maximizes the expected total reward given all the possible variations in harvesting process or application process.

We denote $J_k(H_k, S_k, Q_k)$ as the maximum expected total reward from time slot k to N.

$$J_{N+1}(H_{N+1}, S_{N+1}, Q_{N+1}) = 0 \quad (13)$$

$$J_k(H_k, S_k, Q_k) = \max_\mu \{\mathrm{R}(\mu) + E(J_{k+1}(H_{k+1}, S_{k+1}, Q_{k+1}))\} \quad (14)$$

The optimal action that maximizes $J_k(H_k, S_k, Q_k)$ in (14) is saved in a table, called optimal policy look-up table. At run time, the system keeps track or detects the current system state and picks the right action using this optimal policy look-up table. As shutdown (μ_k =0) is undesirable in harvesting systems, we associate higher reward to actions the system can take and no reward if the energy storage is not sufficient to actuate any action. This inherently makes dynamic programming to choose actions that lead to minimal shutdown time. In addition, at the end of each day, the system needs to maintain a certain level of energy storage to start the system at the beginning of the next day when harvesting is low. Equation (13) encourages the dynamic programming to utilize all energy to optimize system performance. Instead, we modified (13) to associate some reward incentive π to system states whose S_N is greater or equal to the minimum energy storage at the end of a day, as shown in (15).

$$J_{N+1}(H_{N+1}, S_{N+1}, Q_{N+1}) = \pi \qquad (15)$$

The optimal policy lookup table is only needed to be computed once and it only needs updates when harvesting process or application process changes their states and transition probabilities. The overhead is therefore small. Furthermore, the optimal policy look-up table enables the system to react quickly to dynamic changes in harvesting and application processes at runtime, yet maximizes expected system performance in the long run.

VI. EXPERIMENTAL RESULTS

To demonstrate the effectiveness of our stochastic model and optimization framework, we implemented a simulator in Matlab to model the solar-powered embedded system. The experimental setup is described in section VI.A followed by our results in section VI.B.

A. Experiment Setup

We assume that the system has two supercapacitors with *400F* capacitance each, $V_{max}=5V$. In the Monte-Carlo integration (section IV.C.3), the voltage of the supercapacitor is quantized into *10* equal intervals. The empirical constants for supercapacitor leakage are $\alpha=1.26e\text{-}10$ and $\beta=10.43$ according to measurement in [11]. The parameters for DC-DC converters are obtained from [10] and from the datasheet of the corresponding buck-boost converters. The required voltage at the end of each day is set to be *3.5V*.

We assume that processor is similar to PXA270 with V_{dd} of *1.55V* and load current is set according to QoS level. We simulate a smart camera application which captures images by a number of frames per second (set by QoS level). For each frame, it performs image processing tasks such as background subtraction (in event monitoring state) and object contour detection (in event processing state).

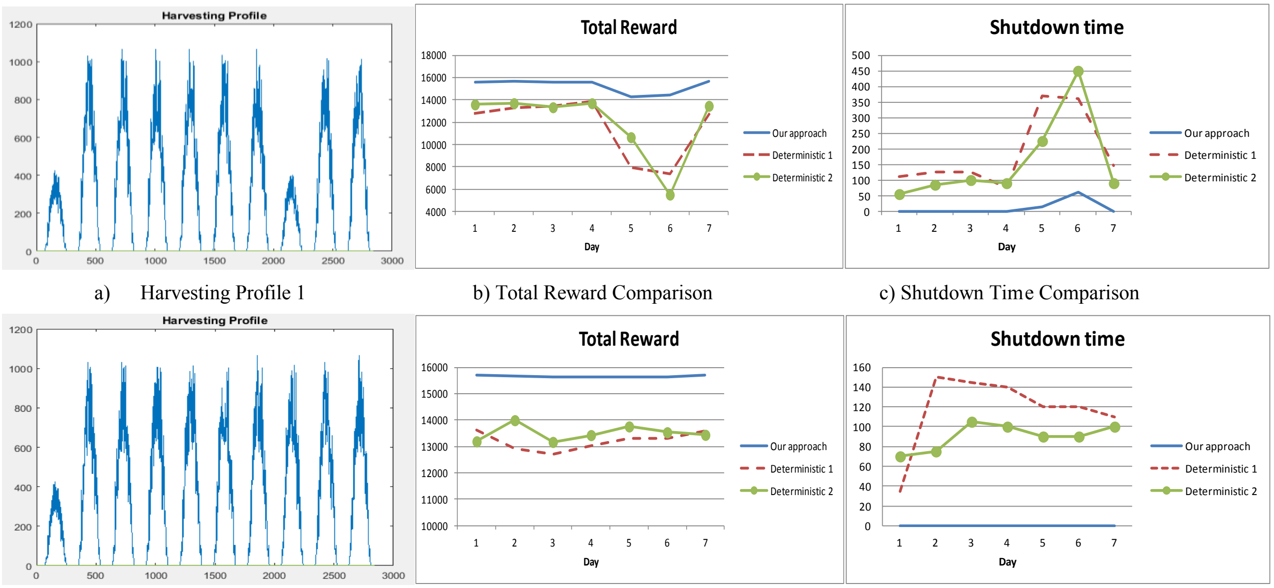
We proposed a general model of harvesting process in section IV.A. For the experiments, we assume to have a harvesting probabilistic model as shown in Fig. 5. Fig. 5a is Markov Chain for weather process during a normal day and Fig. 5b is Markov Chain for a rainy day. The attenuation in each state and the transition probabilities between weather states are denoted in each state and on each edge. This weather process model can be obtained from training the parameters with real data. From this model and a deterministic profile in Fig. 4, we randomly generate harvesting profiles as shown in Fig. 7a and Fig. 7d.

Since there is no direct related work for comparison, we adapt a related work in energy management for supercapacitor-based energy harvesting systems [12]. This work aims to maximize duty cycling on a harvesting sensor node. We adapt it to maximize total rewards of the system. It relies on energy harvesting prediction to plan activities for the next harvesting period. In order to consider DC-DC converter efficiency, it quantizes the voltage of the supercapacitor into *L* intervals (*L=100* in our experiments). A dynamic programming is then employed to plan duty cycling (QoS and reward in our adaptation) for the next harvesting period, considering the predicted energy harvesting, supercapacitor voltage, and DC-DC converter efficiency in each slot (of *30* minutes). It however considers single application state (a special case of our general application process model in section IV.B). We call this Deterministic approach.

We assume the system actually has two application states. The two states are event monitoring (state 1) and event processing (state 2). The Markov Chain model for the application process is shown in Fig. 6. The system has *7* QoS levels with corresponding current (in *mA*) *{51.765, 128.889, 242.609, 312, 422.222, 515.172, 596.774}* in event monitoring or state 1. In event processing state, the application executes more tasks and consumes *1.5* times the load current in state 1 at the same QoS level. The rewards for QoS levels are *{100, 110, 120, 130, 140, 150, 160}* in both states. Since the Deterministic approach is not aware of different stochastic states of the application process, we define two variations, Deterministic 1 and Deterministic 2. Deterministic 1 optimistically assumes the application is always in state 1 and therefore its plan is aggressive. Deterministic 2 assumes the system can be in state 2 at any time for safety and hence, the planning is less aggressive.The metrics used are total reward which reflects system performance and shutdown time which reflects system sustainability. Shutdown time is the duration during which the supercapacitor voltage falls below the minimum operating voltage (*2.2V*). During the shutdown time, the processor is not powered but the supercapacitor is still charged by harvesting power if any.

B. Results

Fig. 7 shows the result running our approach and two Deterministic approach variations for *7* days according to the harvesting profiles in Fig. 7a and Fig. 7d (the first 3 days are for prediction for Deterministic Approach). The second harvesting profile is a series of normal days while the first harvesting profile contains one rainy day with significant less energy harvesting potential. Our approach has 28% improvement in total rewards on average compared to Deterministic 1, and 27% improvement compared to Deterministic 2. Because Deterministic 2 assumes a less



a) Harvesting Profile 1 b) Total Reward Comparison c) Shutdown Time Comparison

d) Harvesting Profile 2 e) Total Reward Comparison f) Shutdown Time Comparison

Fig. 7. Comparison with Deterministic Approach for a week, multiple application states

aggressive planning, we would expect it to have lower total reward than Deterministic 1. Counter to intuition, Deterministic 2 has higher total rewards, thanks to its less aggressive planning which reduces the effect of prediction inaccuracy, leading to less shutdown time. The system under Deterministic 2 therefore provides QoS for a longer time than Deterministic 1 and attains higher total rewards.

Our approach outperforms both Deterministic approach variations in both defined metrics, higher total reward and lower or no shutdown time. Under rainy condition, it is unavoidable that the supercapacitor runs out of energy, our approach shuts down for 15 minutes at the end of the rainy day and another 60 minutes at the beginning of the next day before the supercapacitor recovers above the minimum operating voltage.

VII. CONCLUSION

In this work, we propose a unified stochastic model based on Finite State Markov Chain that captures both energy supply and energy demand variations and the complexity of harvesting system components. This unified model enables a complete cyber physical model and closed loop control for solar-powered supercapacitor-based systems. The proposed optimization framework aims to maximize the expected performance of the systems. Compared to a state-of-the-art deterministic energy management framework, our proposed approach outperforms in term of system performance (QoS reward) and system sustainability (with less shutdown time).

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