Lifespan Extension of an IoT System with a Fixed Lithium Battery

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SUMMARY In an internet of things (IoT) system using an energy harvesting device and a secondary (2nd) battery, regardless of the age of the 2nd battery, the power management shortens the lifespan of the entire system. In this paper, we propose a scheme that extends the lifetime of the energy harvesting-based IoT system equipped with a Lithium 2nd battery. The proposed scheme includes several policies of using a supercapacitor as a primary energy storage, limiting the charging level according to the predicted harvesting energy, swinging the energy level around the minimum stress state of charge (SOC) level, and delaying the charge start time. Experiments with natural solar energy measurements based on a battery aging approximation model show that the proposed method can extend the operation lifetime of an existing IoT system from less than one and a half year to more than four years.

key words: battery aging, energy harvesting, hybrid energy storage, battery lifetime, energy-aware scheduling

1. Introduction

PAPER

Recently, with the rapid increase in the demand for energy harvesting-based internet of things (IoT) devices, the importance of research on power management for improving the performance of related products and extending the operating time has been increasing. Energy is harvested semi-permanently from external sources (e.g. sun, wind, heat, etc.), yet its supply is irregular over time. On the other hand, some harvesting energy based IoT applications such as wearable devices that require continuous operation (e.g., human health monitoring), or wireless sensor network devices (e.g., safety monitoring of natural disasters and industrial structures) require a continuous power supply. Therefore, the harvested energy should be stored in energystorage devices such as Li-ion secondary (2nd) batteries for later use. Accordingly, the existing energy harvesting-based power management schemes reduce energy waste through a dynamic voltage and frequency system (DVFS)-based task scheduling [1] or improve the quality of service (QoS) in a wireless sensor networking (WSN) environment [2] by reflecting some of the characteristics of 2nd batteries.

However, although existing power management schemes have been designed to extend the stable operation of the IoT system, the aging characteristics of the 2nd battery have not been thoroughly considered. In fact, the

Manuscript publicized September 15, 2020.

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DOI: 10.1587/transinf.2019EDP7220

lithium 2nd battery (which is widely used as the main energy storage in various wireless applications due to its low price for capacity and long-term energy storage efficiency) has a significantly rapid aging rate depending on the charging/discharging methods [3]. Furthermore, the rapid aging of the 2nd battery makes it difficult to commercialize the wearable IoT products due to the high maintenance cost of battery replacement. For IoT devices in sensor network application areas that have a large number of distributed nodes, replacing aged batteries is also not feasible.

In this paper, we propose a low-cost scheme to extend the lifetime of 2nd batteries for energy-storage devices operating on an IoT platform that uses a solar energy-based energy harvesting technique. The proposed energy storage method has an efficient charging/discharging sequence policy based on a hybrid-type energy-storage system that takes into account the characteristic differences between 2nd batteries and supercapacitors. Using an existing mathematical aging model, the proposed charging/discharging policy includes a charging/discharging level adjustment method based on the predicted harvesting energy to reduce the effect of cycle aging. It also includes a charging start time adjustment method to reduce the effect of calendar aging. The proposed method was evaluated through comparative experiments using the measured solar energy data of the national renewable energy laboratory (NREL) profile data [4]. The results confirmed that the proposed scheme more effectively extends the lifetime of the IoT system compared to the existing charging/discharging policy, which does not consider 2nd battery aging.

Section 2 discusses the related studies, and Sect. 3 presents the proposed operation lifetime extension scheme of the energy harvesting-based IoT system. Section 4 compares the experimental results for various charging/discharging policies, and Sect. 5 concludes the paper.

2. Related Works

Shaobo Liu et al. [1] proposed an efficient energy harvesting-based power management scheme for real-time systems. This scheme not only reduces the energy waste by applying DVFS to the existing lazy scheduling scheme [5] which is based on the predicted energy harvesting amount, it also improves the consistent quality of task executions. However, since this method does not consider the aging of the energy storage devices caused by charging/discharging operations, the lifetime of the system can be reduced.

Manuscript received August 6, 2019.

Manuscript revised April 20, 2020.

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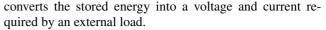
A method has been proposed in which an expensive supercapacitor which also has very high endurance is used instead of the 2nd battery to overcome the aging problem [6]. With the tradeoff between cost and endurance, some researchers have attempted to design a system that employs both the 2nd battery and the supercapacitor [7]. Recently, an adaptive quality recognition energy management scheme considering the aging characteristics of the 2nd battery in a WSN environment was studied [2]. This scheme proposed an energy storage method to improve the QoS of an application by considering both the rapid self-discharge characteristics of the supercapacitor as well as the aging characteristics of the 2nd battery in a solar powered embedded system environment. Although some of the aging characteristics of the 2nd battery are considered in this scheme, it uses a simple aging model of the battery and does not have an active method to extend the lifetime of the system.

In another study, a holistic aging model [8] was proposed that includes both the cyclic aging factor and calendar aging factor in order to more precisely analyze the aging factor and predict the lifetime of Li-ion 2nd batteries. In this aging model, the cyclic aging factor is modeled based on the cycle depth, mean state of charge (SOC), and current rate, and the calendar aging factor is modeled based on the temperature, voltage, and time.

In this paper, we propose a new energy management scheme with the holistic aging model to aggressively extend the lifetime of energy harvesting IoT systems that have both a supercapacitor and a 2nd battery.

3. Proposed Method

The proposed method has been designed to extend the lifetime of energy harvesting-based IoT systems that are powered by natural solar energy. Figure 1 shows the energy and control flow of an energy harvesting-based IoT system to which the proposed scheme was applied. The system control module selects an energy-storage device to be charged by considering the state of the energy-storage devices and solar energy supply devices. It also determines which energy-storage device will be discharged based on the state of the energy-storage devices and the system loads. The input solar energy passes through one of two regulators to convert into a voltage and current suitable for each energy storage device. The energy stored in the energy storage device is then supplied to the system through a converter that



The proposed scheme consists of several policies such as using a supercapacitor as a primary energy storage, limiting the charging level according to the predicted harvesting energy, swinging the energy level around to the minimum stress SOC level of 50% in the case of a lithium battery, and delaying the charge start time. Moreover, the proposed scheme predicts the energy state of the entire system by considering the supply condition of the harvested energy, the energy demands of the system, and the energy level of the energy-storage devices. Based on the predicted information, the proposed scheme aims to avoid undesirable behaviors such as frequent charging and discharging or reaching a high or low charging state, which can lead to the rapid aging of the 2nd battery.

3.1 Hybrid Energy Storage Charging and Discharging

To maximize the reduction of the usage of the 2nd battery, the proposed scheme charges to or discharges from the 2nd battery only if the supercapacitor has no extra charging space or no remaining energy.

Figure 2 shows the charging/discharging state diagram for the proposed hybrid energy-storage device. If sufficient energy remains in the supercapacitor, the system will operate in the supercapacitor only mode. That is, charging and discharging are performed using only the supercapacitor. When the energy in the supercapacitor has been totally consumed, then the 2nd battery is used as a power source. In the 2nd battery discharge mode, the energy in the 2nd battery is consumed while the supercapacitor is being charged if possible in the daytime. The supercapacitor only mode will be set again if the level of energy in the supercapacitor becomes above the threshold value (E_{Th}). The threshold value (E_{Th}) is a marginal value that can prevent frequent mode switching during sunrise. When the energy capacity of the supercapacitor is fully charged, the 2nd battery charge mode is set so that the harvesting energy is not wasted but stored in the 2nd battery. In this mode, tasks use the energy stored in the supercapacitor. Once the energy level of the 2nd battery goes above the target SOC charge level (SOC_{Level}), the supercapacitor only mode will be set again.

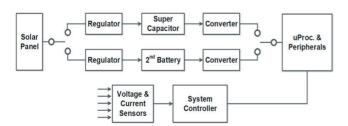


Fig. 1 Energy and control flow for an energy harvesting-based IoT system.

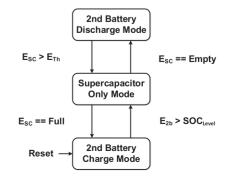


Fig. 2 State diagram for the proposed operating mode changes.

3.2 Energy-Harvesting Prediction for Minimum Swing Cycles

Factors affecting cyclic aging include the cycle depth (ΔDOD) , mean SOC, and current rate in the holistic aging model of the conventional Li-ion 2nd battery [8]. Considering these factors, it is important to maintain the mean SOC of the 2nd battery as close to 50% as possible to reduce the effect of cyclic aging. Thus, the proposed method adaptively adjusts the SOC level to enable charging/discharging of the 2nd battery at an SOC level of approximately 50%, based on the predicted total energy harvesting value per day. To determine the SOC level to be charged during the day time. the energy required for the night and the additional energy required for the next day are calculated if low harvesting energy due to inclement weather is predicted. A 10-tap running average (RA) filter is used to predict the average harvesting energy per day by considering the low computing performance of IoT devices. The seasonal differences also affect the target SOC level decision.

Equation (1) presents the formula used to predict the average harvesting energy per day (d), based on the harvesting energy for the previous 10 days.

$$E_H[d] = \frac{1}{10} \sum_{i=1}^{10} Solar E[d-i]$$
(1)

$$SOC_{Level} = 100 - (\alpha_1 \cdot E_H[d] + \beta_1) \tag{2}$$

The *SolarE* in Eq. (1) represents the total harvesting energy of each previous day. Equation (2) describes how the target SOC charge level is adaptively adjusted according to the predicted energy-harvesting value obtained via Eq. (1). SOC_{Level} is the target SOC charge level, and α_1 and β_1 are the scaling factor and offset value, respectively, which vary according to the location of the IoT device. The values of α_1 and β_1 in our experiments were determined based on the NREL profile data [4].

3.3 Energy-Harvesting Prediction for Delayed Charges

Calendar aging is affected by temperature, voltage, and time [8]. In order to reduce the factors contributing to the calendar aging of the 2nd battery, the voltage of the 2nd battery should be kept low if possible. More specifically, if the 2nd battery is charged early, the voltage of the 2nd battery remains high for a longer period of time, thereby accelerating the calendar aging process. We propose a scheme to delay the charging start time based on the predicted average harvesting energy per day to reduce the effect of calendar aging.

Figure 3 shows the entire flow chart consisting of daily prediction of harvested energy, decision on the charging time and level and updating charging flags. Figure 4 through 6 shows the detailed flow chart for each module. When the date changes according to the system clock, the total harvesting energy for the new day is predicted, as based on the total harvesting energy for the last day. The target charge

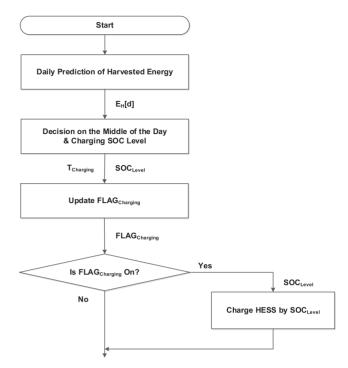


Fig.3 Flow chart for daily prediction of harvested energy, decision on the middle of the day and charging SOC level, updating flags and charge HESS.

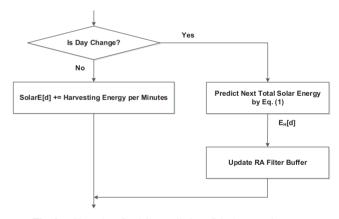


Fig. 4 Flow chart for daily prediction of the harvested energy.

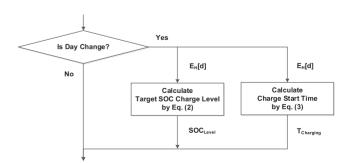


Fig.5 Flow chart for decision on the middle of the day and charging SOC level.

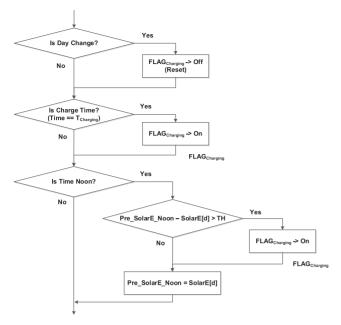


Fig. 6 Flow chart for updating charging flags.

level and the charge start time for the 2nd battery are then determined from the predicted total harvesting energy of a whole day in Eq. (1).

After energy harvesting begins, the cumulative harvesting energy is checked at the predefined time (midday in this case), as this equates to approximately half of the total time available for harvesting; if the cumulative harvesting energy until midday is less than the threshold value, then it is considered to be an extraordinary situation in which weather might result in an insufficient amount of harvested energy, and 2nd battery charging starts immediately. The threshold (TH) is determined by the difference between the cumulative harvest energy of a half day on winter solstice and that of the day before it because the difference is minimum. Equation (3) describes how the charging start time is adaptively adjusted according to the predicted total harvesting energy of a whole day via Eq. (1).

$$T_{Charaina} = \alpha_2 \cdot E_H[d] + \beta_2 \tag{3}$$

 $T_{Charging}$ represents the charging start time, and α_2 and β_2 are the scaling factor and the offset value, respectively, which vary according to the location of the IoT device and are determined based on the NREL profile data [4].

4. Experimental Results and Discussions

To measure the lifespan extension of the proposed method comparing to the existing methods, we used the similar system configuration in the existing methods, which use solar energy and have a DVFS based low-power microprocessor and a low-power task scheduling policy. The system parameters including the power consumption of the system and the total capacity of the energy storage are set for the SOC of the battery to swing full range, from 0% to 100%, but not

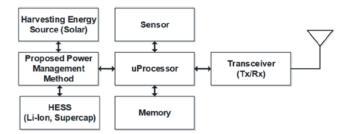


Fig. 7 Energy harvesting-based IoT system model.

 Table 1
 Microprocessor DVFS modes.

DVFS Mode	1	2	3	4	5
Power(mW/min)	40	80	200	400	800

to stop the system operations, so that it can reduce the battery lifespan with the given NREL environment. Figure 7 shows the energy harvesting-based IoT system model used to evaluate the performance of the proposed scheme. The energy-harvesting source module is assumed to be solar energy, which is now the most widely used energy source. To reflect the situation of the actual dynamic energy supply, the NREL's Solar Radiation Research Laboratory (SRRL) Profile (Golden, Colorado) was used from January 1, 2013 to December 31, 2013 [4]. The size of the solar panels was 0.016 m². The existing DVFS-based lazy scheduling scheme [1] was employed for task scheduling. A uniform distribution-based synthetic task set [1] that has been widely used in research on power-management scheduling for existing IoT systems was used to reflect various IoT device tasks related to the sensor, microprocessor, memory, and wireless transmission/receiving operations. For the task model, the number of task types (N) and processor utilization were set to 20 and 0.8, respectively. The initial average harvesting power (Solar E_{avg}) parameter value was set as 0 empirically. To enable continuous task operations, the existing $SolarE_{avg}$ parameter value was set as $2 \times SolarE_{avg}/N$ in order to generate the amount of energy required to perform the tasks, thereby making the total sum of the energy harvested per day greater than or equal to the sum of the amount of energy required for the designated tasks. We considered the five DVFS modes as in the DVFS-based lazy scheduling scheme [1] for the microprocessor, as shown in Table 1.

Schemes using only the 2nd battery and both the supercapacitor and the 2nd battery were independently evaluated for implementation in the energy storage system (ESS) module to investigate the effect of the supercapacitor on the lifetime of the system. The total capacity of the ESS was set as 930,375 mJ based on the night of the winter solstice, during which the supply of solar energy was the lowest in the IoT system, by considering both the random error and the marginal conditions of the weather change. Considering the difference in the typical cost for device configuration, the composition ratio of the supercapacitor to the 2nd battery was set as 1 : 9 [9].

The leakage current of the supercapacitor was set as 0.04 mA [10] at the maximum capacity and the leakage energy change according to the capacity was used the conventional low complexity-based approximation model [11]. Additionally, considering the general state of hybrid energy-storage devices, the initial SOC value of the 2nd battery was set as 50%, and the initial SOC level of the supercapacitor was set as 100%. The energy conversion efficiency was set differently according to the type of energy source and charging and discharging operation as shown in Table 2, considering the normal operation mode of the general IoT system [12], [13].

The existing formula shown in Eq. (4) was used to determine the calendar aging factor for the holistic aging model [8]. Since the range of temperature where IoT devices are used is so wide, the results of lifespan simulations can vary extensively [14], [15] and become hard to analyze. To exclude the wide range of variance due to ther-

 Table 2
 Energy conversion efficiency for energy source type.

No.	Energy Source Type	Regulator	DC-DC Converter
1	Solar	-	91%
2	SC (Super Capacitor)	93%	95%
3	2b (2nd Battery)	90%	93%

mal environment and to focus on the trend of lifetime expansion, the simulation is performed under room temperature condition (25°C). The coefficients presented in the cyclic aging formula given as Eq. (5) were determined by fitting the aging curve of the battery model [8] used for our experiments into the SOC versus open circuit voltage (OCV) curve of the commercial Lithium 2nd battery [16]. In Eq. (4), α_{cap} represents the calendar aging factor depending on the 2nd battery's voltage V in volts and absolute temperature T in kelvins. In Eq. (5), β_{cap} represents the cyclic aging factor depending on the 2nd battery's average voltage V in volts and cycle depth $(\triangle DOD)$ [17]. Equation (6) is a holistic aging model function [8] that combines Eqs. (4) and (5). The B_C is 2nd battery's capacity that is reducing due to the aging factors, where t is the time in days and the B_O is charge throughput in ampere-hours. In the proposed scheme, Eq. (6) was used to estimate the aging rate of the 2nd battery.

$$\alpha_{cap} = (7.543 \cdot V - 23.75) \cdot 10^6 + e^{-\frac{6770}{T}}$$
(4)

$$\beta_{cap} = 0.001204 \cdot (V - 3.7538)^2 + 0.001336 \cdot \Delta DOD +$$

$$B_C = 1 - \alpha_{cap} \cdot t^{0.75} - \beta_{cap} \cdot \sqrt{B_Q} \tag{6}$$

Figure 8 (a) shows the NREL profile-based reconstruc-

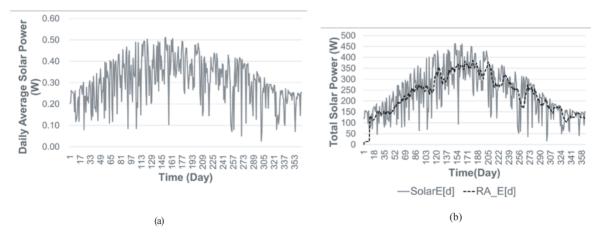
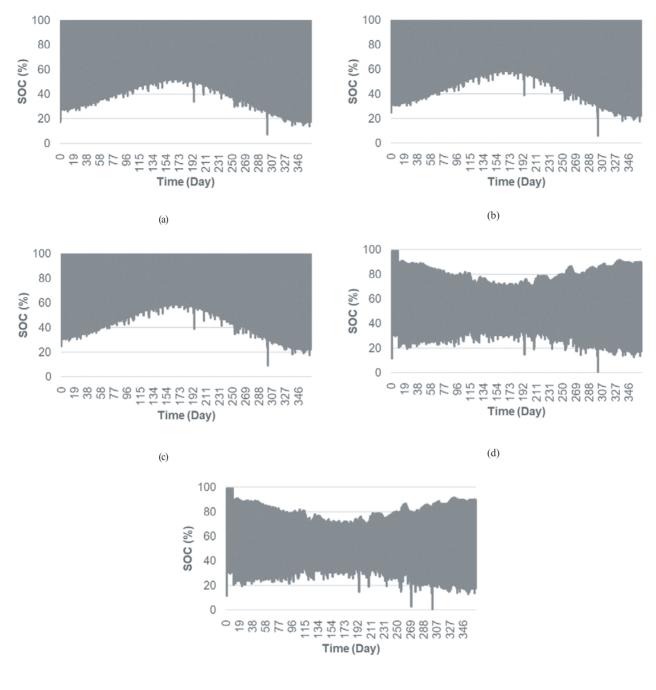


Fig.8 Power generated as a result of solar energy harvesting over a period of one year; (a) NREL average solar power profile data per day, and (b) total solar power per day and corresponding predicted energy-harvesting results (10-tap RA filter).

# of scenario	ESS type	Discharging sequence policy	Charging sequence policy	SOC level adjustment	Charging time adjustment
1	Only 2b	N/A	N/A		
2			2b > SC	×	
3		SC > 2b			^
4			SC > 2b		
5				- 0 -	0

 Table 3
 Charging and discharging policy scenarios.

(HESS: Hybrid energy storage system, SC: Supercapacitor, 2b: 2nd battery, N/A: Not Available)



(e)

Fig.9 1-year SOC (%) swing changes for the 2nd battery. (a) Scenario 1, (b) Scenario 2, (c) Scenario 3, (d) Scenario 4, and (e) Scenario 5.

tion of the average solar power per day over a period of one year, and Fig. 8 (b) shows the predicted results for the total solar power per day, based on the 10-tap RA filter. In order to evaluate the performance of the proposed scheme to extend the lifetime of the related IoT systems, five charging and discharging policy scenarios were designed and tested (Table 3). Scenario 1 only considers and employs the 2nd battery.

The design of Scenario 2 was based on a 1 : 9 hybrid

energy storage system (HESS) that uses both the 2nd battery and the supercapacitor to evaluate the effects of the supercapacitor on extending lifetime. The charging policy of Scenario 2 is to charge to the 2nd battery first to maximize the amount harvesting energy. The charging policy of Scenario 3 is to charge supercapacitor first to evaluate the effect of extending the lifetime according to the proposed scheme.

Scenario 4 incorporates the proposed energy harvesting-based charge level limit scheme into Scenario 3

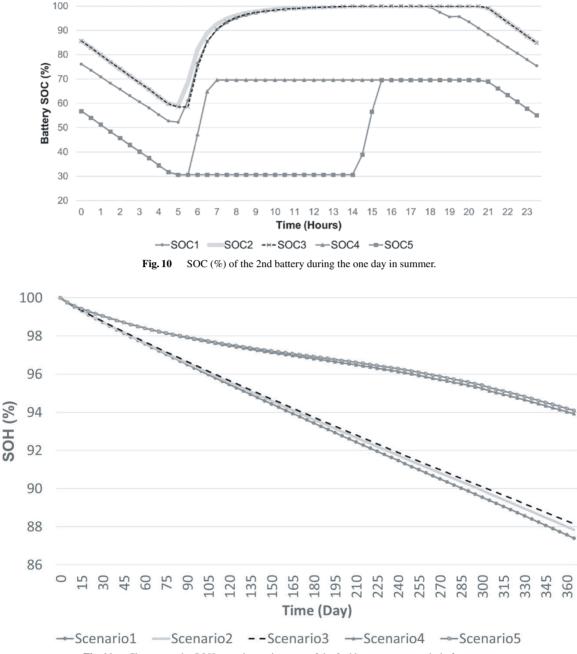


Fig. 11 Changes to the SOH state, i.e., aging rate, of the 2nd battery over a period of one year.

to reduce the cyclic aging factor. Lastly, Scenario 5 incorporates the proposed energy harvesting-based charging start time adjustment scheme into Scenario 4 to reduce the calendar aging factor.

Figure 9 illustrates the 1-yr SOC swing changes for the 2nd battery for each of the charging/discharging policy scenarios, demonstrating the effects of each scenario on the cyclic aging factor. Figure 10 shows the SOC changes of the 2nd battery during the one day in summer related to the calendar aging factor. Figure 11 shows how the state of health (SOH) of the 2nd battery changes throughout the year; the results indicate the degree of overall aging. Table 4 shows the total cycle number and final cyclic aging factor, calendar aging factor, and SOH value.

As is shown in Fig. 9 (a), in the case of Scenario 1, the SOC is frequently swung with the greatest amplitude, and the cyclic aging factor is highest at 9.09%, as given in Table 4. Consequently, after one year, the final SOH value also sharply decreased to 87.41%, as is shown in Table 4. This result indicates that the battery lifetime is less than one and a half year because the life of the 2nd battery ends at 80% of the SOH state [18].

In the case of Scenario 2, as shown in Fig. 9 (b), the combined use of the supercapacitor in the HESS reduces the SOC swing width to less than that in the case of Scenario 1. This consequently reduces cyclic aging by 0.61%,

	8 8	8 81 9			
# of scenario	Cycle No.	Cyclic Aging (%)	Calendar Aging (%)	SOH (%)	Description
1	231.64	9.09	3.49	87.41	Only 2b
2	117.72	8.48	3.67	87.85	HESS (1:9)
3	106.28	8.20	3.64	88.15	Charge Priority (SC > 2b)
4	102.31	3.06	3.01	93.93	Adaptive SOC Level
5	102.21	3.07	2.82	94.10	Charging Start Time

 Table 4
 Total cycle number, cyclic aging factor, calendar aging factor, and SOH result for the five charging/discharging policy scenarios.

(HESS: Hybrid energy storage system, SC: Supercapacitor, 2b: 2nd battery, N/A: Not Available)

as shown in Table 4. Additionally, the final SOH value was 87.85% after one year of simulation. This means that the final SOH value of Scenario 2 was 0.44% higher than that of Scenario 1. Moreover, as illustrated in Fig. 11, the relatively higher final SOH value corresponded to a relatively lower aging rate. In the case of Scenario 3, by changing the charge order to ensure that the supercapacitor is charged before the 2nd battery, the 2nd battery usage can be reduced. As is shown in Table 4, cyclic aging was further reduced by 0.28%, and the final SOH value of Scenario 3 was increased by 0.3% more than that obtained under the conditions of Scenario 2.

As is shown in Fig. 9 (d), in the case of Scenario 4, the SOC swing was shifted to the center at 50% of the SOC as a result of implementing the predictive energy harvestingbased charge level limit scheme. Cyclic and calendar aging were further reduced by 5.14% and 0.63%, respectively (Table 4).

Furthermore, the final SOH value was increased by 5.78% compared to that for Scenario 3, and Fig. 11 shows that the aging rate for Scenario 4 became significantly lower than that for Scenario 3. The results for Scenario 5, as presented in Fig. 10, demonstrate that adding the proposed delayed charge start-time scheme allows the 2nd battery to maintain a relatively low voltage for a longer duration, thus reducing the calendar aging by 0.17% (Table 4). In addition, the final SOH value after one year was the highest at 94.1%, as listed in Table 4. A comparison of the experimental results of the five scenarios in Table 4 reveals that the proposed scheme can extend the operation lifetime of less than one and a half year (Scenario 1) to more than four years (Scenario 5).

5. Conclusion

In this paper, we proposed a low-cost charging/discharging scheme that is able to extend the operation lifetime of realtime IoT systems by implementing a HESS that is powered by harvested energy. The proposed scheme involves policies of using the supercapacitor as a primary energy storage, limiting the charging level according to the predicted harvesting energy, and adjusting the charging time. The comparative experimental results of the five charging/discharging policy scenarios show that the SOH of the proposed scheme is 6.69% higher than that of the basic policy scenario using only the 2nd battery. Future studies should include research on extending the lifetime of IoT systems that harvest energy by considering the various sleep modes in IoT devices and accurately estimating variable weather changes to prevent energy shortages. In addition, the threshold variables between using a supercapacitor or a Li-ion battery can be automatically adjusted based on the information from the IoT device gathers.

Acknowledgments

This work was partly supported by the MOTIE and KSRC (Korea Semiconductor Research Consortium) support program for the development of the future semiconductor device (10080649), by the Global Human Resources Program in Energy Technology of the KETEP granted financial resource from the MOTIE, Republic of Korea (20194010000050), and by the Research Grant of Kwangwoon University in 2020.

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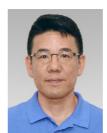
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