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Nonlinear Energy Harvesting-based Available Energy Evolution Model for Cognitive Radio Sensor Networks

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Abstract. *Energy harvesting (EH) technology is a promising solution to solve the energy efficiency problem in cognitive radio sensor networks (CRSNs). However, imperfections of energy storage unit, such as storage inefficiency and energy leakage, limit its potential. Due to the complementary characteristics of battery and super capacitor, they are combined to constitute a hybrid energy storage unit. Current literature generally assumes unlimited capacity of battery or considers about linear EH. These assumptions are beneficial for mathematical derivation and performance evaluation, but they are unrealistic and cannot be applied in practice. In order to solve above problems, a hybrid energy storage unit with limited capacity and storage imperfections is considered in this paper, and an effective available energy evolution model based on nonlinear EH is proposed to manage its energy storage and usage. Simulation results show that our proposal gains obvious advantages over benchmark schemes in prolonging node lifespan and it lays foundations for future protocol and scheme design in EH-based CRSNs.*

Keywords: Cognitive radio sensor networks, Nonlinear energy harvesting, Hybrid energy storage, Available energy evolution model

1. **Introduction.** Wireless sensor networks (WSNs) are composed of a large number of collaborated sensors and they have been widely recognized as a promising paradigm for future Internet of Things [1, 2]. Cognitive radio sensor networks (CRSNs) are smart combinations of cognitive radio (CR) technology and WSNs [3]. Based on CR, idle licensed spectrum of primary users can be opportunistically leveraged to solve the spectrum constraint and interference problem faced by legacy WSNs [4]. However, CRSNs nodes are

powered by limited-capacity battery [5] and they should consume extra energy to perform CR functions, such as spectrum sensing, which results in more severe energy consumption [6]. Energy harvesting (EH) technology allows nodes to harvest energy from ambient or dedicated sources and store the harvested energy into energy storage unit to cover their energy consumption [7]. Therefore, EH becomes one promising solution to solve the energy efficiency problem in CRSNs [8].

Current research on CRSNs generally adopts the energy storage unit which is solely composed of rechargeable battery or super capacitor (SC). Storage imperfections such as storage inefficiency and self-discharging are neglected, that is, storage efficiency is assumed to be 100 percent and there is no energy leakage. Therefore, they cannot be applied in practice. To be specific, the SC suffers low energy storage capacity and β ($0<\beta<\infty$) amount of its stored energy gets leaked per round due to self-discharging. The battery suffers storage inefficiency, that is, η ($0<\eta<1$) portion of the harvested energy can be charged into the storage unit and other parts are wasted. In a word, the energy storage unit which is composed of the SC or the battery alone will limit the potential benefits brought by EH. One possible solution is to adopt hybrid energy storage unit which is composed of both the SC and the battery to take full advantages of their complementary characteristics [9]: (1) leveraging the almost ideal storage of the SC to temporarily store the harvested energy to help reduce the impact of storage inefficiency of the battery; (2) transferring the residual energy to the battery after data transmission to avoid the impact of energy leakage from the SC.

In terms of hybrid energy storage unit, current literature usually assumes unlimited capacity of battery [10] or considers about linear EH [11], which is inconsistent with practice, correspondingly, the obtained results cannot be applied. The unlimited capacity assumption is beneficial for simplifying mathematical derivation, as the harvested energy can be totally stored into the storage unit and the evolution of available energy can be easily obtained. However, there is a capacity limit for the battery in practice, when the harvested energy is more than its remaining capacity, the excessive portion will overflow and cannot be stored. In this case, we need to compare the amount of harvested energy with the maximum amount of energy which can be stored, therefore, the evolution of available energy becomes more complicated. On the other hand, linear EH does not consider about the nonlinear characteristics of end-to-end energy conversion introduced by nonlinear components such as diodes in practical EH circuits [12]. Therefore, it enables the output power of the EH circuits P_{out} to increase linearly with input power P_{in}. Actually, P_{out} will gradually become saturated as P_{in} increases. In order to capture this phenomenon, nonlinear EH model should be adopted to quantify the actual amount of harvested energy. Many scholars have proposed various nonlinear EH models to measure the harvested power, but their effectiveness has not been verified and compared.

Motivated by the limitations of current research, a practical hybrid energy storage unit which is composed of limited-capacity battery and SC with storage imperfections is applied to EH-based CRSNs nodes. Based on carefully selected nonlinear EH model, an effective available energy evolution model is proposed to manage the energy storage and usage of CRSNs nodes. As energy is one of the most valuable resources of CRSNs nodes, effective and accurately-measured energy storage and usage are vital to protocol and scheme design for EH-based CRSNs. The innovations of our proposal are listed below:

(1) In order to select the most reasonable nonlinear EH model to accurately quantify the output power of EH circuits, various nonlinear EH models are evaluated and compared from qualitative and quantitative aspects. In terms of quantitative evaluation, the field data in [13] and Matlab fitting tool are leveraged to obtain their parameter values, based on which their fitting performance is compared to determine the most appropriate model.

(2) Based on the carefully selected nonlinear EH model, a practical hybrid energy storage unit and corresponding available energy evolution model are proposed for EH-based CRSNs. The model takes the impact of limited capacity and storage imperfections into consideration to reasonably quantify and manage the energy storage and usage so that the potential benefits of EH can be fully leveraged.

(3) The proposal is applied to a typical clustering protocol of CRSNs, i.e., cognitive low energy adaptive clustering hierarchy (CogLEACH) [14], and node-level and network-level simulations are carried out to validate the effectiveness of our proposal. Simulation results show that the proposed hybrid energy storage unit and corresponding available energy evolution model are robust to the variations of network parameters, and they can reasonably schedule the energy storage and usage to prolong node lifespan.

2. **Related Works.** We will review and analyze related works from two aspects: EH models and commonly used EH and usage protocols, as they are closely related to available energy evolution model.

2.1. **Nonlinear EH models.** According to the relationship between input and output power of EH circuits, nonlinear EH models can be divided into two types: curvilinear EH models and piecewise linear EH models. Piecewise linear EH models [15-18] are characterized by simple formulas and convenient mathematical derivation, but they suffer low matching degree with field data. Instead, curvilinear EH models [19-23] can model the relationship between practical input and output power more accurately. Among them, the model proposed in [19] has been widely used, and its expression is:

$$P_{out} = \frac{\Psi_j - M_j\Omega_j}{1 - \Omega_j} \tag{1}$$

where $\Psi_j = \frac{M_j}{1+\exp(-a_j(P_{in}-b_j))}$; $\Omega_j = \frac{1}{1+\exp(a_j b_j)}$; M_j is the maximum output power when the EH circuit is saturated; a_j and b_j are parameters related to circuit specification, and their values can be obtained by standard curve fitting tool.

In order to analyze the actual performance of wireless relay and wireless energy transmission, a nonlinear EH model is proposed in [20], and its expression is shown below:

$$P_{out} = \frac{p_2P_{in}^2 + p_1P_{in} + p_0}{q_3P_{in}^3 + q_2P_{in}^2 + q_1P_{in} + q_0} \times P_{in} \tag{2}$$

where p_0, p_1, p_2, q_0, q_1, q_2, and q_3 are fitting parameters. Among them, q_3=1 and other values are obtained by curve fitting tool.

A feasible nonlinear EH substitution model is proposed in [21], and its specific expression is:

$$P_{out} = \alpha_1P_{in}^2 + \alpha_2P_{in} + \alpha_3 \tag{3}$$

where parameters α_1, α_2, and α_3 are determined by data fitting method based on mean square error.

In order to solve the problem of neglecting sensitive characteristics of actual circuit in [19], a nonlinear EH model is proposed in [22] as shown below:

$$P_{out} = \left[\frac{P_{max}}{\exp(-\tau P_0 + \nu)} \times \left(\frac{1 + \exp(-\tau P_0 + \nu)}{1 + \exp(-\tau P_{in} + \nu)} - 1\right)\right]^+ \tag{4}$$

where P_{max} is the saturation threshold of input power; τ and ν control the steepness of the model; P_0 is the sensitivity threshold of input power, $[\cdot]^+$ indicates that the expression in parentheses is positive.

To simplify the model in [20] and make it more suitable for mathematical calculation, a nonlinear EH alternative model is proposed in [23] as below:

$$P_{out} = \frac{aP_{in} + b}{P_{in} + c} - \frac{b}{c} \tag{5}$$

where a, b, and c are constants calculated by curve fitting tool.

Above models are compared by approximating field data, and more details can be found in Section 3.

2.2. **EH and usage protocols.** At present, three kinds of EH and usage protocols are commonly used in literature, that is, harvest-use, harvest-store-use and harvest-use-store protocols [24]. Harvest-use protocol is suitable for nodes without energy buffer temporarily storing their harvested energy. These nodes can only transmit data if they have harvested enough energy to cover their energy consumption. This means that these nodes are totally powered by harvested energy. Harvest-store-use protocol and harvest-use-store protocol are both suitable for nodes with energy buffer, and they are powered by stored energy and harvested energy together. They differ in whether the harvested energy can be immediately used for data transmission. In harvest-store-use protocol, the energy harvested by nodes is temporarily stored into their buffer and can be used at next time instance. Therefore, their data transmission is limited by available energy which excludes the harvested energy at current time instance. By using harvest-use-store protocol, the harvested energy is temporarily stored in the energy buffer and can be immediately used for data transmission if the energy consumption can be covered. After data transmission, the residual energy will be stored for future use. In general, harvest-use-store protocol achieves better performance than harvest-store-use protocol, and they deliver the same performance if the storage efficiency is 100 percent. This motivates us to apply the harvest-use-store protocol to our proposal.

3. Available Energy Evolution Model for Hybrid Energy Storage Unit.

3.1. **Comparison and evaluation of various nonlinear EH models.** As our proposed available energy evolution model is based on nonlinear EH model, we need to select the most appropriate one to ensure accurate measurement of harvested energy. In this subsection, we will compare various nonlinear EH models listed in Section 2 from qualitative and quantitative aspects, and use statistical indicators to evaluate their fitting performance in approximating the field data in [13].

First, these nonlinear EH models are evaluated from qualitative aspects, such as matching degree with practical relationship between input and output power, ease of mathematical derivation and so on. Detailed comparison results are shown in Table 1 below, in which "✓" represents corresponding property can be satisfied while "×" denotes the opposite situation.

Second, curve fitting tool in Matlab and field data are leveraged to evaluate the performance of various curvilinear EH models from quantitative aspect. The fitting results are shown in Figure 1.

In order to evaluate their fitting performance, two statistical indicators, i.e., root mean square error ($RMSE$) and R-squared (R^2) are utilized and their definitions are shown in

TABLE 1. Qualitative comparison results of various nonlinear EH models

Models	Model characteristics				
	Matching degree with field data	Easy for mathematical derivation	Convenient for convex optimization	Considering circuit sensitivity	Unrestricted P_{in}
Model in [15]	Poor	✓	×	×	✓
Model in [16]	Excellent	×	×	✓	✓
Model in [17]	Poor	✓	×	✓	✓
Model in [18]	Poor	✓	×	✓	✓
Model in [19]	Excellent	×	✓	×	×
Model in [20]	Excellent	✓	✓	✓	✓
Model in [21]	Medium	✓	✓	×	×
Model in [22]	Excellent	×	✓	✓	✓
Model in [23]	Medium	✓	✓	×	✓

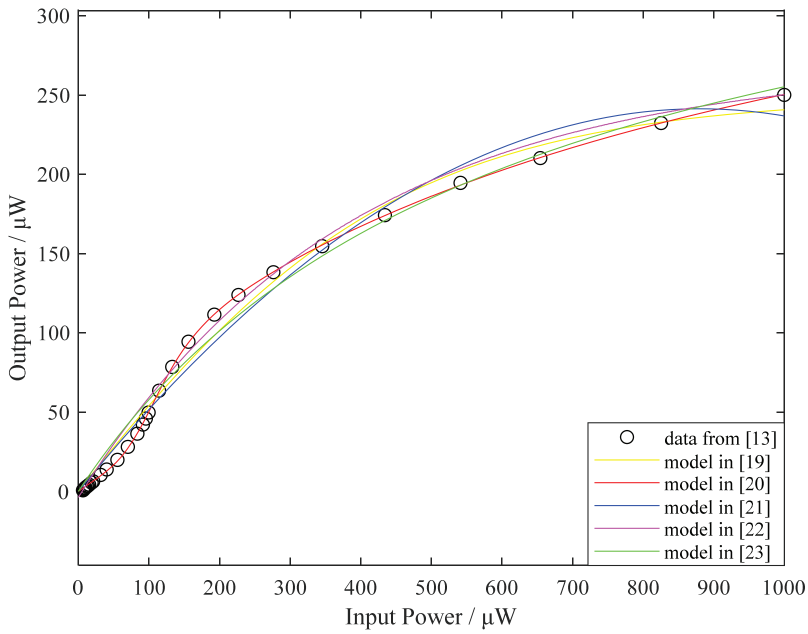

FIGURE 1. Fitting results of various curvilinear EH models

Equation (6) and Equation (7), respectively.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \widehat{y}_i)^2} \tag{6}$$

$$R^2 = \frac{\sum_{i=1}^{n}(\widehat{y}_i - \overline{y})^2}{\sum_{i=1}^{n}(y_i - \overline{y})^2} \tag{7}$$

where n is the total number of data points; y_i is the i^{th} original data point, and $\widehat{y}_i$ is the corresponding data point after curve fitting. $\overline{y}$ is the mean value of original data. $RMSE$ is obtained by calculating the square root of the sum of squares of fitting errors, and the closer the $RMSE$ is to 0, the better the model works. R^2 ranges from 0 to 1, and R^2 moves close to 1 as fitting curve approaches original data. By utilizing these two indicators, the fitting performance of various curvilinear EH models is compared and the results are presented in Figure 2. We can observe that the $RMSE$ value of the model in [20] is the smallest and its R^2 value is the closest to 1. This means that it achieves the best fitting performance, therefore, the nonlinear EH model in [20] is leveraged to describe the relationship between input and output power of EH circuits in this paper.

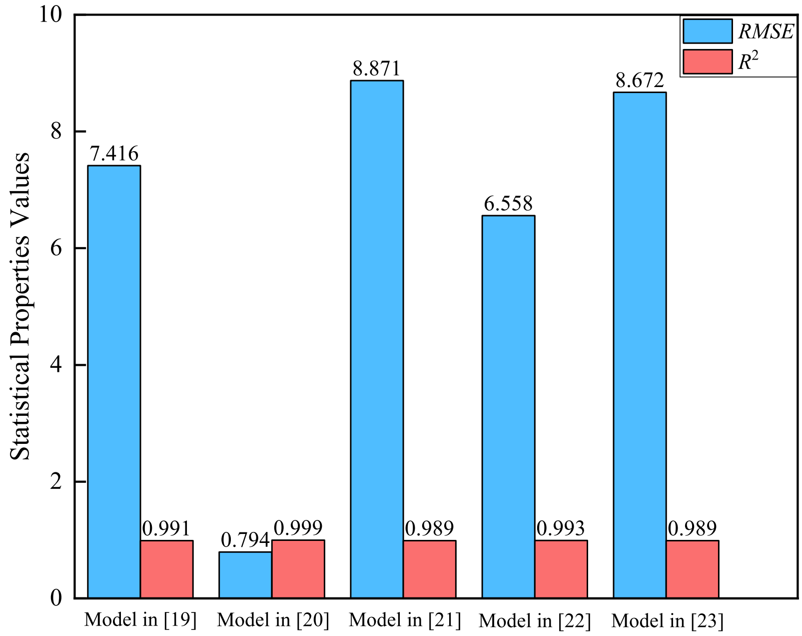

FIGURE 2. Comparison results of various curvilinear EH models in terms of $RMSE$ and R^2

3.2. **Available energy evolution model based on nonlinear EH model.** SC can store energy almost ideally, but it suffers low energy storage capacity and self-discharging which means that β amount of energy in SC gets leaked per round. Battery has high energy storage capacity but is inefficient in storing energy. Here, storage inefficiency of battery means that every E units of energy is stored, only ηE units can be drained from it while other parts are lost. Therefore, SC and battery are combined together as a hybrid energy storage unit to boost storage efficiency. As shown in Figure 3, each EH-based CRSNs node has two energy queues which correspond to the battery and the SC components of the hybrid energy storage unit, and they are with limited size E_{maxb} and E_{maxSC} ($E_{maxb}>E_{maxSC}$), respectively. Harvest-use-store protocol is adopted in this paper. In order to limit the impact of storage inefficiency of the battery on available energy, whenever harvested energy E_{in} arrives, it is temporarily stored in the SC first and can be immediately used. To avoid energy overflow, the excessive portion of harvested energy is stored in the battery if it has residual capacity. After data processing and transmission, the remaining energy is transferred from the SC to the battery and stored for future use, which can help improve self-discharging problem.

As the hybrid energy storage unit is charged by the harvested energy and discharged by energy consumption of active operations such as control information exchange, data transmission and so on, the stored energy evolves over time. Therefore, the available energy evolution model is exploited here to manage the evolution of the stored energy over time. In particular, the available energy evolution processes of the two energy queues from time instance t to $t+1$ are summarized in Equation (8) and Equation (9), and the

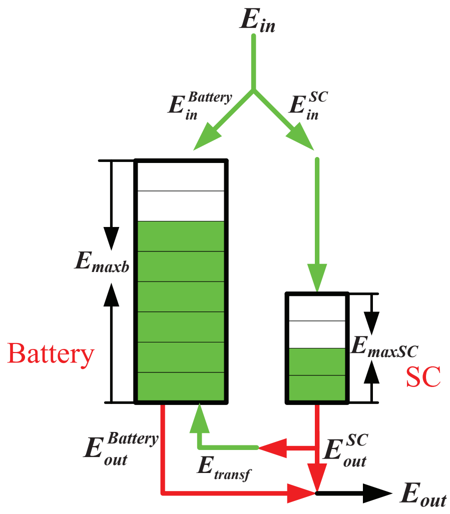

FIGURE 3. Hybrid energy storage unit of EH-based CRSNs nodes

total energy available at node n $E_{n\_res}(t+1)$ is calculated through Equation (10).

$$E_{n\_res}^{SC}(t+1) = \left\lfloor \left\lfloor E_{n\_res}^{SC}(t) + E_{in}^{SC} - E_{out}^{SC} - E_{transf} \right\rfloor^{+} - \beta \right\rfloor^{+} \tag{8}$$

$$E_{n\_res}^{Battery}(t+1) = \left[\left\lfloor E_{n\_res}^{Battery}(t) + \eta \times E_{in}^{Battery} - \left\lfloor E_{out} - E_{out}^{SC} \right\rfloor^{+} \right\rfloor^{+} + \eta \times E_{transf} \right]^{+} \tag{9}$$

$$E_{n\_res}(t+1) = E_{n\_res}^{SC}(t+1) + E_{n\_res}^{Battery}(t+1) \tag{10}$$

where $\lfloor x \rfloor^{+}$=max(0,x), $[x]^{+}$=min($\lfloor x \rfloor^{+}, E_{max}$). $E_{n\_res}^{SC}(t+1)$ and $E_{n\_res}^{SC}(t)$ are residual available energy of the SC at time instances t+1 and t, respectively. Similarly, $E_{n\_res}^{Battery}(t+1)$ and $E_{n\_res}^{Battery}(t)$ are residual available energy of the battery at time instances t+1 and t, respectively. E_{in}^{SC} is the actual amount of radio frequency (RF) energy harvested by the SC, and it can be obtained by using Equation (11).

$$E_{in}^{SC} = \min(E_{in}, E_{maxSC} - E_{n\_res}^{SC}(t)) \tag{11}$$

where E_{in} is the maximum amount of RF energy which can be harvested by node n. In this paper, signal attenuation is assumed to follow free-space path loss model, and E_{in} is:

$$E_{in} = f(P_T \times \frac{G_T G_R \lambda^2}{16\pi^2 d_{tosink}^2}) \times t_{EH} \tag{12}$$

where P_T is the transmission power of the sink; G_T and G_R are the gains of transmitting antenna and receiving antenna, respectively; λ is the wavelength of transmission signal; d_{tosink} is the Euclidean distance from node n to the sink; t_{EH} is the time duration for EH. $f(x)$ is the nonlinear energy harvesting model proposed in [20], and its expression is given by Equation (2).

E_{out} is the total energy expenditure of signal processing, data transmission and so on, which depends on node identity and its activity. E_{out}^{SC} portion of E_{out} drains from the SC and the remainder comes from the battery. E_{out}^{SC} is determined by total available energy in the SC and total energy consumption, as shown in Equation (13).

$$E_{out}^{SC} = \min(E_{out}, E_{n\_res}^{SC}(t) + E_{in}^{SC}) \tag{13}$$

E_{transf} is the total amount of energy transferred from the SC to the battery, and it can be calculated according to Equation (14).

$$E_{transf} = \min\left(\left\lfloor E_{n\_res}^{SC}(t) + E_{in}^{SC} - E_{out}^{SC} \right\rfloor^{+}, E_{maxb} - \left\lfloor E_{n\_res}^{Battery}(t) + \eta \times E_{in}^{Battery} - \left\lfloor E_{out} - E_{out}^{SC} \right\rfloor^{+} \right\rfloor^{+} \right) \tag{14}$$

where $E_{in}^{Battery}$ is the amount of RF energy which can be collected by the battery, as shown below:

$$E_{in}^{Battery} = \min(E_{in} - E_{in}^{SC}, E_{maxb} - E_{n\_res}^{Battery}(t)) \tag{15}$$

4. **Simulation Results and Analysis.** In order to validate the effectiveness of hybrid energy storage unit and our proposed available energy evolution model, they are compared with the energy storage unit which is solely composed of rechargeable battery. In the competitor, the available energy evolution process from time instance t to t+1 is shown by Equation (16).

$$E_{n\_res}^{Battery'}(t+1) = \left\lfloor E_{n\_res}^{Battery'}(t) + \eta \times \min(E_{in}, E_{maxb} - E_{n\_res}^{Battery'}(t)) - E_{out} \right\rfloor^{+} \tag{16}$$

These two energy evolution models are applied to single EH-based CRSNs node and the whole EH-based CRSNs which run CogLEACH protocol [14], i.e., they are compared in both node level and network level. To be specific, if these models are applied to single EH-based CRSNs node, this node is set as cluster head (CH) or cluster member (CM) randomly in each round for simple calculation purpose, and the corresponding energy consumption is calculated from statistical perspective according to CogLEACH protocol, as shown in Equation (17) or Equation (18). The harvestable energy of this node is determined by its Euclidean distance to the sink, as shown in Equation (12). While if they are applied to the whole EH-based CRSNs, the harvestable energy of each node is determined by its individual distance to the sink, and its energy consumption depends on its role (CH or CM) in current round which is up to CogLEACH protocol, detailed control information exchange, data delivery and so on.

$$E_{out}^{CH} = \left[(E_{elec} + \varepsilon_{fs} R_t^2) \times L_1 \times 3 + E_{elec} \times L_1 \times 2 \times (\pi R_t^2 \times \rho - 1) \right] + \left[E_{elec} \times L \times (\pi R_t^2 \times \rho - 1) + E_{DA} \times L \times \pi R_t^2 \times \rho + (E_{elec} + \varepsilon_{fs} d_{tosink}^2) \times L \right] \tag{17}$$

$$E_{out}^{CM} = E_{elec} \times L_1 \times 3 + (E_{elec} + \varepsilon_{fs} d_{toCH}^2) \times L_1 \times 2 + (E_{elec} + \varepsilon_{fs} d_{toCH}^2) \times L \tag{18}$$

where E_{elec} is the energy consumption of electronic circuits for sending or receiving one bit of data; ε_{fs} is the energy consumption coefficient of power amplifier per bit; R_t is the maximum transmission range of CRSNs nodes; ρ is node density; d_{toCH} is the average Euclidean distance from all CMs to their CH; L_1 is the control packet size and L is the length of data packets in bits. The simulation parameter settings are given below: the initial residual energy of the SC is set as 0 for fair comparison and the initial residual energy of the battery is 0.5J; β=0.015mJ, η=0.6; E_{maxb}=1J and E_{maxSC}=0.2J. The EH duration is set as 0.2s while one round lasts for 0.5s. The size of control packets and data packets are set as L_1=200bits and L=1024bits. In order to show the simulation parameters more explicitly, they are listed in Table 2 below.

TABLE 2. Simulation parameter settings

Simulation scenarios	Common parameters	Variations of parameters
Node-level simulation	E_{0_SC}=0J, $E_{0\_battery}$=0.5J, E_{maxb}=1J, E_{maxSC}=0.2J, β=0.015mJ, η=0.6, t_{EH}=0.2s, T=0.5s, R_t=50m, L_1=200bits, L=1024bits.	d_{tosink}=10m, ρ=1/(100π), P_T=40W∼100W.
		d_{tosink}=10m, P_T=100W, ρ=1/(100π)∼1/(25π).
		ρ=1/(100π), P_T=100W, d_{tosink}=10m∼50m.
Network-level simulation		N=100, ρ=1/25, P_T=100W, d_{tosink} is obtained according to node position.
		N=100, P_T=100W, d_{tosink} is obtained according to node position, ρ=1/50∼2/25.

4.1. **Node-level simulation results and analysis.** Node residual energy gradually decreases as the increase of round number, and this mainly results from the fact that the harvestable energy at this node is less than its energy consumption. In order to validate the effectiveness of our proposal, energy consumption ratio $R_{EC}(t)$ is leveraged and it is defined as the ratio between node energy consumption under our proposal and that under battery storage unit in round t, as shown in Equation (19).

$$R_{EC}(t) = \frac{E_0 - E_{n\_res}(t)}{E_0 - E_{n\_res}^{Battery'}(t)} \tag{19}$$

where E_0 is the initial energy of this node. The variation of energy consumption ratio versus round number under different transmission power of the sink P_T is shown in Figure 4 and it is obtained with the following parameter settings: d_{tosink}=10m and ρ=1/(100π). We can observe that energy consumption ratio shows a declining trend as P_T increases,

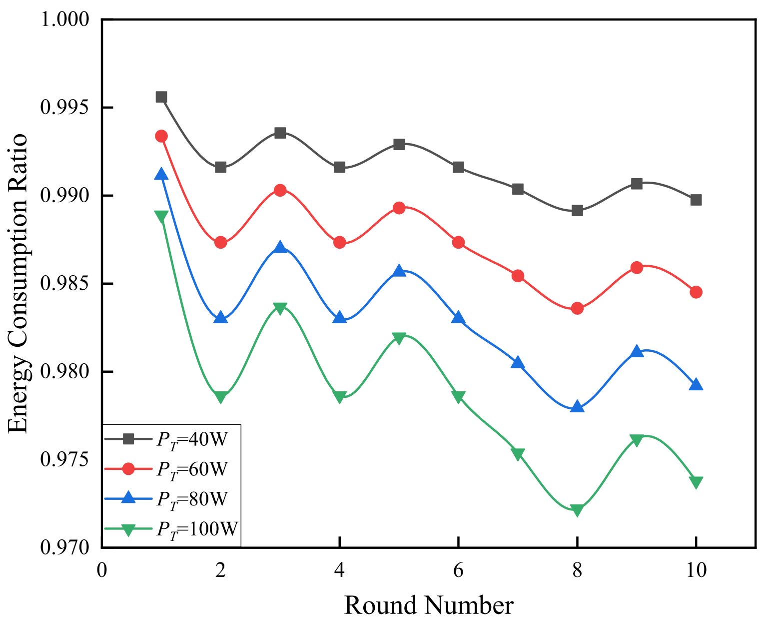

FIGURE 4. Impact of P_T on energy consumption ratio

which means the gap between these two competitors enlarges as P_T increases. The reasons are analyzed below: when node position is fixed, according to Equation (12), the harvestable energy will increase as P_T improves. Consequently, more energy can be left with unchanged node energy consumption. In addition, by utilizing hybrid energy storage unit and corresponding available energy evolution model, node residual energy is always higher than that using battery storage unit. Therefore, the energy consumption ratio is always below 1. The performance improvement of our proposal comes from effective combination of the battery and the SC and reasonable management of these two components. Therefore, energy storage efficiency can be significantly enhanced and energy leakage can be reduced, which contributes to smaller energy consumption ratio.

Energy consumption ratio versus node density ρ is observed by setting d_{tosink}=10m and P_T=100W, and the comparison results are shown in Figure 5. Energy consumption ratio declines as ρ decreases, and the reason is: if node position and P_T are kept unchanged, the harvestable energy is fixed. However, according to Equation (17), node energy consumption is reduced as ρ decreases. Additionally, similar to the results in Figure 4, node energy consumption with hybrid energy storage unit and proposed energy management is still less than that under battery storage unit, which again demonstrates the effectiveness of our proposal.

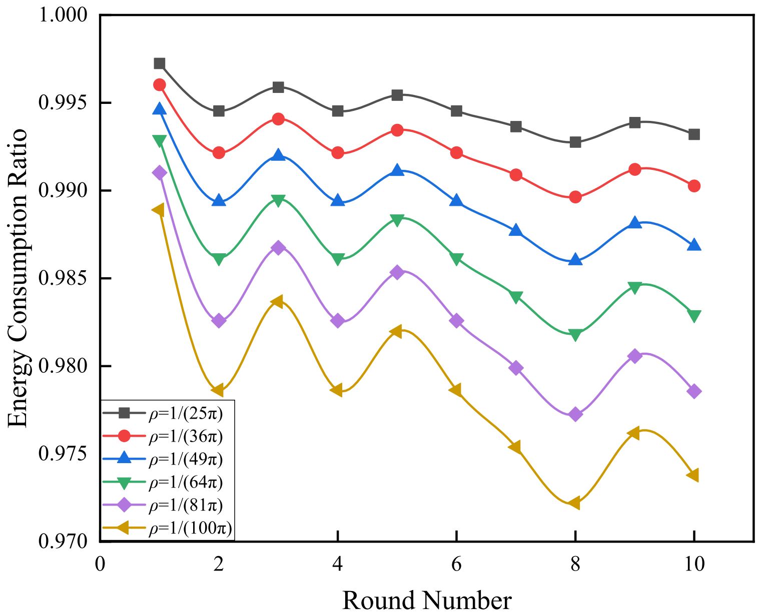

FIGURE 5. Impact of ρ on energy consumption ratio

In order to analyze the impact of Euclidean distance to the sink, d_{tosink} is increased from 10m to 50m while ρ=1/(100π) and P_T=100W. The variation of energy consumption ratio versus round number is presented in Figure 6. According to Equation (12) and Equation (17), d_{tosink} imposes double influence on node residual energy. To be specific, the harvestable energy can be improved if d_{tosink} decreases while P_T is unchanged. At the same time, less energy is required for sending data to the sink. Therefore, more node residual energy is saved. The simulation results in Figure 6 are in accordance with above analysis, and hybrid energy storage unit with reasonable management gains obvious advantages over battery storage unit.

4.2. **Network-level simulation results and analysis.** In order to further illustrate the effectiveness of our proposal, we apply it to a representative clustering protocol for

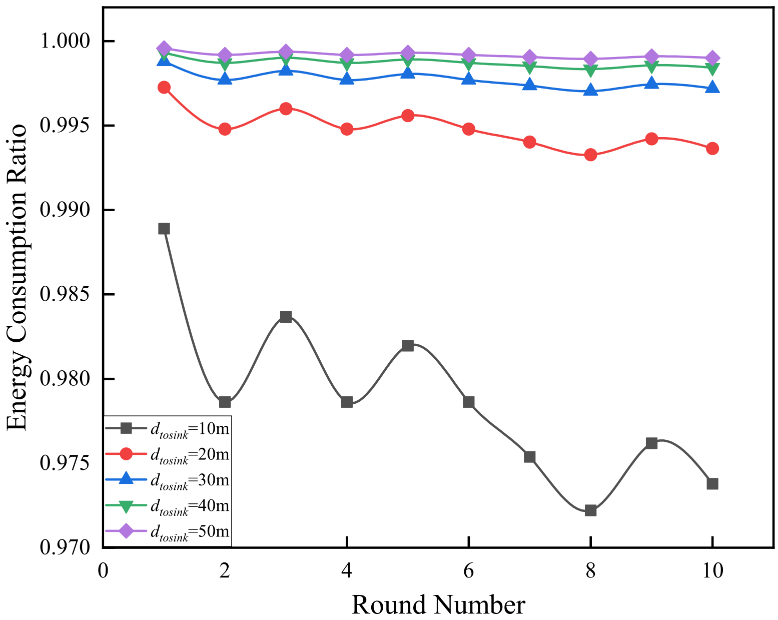

FIGURE 6. Impact of d_{tosink} on energy consumption ratio

CRSNs, that is, CogLEACH. 100 CRSNs nodes are randomly and evenly distributed in a 50m×50m area, i.e., node density is ρ=1/25. The sink is located at the center of the network with transmission power P_T=100W. The Euclidean distance to the sink d_{tosink} is varied among CRSNs nodes and it can be obtained according to their positions or received signal strength. The variation of node remaining energy as network operation goes on is recorded and the relationship between total residual energy of all CRSNs nodes, network lifetime and round numbers is presented in Figure 7 and Figure 8, respectively. When reasonable management of hybrid energy storage unit is achieved, total residual energy of all CRSNs nodes is dramatically improved. The rounds in which the first-death node appears under the two competing models are round 1493 and 1386, respectively. This means that network lifetime can be extended, and network surveillance capability is significantly enhanced.

In addition, 4 random rounds are selected to observe node residual energy, i.e., round 1000, 1500, 1700 and 2000, and the simulation results are shown in Figure 9. In Figure 9(a), residual energy of all CRSNs nodes is higher than 0, which means that all CRSNs nodes are alive in round 1000. However, residual energy fluctuates among nodes. The reasons are analyzed as follows: Different Euclidean distance to the sink results in distinction in harvestable energy; Nodes may play different kinds of roles, and the energy consumption of CH and CM varies greatly. As network operation continues, a large number of CRSNs nodes die due to lack of energy, and only a small number of nodes are still alive, as shown in Figure 9(b)∼ Figure 9(d). The advantage of our proposal is still obvious, for example, there are 73 nodes alive under hybrid energy storage unit while there are only 64 under battery storage unit in round 1500. Node 16 is close to the sink, so its harvestable energy from the sink is nearly the same with its energy consumption, which results in nearly unchanged residual energy. This results from the random deployment of CRSNs nodes and the random CHs selection of CogLEACH protocol.

In order to further validate the robustness of our proposal to the variations of network parameters, node density ρ is changed by varying the number of CRSNs nodes deployed in the area. The number of living nodes versus round number is shown in Figure 10.

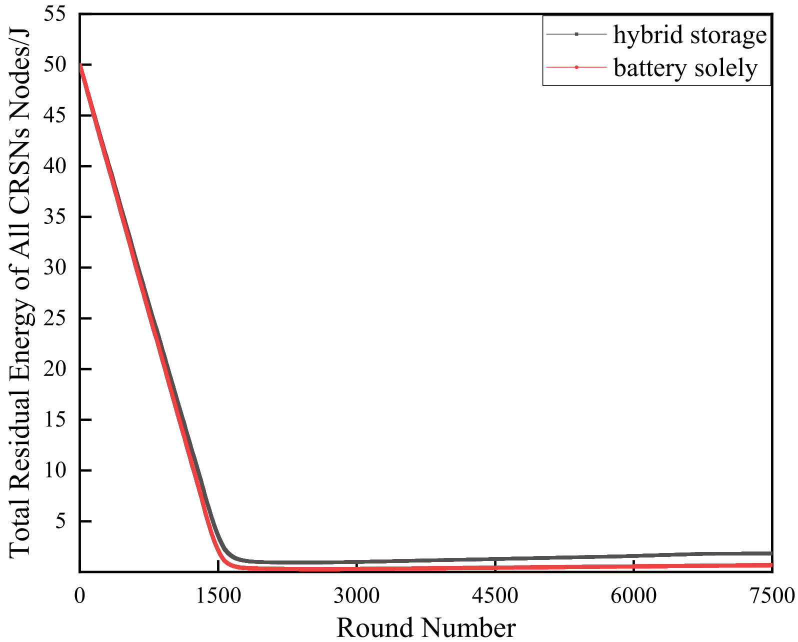

FIGURE 7. Comparison results of total residual energy

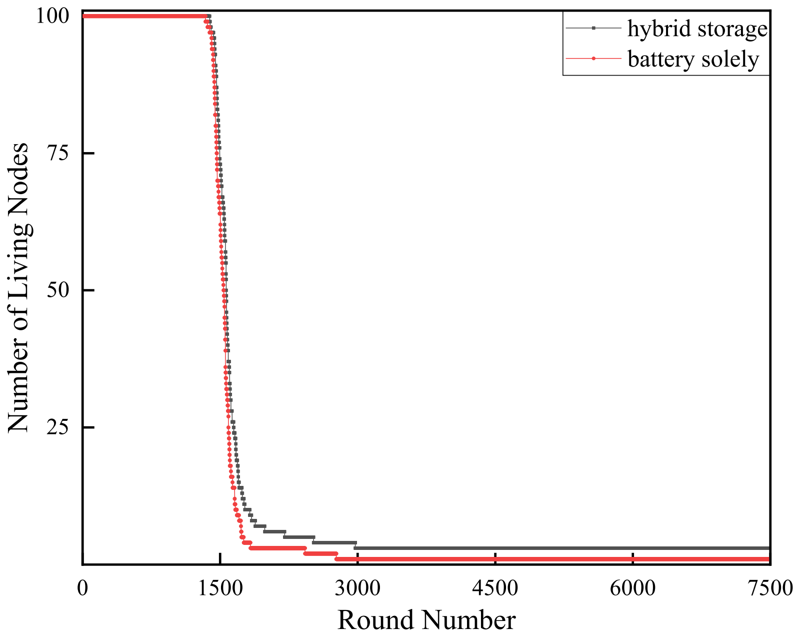

FIGURE 8. Comparison results of network lifetime

From Figure 10, we can observe that the hybrid energy storage unit with corresponding available energy evolution model still gains obvious advantages over its competitor. As node density ρ increases, more energy can be conserved by using our proposal, therefore, more nodes can survive longer. From above results, we can conclude that our model is robust to the variations of network parameters.

As stated above, our proposal is influenced by parameters such as P_T, ρ and d_{tosink}, and its performance is superior to battery storage unit, no matter in node level or network

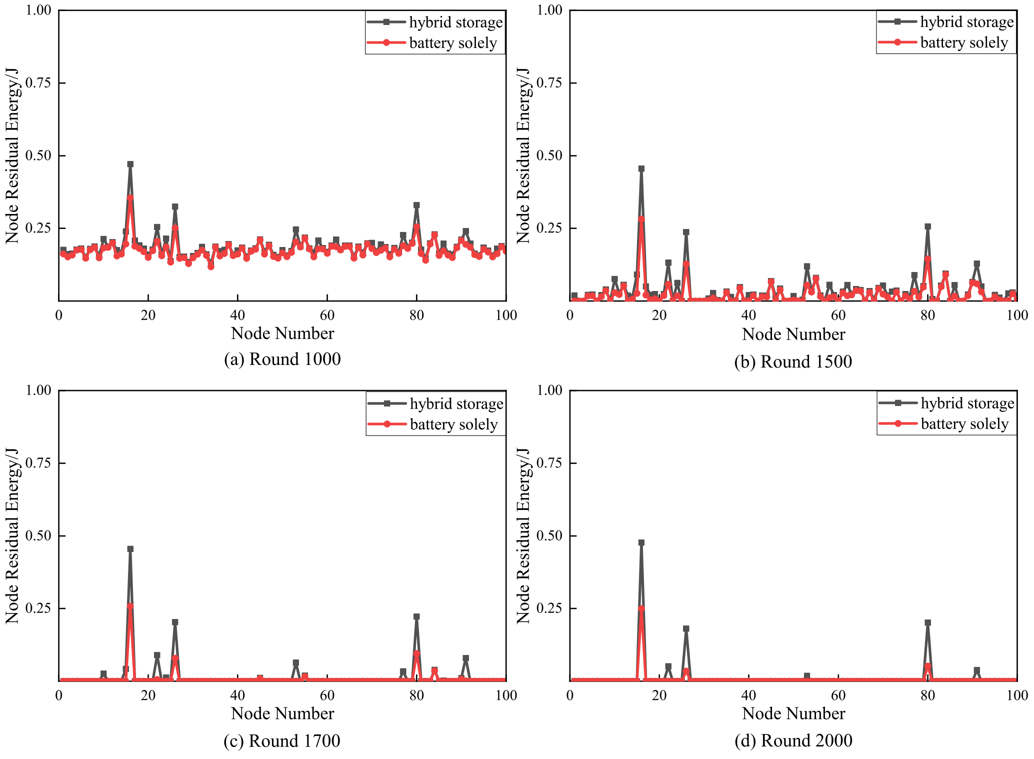

FIGURE 9. Node residual energy in 4 randomly selected rounds

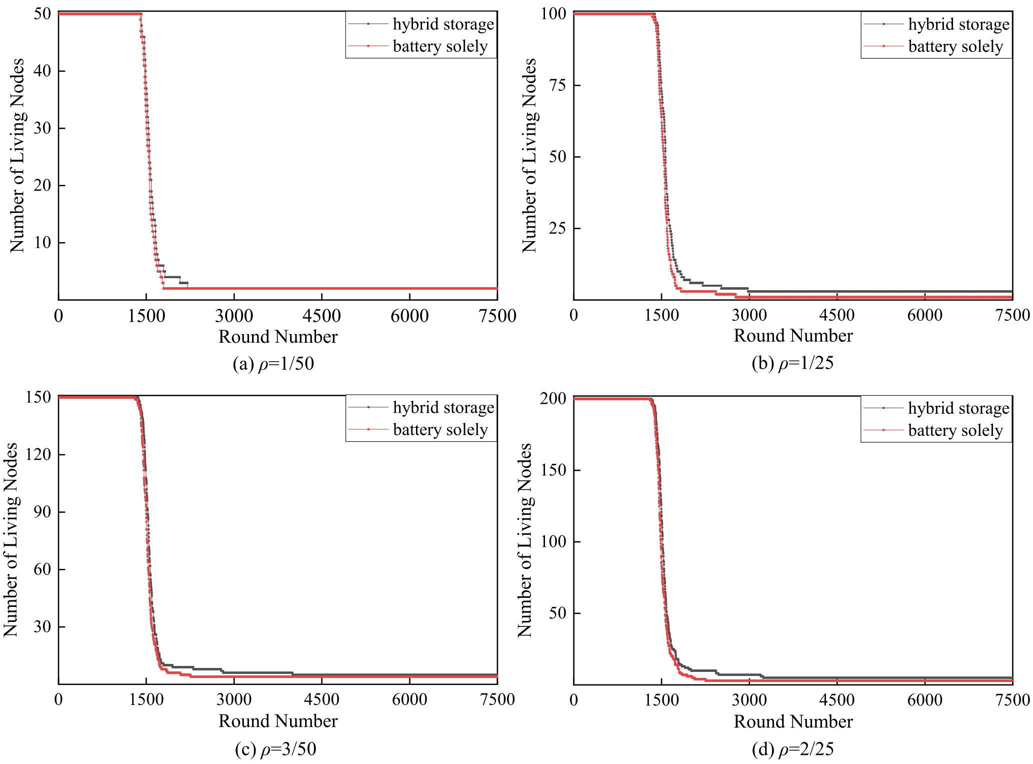

FIGURE 10. Robustness of our proposal to variation of node density ρ

level. Therefore, our proposal lays foundations for future protocol and scheme design in EH-based CRSNs.

5. **Conclusions.** Current research on EH-based CRSNs usually adopts rechargeable battery or SC to store the harvested energy and ignores the storage imperfections. Even hybrid energy storage unit is utilized, it is assumed to possess unlimited capacity or linear EH model is applied to quantify the amount of harvested energy. The potential benefits of EH are restricted and the obtained results cannot be applied in practice. Aiming at solving above problems, a hybrid energy storage unit with practical constraints and corresponding available energy evolution model are proposed for EH-based CRSNs. First, in order to identify the most reasonable nonlinear EH model and guarantee accurate measurement of harvested energy, qualitative and quantitative evaluation are leveraged to compare various nonlinear EH models and test their fitting performance. Second, based on the carefully selected nonlinear EH model, the impact of limited capacity and storage imperfections are taken into consideration to model the evolution process of available node energy over time. In this case, the energy storage and usage can be effectively quantified and reasonably managed. Third, the effectiveness of our proposal is validated through node-level and network-level simulations, and it is robust to the variations of network parameters. In our future work, we will design clustering routing protocols and resource allocation schemes for EH-based CRSNs based on our proposed hybrid energy storage unit and corresponding available energy evolution model.

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