Software Defined Energy Harvesting Networking for 5G Green Communications

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***Abstract*—Energy and spectrum resources play significant roles in fifth generation (5G) communication systems. In industrial applications of the 5G era, green communications are a great challenge for sustainable development of networks. Energy harvesting technology is a promising approach to prolong network lifetime. In energy harvesting networks, nodes may replenish energy from a mobile charger to overcome variations of renewable energy. In this article, energy-rich nodes are stimulated to upload surplus energy to the mobile charger, leading to a bi-directional energy flow. This creates a new paradigm that energy flows coexist with data flows, which gives rise to new problems on controlling the energy flows and the data flows. Software defined networking enables centralized control to optimize flow scheduling. We propose a Software Defined Energy Harvesting Network (SD-EHN) architecture for 5G green communications. In the SD-EHN, the data plane, the energy plane and the control plane are decoupled to support flexible energy scheduling and improve energy efficiency, thus to facilitate sustainability in energy harvesting networks. A scenario with a mobile charger acting as a mobile data collector is presented to introduce an energy trading model in SD-EHN. We use stochastic inventory theory to determine the optimal energy storage levels of the nodes. A Nash bargaining game is proposed to solve the benefit allocation problem for energy trading. Numerical results indicate that SD-EHN optimizes energy utilization and saves energy.**

***Index Terms*—Software defined networking, 5G, energy harvesting network, energy trading, Nash bargaining game**

I. Introduction

The fifth generation (5G) communication systems aim to continuously provide mobile users with higher data rate, lower energy consumption and improved quality-of-experience [1]. In 5G communication systems, energy and spectrum resources play vital roles to achieve these goals. Especially, in industrial applications of 5G systems (e.g., Internet of Things), green communications are a great challenge for achieving long-term and self-sustainable operations [2]. Recently, energy harvesting technology has emerged as a promising method to prolong network lifetime. In energy harvesting networks, nodes perform data communication and energy harvesting simultaneously. Energy-efficient network architecture needs to be considered in existing energy harvesting networks for 5G green communications.

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Some key features of energy harvesting networks have been studied for 5G green communications. As spatial-temporal profiles of renewable energy sources exhibit great variations, a mobile charger has recently been proposed to provide energy replenishment for the nodes in the emerging Internet of Things [3]. Similar to data transmission, energy-deficient nodes “download” energy from a mobile charger. An energy link from a mobile charger to the nodes is established and named *energy downlink*. In turn, nodes that stay idle but harvest energy continuously can accumulate and “upload” their surplus energy to the mobile charger, which forms an *energy uplink*. This means that the energy flows between the mobile charger and the nodes can be bi-directional, which enables large-scale and on-demand energy scheduling. These features can be summarized as follows.

- *Integration of renewable energy*: Various renewable energy sources can be introduced into an energy harvesting network. But prior knowledge of energy harvesting process is necessary to exploit them properly for 5G green communications.
- *Mobile charger*: A mobile charger provides energy replenishment for nodes. With this additional alternative, the lifetime of nodes can be further prolonged.
- *Bi-directional energy flows*: Through the mobile charger, surplus energy from energy-rich nodes is uploaded and transferred to energy-deficient nodes. This addresses the limitation caused by the distance between the nodes, for energy cooperation among the nodes [4].

Motivated by these developments, a new energy harvesting networking paradigm wherein data flows coexist with energy flows, is expected. However, this gives rise to new problems about the control of the energy flows and the data flows. Based on the prior knowledge of the energy harvesting process, the energy flows are regular and can be scheduled. As data transmission and energy transfer are coupled, the control of the data flows must take the nodes' energy states into consideration for reliable communication. In turn, workloads of data transmissions determine the directions of the energy flows. To simplify network management to achieve flexibility, control logic can be abstracted from underlying implementation, which means that, the control flows are separated from the data flows and the energy flows. Besides, a global view with logically centralized characteristic is necessary for the control flows to make decisions for optimal control of the data flows and the energy flows.

In this article, we present a new architecture named Software Defined Energy Harvesting Network (SD-EHN) for 5G green communications. We exploit Software Defined Networking (SDN) technology to dynamically schedule the data flows and the energy flows from a global perspective. There are three separated planes in SD-EHN: control plane, energy plane and data plane, which are responsible for decision making, energy transfer and data transmission, respectively. By extending the programmability of these planes, SD-EHN brings flexibility to energy scheduling and improves energy utilization, consequently facilitating green communications in 5G systems.

The integration of SDN technology enables energy harvesting networks by including the following properties in our proposed SD-EHN architecture.

- *Flexibility*: The flexible software-based control of the data flows and the energy flows is based on the flows instead of destinations.
- *Programmability*: SD-EHN brings high reconfigurability and programmability to network devices, so other third-party tools are convenient to debug, verify and test [6].
- *Controllability*: The on-demand network configuration and the global view of dynamic network states significantly improve the network controllability.

The rest of the article is organized as follows. We introduce our proposed SD-EHN architecture in Section II. In Section III, we develop the scenario where a mobile charger also acts as a mobile data collector in SD-EHN. We address the energy trading problem using stochastic inventory theory and Nash bargaining game. We present numerical results about performance evaluation in Section III and draw conclusions in Section IV.

II. Software Defined Energy Harvesting Networks

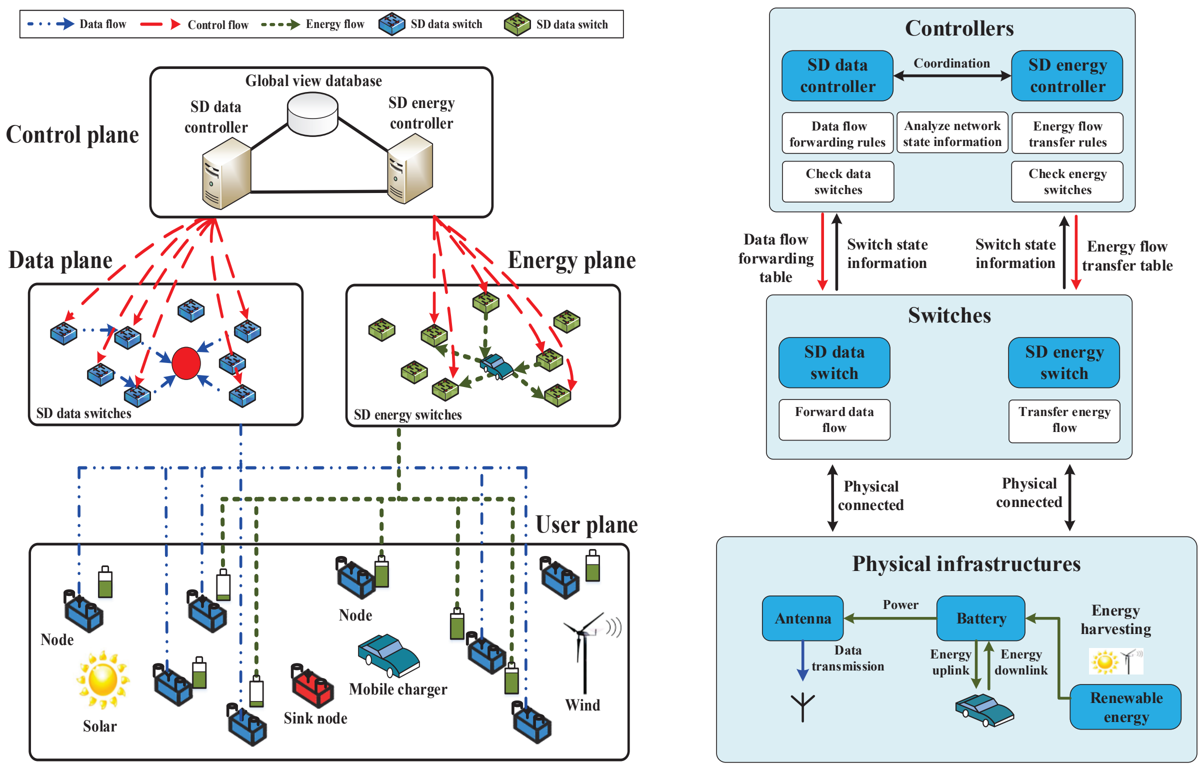
In this section, we leverage software defined wireless networks [7] to present an energy-efficient architecture named SD-EHN for supporting flexible energy scheduling and facilitating energy utilization optimization in 5G networks.

A. A Hierarchical Architecture with Four Planes

In a typical energy harvesting network, there are two queues in a node, namely, a data queue in the data buffer and an energy queue in the battery. Sensory data in monitoring areas is generated by the nodes and transferred to a sink node by multi-hop routing. Transmitting and receiving the sensory data lead to energy consumption while harvesting renewable energy (e.g., solar, wind and geothermal) makes a positive contribution to the energy queue.

SD-EHN provides programmability to data traffic and energy routing, which efficiently supports various high-quality applications through programming. The core idea in SD-EHN is to logically separate the control plane, the data plane and the energy plane. Compared to the software defined wireless network, an energy plane is added and utilized to provide flexible energy scheduling in the network. The energy plane and the data plane are to perform energy scheduling tasks and data transmission tasks, respectively. The logically centralized control plane obtains and updates the network states, and then schedules the energy flows and the data flows dynamically. The flow rules (i.e., data forwarding rules and energy transfer rules) are implemented in a software defined data controller (SD data controller) and a software defined energy controller (SD energy controller) respectively, in the control plane. These rules are sent to the data plane and the energy plane to instruct software defined data switches (SD data switches) and software defined energy switches (SD energy switches). The SD data switch connects to the data buffer and forwards data in the data queue. The SD energy switch connects to the battery to transfer energy in the energy queue. According to the flow rules, the nodes take actions on incoming data and energy. For example, a node works as a relay to transmit the sensory data, or uploads surplus energy in the energy queue to the mobile charger. To realize the separation of the planes in SD-EHN, a well-defined application programming interface between the switches and the controllers is crucial. The separation can be done by the enhanced OpenFlow protocol [8], which is considered as a typical example of such an application programming interface. More details about the proposed SD-EHN architecture are shown in Fig. 1(a) as follows.

- *Control plane*: The SD data controller and the SD energy controller are deployed in the control plane. A global view database mainly stores prior knowledge of network states, e.g., network traffic and energy harvesting characteristics of the nodes. Based on collecting and analyzing the real-time global information, the SD data controller and SD energy controller dynamically control the data flows and the energy flows from a global perspective. Two SDN controllers communicate and cooperate with each other to ensure logically centralized control.
- *Data plane*: The nodes connect to the SD data switches, which are responsible for forwarding data in the data plane. Based on the data forwarding rules designed by the SD data controller, the nodes optimize routing of data packets in the network. Data packets are routed among those nodes with sufficient energy for reliable communications, greatly improving network throughput.
- *Energy plane*: The SD energy switches connect to the batteries of the nodes and energy in the nodes can be scheduled in the energy plane. In the energy plane, the energy flow is bi-directional between the nodes and the mobile charger. According to the energy transfer rules designed by the SD energy controller, the nodes determine whether to stay idle or work in an energy downlink or energy uplink mode.
- *User plane*: The user plane includes all physical network entities. SD-EHN directs the flows along the optimal paths from or to the entities according to i) the nodes' position in the topology and their attributes, ii) the types of ambient renewable energy, and iii) the charging route of the mobile charger. As the control plane is decoupled from the data plane and the energy plane, physical infrastructures can be developed and updated independently.



(a) The architecture of SD-EHN.

(b) Function blocks in SD-EHN architecture.

Fig. 1: The architecture, function blocks and components in SD-EHN.

B. Function Blocks and Components

Fig. 1(b) shows the function blocks in SD-EHN, consisting of three layers with different network components as follows.

- *Controllers*: The SD data controller and the SD energy controller analyze the network state information and cooperate with each other to design the forwarding rules in the data flow forwarding table and energy flow transfer table. At the same time, the controllers monitor the state information of switches to check whether the switches work as expected.
- *Switches*: According to the data flow forwarding table, the SD data switches forward data among the nodes. The SD energy switches transfer energy between the nodes and the mobile charger according to the energy flow transfer table. Both the SD data switches and SD energy switches physically connect to the nodes.
- *Physical infrastructure*: There are different physical entities, including a mobile charger, nodes with a battery, an antenna and various energy harvesting devices. With the utilization of the antenna, the nodes transmit and receive the sensory data. The battery is to store renewable energy. The mobile charger works as an energy transporter with a high capacity battery, which replenishes energy to or collects energy from the nodes through wireless energy transfer technologies [9]. This bi-directional energy transfer scenario aims to flexibly schedule energy in SD-EHN. According to the data forwarding rules, the antenna is powered by the energy in the battery to support data transmission.

C. Benefits for 5G Green Communications

SD-EHN abstracts the network functions and manages the network in a centralized manner. The flow rules are logically centralized due to the global view of network states. With the optimal control of the energy flows and the data flows, SD-EHN enables flexible energy scheduling and efficient energy utilization. Ultimately, sustainable development of the network is achieved. 5G green communications can get benefits from SD-EHN, which are summarized as follows:

- *Flexible energy scheduling*: Energy cooperation among the nodes is enhanced to enable more nodes to join into and get benefits from energy scheduling. In SD-EHN, energy can be scheduled flexibly to optimize energy transfer in the energy plane.
- *Efficient energy utilization*: The SD data controller and the SD energy controller obtain global information of workloads and energy states of all nodes, respectively. So energy utilization is improved from a global perspective.
- *Sustainable development*: As the energy is scheduled on demand and utilized with higher efficiency, green communications are ensured to improve network throughput and save energy for sustainability, ultimately prolonging network lifetime.

III. Energy Trading in SD-EHN

In this section, we consider that a mobile charger can also act as a mobile data collector to periodically collect data from nodes [10]. Specific circuits for harvesting energy are easily included in a conventional receiver, so the mobile charger can practically undertake data collection tasks. A mobile charger is scheduled to provide energy replenishment to energy-deficient nodes or collect surplus energy from energy-rich nodes, which causes an energy trading problem. An optimal energy storage level is used to indicate a rational constraint of energy trading. We use a Nash bargaining game to solve the benefit allocation problem when energy-rich nodes upload their surplus energy to the mobile charger. Finally, we provide numerical results to evaluate the performance of SD-EHN.

A. Mobile Data Gathering and Bi-directional Energy Transfer

Fig. 2 shows a mobile data gathering and bi-directional energy transfer scenario consisting of rechargeable nodes, sink nodes, a service station and a mobile charger. The nodes are employed by the service station to perform sensing tasks and send sensory data to a local sink node in a monitoring area. The mobile charger acts as a mobile data collector and an energy transporter, which periodically travels around all the sink nodes and collects sensory data in different monitoring areas, thus sends the sensory data to the service station for network monitoring and further analysis. Here, the mobile charger belongs to a charging service provider and is managed to recharge energy-deficient nodes or collect surplus energy. There exist multiple energy trades between the nodes and the charging service provider in this scenario.

We provide more details about physical implementation of the bi-directional energy transfer according to the SD-EHN components in Section II-B. Fig. 2 shows that there are an oscillator, an AC/DC converter, two resonant coils including transmitting receiving coils in the mobile charger and nodes to support bi-directional energy transfer. More details are as follows.

- *Energy downlink*: When the mobile charger charges a node via an energy downlink, the oscillator converts direct current (DC) from its battery into high-frequency alternating current (AC). The transmitting coil in the mobile charger works as an energy transmitter. There is an energy receiver in each node, which consists of 1) a receiving coil tuned to exactly resonate at the same frequency as the transmitting coil, 2) an AC/DC converter, and 3) a regulator. By establishing an oscillating magnetic field between the transmitting coil and the receiving coil, an AC is then induced in the receiving coil and is regulated to charge the battery of the node quickly [9].
- *Energy uplink*: To establish an energy uplink, each node is equipped with similar circuits and components of energy transmission. The node changes working mode according to the energy flow transfer table in its SD energy switch. When working as an energy transmitter, the node transfers surplus energy to the mobile charger in a similar way. The energy in the battery can be utilized by the antenna to support data transmission according to the data flow forwarding table in the connected SD data switches [9].

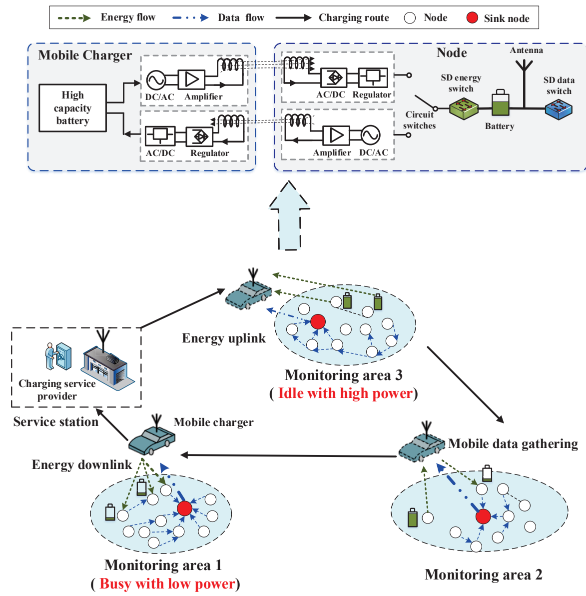


Fig. 2: A scenario of mobile data gathering and bi-directional energy transfer in SD-EHN.

B. Problem Formulation: An Optimal Energy Storage Level in Nodes

The mobile charger periodically visits each sink node to gather real-time sensory data. The duration of time period is denoted by T. At the same time, the mobile charger offers charging services to the nodes with energy requests. A node can also harvest energy from the environment. The total amounts of energy harvested by node i in the j_{th} data gathering period is denoted by h_i^j. To formulate the dynamic nature of harvested energy, we consider that the energy harvesting process during T is a sequence of independent identically distributed (i.i.d.) random variables over time. Similarly, the sensory data arrival process of a node follows an i.i.d. process. Node i needs to send the total amounts of sensory data, λ_i^j to sink nodes in time. For estimating the random variables of energy harvesting and the data arrival process, available prior knowledge of the workloads and the energy harvesting process can be obtained. For simplicity, the energy consumption of each data packet transfer is one energy unit [11]. We consider that node i can monitor its residual energy R_i^j at the beginning of the time period. The mean value of h_i^j and λ_i^j are defined by $\mathbb{E}h_i^j$ and $\mathbb{E}\lambda_i^j$. Clearly, when $R_i^j + \mathbb{E}h_i^j T < \mathbb{E}\lambda_i^j T$, node i should replenish energy from the mobile charger. Otherwise, it can consider to work in the energy uplink mode. In these two cases, node i needs to determine either 1) how much energy should be obtained from the mobile charger via the energy downlink, or 2) how much energy should be uploaded to the mobile charger via the energy uplink.

Fig. 3 illustrates the optimal energy storage level in nodes from an economic perspective using an analogy. Each node is like a salesman, who sells the products (sensory data) to the customer (service station) for earning benefits. Meanwhile, a node can replenish the energy (raw material) from the mobile charger (manufacturer) at certain costs, denoted as the charging service costs. In addition, a node typically utilizes a capacitor as its battery (energy inventory) to store energy. The energy storage costs cannot be ignored because of potential self-discharging in the battery [12]. The energy storage costs are proportional to the energy storage level. Thus, a node has to consider earning benefits, payments for replenished energy and storage costs for maximizing the total economic benefits. The total economic benefits are related to the energy storage level of the node, so we formulate the problem of determining the energy storage level of the node as a typical inventory control problem in a supply chain.

We utilize stochastic inventory theory to analyze energy demand of the nodes in SD-EHN. The optimal energy storage level is used to describe the nodes' optimal strategy for economic benefit maximization in every data gathering period. Utilizing the prior knowledge of the data arrival process, a node can determine its optimal energy storage level, Q_i^{j*}, considering the charging service costs and storage costs and its benefits. When incorporating the additional energy of harvesting from the environment, there is a constraint for node i working in the energy uplink mode. The maximal amount of uploading energy is less than $R_i^j + \mathbb{E}h_i^j T - Q_i^{j*}$.

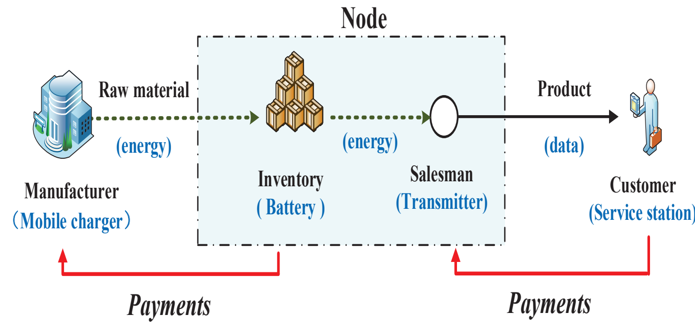


Fig. 3: The optimal energy storage level in nodes from an economic perspective.

C. Solutions: A Nash Bargaining Game for Energy Trading

In one data gathering period, T, some busy nodes can request charging services to obtain energy replenishment for performing sensing tasks. Besides, energy-rich nodes can sell their surplus energy to the mobile charger via the energy uplinks. In an energy market, the energy uplinks need to be stimulated by some incentive policies. On one hand, the charging service provider announces an energy purchase price to the nodes according to the dynamic energy demand of the nodes. On the other hand, each energy-rich node makes a decision on the optimal amount of traded energy to maximize its own benefit. This decision is made according to the different energy purchase prices set by the charging service provider and the rationality of the node. Total benefits of an energy trade are allocated to the charging service provider and an energy-rich nodes. This gives rise to a benefit allocation problem in the energy trade. Here, we utilize a Nash bargaining game approach to solve this problem.

The charging service provider first determines the dynamic energy purchase price. The charging service provider records the total energy demand in each data gathering period. Then the energy purchase price can be dynamically changed to match with the trend of energy demand in the network. In the j_{th} data gathering period, the energy purchase price P_j for one unit of energy is related to the total energy demand in the last data gathering period, D_{j-1}. Here, the energy purchase price is denoted by $P_j = \alpha(\frac{D_{j-1}}{\beta})^{\gamma}$, where α, β and γ are three predefined parameters set by the charging service provider.

Before an actual energy trade, a negotiation process is carried out between the charging service provider and an energy-rich node. The mobile charger also represents the charging service provider and can perform multiple negotiation processes at the same time. As shown in Fig. 4, we use a Nash bargaining game approach to describe these negotiations as follows.

- A risk-neutral energy seller and a risk-neutral energy buyer negotiate the benefit allocation. The seller and the buyer in the game obtain allocations according to the Pareto optimality of a Nash bargaining solution or a disagreement after the negotiation. In this article, we normalize the disagreement points of a negotiation to zero [13].
- Next, we focus on analyzing the detailed benefits of the seller and the buyer in every Nash bargaining process. Let π_i^j and $\pi_{c,i}^j$ denote as the benefits of node i and the charging service provider in the j_{th} data gathering period, respectively. In the j_{th} time period, if the amount of traded energy is x_i^j, for node i, its benefits can be expressed as

$$\pi_i^j = s_i^j P_j x_i^j - \Delta L(x_i^j), \tag{1}$$

where s_i^j is the share of node i in percentage obtained from the total benefits of the energy trade. Let us denote the potential loss caused by selling x_i^j amounts of energy by $\Delta L(x_i^j)$, which can be expressed as $\Delta L(x_i^j) = d_i^j (x_i^j)^2$. Here, d_i^j is defined as the loss factor, which is negatively correlated to the residual energy. For the charging service provider, its benefits are calculated as

$$\pi_{c,i}^j = (1 - s_i^j) P_j x_i^j - c x_i^j, \tag{2}$$

where $(1 - s_i^j)$ is the share of the charging service provider in percentage, and c is the average fixed cost for transferring one unit of energy. The charging service provider undertakes the energy transfer costs in the energy uplink.
- If π_i^j and $\pi_{c,i}^j$ are given, the objective function of the negotiation is expressed as $U(r) = (\pi_i^j - 0)^{\tau_i^j} (\pi_{c,i}^j - 0)^{1-\tau_i^j}$. The indexes τ_i^j and $(1 - \tau_i^j)$ are defined as the individual negotiation power of node i and the charging service provider, respectively. The individual negotiation power of a node is determined by its maximum amount of energy trading. We utilize the S function with respect to the maximum amount of energy

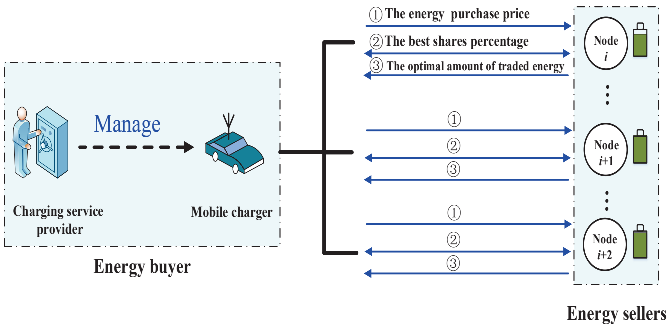


Fig. 4: The negotiation process between the charging service provider and energy-rich nodes.

trading to describe τ_i^j. To maximize the utility of the negotiation, $\ln U$ is differentiated with respect to s_i^j. Clearly, the objective function of the negotiation is concave, which indicates that the maximal value of this function exists. Therefore, using the first-order optimality condition, we obtain the best response of the negotiation in terms of node i, as follows,

$$s_i^j * = \frac{(1-\tau_i^j)d_i^j(x_i^j)^2 + \tau_i^j P_j x_i^j - \tau_i^j c x_i^j}{P_j x_i^j}. \quad (3)$$

Equation (3) shows the final share of node i in percentage obtained from an energy trade. The equation encourages fairness of energy trading as the charging service provider actually gives the payments ($P_j x_i^j$) to node i and also undertakes the energy transfer costs ($c x_i^j$). So the final share of node i in percentage decreases with increasing payments and energy transfer costs. On the other hand, the charging service provider aims to stimulate energy-rich nodes to upload more energy. So the nodes can obtain higher shares when they are more willing to upload their surplus energy.

- By substituting s_i^j* into π_i^j, we can see that the benefit function of node i can be converted into an optimal function in terms of x_i^j. We take the first and second derivatives of π_i^{j*} with respect to x_i^j and find that the optimal function is concave. As a result, the optimal amount of traded energy for node i takes the form $x_i^{j*} = \tau_i^j(P_j - c)/(2d_i^j)$.

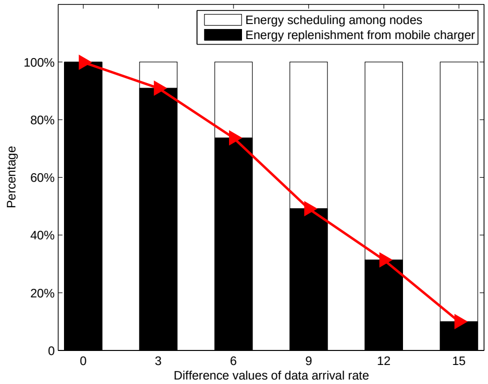
D. Illustrative Results

We consider an energy harvesting network consisting of four monitoring areas. Every monitoring area ($20m \times 20m$) has 20 randomly deployed nodes. The capacity of each node battery is 15mAh and a mobile charger travels around all the monitoring areas to gather data every 30 minutes [10]. The data arrival process of the nodes is a sequence of independent identically distributed random variables, which follows a Poisson distribution and takes values from [5, 20] Kb per minute. The energy harvesting devices of the nodes are similar to the devices in [14], whose power is a random value in the range of [1, 10] mw. Some parameters are chosen for the simulation are: $p_e = 1, p_c = 0.8, p_s = 0.16$. These parameters indicate the earning benefits, charging service costs, and storage costs for one unit of energy, respectively. Three predefined parameters, $\alpha = 0.2, \beta = 1.5$, and $\gamma = 1$, are set to determine the energy purchase price.

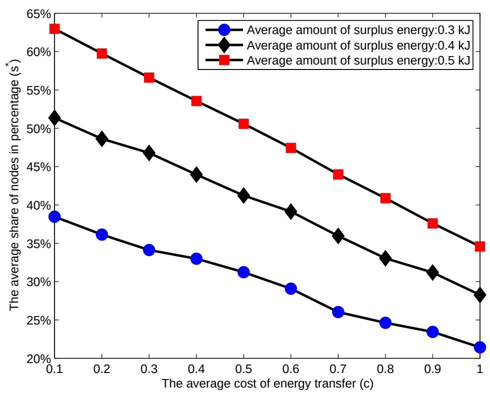
In SD-EHN, energy-deficient nodes can replenish energy through two ways: i) energy replenishment from the mobile charger, and ii) energy scheduling among nodes. For energy scheduling, the energy-rich nodes in SD-EHN are stimulated to upload their surplus energy to the mobile charger, who can transfer the surplus energy to energy-deficient nodes. We consider that there are two busy monitoring areas with higher workloads and two idle monitoring areas with lower workloads.

Fig. 5(a) shows the percentage comparison between energy scheduling among nodes and energy replenished from the mobile charger. There are six kinds of load difference values between idle monitoring areas and busy monitoring areas. When the value of load difference increases, the percentage of energy replenishment from the mobile charger is decreasing (the solid line with triangles), while the percentage of energy scheduling among nodes is increasing. When most of the nodes are busy (the value of load difference is 0), the nodes demand energy resulting in inexistence of energy uplinks. As a result, energy-deficient nodes replenish energy from the mobile charger. However, when the value of load difference is bigger (e.g., the value is 12), the percentage of energy scheduling among nodes is about 180% higher than that of energy replenishment from the mobile charger. Surplus energy from the energy-rich nodes encourages more energy uplinks when the values of load difference increase. More energy-deficient nodes can benefit from this flexible energy scheduling, which supports large-scale energy transfer. By energy scheduling among the nodes in SD-EHN, it is beneficial to decrease external energy replenishment to the network. The results indicate that SD-EHN enables flexible energy scheduling and optimizes the energy utilization, especially when the value of load difference of the nodes is big.

Fig. 5(b) shows the performance comparison of benefit shares (i.e., s_i^j*) with respect to different amounts of surplus energy from the nodes and different average costs for transferring one unit of energy (c). In a monitoring area, the average value of the data arrival process for all nodes is set as 8 Kb per minute. The average amount of surplus energy in batteries, takes three values: 0.3, 0.4 and 0.5 kJ. The energy trades between the nodes and the charging service provider are affected by the amount of surplus energy from the nodes. Higher amounts of surplus energy brings more traded energy to the charging service provider. Finally, the higher average share in the energy trades can be obtained, as shown in Fig. 5(b). Thus, energy trading considerably improves the benefits for the nodes. Moreover, when the energy transfer costs undertaken by the charging service provider are increasing, the average share of the nodes decreases. The charging service provider undertakes higher energy transfer costs, and the final share of the charging service provider increases while the final average share of the nodes decreases.



(a) The comparison of energy from external replenishment and internal scheduling in percentage.



(b) The comparison of average share of nodes in the energy trading.

Fig. 5: The performance comparisons of the SD-EHN.

IV. Conclusion and Open Issues

In this article, we presented an energy-efficient architecture named SD-EHN for 5G green communications. Energy harvesting networking is enhanced by supporting flexible energy scheduling and improving overall energy efficiency of the network. We investigated a mobile data gathering scenario in SD-EHN. We proposed an energy trading model for nodes using stochastic inventory theory and a Nash bargaining game. Numerical results indicate that our proposed SD-EHN supports flexible energy scheduling, which improves energy efficiency and achieves energy saving.

There are several interesting problems that are worthy of further study. For example, multiple local controllers may be required for alleviating loads and localized decision making, so SD-EHN may focus on the usage of distributed local controllers as well as the coordination among them for centralized network control. Besides, other technologies also promote development of 5G communication systems, e.g., mmWave. Future communication systems are the organic combinations of the advanced technologies but the coming challenge is how to integrate them and make them work with high efficiency.

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