Efficient Wireless Power Transfer in Software-Defined Wireless Sensor Networks

Waleed Ejaz, Muhammad Naeem, Mehak Basharat, Alagan Anpalagan, and Sithamparanathan Kandeepan

***Abstract*— The ever-growing increase in modern and ubiquitous applications of wireless sensor networks (WSNs) is causing energy scarcity, which is a serious threat to the lifetime of the network. Wireless power transfer emerges as a promising solution to replenish the sensor nodes. In wireless power transfer, energy is transferred to sensor nodes through dedicated energy transmitters. In addition, software-defined WSNs (SDWSNs) have been recently realized to fully explore and efficiently utilize the resources of WSNs. In this paper, we present an energy efficient SDWSN with wireless power transfer. We propose a mechanism to place energy transmitters and determine minimum number of energy transmitters. For placement of energy transmitters, a tradeoff between maximum energy charged in the network and fair distribution of energy is studied. We present this mechanism by defining a utility function to maximize both total energy charged and fairness. For minimum number of energy transmitters, an optimization problem is formulated and solved while satisfying the constraint on minimum energy charged by each sensor node. We also propose an energy-efficient scheduling scheme for energy transmitters for the given tasks of energy charging. The focus is to minimize the energy consumption of energy transmitters while keeping sensor nodes sufficiently charged. Finally, this paper is supported by extensive simulation results, which illustrate the performance of energy-efficient SDWSNs with wireless power transfer in terms of energy charged, fairness, number of energy transmitters, number of tasks, and energy consumption.**

***Index Terms*— Optimal node placement, optimization, RF energy harvesting, wireless sensor networks.**

I. Introduction

WIRELESS sensor networks (WSNs) play a critical role in numerous applications including smart grids, intelligent transport systems, health care, smart homes, environment monitoring, public safety networks, etc. Research has been done to enhance the performance of WSNs, where most of them considered sensors that can perform a specific task, e.g., monitoring of temperature, humidity, etc. However, modern WSN applications are characterized by various different requirements and scenarios. Software-defined wireless sensor networks (SDWSNs) appear as a convincing solution to this problem [1]–[4]. In SDWSNs, a node can be equipped with different type of sensors (e.g., ultrasonic, photoelectric, infrared, etc.) and the functionality of node can be dynamically configured by a controller to perform a specific sensing task. Nevertheless, the limited battery life of sensor nodes is one of the major threats for the performance of WSNs and SDWSNs. Many energy efficient schemes have been proposed in the literature to reduce energy consumption in WSNs [5]–[8] and only limited study has been done on energy efficiency in SDWSNs [9].

RF energy harvesting and wireless power transfer are considered as a potential solution to increase lifetime of WSNs [10]–[13]. In RF energy harvesting, sensor nodes harvest energy from ambient RF sources; however, the availability of ambient energy sources is not always guaranteed. In wireless power transfer, the external energy sources are intentionally deployed in surroundings to extend the lifetime of WSNs [14]. It was assumed that all the energy sources are always on or periodically on, which in turn increases the energy consumption by energy transmitters. Another paradigm is wireless passive sensor networks to enhance the lifetime of WSNs by providing energy using external RF sources. Modulated backscattering design is considered in which sensor nodes switch their antenna impedance and reflect the incident signal coming from an RF source in order to transmit their data [15], [16]. Similar to wireless power transfer, wireless passive sensor networks assume one or more dedicated RF energy transmitters which will transfer energy without considering the charging/ harvesting demand of sensor nodes.

RF energy harvesting or wireless power transfer has not been widely explored in SDWSNs yet. SDWSNs provide more flexibility to sensor nodes for energy charging/ harvesting according to their own requirements and scenarios. An SDWSN with wireless power transfer capability is equipped with a number of dedicated energy transmitters, where energy transmitters can dynamically reconfigure their functions according to the real time charging

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requirements of sensor nodes. Energy-efficiency is a serious problem in SDWSNs much like in traditional WSNs. The number of active energy transmitters is directly proportional to the energy consumed. In other words, if the number of active energy transmitters is less, then the less energy will be consumed. However, sensor nodes interested in charging may be nearby or far from each other and also require a certain amount of energy charged. Therefore, it is important to investigate the efficient wireless power transfer in SDWSNs.

In this paper, we will focus on wireless power transfer in SDWSNs, in which dedicated energy transmitters are deployed. The goal of wireless power transfer in SDWSNs is to enhance the energy efficiency and performance with uninterrupted network operation. In a SDWSN with wireless power transfer capability, each node can be equipped with multiple sensors and a wireless interface through which it can transmit and receive data. The same wireless interface can be used for energy charging to save the cost and reduce the complexity of nodes. However, an additional energy conversion circuit is required which converts RF energy into DC electricity and can store it in energy storage. Later, the charged energy can be used for sensing operation, processing, and data transmission and reception. The amount of energy charged by each node depends on the sensitivity of harvesting circuit and the distance between sensor node and energy transmitter [17]. The nodes which are spatially distant from the energy transmitters can result in uneven charging of energy. This can result in energy depletion of nodes which are far from the energy transmitters and thus reduce the lifetime of network. Therefore, optimal placement and number of dedicated RF energy transmitters are crucial issues in SDWSNs with wireless power transfer. Further, energy consumption by energy transmitters can be reduced by introducing task based energy charging, where energy transmitters can be scheduled for wireless power transfer based on the charging requirements of sensors. However, a wireless power transfer needs certain level of coverage and sufficient time to harvest. Therefore, scheduling of energy transmitters with guaranteed coverage and duration is vital for the energy efficiency in SDWSNs with wireless power transfer.

We consider a SDWSN with wireless power transfer which consists of a controller, sensor nodes, and energy transmitters as shown in Fig. 1. To our best knowledge, we are the first to investigate efficient wireless power transfer in SDWSNs. We investigate the problems of optimal placement and minimum required number of energy transmitters, and energy-efficient scheduling of energy transmitters. SDWSNs are expected to be an integral part of Internet of Things (IoT) where sensor nodes can dynamically join Internet. Thus, the proposed work can be adopted in IoT to improve energy-efficiency and enhance network lifetime. The main contributions of this paper are as follows:

- First, the target is to cover all the sensors in the range of energy transmitters. To achieve this, we propose an optimal placement mechanism with joint maximization of energy charged in the network and fair distribution of energy among sensor nodes. We also present the trade-off between energy charged and fairness to further optimize the applicability of the proposed strategy in varying conditions of sensor nodes.
- Second, we determine the minimum number of energy transmitters while satisfying the minimum energy charging constraint for each sensor node.
- Third, we propose an energy-efficient scheduling scheme to minimize energy consumption of energy transmitters. We formulate a problem to activate energy transmitters with an objective to minimize energy consumption while considering the coverage constraint, charging duration, and minimum energy charged.
- Finally, extensive simulations are conducted to validate proposed schemes.

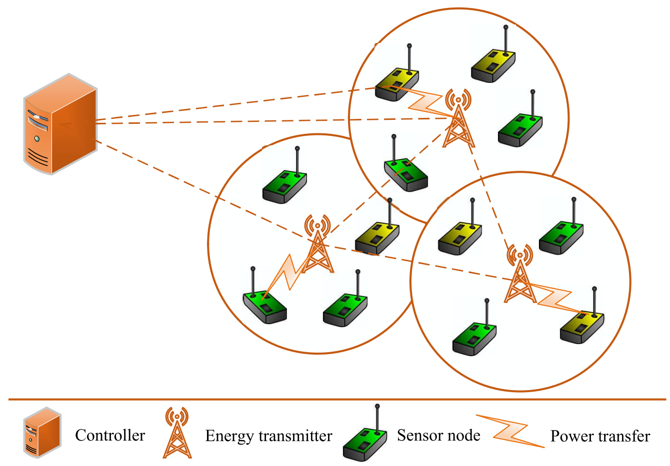

Fig. 1. An illustration of SDWSNs with wireless power transfer.

The rest of the paper is organized as follows. We briefly review related works in Section II. Section III introduces the system model. Then, we present strategies for the optimal placement and minimum number of energy transmitters, and energy efficiency scheduling scheme for energy transmitters in Section IV. We illustrate the simulation results and performance evaluation in Section V. Finally, Section VI states the conclusions.

II. Related Works

In this section, we present a brief overview of SDWSNs, and recent works in the area of energy harvesting and wireless power transfer in WSNs.

A. Software-Defined Wireless Sensor Networks

Recently, software defined networking approach is extended to the wireless sensor networks to reduce complexity in network management. Few investigations have been done in literature which legitimate the feasibility of SDWSNs. Introduction and technical challenges faced to extend SDN to WSNs are presented in [1] and [2]. In [3], SDWSN is described with the aim to reduce the information exchanged between sensor nodes and controller, and to make sensor nodes programmable. The paper provides the benefits offered by SDWSNs over traditional WSNs and a prototype has been implemented. A TinySDN is presented for WSNs in [4], which enables multiple controllers for SDWSNs. An energy-efficient sensor activation strategy is proposed in [9]. Authors investigated the sensor activation (number of sensors activated for a given target), task mapping (the assignment of tasks to each sensor node), and sensing scheduling (the rate at which sensors perform sensing for a target) to achieve quality-of-sensing for all tasks in SDWSNs. An energy minimization problem for sensor activation is formulated as mixed-integer with quadratic constraints programming (MIQP) while considering both sensor activation and task mapping. A distributed information extraction in WSNs using multiple software agents with dynamic itineraries is proposed in [18], where multiple multiple software agents are transmitted to perform assigned tasks.

B. Energy Harvesting and Wireless Power Transfer in WSNs

Energy harvesting from the ambient energy sources has been studied in the recent past. Detailed reviews of energy harvesting schemes for WSNs are presented in [10] and [19]. In [20] authors study the feasibility of RF energy harvesting for WSNs. The measurements are presented for RF power density on GSM 900 and GSM 1800 bands. It is concluded that the harvested energy can be stored in a super-capacitor and later it can be used to power WSN. However, the availability of ambient energy sources is not always guaranteed. Recently, wireless power transfer received attention for controlled energy harvesting. Energy models and analysis of WSNs with wireless power transfer are presented in [21]. In [22] and [23], authors studied the impact of energy transmitters and chosen frequencies on the charging time of sensors.

Medium access control (MAC) protocols are designed with the aim to optimize the energy charged by sensor nodes while minimizing the disruption to the data communication. The performance of overlaid wireless sensor transmission with RF energy harvesting is investigated in [24]. The delay sensitive and insensitive scenarios are considered for the performance evaluation. In [25], cross-layer optimization scheme is proposed by exploiting unbalanced energy charging rate in WSNs to improve the performance of the network. Numerical results are presented to show performance enhancement by joint consideration of routing, MAC, and power control. A directional energy transmission/ reception model is considered for WSNs with wireless power transfer in [26]. This can help to overcome the path losses of RF signals and enable sensor nodes to charge energy from a distance. In [27] and [28], energy harvesting is also considered for cognitive radio networks with an aim to maximize throughput.

The problem of mission-aware placement of energy transmitters is presented in [29]. An integer linear programming model is used to optimize the mission-aware placement of RF energy transmitters to increase the network lifetime. This optimization is done for a particular scenario. Hence, it could not address the issue of optimal energy transmitter placement in general. Optimal placement and number of energy transmitters in WSNs with RF energy harvesting are presented in [30]. A utility function is defined which maximizes both the total energy harvesting and fairness. In [31], a joint optimization of charger placement and power allocation is considered for wireless power transfer. The location of charger and corresponding power allocation is done in order to maximize the charging quality with constraint on power budget. Another approach for placement optimization of energy and information chargers is presented in [32]. The objective is to minimize the network deployment cost with minimum number of energy chargers, subject to the harvesting and performance requirements of nodes. In [33] and [34], authors considered optimal deployment of wireless chargers using greedy algorithms for wireless rechargeable sensor networks.

In a summary given in Table I, existing literature on WSNs with wireless power transfer assume that the energy transmitters are continuously transmitting for power transfer. However, they do not address more realistic cases in which a subset of energy transmitters can be activated for wireless power transfer in a desired region. Hence, we study the scheduling of energy transmitters in this paper. Further, wireless power transfer has not been considered in SDWSNs in the literature.

III. System Model

A. Network Model

We consider a SDWSN with wireless power transfer that consists of N_S number of nodes (each node is equipped with multiple sensors having different sensing capabilities and energy harvesting circuit), N_E number of energy transmitters, and network size S. We assume that the nodes are distributed randomly in the network area. The nodes can request for power transfer to controller which is considered as a task t. The controller can assign multiple tasks from T (T is the set of tasks) to the energy transmitter $e \in \{1, 2, \ldots, N_E\}$. The transmit power of *e-th* energy transmitter is denoted by P_e. It is also assumed that all nodes have only one wireless interface. Therefore, sensor nodes can operate in either transmission and charging mode. The energy transmitter e can transfer power to a task $t \in T$ if the requesting node is in the harvesting range of e. It can be represented as:

$$\phi_{et} = \begin{cases} 1, & \text{if task } t \text{ is in harvesting range of } e \\ 0, & \text{otherwise.} \end{cases} \tag{1}$$

The energy transmitters may have different harvesting ranges for given tasks. The value of ϕ_{et} can be found once the controller has location information of node(s) and energy transmitter(s). In SDWSN, a controller is responsible for the network control and management. It is assumed that the sensor nodes initially exchange messages with controller, and the controller has the information of network topology. In SDWSN, energy transmitter needs to be programmed before conducting power transfer. An efficient scheduling on the energy transmitters can help to reduce energy consumption, in which only a subset of energy transmitters shall be activated for the power transfer. Let $\delta_{e,H}$ be the harvesting duration/ slot for which energy transmitter e will be activated for a given set of tasks. The harvesting duration is not fixed and can vary from $\delta_{e,H_{min}}$ to $\delta_{e,H_{max}}$ depending on the requirements of sensor node. Thus, energy transmitter can be in an active

TABLE I

SDWSNs AND RELATED WORK IN TRADITIONAL WSNs AND SDWSNs

Type	Ref.	H[a]	D[b]	Objective	Solution
SDWSNs	[1]	✗	✗	Reduce rigidity to policy changes and management issues	SDWSN architecture is proposed and address the main technical challenges
	[3]	✗	✗	To reduce the amount of information exchange between Sensors and controller, and to program sensor nodes as finite state machine	A prototype of SDWSN is implemented
	[4]	✗	✗	To reduce the amount of control data in SDWSNs	TinySDN is designed and implemented that enables multiple controllers in SDWSNs
	[9]	✗	✗	Energy minimization in multi-task SDWSNs	An energy-efficient sensor activation strategy is proposed
Traditional WSNs	[22]	✓	✓	Optimize the energy charging by sensors while minimizing disruption to data communications	RF-MAC protocol is proposed
	[23]	✓	✓	Optimization of energy delivery to energy hungry sensors	MAC protocol is proposed
	[29]	✓	✓	Maximize the number of nodes receiving power	Deploy mission aware placement of wireless energy transmitters
	[24]	✓	✗	Optimize the design of energy storage capacity of sensor nodes and minimize the average packet delay	An optimal design is proposed which consider the delay sensitive and insensitive scenarios
	[25]	✓	✗	Balance the available energy among sensor nodes	A cross layer approach is used which considers routing, scheduling, and power control
	[26]	✓	✓	Overcome the path losses of RF signals and to enable sensor nodes to charge energy from a distance	A directional energy transmission/ reception model is proposed
	[30]	✓	✓	Placement of minimum number of energy transmitters	Energy transmitters are placed while jointly maximizing total energy and fairness
	[31]	✓	✓	Joint optimization of energy transmitter placement and power allocation	Optimal placement of energy transmitter is done in order to maximize the charging quality
	[32]	✓	✓	Minimize the network deployment cost with minimum number of energy transmitters	Energy transmitters are placed while satisfying the harvesting and performance requirements
	[33], [34]	✓	✓	Placement of energy transmitters	Energy transmitters are placed optimally using greedy algorithms

[a](H)arvesting or wireless power transfer.
[b](D)edicated energy transmitters.

mode or sleep mode. The energy consumption over $\delta_{e,H}$ by the *e-th* energy transmitter in active mode can be represented as [35]:

$$\xi_{e,A} = (P_{HC} + P_{RF} + P_{RP} + P_e) \times \delta_{e,H}, \tag{2}$$

where P_{HC} and P_{RF} are the power consumption of the hardware circuit (e.g. control units and processing) and RF module, respectively. P_{RP} is the power consumption in reception and processing of packets exchanged by energy transmitter with controller. Our aim is to schedule the activation of energy transmitters to minimize the energy consumption while guaranteeing the coverage. The energy consumption by the *e-th* energy transmitter in sleep mode can be represented as $\xi_{e,S}$.

Let $\delta_{i,D}$ be the duration of data transmission slot for *i-th* sensor node. The energy consumed $\xi_{i,D}$ by the *i-th* sensor node can be represented by [8]:

$$\xi_{i,D} = (P_S + P_R + P_{HC} + P_{RF} + P_{i,D}) \times \delta_{e,D}, \tag{3}$$

where P_S and P_R are the power consumed in sensing and processing by sensor nodes respectively. $P_{i,D}$ is the transmit power of *i-th* sensor node.

B. Energy Charging Model

It is assumed that the energy transmitters have capability of omni-directional transmission. The amount of energy charged by nodes depends on the transmit power of energy transmitter,

TABLE II
DESCRIPTION OF THE SYMBOLS USED IN THE MODEL

Symbol	**Description**
N_S	Number of sensor nodes
N_E	Number of energy transmitters
S	Network size
T	Set of tasks
P_e	Transmit power of *e-th* energy transmitter
ϕ_{et}	Charging range of energy transmitter e for task t
$\delta_{e,H}$	Harvesting duration of energy transmitter e
$\xi_{e,A}$	Energy consumption by energy transmitter e in active mode
$\xi_{e,S}$	Energy consumption by energy transmitter e in sleep mode
P_{HC}	Power consumption of the hardware circuit
P_{RF}	Power consumption of the RF module
L_T	Path loss
d_0	Distance of a reference location from transmitter
d	Distance between transmitter and receiver
ω	Path loss constant
$E_{C_{i,e}}$	Energy charged by node i from energy transmitter e
ρ_i	Power consumed by node i for reception
η	Energy charging efficiency
α	Trade-off factor
$\{\widehat{x_e},\widehat{y_e}\}$	Optimal placement of energy transmitter e
$\overline{E_C}$	Minimum required energy charged by sensor
ς	Acceptable error margin
$\widehat{N_E}$	Minimum number of energy transmitters
ξ_{Th}	Pre-set threshold of residual energy for RFP

harvesting circuit, and propagation properties of the environment. In terrestrial environment, the obstacles of different sizes cause reflection, refraction, and scattering of signals. Thus, the path loss in terrestrial environment is higher than free space path loss and can be modeled as [36]:

$$L_T(d) = L_0(d_0) + 10\ \omega\ \log(d/d_0) + X_f, \tag{4}$$

where d_0 is the distance of a reference location from transmitter with measured path loss $L_0(d_0)$ which depends on the signal frequency, d is the physical distance between transmitter and receiver, ω is the path loss exponent for the radio environment and the Gaussian random contributor X_f with zero mean and standard deviation σ, which represents shadowing effects.

The energy charged $E_{C_{i,e}}$ by *i-th* node from *e-th* energy transmitter over $\delta_{e,H}$ time is:

$$E_{C_{i,e}} = \left[(P_e - L_T - \rho_i) \times \delta_{e,H}\right] \times \eta, \tag{5}$$

where η is the energy charging efficiency which depends on harvesting circuit and ρ_i is power consumed in reception by *i-th* sensor node.

A detailed list of symbols and their description is provided in Table II.

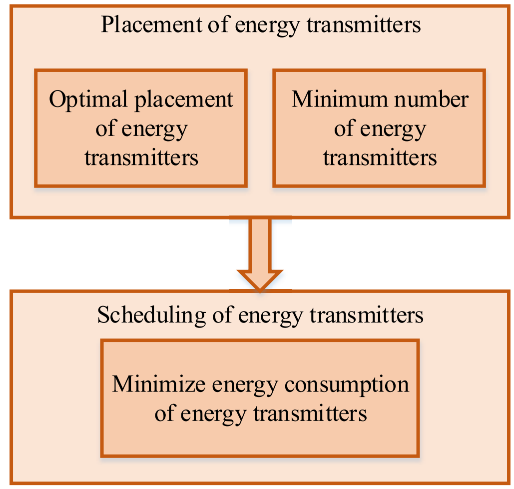

Fig. 2. A two-stage energy-efficient wireless power transfer in SDWSNs.

IV. ENERGY-EFFICIENT WIRELESS POWER TRANSFER IN SDWSNs

At top level, the energy-efficient wireless power transfer in SDWSNs is organized in two main components as shown in Fig. 2. 1) Placement of energy transmitters and 2) Scheduling of energy transmitters. We now describe the detailed operations of both components.

A. Placement of Energy Transmitters

The optimal placement and the number of energy transmitters are most crucial aspects of wireless power transfer in SDWSNs. Here, we provide the strategies adopted for optimal placement of energy transmitters and determining minimum number of energy transmitters during the initial process to maximize the energy charged in the network and fair distribution of energy among all the sensor nodes. The controller in SDWSN is in-charge of all these operations since it has the complete knowledge of network topology. Thus, the controller is responsible for the placement of energy transmitters. The problem of placement of energy transmitters in SDWSNs with wireless power transfer can be solved with different objectives. However, simultaneous optimization for energy charged and fairness of energy distribution may not be possible always. In many cases, there exists a trade-off between maximum energy charged in the network and fairness. Here, we present a trade-off between two parameters based on the internal policies. Let α be the trade-off factor, then we can define a utility function for the *e-th* energy transmitter placed at a position $\{x_e, y_e\}$, as

$$U(x_e, y_e) = (1-\alpha) \min_{\forall j \in \{1,2,\ldots,N_S\}} \sum_{e=1}^{N_E} E_{C_{j,e}} + \alpha \sum_{i=1}^{N_S} \sum_{e=1}^{N_E} E_{C_{i,e}}, \tag{6}$$

where trade-off factor is $\alpha \in [0, 1]$. $E_{C_{i,e}}$ and $E_{C_{j,e}}$ are the energy charged by node i and j from energy transmitter e, respectively. The corresponding optimal placement of *e-th* energy transmitter for a given α can be obtained by maximizing the utility function given by,

$$\{\widehat{x_e}, \widehat{y_e}\} = \underset{\{x_e, y_e\}}{\text{argmax}}\ U(x_e, y_e), \tag{7}$$

where $\{\widehat{x_e}, \widehat{y_e}\}$ represents the optimal position of *e-th* energy transmitter for the given α.

The optimization problem in (7) is a trade-off between fairness of energy distribution among all sensor nodes and maximum energy charged in the network. For fairness we first calculate the minimum energy charged by each sensor from energy transmitters and then choose the maximum of that to ensure that each sensor avails the opportunity of charge from energy transmitters. However, when we maximize the energy charged in the networks, the energy transmitters will be placed close to the area where density of sensors is high. In this case, some of the sensors may not be able to charge energy. Here, the difference in ordering of magnitude of the first and second terms of (6) is worth to note. Therefore, it is difficult to set the value of α for quantitative trade-off between maximum energy charged and fairness. We could either normalize or scale the two terms such that they have approximate same orders of magnitude for absolute quantitative trade-off. Here, for (6), we scale the first term with respect to the second term. Let $A = \sum_{i=1}^{N_S} \sum_{e=1}^{N_E} E_{C_{i,e}}$ and $B = \min_{\forall j \in \{1,2,...,N_S\}} \sum_{e=1}^{N_E} E_{C_{j,e}}$ in (6). Then, B can be scaled with respect to A using the minimum and maximum values of A and B as [30]:

$$\Theta = \left\{ \frac{B - \min(B)}{[\max(B - \min(B)) - \min(B - \min(B))]} \times (\max(A) - \min(A))\} + \min(A) \right\}, \tag{8}$$

where Θ is scaled version of B with respect to A. The utility function in (6) can be rewritten based on the scaled version of B is then given by,

$$U(x_e, y_e) = (1 - \alpha)\Theta + \alpha \sum_{i=1}^{N_S} \sum_{e=1}^{N_E} E_{C_{i,e}}. \tag{9}$$

From (9), we can say that trade-off between maximum energy charged and fairness is quantitative for a given value of α. Moreover, it can be observed from (8) that Θ will change over the time depending on the minimum energy charged by any sensor node.

For $\alpha = 1$ the placement of energy transmitters is done based on the maximum energy charged in the network. Similarly, for $\alpha = 0$ the energy transmitters are placed such that the fairness of energy distribution is ensured among all the sensor nodes. We can give equal emphasis to both maximum energy charged and fairness by choosing $\alpha = 0.5$. Thus, we can try to achieve both requirements by choosing $0 < \alpha < 1$.

The maximum energy charged in the network may come up at the cost of unfair distribution of energy. It is important that all sensor nodes charge a minimum energy in each cycle to increase lifetime of the network. Therefore, the next objective is to find minimum number of energy transmitters such that each sensor node can charge minimum $\overline{E_C}$ energy from N_E number of energy transmitters. Mathematically, the minimum

Algorithm 1: Minimum Number Energy Transmitters

```
Set ς, a = 1, N_E = 1, and N̂_E = 0
N_S sensor nodes are distributed randomly
Controller has topology of network after exchanging messages with sensor nodes
while (a) do
    for e = 1 : N_E do
        Place e-th energy transmitter according to the placement strategy given in (7)
    end for
    Calculate E_{C_{i,e}}, ∀ i ∈ {1, 2, ..., N_S}, ∀ e ∈ {1, 2, ..., N_E}
    if E_{C_{i,e}} ≥ \overline{E_C} − ς, ∀ i ∈ N_S then
        N̂_E = N_E
        a = 0
    else
        N_E = N_E + 1
    end if
end while
```

number of energy transmitters problem can be formulated as follows:

$$\widehat{N}_E = \text{argmin}\{N_E \text{ such that } E_{C_i} \geq \overline{E_C}\} \tag{10}$$

where $\widehat{N}_E$ represents the minimum number of energy transmitters and $E_{C_i} = \sum_{e=1}^{N_E} E_{C_{i,e}}$.

We define ς as acceptable error margin for energy charging by sensor node, where $\varsigma = \overline{E_C} - E_{C_i}$. There exists a trade-off between acceptable error margin and required number of energy transmitters. If we set a high ς, then the required number of energy transmitters can be reduced. The algorithm to solve (10) for a given ς is shown in Algorithm 1 which enumerates all possible combinations for the placement of energy transmitters (that is a brute force method). Hence, we achieve the optimal placement, however, at the cost of computational complexity.

B. Scheduling of Energy Transmitters

Fig. 3 shows the stages considered for the energy-efficient scheduling of energy transmitters activation: 1) request for power transfer, 2) energy transmitter activation optimization, and 3) energy transmitter confirmation.

1) Request for Power Transfer: The nodes in SDWSNs request the controller for power transfer by sending request for power (RFP) packet if their residual energy is less than a pre-set threshold ξ_{Th}. The threshold is set while considering that the node has sufficient energy for critical operations. The RFP packet contains the requesting node's ID, controller's ID, and energy charging requirements. Here, we adopt RF-MAC protocol proposed in [22]. The sensor node with residual energy less than a pre-set threshold can send RFP for instant charging through access priority mechanism (for details about this mechanism, see [22]) which ensures that the node with residual energy $\leq \xi_{Th}$ gets channel access before data transmission by other sensor nodes. The nodes which have data to transmit are forced to freeze their back-off timers as data transmission is not possible at this time. The controller

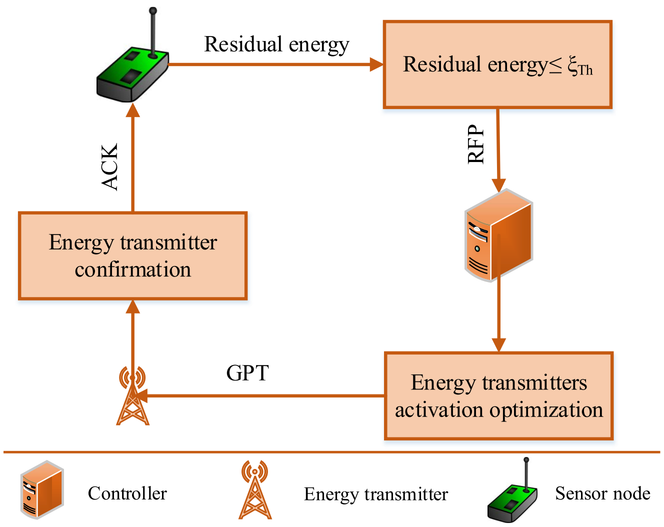

Fig. 3. Three stages of energy transmitter activation in P-MAC protocol.

Algorithm 2: Scheduling of Energy Transmitters in SDWSNs Using Branch and Bound Algorithm

Set $\psi_e^* = 0$ $\forall e \in \{1, 2, ..., N_E\}$ and $Z^* = 0$
while there are some active nodes **do**
  Select an active node k and mark it as inactive
  Solve linear programing (LP) relaxation: denote solution as $\psi(k)$ and LP relaxation of Problem(k) as $Z_{LP}(k)$
  if $Z_{LP}(k) \geq Z^*$ **then**
    Prune node k
  else if $Z_{LP}(k) < Z^*$ and $\psi(k)$ is feasible for integer program **then**
    $\psi^* = \psi(k)$
    Prune node k
  else if $Z_{LP}(k) < Z^*$ and $\psi(k)$ is infeasible for integer program **then**
    Mark the children of node k as active
  end if
end while
return the best solution and it's minimum value

receives this packet and processes it to activate the energy transmitter(s).

2) Energy Transmitter Activation Optimization: The controller receives the RFP packet for task t and calculate ϕ_{et} using (1) for all energy transmitters. An energy transmitter $e \in \{1, 2, \ldots, N_E\}$ can be activated for harvesting the target node(s) if and only if 1) task t is within the harvesting range of e, i.e., $\phi_{et} = 1$, and 2) task t is scheduled on e. We define a binary variable ψ_e to denote whether the energy transmitter e is scheduled or not as follows:

$$\psi_e = \begin{cases} 1, & \text{if energy transmitter } e \text{ is scheduled} \\ 0, & \text{otherwise.} \end{cases} \tag{11}$$

Our objective is to minimize the total energy consumption by minimizing the number of active energy transmitters. Further, a minimum harvesting duration $\overline{\delta_{e,H}}$ must be ensured from all energy transmitters for corresponding tasks. The scheduling program shall be invoked according to the required harvesting duration and energy charging requirements. The energy minimization problem can be formulated as:

$$\begin{aligned} \min_{\psi_e, \delta_{e,H}} &: Z = \sum_{e \in \{1,2,\ldots,N_E\}} \psi_e \xi_{e,A} + (1 - \psi_e) \xi_{e,S}, \\ Subject\ to &: \psi_e = \psi_e \phi_{e,H}, \forall e \in \{1, 2, \ldots, N_E\}, \\ & \delta_{e,H} \geq \psi_e \overline{\delta_{e,H}}, \forall e \in \{1, 2, \ldots, N_E\}, \\ & \sum_{e \in \{1,..,N_E\}} \psi_e E_{C_{et}} \geq \overline{E_C}, \forall t \in T, \\ & \psi_e \in \{0, 1\}, \end{aligned} \tag{12}$$

where $E_{C_{et}}$ is the energy charged by task t from energy transmitter e given in (5). The first constraint ensures that the task t is in the harvesting range of e-th energy transmitter. The second constraint guarantees the minimum harvesting duration, and the third constraint is to satisfy the minimum charging requirements.

The problem in (12) is mixed integer programming. These problems are generally NP hard. One way to get optimal solution is to enumerate over all possible combinations of ψ_e, which is computationally expensive and unrealistic for a large number of energy transmitters and tasks. Therefore, we consider branch and bound algorithm for scheduling of energy transmitters in SDWSNs given in Algorithm 2. Branch and bound algorithm is guaranteed to provide optimal solution. The computational complexity of branch and bound algorithm in worst case is exponential; however, worst case complexity in NP hard problems cannot be considered as performance indicator. The average complexity of branch and bound algorithm is notably low which can be considered as rational estimate of the performance [37].

Once the activation of energy transmitters is optimized at controller, then a grant for power transfer (GPT) packet is sent to the energy transmitters which are selected for wireless power transfer.

3) Energy Transmitter Confirmation: The energy transmitter(s) after receiving GPT packet will start transmitting power. Finally, energy transmitter(s) send the acknowledgment (ACK) to the nodes. This packet has the information of central frequency of energy transmitter and the duration of energy charging.

V. Performance Analysis

In this section, we evaluate the performance of proposed strategies for the optimal placement of energy transmitters, minimum number of energy transmitters, and energy efficient scheduling of energy transmitters. For the sake of simplicity, we consider omni-directional energy transmitters which radiate waves with 46 dBm. The proposed schemes can be modified to use with directional energy transmitters to overcome path losses which can certainly help to improve the charging efficiency. This can be one of the future works in this area of research. The transmit and receive energy for sensor nodes is considered from MICA2 specifications [38]. All the sensor nodes are randomly distributed in a rectangular field. Detailed simulation parameters are given in Table III.

TABLE III
SIMULATION PARAMETERS

parameter	**Value**
Network size	100m × 100 m
Max T_E	46dBm
E_T antenna gain after cable loss	14dBi
Path loss constant ω	2
Frequency	2×10^9
$\overline{E_C}$	3×10^{-6} J
η	70%

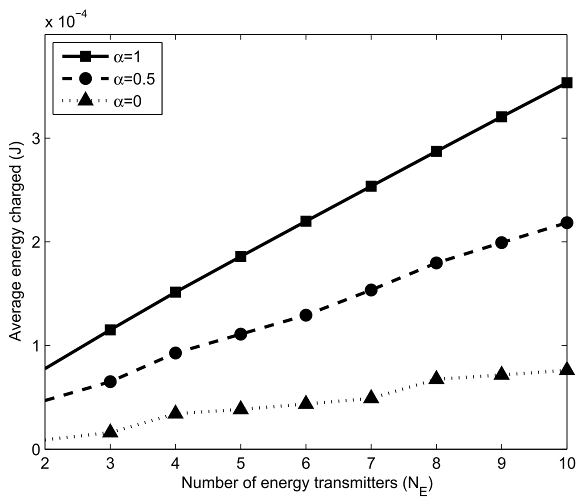

Fig. 4. Impact of number of energy transmitters on average energy charged ($N_S = 200$).

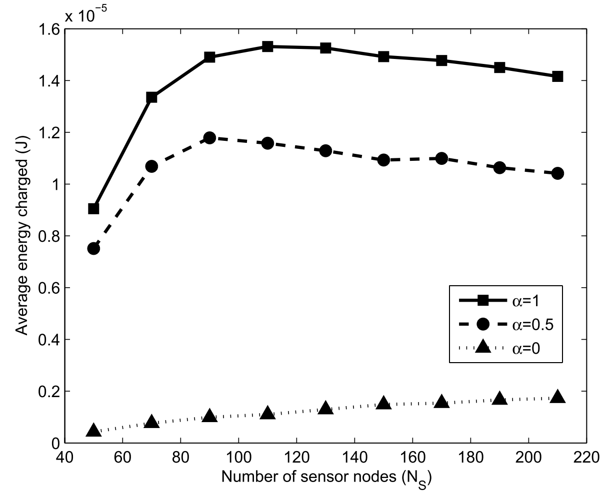

Fig. 5. Impact of number of sensor nodes on average energy charged ($N_E = 6$).

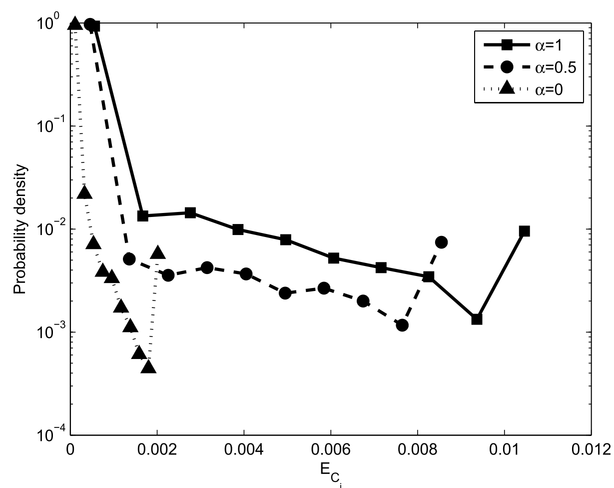

Fig. 6. Probability density functions for energy charged ($N_S = 200$, $N_E = 6$).

A. Optimal Placement and Number of Energy Transmitters

1) Impact of Energy Transmitters: Fig. 4 shows the impact of energy transmitters on the energy charged for different values of trade-off factor (α). It can be observed that the energy charged by sensor nodes increase by increasing number of energy transmitters in the vicinity. Here, we fixed the number of sensor nodes to 200. For $\alpha = 1$, the energy transmitters are placed optimally while maximizing the energy charged in the network. It is clear that the average energy charged is highest in this case. However, energy is not fairly distributed among sensor nodes. For $\alpha = 0$, the energy transmitters are placed optimally such that fair distribution of energy is ensured among all sensor nodes. The average energy charged is significantly dropped in this case when compared with $\alpha = 1$ case. For $\alpha = 0.5$, we tried to maximize the energy charged in the network and fairness simultaneously with equal weight. The average energy charged is in between the cases for $\alpha = 1$ and $\alpha = 0$.

2) Impact of Sensor Nodes: Fig. 5 shows the impact of sensor nodes on average energy charged for different values of α. We uniformly distribute varying number of sensor nodes. The N_S varies from 50 to 210 for a fixed number of energy transmitters, i.e., $N_E = 6$. The average energy charged increases initially with the increase in number of sensor nodes and then stabilized. For $N_S = 1$ to 90, the average energy charged increases with the increase in sensor nodes. On the contrary, for $N_S > 90$ the change in average energy charged is not significant. This is because each sensor node can charge energy from all the available energy transmitters which is fixed in this case. The average energy charged for different values of α follows the same trend as in Fig. 4.

3) Fairness of Energy Distribution: Fig. 6 shows the probability density of sensors versus energy charged E_{C_i} by *i-th* node. The number of sensor nodes N_S and number of energy transmitters N_E considered in this case are 200 and 6, respectively. It is observed that the distribution is wide in case of $\alpha = 1$, which means that some sensors are charging more energy than the others. For $\alpha = 0$, the distribution is concentrated in a particular region, which shows the fair distribution of energy among sensor nodes. However, the total energy charged by all the sensors is less in this case. For $\alpha = 0.5$, we tried to maximize energy charged and fairness. Therefore, the width of distribution is in between the cases for $\alpha = 0$ and 1.

The fairness of energy charged can be estimated by normalized cumulative distribution function (CDF) of energy

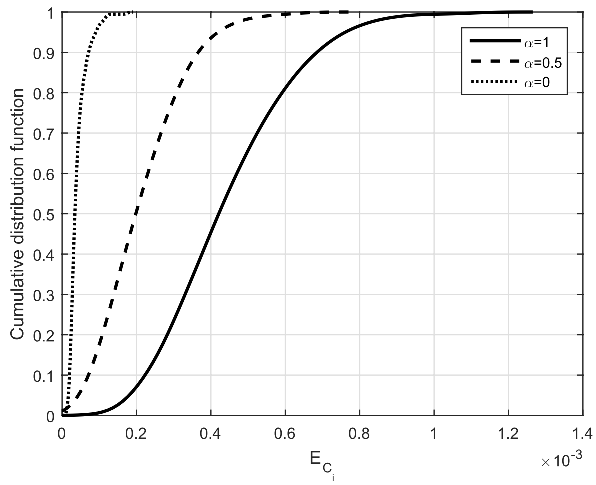

Fig. 7. Comparison of fair energy distribution and min-max energy charged ($N_S = 200$, $N_E = 6$).

charged by sensor nodes. Therefore, the fairness and min-max energy charged is illustrated in terms of normalized CDF for $N_S = 200$ and $N_E = 6$. It can be seen from Fig. 7 that $\alpha = 1$ leads the escalation of energy charged when compared with the cases of $\alpha = 0$ and $\alpha = 0.5$. Quantitatively, for $\alpha = 1$ the energy charged ranges from 0 to 1.2 mJ, whereas, for $\alpha = 0$ the energy charged ranges within 0 to 0.2mJ. Moreover, $\alpha = 0.5$ exhibits the energy charged between 0 to 0.8mJ. Thus, it can be deduced that the distribution of energy is fair for $\alpha = 0$ whereas the total energy charged is high when $\alpha = 1$.

4) Minimum Number of Energy Transmitters: Fig. 8 shows the minimum number of energy transmitters versus error margin (ς) in order to satisfy the constraints of minimum charged energy ($\overline{E_C}$) for $N_S = 200$. It is notable that the minimum number of energy transmitters decreases with an increase in ς for all given cases of α. However, it is obvious that the minimum number of energy transmitters is more for $\alpha = 1$ when compared with the case of $\alpha = 0$. This is because of the fair distribution of energy in the case of $\alpha = 0$, in which all the sensor nodes are able to satisfy the requirement of minimum energy charged with less number of energy transmitters.

B. Energy Efficient Scheduling of Energy Transmitters

We compare the performance of branch and bound algorithm with exhaustive search in SDWSNs and traditional WSNs with wireless power transfer [30]. We consider the placement of energy transmitters is done when $\alpha = 0.5$. In case of SDWSNs, the energy consumption also depends on the location of the requesting nodes. Here, we generate requests randomly for given number of sensor nodes.

1) Impact of Energy Transmitters: Fig. 9 shows the impact of energy transmitters N_E on energy consumption for the branch and bound algorithm, exhaustive search, and traditional WSNs under varying number of tasks T. It can be noticed that the energy consumption for energy-efficient scheduling scheme is not much effected by the increase on energy transmitters N_E for given number of tasks ($T = 5$ and $T = 15$) and network size, i.e., 100m × 100 m. This is

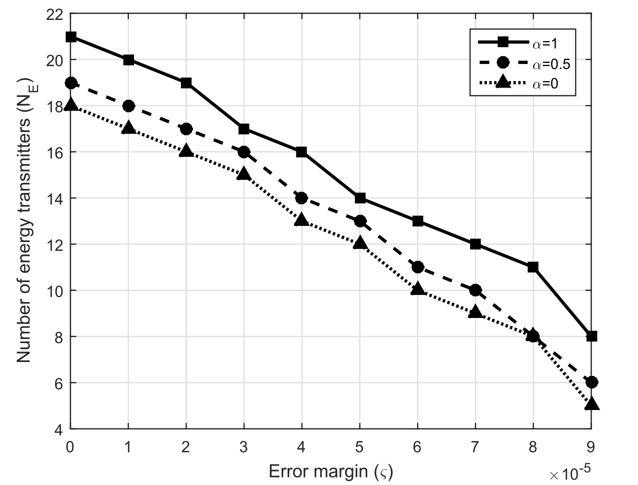

Fig. 8. Minimum number of energy transmitters ($\widehat{N}_E$) versus error margin (ς) for $N_S = 200$.

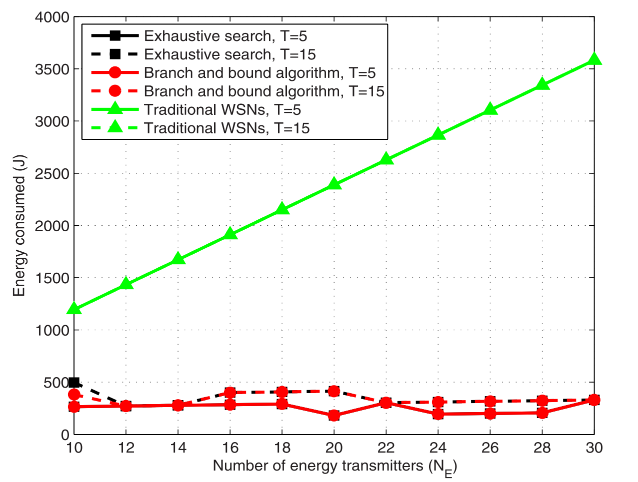

Fig. 9. Impact of number of energy transmitters (N_E) on the energy consumption for different number of tasks T (Network size $S = 100\text{m} \times 100$ m).

because when network size is small and the probability that the tasks are spatially nearby is high. Thus, less number of energy transmitters need to be activated by the controller in SDWSNs. In contrast, traditional WSNs activate all the energy transmitters which results in linear increase of energy consumption. The SDWSN approach clearly outperforms the traditional WSNs approach for wireless power transfer. In addition, branch and bound algorithm offers similar results as of exhaustive search with less complexity.

Fig. 10 compares the energy consumption versus number of energy transmitters for energy efficient scheduling scheme (using branch and bound algorithm and exhaustive search) and traditional WSNs. Here, we study the effect of network size on energy consumption in both SDWSNs and traditional WSNs. The energy consumption for proposed scheduling scheme using branch and bound algorithm, and exhaustive search increases with the increase in network size. This is because the energy transmitters are placed according to the network size given in Section IV-A and more energy transmitters need

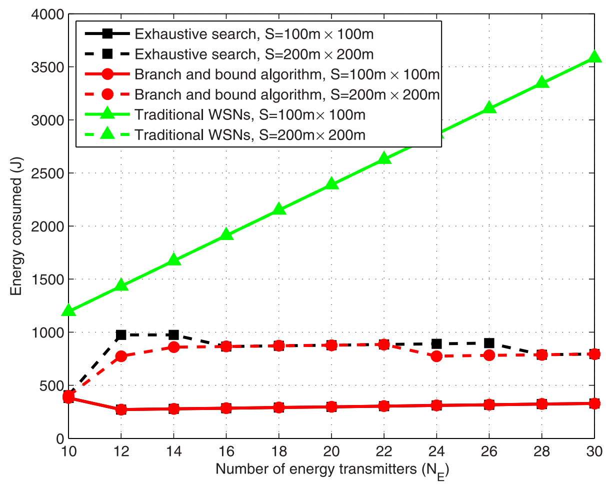

Fig. 10. Impact of number of energy transmitters (N_E) on the energy consumption for different network sizes ($T = 9$).

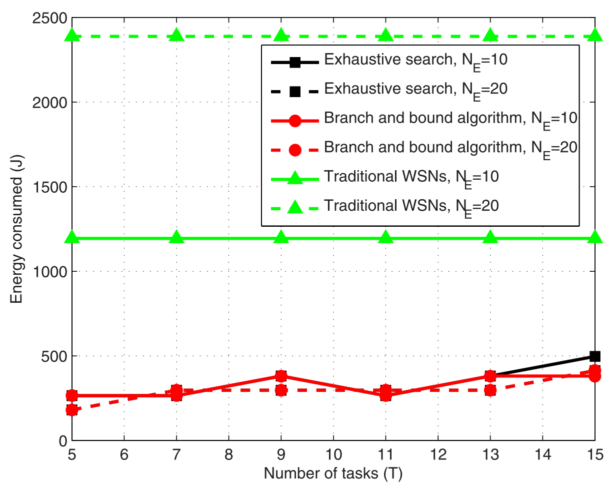

Fig. 11. Impact of number of tasks T on the energy consumption for different number of energy transmitters (N_E) (Network size $S = 100\text{m} \times 100$ m).

to be deployed to satisfy the energy charging requirements. Thus, increasing network size needs more energy transmitters which result in more energy consumption for given number of tasks. It should be noted that energy consumption in traditional WSNs remains same regardless of number of energy transmitters. Therefore, the proposed energy-efficient scheduling scheme can be very effective for large network size.

2) Impact of Tasks: Fig. 11 illustrates the impact of number of tasks on energy consumption for energy-efficient scheduling scheme (branch and bound, and exhaustive search) and traditional WSNs. We consider number of energy transmitters $N_E = 10$ and $N_E = 20$, and network size S $= 100\text{m} \times 100$ m. In the energy efficient scheduling scheme, energy transmitters are activated based on the task requests. It is observed that the energy consumption is increased slowly with the increase in number of tasks in case of energy-efficient scheduling scheme for SDWSNs. Moreover, results of branch and bound algorithm are very similar to exhaustive search case with less complexity. However, the energy consumption is constant for given number of tasks in case of traditional WSNs. The energy

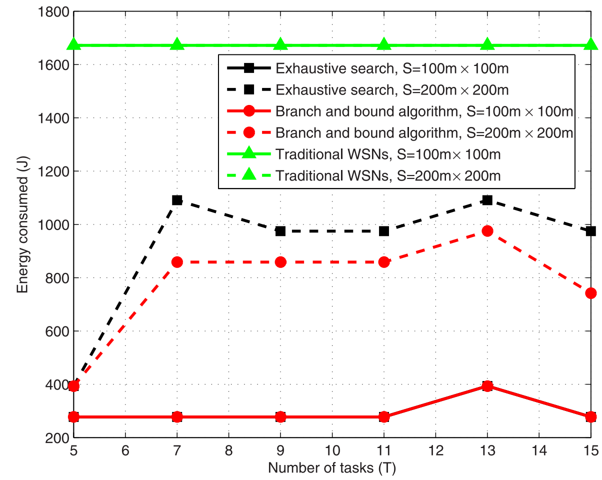

Fig. 12. Impact of number of tasks T on the energy consumption for different network sizes ($N_E = 14$).

consumption is high with the increase in number of energy transmitters.

Fig. 12 shows the energy consumption versus number of tasks for a given number of energy transmitters ($N_E = 14$) and different network sizes (S $= 100\text{m} \times 100$ m and S $= 200\text{m} \times 200$ m). We compare the energy-efficient scheduling scheme (using branch and bound algorithm, and exhaustive search) with the tradition WSNs case. It is noted that the energy consumption is increased with the network size. In addition, energy consumption initially increased with the increase in number of tasks and after that there is minute difference in energy consumption. The energy consumption also depends on the location of the requesting nodes. Thus, energy consumption will be less if all the requesting nodes are spatially nearby. This is the reason of uneven energy consumption with changing number of tasks. Once again, the energy consumption of traditional WSNs is constant for a given number of energy transmitters regardless of network size. Moreover, energy consumption in case of energy-efficient scheduling in SDWSNs is significantly less when compared with traditional WSNs.

VI. Conclusions

The advanced and ubiquitous applications with various requirements have shifted the paradigm of wireless sensor networks (WSNs) to software-defined WSNs (SDWSNs). Wireless power transfer is the key technique to sustain the operation of sensors in SDWSNs. We considered an optimal placement, minimum number of energy transmitters, and energy-efficient scheduling of energy transmitters in SDWSNs. We first formulated the problem for optimal placement of energy transmitters. We have proposed an optimal placement mechanism for energy transmitters which jointly optimizes total energy charged in the network and fair distribution of energy among sensor nodes. We then built a formulation to minimize number of energy transmitters while satisfying the constraint on minimum energy charged. We have also studied the trade-off between energy charged and fair distribution of energy. In addition, we proposed an energy-efficient scheduling scheme to minimize the energy consumption of energy transmitters. We formulated a binary integer linear programming problem to minimize energy consumption while satisfying the constraints on coverage, harvesting duration, and energy harvested. The branch and bound algorithm is used to find the optimal solution. The paper is supported by extensive simulation results that exhibit the performance of SDWSNs with wireless power transfer. We further studied the impact of number of energy transmitters, number of sensor nodes, and number of tasks on harvested energy and energy consumption by energy transmitters. It is emphasized that the scheduling of energy transmitters in SDWSNs can significantly reduce energy consumption in comparison with traditional WSNs with wireless power transfer. The given simulation results can be used as guidelines by network designers.

Future work can involve directional energy transmission for the requesting sensor nodes to overcome path losses. Moreover, the use of energy transmitters with variable transmission power in accordance to the harvesting requirements can be an interesting investigation in SDWSNs. For the placement of energy transmitters, the sub-optimal solution compromising the performance for complexity can be developed that may be realized in polynomial time.

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