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Maximizing Lifetime in Wireless Sensor Network for Structural Health Monitoring With and Without Energy Harvesting

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ABSTRACT This paper presents an optimization framework to maximize the lifetime of wireless sensor networks for structural health monitoring with and without energy harvesting. We develop a mathematical model and formulate the problem as a large-scale mixed integer non-linear programming problem. We also propose a solution based on the Branch-and-Bound algorithm augmented with reducing the search space. The proposed strategy builds up the optimal route from each source to the sink node by providing the best set of hops in each route and the optimal power allocation of each sensor node. To reduce the computational complexity, we propose heuristic routing algorithms. In this heuristic algorithm, the power levels are selected from the optimal predefined values, the problem is formulated by an integer non-linear programming, and the Branch-and-Bound reduced space algorithm is used to solve the problem. Moreover, we propose two sub-optimal algorithms to reduce the computation complexity. In the first algorithm, after selecting the optimal transmission power levels from a predefined value, a genetic algorithm is used to solve the integer non-linear problem. In the second sub-optimal algorithm, we solve the problem by decoupling the optimal power allocation scheme from the optimal route selection. Therefore, the problem is formulated by an integer non-linear programming, which is solved using the Branch-and-Bound space-reduced method with reduced binary variables (i.e., reduced complexity), and after the optimum route selection, the optimal power is allocated for each node. The numerical results reveal that the presented algorithm can prolong the network lifetime significantly compared with the existing schemes. Moreover, we mathematically formulate the adaptive energy harvesting period to increase the network lifetime with the possibility to approach infinity. Finally, the minimum harvesting period to have infinite lifetime is obtained.

INDEX TERMS Structural health monitoring, wireless sensor networks, network lifetime, energy harvesting.

I. INTRODUCTION

The new advances in sensor device technologies make wireless sensor networks (WSNs) more effective and economically-viable solutions for a wide variety of applications, such as environmental monitoring, scientific exploration, and target tracking [1], [2]. Structural health monitoring (SHM) systems are implemented for civil structures (including buildings, bridges, tunnels, aircraft, among others) to monitor their operations and health status. The monitoring of civil structures enables damage prediction and therefore, repairs anticipation thus avoiding accidents. WSNs are becoming an enabling technology for SHM that are more prevalent and more easily employable than current wired systems.

Traditionally, a sensor node is mainly powered by a non-rechargeable battery, which has a limited energy storage capacity. As a result, a WSN can only function for a limited amount of time. A lot of research efforts have been dedicated to prolong the lifetime of a WSN by improving its energy efficiency. Joint energy efficient routing and node placement algorithm, namely JR-SPEM, presented in [3], reduces energy consumption in structural health monitong WSN to prolong the network lifetime. Moreover, the MWCDCT algorithm, proposed in [4], investigated the sleep-mode scheduling problem in order to maximize the network lifetime by only turning on the specific subset of sensor nodes for monitoring the target spots and for exploiting the transmission of the sensed data over multiple hops toward the base station. Alternatively, the idea of energy harvesting was proposed to address the problem of limited lifetime in a WSN by enabling the wireless sensor nodes to replenish energy from ambient sources. There are a number of studies on energy harvesting, recharging and their implications in WSN, such as [5] and [6]. Akhtar and Rehmani [5] focus on energy harvesting from renewable as well as traditional energy resources in sustainable WSNs. In this paper ([5]) the available sources for different applications of WSNs, techniques used for scavenging, storage methods and deployment architecture are discussed. In the MC-OMLU algorithm [6], the rechargeable batteries are augmented with the solar energy harvesting panel and the authors proposed maximum lifetime utility function which seek a balance between maximum total remaining energy and maximum minimum remaining energy in order to maximize network lifetime.

Currently, the main sources of ambient energy that are considered suitable for use with WSNs are solar, thermal energy, and mechanical (vibration or strain) [7], [8]. Solar power is the most common and matured among the different forms of energy harvesting. However, it has the drawback of being able to generate energy only when there is sufficient sunlight or artificial light [9]. Thermal energy harvesting uses temperature differences or gradients to generate electricity, e.g. between the human body and the surrounding environment [10]. Thermal energy harvesting systems are easy to integrate with micro devices; however, their use is limited to space and terrestrial applications. Vibration, dynamic and mechanical energy generated by movements of objects can also be harvested. Vibrations are present all around us and especially prominent in bridges, roads and rail tracks. The methods of harvesting vibration energy is through the use of a electrostatic generator [11], piezoelectric capacitor [12], or micro electromagnetic generator [13]. Advantage of electrostatic harvesting devices is ease of integration and no need for smart materials and the output voltage is high. However, electrostatic devices are highly dependent on the external voltage source. Piezoelectric energy harvesters require no external voltage source and the output voltage is relatively high. However, piezoelectric materials, such as PZT, are often brittle and their material properties change through operational life. Electromagnetic generators are simple and rugged, but are difficult to manufacture in micro scale.

The commercial energy harvesting devices, such as the solar energy harvesting development kits produced by Texas Instruments are augmented with the rechargeable batteries [14]. However, some advanced commercial energy harvesters can even replace batteries and be used to power wireless sensor nodes alone [15] with the help of super capacitors. Typically, in the traditional commercial energy harvesting systems, the energy harvested from environmental resources firstly arrives at the boost converters that scale up the voltage, and it is followed by battery management systems where the energy is stored. By doing this, the energy is converted into a useful and regulated form for many applications, such as wireless sensor networks.

The rechargeable battery of an energy harvesting sensor node can be modeled as an energy buffer, where the harvested energy can be stored according to a given battery charging characteristics. Unlike a traditional wireless sensor network (WSN) powered by non rechargeable batteries, the energy management policy of an energy harvesting WSN needs to take into account the energy replenishment process. Therefore, due to the random and uncertainty of the energy supply in energy harvesting systems, the design and considerations in the energy harvesting WSNs are different from a non-rechargeable battery powered WSNs in many ways and the energy management strategy for an energy harvesting WSN needs to take into account the energy replenishment process. As a result, the existing protocols to prolong the network lifetime in WSNs are no more valid for the energy harvesting WSNs.

The wireless sensor network lifetime definition varies depending on the specific application, on the objective function and on the network topology considered and it can be defined as follows: (1) the time instant at which a certain number of nodes in the network depleted their batteries [16], [17], (2) the lifetime of the specific sensor node associated with the highest energy consumption rate [18], (3) the instant, when the first data collection failure occurred [19], and (4) the duration of time before the first node in the network was depleted (or become unavailable) [20]. In this paper, assuming the latest definition for the network lifetime, we propose a framework to maximize network lifetime with and without energy harvesting. Lifetime maximization in WSNs is a well studied topic; however, to the best of our knowledge, there is no analytical model which can accurately formulate optimum routing to maximize lifetime of energy harvesting WSN for structural health monitoring.

The remainder of this paper is organized as follows. In Section II, we illustrate the system model and formulate our optimization task. In Section III, we develop a mathematical model and we formulate the problem to maximize the network lifetime by optimizing the routing algorithm and power allocation in the energy harvested model jointly. In Section IV, we propose the optimal, near-optimal, and sub-optimal solution to the problem. In Section V, the results and performance evaluation are given. Finally, we conclude the paper in Section VI.

II. SYSTEM MODEL

We consider a set of N wireless sensor nodes, $\mathbb{N}$, deployed on the structure that needs to be monitored. In other words, the location of the nodes and the sink is predetermined. We assume that the distance-based attenuation follows the generic exponential path-loss model with an exponent γ. To compute the energy consumption of each node, we use a well-accepted transmission model [21]. This assumes that the total energy consumption includes the transmission and reception energy. Let E_n^C be the total energy consumption of node n in one cycle duration which is equal to

$$E_n^C = E_n^T + E_n^R, \tag{1}$$

where E_n^T and E_n^R are the transmission and reception energy consumption of node n respectively. The total transmission energy consumption of node n is defined as the energy consumption of all transmission links that node n is the transmitter for, i.e.,

$$E_n^T = \sum_{i \in \mathbb{N}} e_{n,i}^T, \tag{2}$$

where $e_{n,i}^T$ is the transmission energy consumption of node n when it is transmitting to node i, which can be expressed as below

$$e_{n,i}^T = x_{n,i} \left[\left(\epsilon_t + \epsilon_{amp} r_{n,i}^{\gamma} \right) u_b \right], \tag{3}$$

where u_b is the number of bits per packet and the radio parameter ϵ_{amp} and ϵ_t are the transmitter amplifier and the transmission coefficient, respectively. $r_{n,i}$ is the distance between node n and node i. We are defining $x_{n,i}$ as an integer variable to specify the number of times that the link between n to i is used per cycle duration in the routing solution. We assume that each node is generating one packet flow in each cycle duration; therefore, we are defining $x_{i,i}$ is equal to 1.

The reception energy consumed by node n in one cycle duration, E_n^R, is defined as the total amount of energy consumed by node n due to reception from other nodes in the network and can be expressed as follows

$$E_n^R = \sum_{j \in \mathbb{N}} e_{j,n}^R, \tag{4}$$

where $e_{j,n}^R$ is the reception energy consumption of node n when it is receiving from node j and can be defined as below

$$e_{jn}^R = x_{j,n} \epsilon_r u_b, \tag{5}$$

where ϵ_r is the energy coefficient for the reception.

In this paper, we are assuming that the nodes are using Time Division Multiple Access (TDMA) mechanism for channel access. Employing TDMA scheme, nodes transmit their packet in their allocated time slot of the cycle duration. Assuming the time slots of the nodes in the network is defined as in Fig. 1, the forwarding and harvesting duty cycle ratio of sensor nodes in the network, denoted as DCR_F and DCR_{EH}, respectively, are given by

$$DCR_F = \frac{T_F}{T_{CD}}, \quad DCR_{EH} = \frac{T_{EH}}{T_{CD}}, \tag{6}$$

where T_F and T_{EH} are the data forwarding period and energy harvesting period, respectively, within the cycle duration.

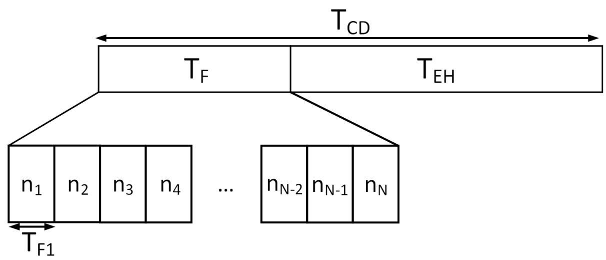

FIGURE 1. Cycle duration, forwarding period, and harvesting period in a cycle.

Each cycle duration, T_{CD}, is equal to the sum of the forwarding and harvesting duration, i.e., $T_{CD} = T_F + T_{EH}$. The data forwarding period, T_F, is the duration during which nodes forward packets to the sink node. In other words, during T_F in Fig. 1, each node collects packets from other nodes and transmits the packet to the sink node (directly or through multiple hops). If the node is neither receiving nor transmitting packets during the forwarding period, it will be harvesting energy. For instance, node i is harvesting energy during T_{Fj} ($\forall j \neq i$), in which node j is relaying packets of the other nodes. Therefore, each sensor node during T_F forwards its own generated packet and relays the received packet(s); moreover, node harvests energy during the other node's forwarding time slot. Moreover, all sensor nodes are harvesting during harvesting period, T_{EH}. Therefore, total harvesting period of a node is a combination of the time duration that other nodes in the network are forwarding in their time slots and the harvesting period, T_{EH}(duration of time that all nodes are harvesting). We are assuming a deterministic energy harvesting model and as can be seen in Fig. 2, the rate of harvested energy defined by ρ.

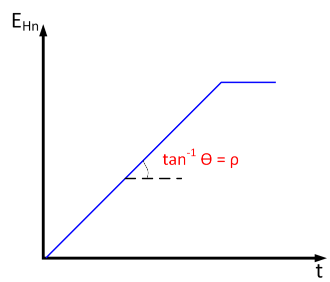

FIGURE 2. Energy harvesting characteristic of a harvesting system in sensor node.

III. PROBLEM FORMULATION

The goal of the proposed algorithm is to find the route from source node to the sink that maximizes the network lifetime. In this paper, the network lifetime is defined as the duration of time before the earliest node depletes its battery and therefore, the duration of time before the first node in the network becomes unavailable due to its energy replenishment [20].

In order to maximize the network lifetime, the variance of the residual energy level needs to be maximized while the total energy consumption is minimized. By doing this, when the energy of the first node is depleted, the other nodes have a very low residual energy level (because of the limitation on the variance of the residual energy levels). Therefore, before the first node energy depletion, the network has utilized the maximum amount of the energy of the other sensor nodes in the network and as a result ensure longevity of the network. Panigrahi *et al.* [22] and Randriatsiferana *et al.* [23] proved that minimizing variance of residual energy, while minimizing the total energy consumption, leads to maximizing the network lifetime.

The residual energy of a node at the cycle duration m is given by

$$E_n^{RS} = E_n^I - m\left(E_n^C - E_n^H\right), \tag{7}$$

where E_n^{RS} is the residual energy of node n, E_n^I denotes the initial energy of node n, and E_n^H is the harvesting energy of node n per cycle duration. Therefore, the variance of the residual energy is given by

$$\begin{aligned}&\frac{1}{N-1}\sum_{n=1}^{N}\left(E_n^{RS} - E_{avg}^{RS}\right)^2\\ &\quad = m^2\frac{1}{N-1}\sum_{n=1}^{N}\left(E_n^{\mathtt{net\_C}} - E_{avg}^{\mathtt{net\_C}}\right)^2,\end{aligned} \tag{8}$$

where $E_n^{\mathtt{net\_C}}$ is the net energy consumption per cycle which is $E_n^C - E_n^H$. E_{avg}^{RS} and $E_{avg}^{\mathtt{net\_C}}$ are the mean value of the residual and net energy consumption, respectively.

As mentioned earlier, the goal of the algorithm is to find the route from each source to the sink such that each route maximizes the lifetime. From Eq. (8), maximizing the lifetime is equal to minimizing the total net energy consumption, $E_T^{\mathtt{net\_C}}$, while keeping the variance of the constraint to minimize the variance of $E_T^{\mathtt{net\_C}}$ as low as possible (Constraint $C1$ in Eq. (9)). Therefore, the optimization problem can be formulated as below

$$\begin{aligned}&\underset{\mathbf{X},\mathbf{P^t}}{Min.}\ E_T^{\mathtt{net\_C}},\\ &\quad C1:\ \frac{1}{N-1}\sum_{n\in\mathbb{N}}\left(E_n^{\mathtt{net\_C}} - E_{avg}^{\mathtt{net\_C}}\right)^2 \le \delta,\\ &\quad C2:\ 1 \le \sum_{\substack{m\in\mathbb{N}\\ n\neq m}} x_{n,m} \le N, \quad \forall n\in\mathbb{N}\\ &\quad C3:\ x_{n,n} + \sum_{\substack{k\in\mathbb{N}\\ k\neq n}} x_{k,n} = \sum_{\substack{m\in\mathbb{N}\\ m\neq n}} x_{n,m}, \forall n\in\mathbb{N}-\{D\}\\ &\quad C4:\ \sum_{\substack{n\in\mathbb{N}\\ n\neq D}} x_{n,D} = N-1,\\ &\quad C5:\ \sum_{\substack{n\in\mathbb{N}\\ n\neq S}} x_{D,n} = 0, \quad \forall S\in\mathbb{S}\\ &\qquad\quad 0 \le P_n^t \le P^{t_{max}},\\ &\qquad\quad x_{n,m}\in\{0,1\},\end{aligned} \tag{9}$$

where $\mathbf{X}$ and $\mathbf{P^t}$ are the the optimization decision variables. Each element in matrix $\mathbf{X}$ (i.e., $x_{n,m}$) represents the number of flows that use a particular link and each element of the vector $\mathbf{P^t}$ (i.e., P_n^t) represents the transmission power level of a node in routing. $P^{t_{max}}$ is the maximum transmission power level for the IEEE 802.15.4 devices.

As explained earlier, to maximize the lifetime the variance of the net energy consumption of all nodes in the network forced to be bounded; in other words, the net energy consumption of the nodes in the network should not deviate strongly the average. Constraint C1 in Eq. (9) enforces that the variance of the energy level of each node, $E_n^{\mathtt{net\_C}}$, is limited. In other words, the remaining energy level of the all nodes are close to each other, such that as the first node's energy is depleted, the other nodes have the minimum energy. Therefore, constraint C1 is imposed to keep the variance as low as possible. The upper bound of the variance (δ) is found by solving the optimization problem iteratively (by increasing δ) until the minimum value of delta that satisfies constraint C1 is found. By doing so, we guarantee that the variance of the residual energy is minimized. Constraint C2 forces the range for the number of the times (per cycle) that a link is used. Constraint C3 formulates the flow balance at an intermediate node along the path between the source node and destination node D. This constraint, C3, enforces that the number of input flows to a sensor node plus the number of generated traffic of the node itself is equal to the number of output flows (excluding the sink). Finally, we impose that all packets should reach the destination node and the destination node does not transmit any packets to other nodes in the network. These constraints are expressed by C4 and C5, respectively. We are also defining that nodes n and m are disconnected from each other, $Con_{n,m} = 0$, if $r_{n,m} \ge R_d$, where Con is the connectivity indicator and R_d is the connection distance threshold. Otherwise, node n and m are connected and $Con_{n,m} = 1$.

Obviously, Eq. (9) is a *Mixed Integer Non-Linear Programming* (MINLP) problem, since the binary variables, $x_{n,m}$ and real variables, P_n^t are involved in the non-linear objective function and constraints.

IV. PROPOSED SOLUTION PROCEDURE

The Branch-and-Bound algorithm is by far the most widely used tool for solving integer optimization problems. Obviously, the optimal value of the objective function in a continuous linear relaxation of a problem will always be a lower bound on the optimal value of the objective function. Moreover, in any minimization, any feasible point always specifies an upper bound on the optimal objective function value. The idea of the Branch-and-Bound is to utilize these observations to subdivide MINLP's feasible region into more-manageable subdivisions and then, if required, to further partition the subdivisions. These subdivisions make a so-called enumeration tree whose branches can be pruned in a systematic search for the global optimum.

TABLE 1. Optimal solution using branch-and-bound space reduced pseudo code.

Input: A predetermined located set of nodes, $\mathbb{N}$,
A set of source nodes, $\mathbb{S}$, and a destination node, D
1: define set Ω of sub-problems;
2: $\Omega \leftarrow \omega 0$; $B_U \leftarrow \infty$;
3: solve linear relaxation of $E_T^{\mathtt{net\_C}}$ and denote its minimum objective function by B_L;
4: **while** $\Omega \neq \emptyset$ **do**
5: select a problem $\omega \in \Omega$ with the minimum B_{L_ω};
6: let $B_L \leftarrow B_{L_\omega}$;
7: set B_{U_ω} a feasible solution for ω via local search;
8: **if** $B_{U_\omega} < B_U$ **then**
9: $B_U \leftarrow B_{U_\omega}$, $\Omega^* \leftarrow \Omega$
10: **if** $B_L \geq (1-\epsilon)B_U$ **then**
11: **return** B_{U_ω};
12: **else**
13: remove all problems $\omega i \in \Omega$ with $B_{L_\omega} \geq (1-\epsilon)B_U$;
14: **end if**
15: **end if**
16: remove all problems that includes disconnected link;
17: select two sub-problem $\omega 1$ and $\omega 2$;
18: solve linear relaxation of $\omega 1$ and $\omega 2$ and denote their optimal objective functions by $B_{L_{\omega 1}}$ and $B_{L_{\omega 2}}$;
19: **if** $B_{L_{\omega 1}} \leq (1-\epsilon)B_U$
20: $B_L \leftarrow B_L \cup \{\omega 1\}$
21: **end if**
22: **if** $B_{L_{\omega 2}} \leq (1-\epsilon)B_U$
23: $B_L \leftarrow B_L \cup \{\omega 2\}$
24: **end if**
25: **end while**
26: **Output** the $(1-\epsilon)$ optimal solution B_U.

A. BRANCH-AND-BOUND SPACE REDUCED ALGORITHM

We enhance the Branch-and-Bound algorithm and develop a *Branch-and-Bound Space Reduced* algorithm to solve the MINLP. This proposed algorithm reduces the Branch-and-Bound area of a search and implements the Branch-and-Bound relaxation and separation strategy [24], [25] to solve the problem.

The pseudocode of the proposed framework, using the Branch-and-Bound Space Reduced, is described in Table 1. In this algorithm, Ω represents optimization problem set and Ω^* denotes the global minimum of the objective function $E_T^{\mathtt{net\_C}}$ in Eq. (9). Therefore, the algorithm provides a (1- ϵ) tolerance of optimal solution Ω_ϵ, which means Ω_ϵ is close enough to Ω^* such that $\Omega^* \geq (1-\epsilon)\Omega$. Initially, Ω includes the original problem, denoted by $\omega 0$. A lower bound of the objective function is first derived through solving a linear relaxation of $E_T^{\mathtt{net\_C}}$ denoted by (B_L) (line 3 in Table 1). Construction of the linear relaxation is described in the next subsection. Since any feasible solution of problem ω can serve as an upper bound, the one obtained by rounding under the satisfaction of all constraints is used and denoted as B_U.

The process of finding the lower and upper bound for the objective function, is called *bounding*. If the derived upper and lower bounds are within the ϵ-vicinity of each other, the algorithm terminates (line 10, 11). Otherwise, it divides the feasible region of the problem into two narrower subsets (*branching* step), and the problem ω will be replaced with two subproblems $\omega 1$ and $\omega 2$ constructed by branching binary variable $x_{i,j}$ (see line 17). Other variables in Eq. (9) can be quickly determined after they have been fixed because the resulting problem becomes a tractable problem. After dividing the original problem into two new subproblems, the algorithm performs relaxation and local search on these two new subproblems. Now, we have lower bounds $B_{L_{\omega 1}}$ and $B_{L_{\omega 2}}$ for subproblems $\omega 1$ and $\omega 2$, respectively. Since the relaxation in subproblems $\omega 1$ and $\omega 2$ are both tighter than that in ω, we have $min\{B_{L_{\omega 1}} B_{L_{\omega 2}}\} \geq B_{L_\omega}$ and $min\{B_{U_{\omega 1}} B_{U_{\omega 2}}\} \leq B_{U_\omega}$. For minimizing the collision probability (minimization problem), the lower bound of the original problem is updated from $B_{L_\omega} = B_{L_{\omega 1}}$ to $B_{L_\omega} = min\{B_{L_{\omega 1}}, B_{L\omega 2}\}$. Also, the upper bound of the original problem is updated from $B_{U_\omega} = B_{U_{\omega 1}}$ to $B_{U_\omega} = min\{B_{U_{\omega 1}}, B_{U\omega 2}\}$.

The Branch-and-Bound Space Reduced algorithm reduces the feasible integer variable space by eliminating the unwanted search space. In the algorithm, all subsets that include the disconnect integer variables (i.e., disconnected next hops $\left(x_{i,j} = 1 \& Con_{i,j} = 0\right)$ are removed and the subsets area of search is reduced.

Through an iterative branching procedure, subsets are further divided into smaller ones to build the enumeration tree. The structure of the enumeration tree allows the algorithm to remove some branches and search for the solution in a very effective way. Moreover, narrowing down the subsets of the optimization variables makes the linear relaxations tighter (i.e., increases B_L) and provides the next local search processes with a closer starting point to the optimal solution (i.e., reduces B_U). Hence, the gap between B_L and B_U is reduced as the process continues. More precisely, the global lower bound B_L is updated in each iteration, in order to contain the minimum of the lower bounds of all subsets (lines 5, 6). The global upper bound B_U is also updated at each iteration (lines 8, 9) and the branches with a lower bound greater than $(1-\epsilon)B_U$ are pruned (line 13). This approach is continued until the difference between the global lower and upper bounds satisfy the accuracy ϵ (lines 10, 11). Clearly, we may lose the global optimum by pruning the branches. However, if the global optimum in a pruned branch with the lower bound is B_{L_ω}, then $\Omega^* \geq B_{L_\omega}$, and consequently, $\Omega^* \geq (1-\epsilon)B_U$. Therefore, the current best feasible solution with objective value B_U is already an $(1-\epsilon)$-optimal solution, and we can still guarantee $(1-\epsilon)$ optimality. Therefore, the solution procedure provides $(1-\epsilon)$-optimal solutions, with ϵ being the desired approximation error bound. In fact, this guarantee is the key feature of the algorithm, which makes it very effective in solving the MINLP.

B. HEURISTIC ENERGY HARVESTING LIFETIME MAXIMIZATION ROUTING

We propose a heuristic routing algorithm which, at first obtains optimal power levels of all connection links and then solves the routing problem. Employing the power levels turns the problem to Integer Programming problem that can be solved using BnB Space Reduced algorithm.

To obtain the optimal power allocation from Eq. 3, the

TABLE 2. Heuristic energy harvesting lifetime maximization algorithm.

Input: A predetermined located set of nodes, $\mathbb{N}$,
A set of source nodes, $\mathbb{S}$, and a destination node, D;
1: $\mathbf{P^t} \leftarrow \mathbf{P^{top}}$, ;
2: $E_T^{\text{net\_C\_prim}} = \{E_T^{\text{net\_C}} |_{\mathbf{P^t}=\mathbf{P^{top}}}\}$;
3: solve the integer problem using BnB space reduce Algorithm in Table I and denote its results as E_T^*;
4: optimal power allocation for E_T^*;
5: obtain optimal power allocation for each transmitter
6: **Output** Optimal path with optimal power allocation.

TABLE 3. Power disjoint energy harvesting lifetime maximization.

Input: A predetermined located set of nodes, $\mathbb{N}$,
A set of source nodes, $\mathbb{S}$, and a destination node, D;
1: $\mathbf{P^t} \leftarrow P_f^t$ dBm, ;
2: $E_T^{\text{net\_C\_prim}} = \{E_T^{\text{net\_C}} |_{\mathbf{P^t}=P_f^t}\}$;
3: solve the relaxed problem using BnB space reduce Algorithm in Table I and denote its results as E_T^*;
4: optimal power allocation for E_T^*;
5: obtain optimal power allocation for each transmitter
6: **Output** Optimal path with optimal power allocation.

received signal-to-noise ratio (SNR) must be greater than or equal to the detection threshold (β). Therefore, the optimal power that minimizes energy consumption for the transmission from node i to node j is given by

$$P_i^{top} = \frac{\beta N_o r_{i,j}^{\gamma}}{\epsilon_{amp}}, \tag{10}$$

where N_o is the noise power. The proposed heuristic routing algorithm is presented in Table 2. The calculated power level is employed in BnB and therefore, the complexity of the algorithm is reduced due to elimination of the non-integer variables in the optimization problem.

C. POWER DISJOINT ENERGY HARVESTING LIFETIME MAXIMIZATION

In order to reduce the computational complexity caused by obtaining optimal power levels of all potential connection links, we propose a new algorithm in which the optimal transmission power is allocated after the routing solution.

The proposed sub-optimal lifetime maximization algorithm is presented in Table 3. This algorithm uses equal, fixed transmission power, P_f^t, in the objective function and the constraints. Therefore, the problem is simplified to an Integer Programming Problem. The objective function of the algorithm is defined as $E_T^{\text{net\_C}} |_{\mathbf{P^t}=P_f^t}$. The BnB Space Reduced algorithm, which is discussed in Subsection IV.A, is employed to solve the problem as well (line 3). After optimal path selection using BnB Space Reduced algorithm, the optimal power allocation is allocated to each hop.

D. SOLUTION OF THE GENETIC ALGORITHM

Assuming the predetermined location for the sensor nodes in Eq. (10), the optimal power allocation can be defined in $N(N-1)$ discrete levels in the network. Using the discrete power levels, the problem in Eq. (9) turns to integer problem and Genetic Algorithm will be able to create a high quality solution. Genetic Algorithm (GA) is a well-known approach for solving optimization problems because of their capability to check partially ordered search space for various trade-offs as demonstrated in [26]. GAs evaluate several solutions for the optimization problem in Eq. (9) simultaneously and find the near-optimal solution by combining efficient solutions. Therefore, the near optimal power level and routing solution is obtained with the reduced complexity.

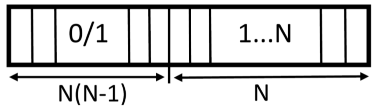

FIGURE 3. GA chromosome.

Each solution of the optimization problem in GA is called a chromosome. The chromosome is represented by a list of variables called genes [26]. A chromosome's size should be equal to the number of possible power levels plus the number of possible links as shown in Fig. 3. The genes representing link utilization $x_{i,j}$ and the power levels that are not binary (but rather integer variables in the rang $[0, N]$). GAs create a number of solutions randomly to form an initial population, and then the fittest survived solutions move on to the next generation. The generated solutions share some features taken from each possible solution. A new population of generated solutions is produced by the selection of the best solutions for the current generation and then performing crossover between them to produce the next generation. Mutation is also used to introduce some randomness to the new generation creation. The process of generation and selection is repeated until the stopping criteria is reached. The population will converge to a near-optimal solution when the GAs parameters, such as the crossover rate, are properly tuned as shown in [27]. Roulette-wheel selection is used in which the chromosome that has a large fitness function value has a higher probability to survive to the next generation over the others. During the crossover operation, the chromosomes are recombined resulting in two new child chromosomes to be appended to the next generation population. The probability of crossover is equal to Pr^c. Increasing this value improve performance, which leads to increasing the crossover occurrence. In this paper, the single point crossover operator is used. After selecting the chromosomes, GAs generate random numbers to select where to split the chromosome into two parts to then be recombined. Lastly, the mutation operator flips some of the genes of the chromosome. Similar to the crossover operator, increasing this probability will increase the mutation occurrence. A mutation probability of Pr^m is taken in order to make our GAs search visit the corners of the search space to check for isolated solutions.

The objective function in Eq. (9) is used to measure the chromosome fitness or performance. As a result, the GAs try to find the smallest fitness function value in order to get sub-optimal routing and power allocation. GAs then check for the

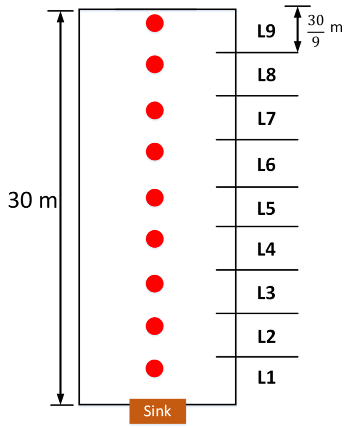

FIGURE 4. The nine floor building model.

best chromosome found in the population. A larger fitness function value means a higher upper-limit information quality and minimum energy consumption. Nevertheless, after the number of runs is larger than or equal to N^2 multiplied by the number of variables, the variations in GAs result will be low. Consequently, GAs are terminated immediately after a specified number of generations is reached.

V. RESULTS AND PERFORMANCE EVALUATION

In this section, we evaluate the performance of the proposed algorithms. We consider predetermined node locations consisting of 9 sensor nodes in 9 floor building (i.e., one sensor node in each floor as shown in Fig. 4). The evaluation scenario is similar to the one used in [3]. We assume that the path-loss exponent (γ) equals 2, the noise power (N_o) is equal to -93.83 dBm, and the detection SNR threshold equals 10 dB. The initial energy E_I is chosen to be 1200 mAhr as in [21]. The packet arrival follows the Poisson distribution with an average arrival rate $\lambda = 100$ packets per second and the number of bits per packet u_b is equal to 2 Kb [28]. The radio parameters are selected as in [21] where the transmission energy cost, ϵ_t, is equal to 50 nJ/bit, the reception energy cost, ϵ_r, is equal to 50 nJ/bit, and the power amplifier energy cost, ϵ_{amp}, is equal to 100 $pJ/bit/m^2$. The building's height is considered to be a 30 m as shown in Fig. 4 and the sink node located at level one with a floor height of 3.33 m.

GAs parameters are chosen as follows: the crossover probability is 0.8 and the mutation probability is 0.1. Assume all sensor nodes have the same transmission range and that sensor node candidate locations are one location in each floor on the nine-floor building. Moreover, the solar energy is used as the source of energy harvesting. The harvesting ratio of the applied solar system is equal to to 3.2 $\mu J/s$ [29].

A. COMPARISON BETWEEN THE PROPOSED LIFETIME MAXIMIZATION ALGORITHMS

The proposed routing algorithms: optimal routing solution using BnB space reduced, heuristic routing solution, sub-optimal routing solution, and solution using GA are shown in Figs. 5 (a)-(d), respectively for the network with 9 sensor nodes in a nine-floor building. The proposed solutions are also compared with JR-SPEM, presented in [3], shown in 5 (e). The objective function of the JR-SPEM is to minimize the total energy consumption of a structural health monitoring system. As shown in the figure sensor nodes are located on predetermined locations in each floor. We are also assuming that the fixed initial transmission power equals to 0 dBm, that is the standard value in IEEE 802.15.4 devices [30]. Fig. 5, compares the proposed solutions in (a)-(d) with the existing algorithm, JR-PSEM, in (e). It can be seen that in the proposed solutions, nodes close to the sink are using shorter hops than nodes located in higher levels, far from the sink node. Therefore, nodes closer to the sink node, which are consuming relatively lower path loss energy (because the path loss attenuation is proportional to the distance between receiver and the transmitter nodes) are responsible for carrying multiple flows. However, there is a trade-off between the consumed energy due to the number of flows and the energy consumed to compensate the path-loss attenuation.

Network lifetime and net energy consumption of the optimal routing solution using BnB space reduced algorithm and that of the heuristic algorithm, sub-optimal solution, and GA algorithm along with JR-SPEM algorithm presented in [3] are compared in Figs. (6) and (7), respectively. It is evident that routing solution using BnB space reduced solution performance is similar to that of the heuristic algorithm. The reason of the equal performance for the heuristic algorithm and optimal solution is that the heuristic method is obtainig the same optimal power level allocation as the optimal solution and it solves the problem employing the same method with a lower complexity. The results show that routing using the BnB solution and the heuristic algorithm outperform the other routing algorithm and the lifetime of routing using BnB solution and the heuristic algorithm increased by 11%, 23%, and 58% compared to sub-optimal lifetime maximization, GA, and JR-SPEM, respectively. This lifetime improvement is expected because in routing solution using BnB space reduced and heuristic method, unlike sub-optimal algorithm, power allocation is involved (from the initial routing decision process) in the routing selection to maximize lifetime and unlike GA they don't select the transmission power from the predefined levels. However, the price for achieving optimal performance is the higher computational complexity of BnB space reduced algorithm. Moreover, unlike the proposed algorithms in our paper, the main objective of JR-SPEM in [3] is to minimize the total energy consumption. Therefore, comparing the lifetime of proposed algorithms in our paper with that of JR-SPEM shows that minimizing the total energy consumption of the network itself, does not necessarily maximize the network lifetime.

The energy consumption and lifetime of the sensor node in each floor of the optimal solution, and that of the heuristic algorithm, power disjoint, and GA are compared in Fig. (8) and (9), respectively. It is evident that the nodes that are carrying more traffic flows have higher net energy con-

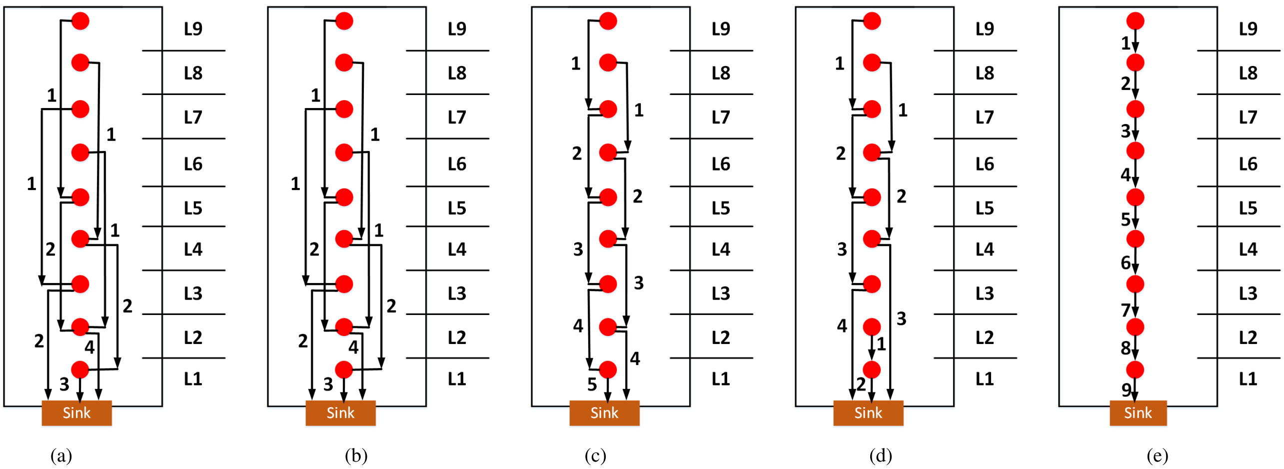

FIGURE 5. Comparing the routing obtained from optimal solution using space reduced BnB, Heuristic solution, Power disjoint solution, GA, and Algorithm presented in [3]. (a) Optimal solution using space reduced BnB. (b) Heuristic solution. (c) Power disjoint solution. (d) Solution using GA. (e) JR-SPEM.

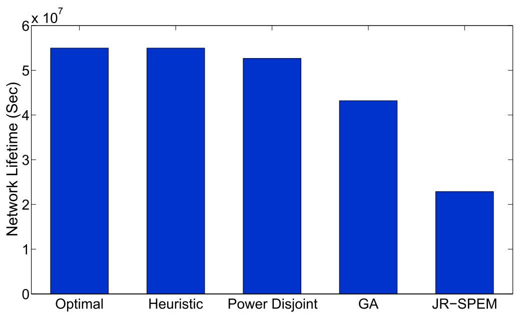

FIGURE 6. Comparing network lifetime of optimal solution using space reduced BnB, Heuristic solution, Power disjoint solution, Solution using GA, and algorithm presented in [3].

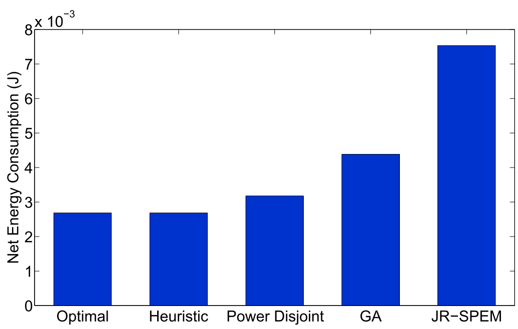

FIGURE 7. Comparing network energy consumption of optimal solution using space reduced BnB, Heuristic solution, Power disjoint solution, Solution using GA, and algorithm presented in [3].

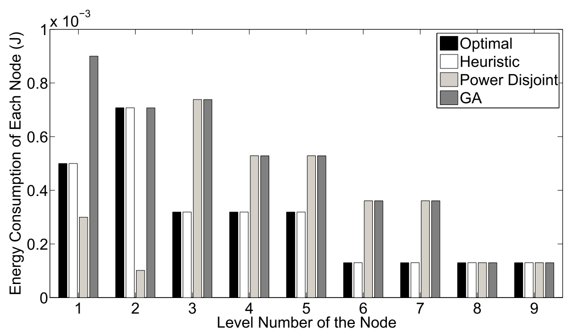

FIGURE 8. Comparing energy consumption of nodes in each floor level using the optimal solution algorithm, Heuristic algorithm, power disjoint, and GA.

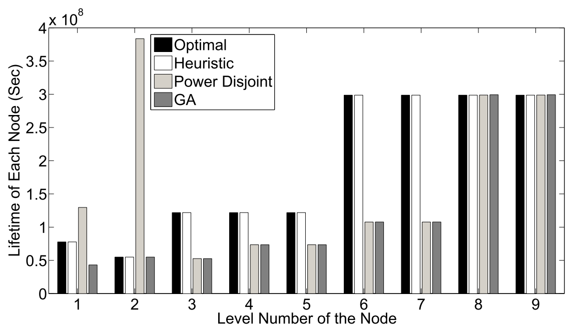

FIGURE 9. Comparing lifetime of nodes in each floor of the structure using the optimal solution algorithm, Heuristic algorithm, power disjoint, and GA.

sumption and lower lifetime and therefore, become unavailable sooner. From Fig. (8), it can be seen that in the optimal solution and heuristic algorithm the variance of the energy consumption for the nodes in each floor is minimized compared to that of power disjoint and GA. Consequently, in the optimal solution and heuristic the variance of the lifetime for the nodes in each floor is minimized compared to the power disjoint and GA. Moreover, it is evident that node in level 2 in the optimal solution and heuristic algorithm is the *critical* node in the network, since it becomes unavailable sooner than the other nodes in the network. In the power disjoint and GA nodes in level 3 and 1 are the critical nodes of the network, respectively.

B. COMPARISON BETWEEN THE PROPOSED ALGORITHM AND THE EXISTING LIFETIME MAXIMIZATION ALGORITHMS

We compare the performance of the proposed optimal routing solution using BnB space reduced algorithm with that of the existing algorithms, MWCDCT presented in [4] and

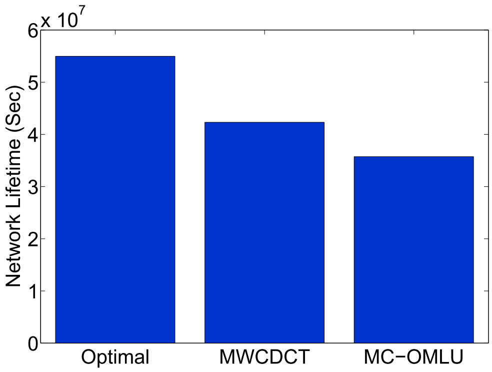

FIGURE 10. Comparing network lifetime of optimal solution using space reduced BnB, MWCDCT in [4] and MC-OMLU in [6].

MC-OMLU [6]; these are well-known routing algorithms presented recently to maximize the network lifetime, in which the assumed scenario is compatible with our proposed routing algorithm. Fig. 10 compares the network lifetime of the routing using the optimal algorithm and that of the MWCDCT and MC-OMLU algorithms. It is evident that the routing solution using BnB space reduced algorithm outperforms the other schemes and has the maximum lifetime. The results show that the lifetime of the routing using BnB space reduced solution algorithm increased by 23% and 35% compared to MWCDCT and MC-OMLU, respectively. This lifetime improvement is expected because the routing solution using BnB space reduced algorithm selects the optimum route and allocates the optimal power that minimizes the total energy consumption of the network while limiting the variance of the energy level of each node. By doing that, all nodes are utilizing their maximum amount of energy before the first node becomes unavailable and when the energy of the first node is depleted, the other nodes have a very low residual energy level. Unlike the optimal solution using BnB reduced algorithm, in the MWCDCT and MC-OMLU algorithms, approximation methods are used to obtain the routing algorithms; moreover, in MWCDCT, the transmission power is assumed to be a constant value. Furthermore, in the MWCDCT algorithm, unlike the optimal solution using BnB reduced algorithm and the MC-OMLU algorithm, the harvesting mechanism is not employed to improve the remaining energy of the network and as a result it is not used to prolong the network lifetime.

C. ADAPTIVE DUTY CYCLE

To investigate the effect of energy harvesting system parameters, we develop an adaptive energy harvesting duty cycle ratio (adaptive DCR_{EH}) mechanism that allows extension of the energy harvesting period, T_{EH}, and nodes can spend more time on harvesting energy in a cycle duration. Therefore, in Eq. 6, the duration of the harvesting time, T_{EH}, is extended to increase the network lifetime. The extension of the harvesting period can be done (a) as soon as it is required, i.e., before *critical* node (node that becomes unavailable first) becomes unavailable in the next coming cycle duration, (b) as soon as the remaining energy of the *critical* node gets below a specific threshold level, or (c) as a minimum fixed time duration that calculated to have enough remaining energy for the infinite lifetime.

1) HARVESTING EXTENSION AS REQUIRED

In this case the energy harvesting period extended as soon as the amount of residual energy E_{cr}^{RS} in the critical node, cr, gets below the amount of required consumption energy for one cycle duration E_{cr}^{C}. Therefore, the energy harvesting period can be defined as below

$$T_{EH_{cr}} = \frac{E_{cr}^{C} - E_{cr}^{RS}}{\rho}, \tag{11}$$

Employing Eq. (11), the cycle duration in duty cycle can be obtained as follows

$$T_{CD} = max\{T_F, T_F + T_{EH_{cr}}\}, \tag{12}$$

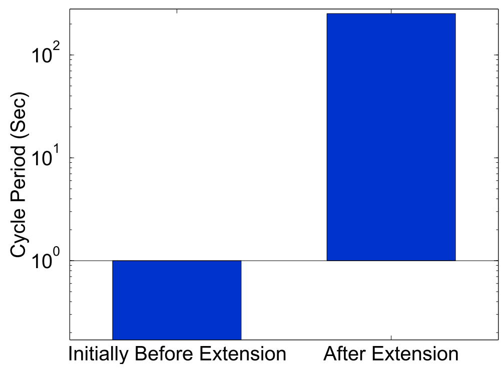

FIGURE 11. Cycle duration using adaptive energy harvesting period; harvesting extended as required (in log scale).

For the solution obtaind using BnB space reduced algorithm in Fig. 5 (a), initially the duty cycle is equal to 17 time-slots in which $E_{cr}^{C} \leq E_{cr}^{RS}$. Therefore, in Eq. (12), $T_{CD} = T_F$ and nodes are consuming energy during their own packet transmission and reception slots (their own time slot) and harvests energy, while the other nodes are in their forwarding period. For instance, node in level one harvests in 12 time slots and consumes energy in 5 time slots. As can be seen from the lifetime of each node in the network in Fig. 9, after 5.4962×10^7 seconds, when node 2, critical node, suffers from lack of energy (i.e., the consumed energy is greater than residual energy), T_{CD} changes and the cycle duration expands by the amount of value for the harvesting duration, T_{EH_2} (node 2 is the critical node); therefore, as can be seen in Fig. 11 the cycle duration increases significantly by the amount of 2.5274×10^2 seconds. Therefore, after 5.4962×10^7 seconds the harvesting duration extended. Employing this method of harvesting energy leads to an infinite lifetime.

2) HARVESTING EXTENSION AS GETTING BELOW THRESHOLD

In this case, the extension starts as soon as the residual energy of the critical sensor nodes gets below a certain threshold

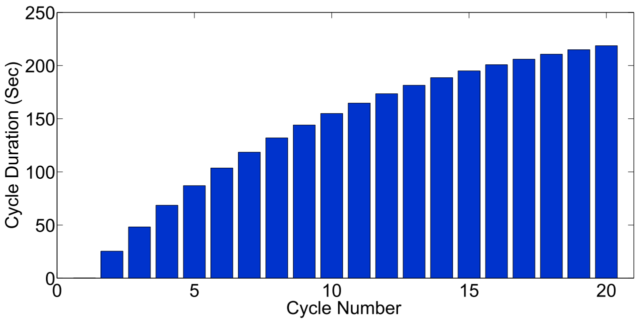

FIGURE 12. Cycle Duration using adaptive energy harvesting periods; harvesting extended as getting below threshold.

value. Therefore, the energy harvesting period can be defined as below

$$T_{EH_{cr}} = \frac{\theta E^I - E_{cr}^{RS}}{\phi\rho}, \tag{13}$$

where $\theta \leq 1$ and $\phi \geq 1$ are adjustable variables that are used to set the threshold and the rate of charging, respectively. Similar to case (1), the cycle duration in duty cycle can be obtained from Eq. (12). Assuming $\theta = 0.1$ and $\phi = 10$, for the optimal solution obtained from the BnB space reduced algorithm, after 4.9465×10^7 seconds, when the amount of residual energy is below 90% of the initial energy, T_{CD} changes and the cycle duration expands by the value of $T_{EH_{cr}}$; therefore, as can be seen in Fig. 12 the duty cycle increases gradually, because of increasing the harvesting period. After 20 duty cycles, the amount of harvesting period reaches to 2.1851×10^4 packet duration or 2.1851×10^2 seconds.

3) MINIMUM FIXED HARVESTING EXTENSION

In this case, the minimum harvesting period to have the infinite lifetime is calculated and the harvesting period is fixed from the beginning of the network lifetime. It means, the calculated harvesting period in a cycle attempts to be the minimum time duration to achieve the infinite lifetime. Assuming that m is the cycle number, the network is alive in cycle m, if the residual energy is greater than the battery cutoff energy (the minimum amount of energy required for a successful sensor communication). The residual energy of a sensor node is obtained by subtracting the consumed energy from the initial energy and harvested energy; therefore,

$$E^I + mT_{EH}\rho - mE^C \geq E^{cut\ off}, \tag{14}$$

where $E^{\mathtt{cut\_off}}$ is the cutoff energy of the battery and a node becomes unavailable if the amount of residual energy is below the cutoff value; therefore,

$$T_{EH} \geq \frac{mE^C + E^{cut\ off} - E^I}{m\rho}. \tag{15}$$

Therefore, in order to have the infinite lifetime, $m \to \infty$, the minimum harvesting duration is obtained as follows

$$T_{EH} = \frac{E^C}{\rho}, \tag{16}$$

For the solution obtained from the BnB space reduced algorithm in Fig. 5 (a), where E^C is the consumed energy during T_{F2}, forwarding period of the critical node (node 2). Therefore, in Eq. (16), the minimum value for T_{EH} is equal to 2.5274×10^4 seconds.

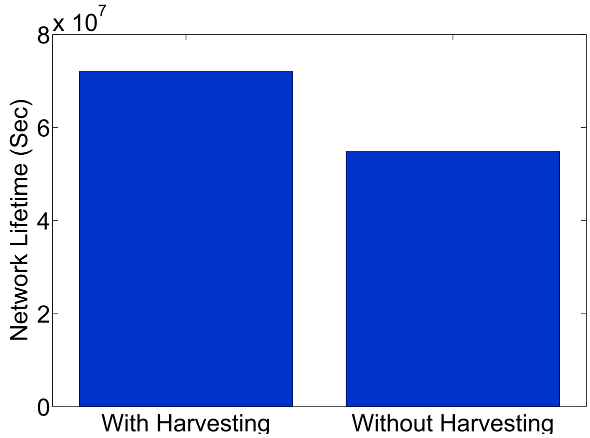

FIGURE 13. Lifetime comparison for the network with energy harvesting versus a network without energy harvesting.

D. EVALUATING THE EFFECT OF ENERGY HARVESTING

In order to investigate the effect of energy harvesting mechanism in the lifetime maximization, we evaluate the lifetime of WSN using optimal routing solution while T_{EH} is assumed to be 60 seconds compared to the case that T_{EH} equals 0, which is the case without energy harvesting. Therefore, in the harvested network, the nodes are harvesting for 60 seconds and then receive or forward the packet in their cycle duration. However, in the network without energy harvesting, nodes only forwards or receive the packet and the net energy in the network defined as $E_T^{\mathtt{net\_C\_prim}}$ is equal to $E_T^{\mathtt{net\_C}}|_{E_n^H=0,\ T_{EH}=0}$. The results are compared in Fig. 13 showing that the lifetime improved by 26%, in the network with energy harvesting compared to the case without energy harvesting.

E. ENERGY HARVESTING RATE EVALUATION

The ability to harvest from several sources of ambient energy provides robustness against varying environmental conditions, and allows the system to remain alive in the case where ambient energy is no longer available from one or more of the sources. Depending on the energy harvesting sources to supplement batteries, the energy harvesting ratio, and consequently the power levels available from state-of-the-art energy harvesting devices, varies. Therefore, in order to investigate the effect of energy harvesting ratio on the algorithm's performance, we are considering several energy harvesting sources. As we discussed before, the main sources of ambient energy considered suitable for use with WSNs are solar, mechanical (vibration or strain) and thermal energy.

Table 4 gives a comparison of energy harvesting rates presented in [7] and [8]. The harvesting rates are obtained on

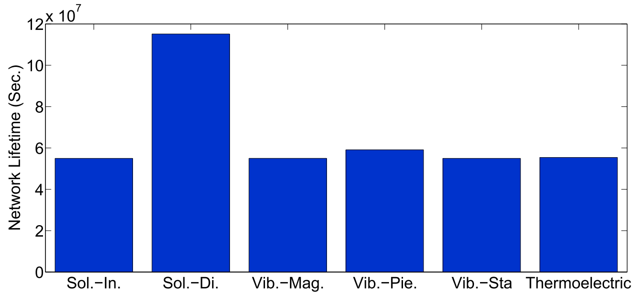

FIGURE 14. Lifetime comparison for the network with different energy harvesting sources presented in Table 4.

TABLE 4. Comparing energy harvesting rate.

Technology	Energy Harvesting Rate ($\mu J/sec$)
Solar - Indoor (Sol.-In.)[9]	3.2
Solar - Direct (Sol.-Di.) [9]	3700
Vibration - Electromagnetic (Vib.-Mag.) [13]	4.0
Vibration - Piezoelectric (Vib.-Pie.) [12]	500
Vibration - Electrostatic (Vib.-Sta.)[11]	3.8
Thermoelectric [10]	60

a 10 cm^2 material which is about the same size as the sensor node. Using the energy harvesting rates presented in the table, in Fig. 14, we compare the network lifetime of the optimal routing algorithm for various energy harvesting sources. It is evident that the network lifetime increases significantly employing the direct solar energy compared to the other energy harvesting sources, such as vibration and thermal energy harvesting system. The results in Fig. 14 show that, compared to the indoor solar harvesting system, the network lifetime increased by 52%, 0.013%, 7%, 0.009%, and 0.8% using direct solar, electromagnetic vibration, piezoelectric vibration, electrostatic vibration, and thermostatic harvesting sources, respectively. Therefore, excluding the direct solar system, network lifetime gains of different types of energy harvesting sources are relatively the same.

F. COMPLEXITY

In this Section, the worst case computational complexity of the proposed algorithms is characterized. In the optimal solution using space reduced BnB algorithm, the complexity grows exponentially with the number of integer variables. In other words, a problem with n_i integer variable requires solving 2^{n_i} non-linear programming problems [25]. Although actual run-time is reduced, due to the search space reduction, the complexity of the algorithm remains exponential. The heuristic and sub-optimal algorithms are proposed to reduce the computational complexity of the routing problem. In the heuristic solution and the sub-optimal solution the number of integer variables in BnB is reduced because of decoupling power allocation from the routing. However, the complexity still remaining exponential. The computational complexity of the sub-optimal routing using GAs implementation is equal to $O(N^6)$ since the complexity of GAs is the cubic order of the building blocks [26] of routing and power allocation, and the building blocks have the computational complexity in the order of two. Therefore, the price for achieving higher performance of the optimal solution using BnB is the computational complexity.

VI. CONCLUSION

In this paper, we presented the optimal solution to maximize the lifetime of wireless sensor network for structural health monitoring system by joint use of optimal power and route selection with and without energy harvesting. This optimization problem is inherently complex due to its mixed-integer nature, non-linearity, and a large solution space. We developed an efficient solution procedure based on the Branch-and-Bound technique augmented with a space reduction algorithm to speed up the computation. Then, we proposed the heuristic routing algorithm to reduce the computational complexity by decoupling transmission power allocation in the routing algorithm from the optimal route selection. Results reveal that the heuristic routing algorithm performs similar to the optimal routing using Branch-and-Bound space reduced algorithm. We also proposed two sub-optimal routing to reduce the computational complexity. In the first algorithm the fixed transmission power is used in the routing selection and then transmission power is allocated. In the second sub optimal algorithm the Genetic Algorithm is used to solve the optimization rather than the Branch-and-Bound algorithm. The optimal solution and heuristic solution outperform the sub-optimal routing solutions. The performance of the proposed routing algorithms is compared with existing algorithms and the results demonstrate the significant gains that can be achieved by incorporating energy harvesting and power allocation in route selection for maximizing the lifetime of wireless sensor networks. Moreover, we presented the adaptive energy harvesting period and the infinite lifetime achieved using the minimum energy harvesting period. There are several directions for future work, including development of a dynamic routing algorithm that establish rerouting automatically as soon as the critical node depletes to a predefined remaining energy.

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