IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received March 7, 2018, accepted April 8, 2018, date of publication April 16, 2018, date of current version May 9, 2018.

Digital Object Identifier 10.1109/ACCESS.2018.2827082

Joint Hybrid Transmission and Adaptive Routing for Lifetime Extension of WSNs

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This work was supported by the Ministry of Science and Technology of Taiwan under Grant MOST 106-2221-E-008-014, Grant MOST 106-2221-E-216-002, and Grant MOST 106-2221-E-009-050.

ABSTRACT In this paper, two hybrid multi-hop/single-hop opportunistic transmission strategies with adaptive routing are investigated for prolonging the network lifetime of wireless sensor networks (WSNs). To achieve this goal, a systematic decision model that contains a network distribution block, a routing algorithm block, a traffic pattern block, and an optimal policy block is presented to determine the optimal transmission probability of each node. With packet transmission via adaptive shortest paths, two optimization strategies are proposed in the optimal policy block: a power efficiency optimization strategy and a power utilization optimization strategy. The power efficiency strategy aims to minimize the overall power consumption and the power utilization strategy endeavors to minimize the maximum power consumption among nodes. Computer simulations show that the power utilization strategy can achieve almost triple the network lifetime extension compared with the power efficiency strategy. Furthermore, the power utilization strategy is superior to the power efficiency strategy in terms of residual energy utilization for various network sizes.

INDEX TERMS Wireless sensor networks, topology distribution, network lifetime, routing algorithm, optimization strategy.

I. INTRODUCTION

Recently wireless sensor networks (WSNs) [1] have been widely deployed and have attracted much attention due to their extraordinary varied applications, such as home health care, ecological environmental monitoring, industry automation, and video surveillance. The lifetime of sensors mainly depends on the capacity of the equipped battery. There are many ways to reduce unnecessary energy consumption, such as signal processing, power adjustment [2], and energy-efficient sensor routing [3]. However, simply reducing the power consumption of a single sensor may not achieve the maximum network lifetime.

Currently, many applications in WSNs require a many-to-one traffic pattern, and multi-hop forwarding via a shortest path algorithm has been proposed in the literature. However, this method may cause an energy imbalance problem, since all data traffic must be forwarded via the sensors around a data sink, thereby generating a hotspot around the sink [4]. Since the hotspot needs to forward a disproportionately higher amount of data traffic than other sensors that are very far from the data sink, the nodes usually deplete their battery capacity in earlier stages.

In the WSN, the network lifetime is defined as the number of complete data cycles before the first sensor node runs out of energy and results in the first sub-regional being left unmonitored. To avoid unmonitored network areas, it is essential to perform an energy consumption balance so that those sensors around the data sink do not deplete their battery capacity much earlier than the others. As a result, the major research challenges for designing energy-efficient WSNs are to balance the energy consumption of hotspot nodes and to achieve better energy utilization of the other sensors in order to prolong the network lifetime [5], [6].

In general, the multi-hop packet forwarding between a data source and the data sink is more energy-efficient than the direct transmission because of wireless channels characteristics. However, the multi-hop forwarding may cause an energy imbalance problem for hotspot sensor nodes in a sink connectivity area (SCA) [7] and reduce the energy utilization of other sensors. On the other hand, the energy hotspot commonly appears at the outermost peripherals for the single-hop direct transmission. From the perspective of achieving energy balance, the direct transmission by sensors can reduce the amount of packets forwarded through the hotspot.

As a result, there exists a performance tradeoff between energy efficiency and energy utilization in a hybrid transmission strategy [8], [9].

In [8], an energy-balanced transmission protocol, called EBDG, is presented to formulate the energy balance problem based on a corona-based model. To combine the idea of corona-based network division and mixed-routing strategies, the situation is formulated as a problem of optimal data aggregation allocation, which results in the same probability for all nodes in the same corona hop-by-hop and direct transmission. In [9], the transmission distance of the conventional multi-hop scheme is decomposed into ring thickness and hop size by considering concentric rings around the sink. Three transmission strategies, fixed hop size, synchronous variable hop size and asynchronous variable hop size, are proposed. The schemes among these nodes differ in their flexibility degrees, and are associated with variable transmission ranges and corresponding duty cycles. In [10], a hybrid multi-hop/single-hop transmission scheme is investigated for the power efficiency and power utilization of WSNs.

Currently, existing works consider the hybrid transmission schemes [8], [9] and routing protocol [11] as two separate issues; however, there exist some research issues to jointly design the routing scheme and hybrid transmission of WSNs. In this paper, two hybrid multi-hop/single-hop opportunistic transmission strategies with adaptive routing protocols are proposed for WSNs to effectively alleviate the hotspot problem and prolong the network lifetime. To achieve these two goals, a systematic decision model that contains a network distribution block, a routing algorithm block, a traffic pattern block and an optimal policy block is presented to determine the optimal transmission probability. In our systematic decision model, three main findings are concluded as follows.

First, a load path clustering phenomenon is generated by the routing algorithm, which makes hotspot nodes unevenly distributed around the sink. Second, the optimal energy balance probabilities exist between the multi-hop and single-hop network transmissions for each sensor node with the adaptive shortest routing paths. Finally, two optimization strategies in the optimal policy block are proposed, namely the power efficiency and power utilization optimization strategies. With the multi-hop routing paths and direct transmission, the power efficiency optimization strategy can achieve the best power efficiency with the minimum overall network power consumption, and the decision behavior bears resemblance to the multi-hop transmission. Thus, the systematic decision model is investigated to jointly design the node deployment, adaptive routing, varied traffic, and optimal strategy to achieve the goal of network energy equilibrium.

The remainder of this paper is arranged as follows. Section II presents an illustrated example to motivate the design goal of the proposed methods for WSNs. In Section III, a systematic decision model is introduced to achieve the optimal power efficiency and utilization. In Section IV, a performance tradeoff between power efficiency and utilization is demonstrated using computer simulations. Finally, conclusions are drawn in Section V.

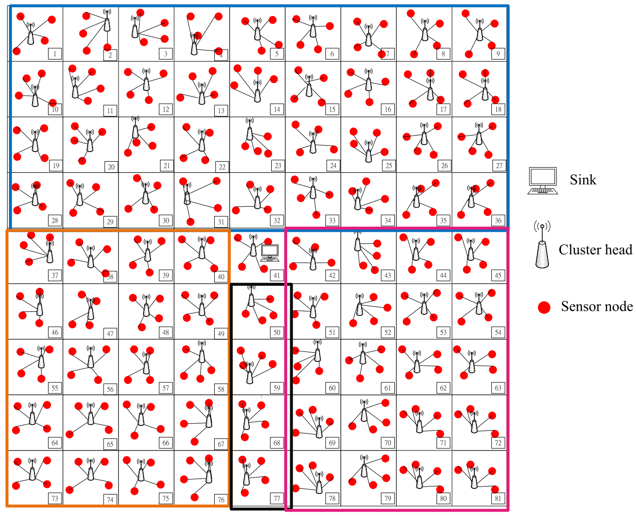

FIGURE 1. An 81-cluster example for WSN deployment.

II. MOTIVATION AND PROBLEM STATEMENT

A. MOTIVATION

Unbalanced energy consumption is an inherent problem for nodes in WSNs, and this problem becomes more severe when multi-hop routing with a many-to-one traffic pattern is considered. However, the multi-hop routing method can obtain better network power efficiency than the single-hop routing method. In the multi-hop routing method, each sensor node can transmit packets periodically or through the shortest path to the data sink when it is triggered. Thus, hotspot nodes emerge when traffic patterns converge. Sensors closer to a data sink usually forward a larger amount of traffic than those sensors farther from the sink. Accordingly, the hotspot sensors deplete batteries more quickly than other sensors. Since the network lifetime is commonly defined as the first sub-region left unmonitored, the residual energy of the other sensors can be regarded as underutilized energy, and this discrepant energy dissipation phenomenon can significantly reduce the network lifetime.

In the existing study [12], the hotspot refers to all adjacent nodes within the communication distance of the data sink and is evenly distributed around the SCA. In the multi-hop network, the sensing nodes usually calculate the shortest paths to the data sink using a specific routing algorithm. As a result, our study finds that most of the calculated paths are concentrated on some specific forwarding sensors around the sink, rather than being evenly distributed. This phenomenon is called a clustering of routing paths, and the foremost hotspot is the cluster head of the generated paths.

Herein, an evenly distributed two-dimensional network [13] is designed to exemplify the paths' clustering phenomenon caused by the routing path. Fig. 1 shows a hierarchical WSN routing scenario, including 80 clusters and

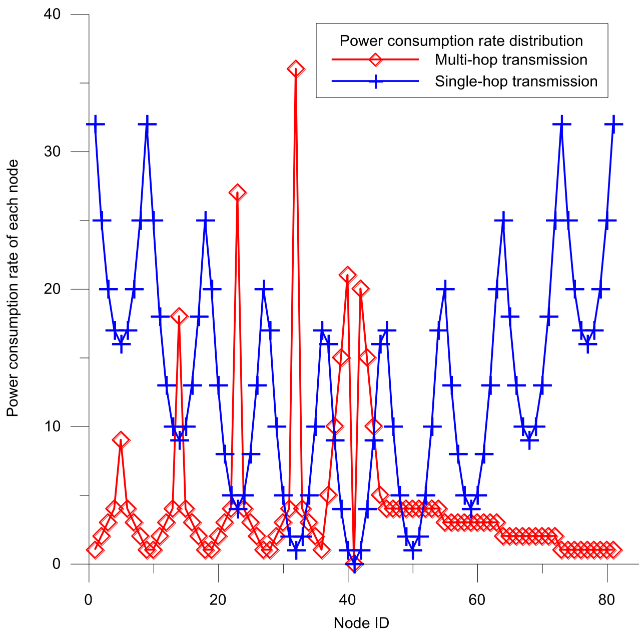

FIGURE 2. **The multi-hop and single-hop transmission power consumption rates of an 81-node example.**

a data sink. A cluster head is elected from sensor nodes in the cluster. Each cluster head is responsible for managing the sensing nodes in the cluster and aggregates all the sensing data in a cluster, and then the cluster head transmits the collected data to the sink node. To achieve uniform power utilization in a cluster, each cluster takes turns to elect a node that has the largest remaining battery capacity to serve as the cluster head [14], [15].

In this WSN example, it is assumed that the nodes are deployed with a uniform distribution, the communication distance between two adjacent nodes is d, and each node transmits the sensing data to the data sink through forwarding nodes with the shortest path. Note that the shortest path from each node to the sink is computed by the Dijkstra algorithm [16]. From the perspective of data applications, the generated traffic pattern in each node is periodically sent to the destination sink with a constant data rate.

Taking the scenario Fig. 1 as an example, data packets are transmitted from all cluster heads to the data sink as follows. Assume that the cost of each path is the same in the Dijkstra algorithm, and all paths from the cluster head to the data sink are calculated according to the generated shortest paths. In each cycle, each cluster head periodically sends its sensing data to the data sink at a constant data rate. After a specific network operation period, each node counts the number of packets that it transmits and forwards and then sends the statistics of the average forwarded and transmitted packets with the data packets to the destination sink. Finally, the statistics of each node are calculated by the sink. The simulation results of the average power consumption rate in each node are generated, and the power consumption distributions of each node in the cases of multi-hop and single-hop transmissions are shown in Fig. 2.

From the red curve in Fig. 2, an interesting phenomenon can be observed. Even with a uniform node distribution and transmission rate, it results in an unbalanced power consumption rate distribution of nodes in a network, where the power consumption rate is calculated by the total number of the transmitted and forwarded packets in a cycle of each node. In the network, all nodes send and forward packets to the sink node numbered 41, and the packet forwarding is mainly sent to the sink via four primary nodes directly linked to the sink. The four primary forwarding nodes are identified as 32, 40, 42 and 50. However, simulation results show that the power consumption rates of the four primary forwarding nodes are not identical. One can find that nodes 32, 23, 14, 40 and 42 experience larger power consumption than others. From the simulation, the three most forwarding paths are aggregated at paths 5-14-23-32, 37-38-39-40, and 45-44-43-42.

It is observed in Fig. 1 that the packets of nodes 1-36 are mainly forwarded to the sink via path 5-14-23-32. From the perspective of transmission paths and power consumption rates, this routing path's behavior results in power consumption rates of 36 and 27 at nodes 32 and 23, respectively, while nodes 14 and 5 have power consumption rates of 18 and 9, respectively. Moreover, the packet power consumption forwarding rates via nodes 40 and 42 are both 20. One may infer that the four primary forwarding nodes 32, 40, 42 and 50 achieve a balanced power consumption rate at each cycle. Unfortunately, there exists a non-uniform forwarding packet load distribution phenomenon in the SCA, since the Dijkstra algorithm seeks to adopt the first shortest path.

The Dijkstra algorithm calculates the first shortest path for each sensor node and does not take into account subordinate shortest paths. The resulting paths determined by the algorithm concentrate the network traffic flow on several specific forwarding paths instead of uniform load paths among the sinks. The observation in this example is called a load path clustering phenomenon, in which the most congested node in each path is called the cluster head of the heavy load paths.

Furthermore, the battery capacity of node 32 is depleted first, since the number of packets forwarded by the primary forwarding nodes adjacent to the sink exhibits an uneven distribution. The earliest depleted node also causes a subregion network to be unmonitored, thereby reducing the whole network lifetime. For example, in Fig. 1, there are 35 nodes with good battery conditions, but these nodes are unable to transmit packets to the sink via the primary forwarding node 32. As a result, the average remaining battery capacity is approximately 87% of the other 79 nodes in the network, causing underutilization of the overall network energy.

In addition, if the single-hop network transmission is considered in Fig. 1, each node directly transmits packets to the sink in a single-hop manner. Assuming that the average distance of each cluster node is d and the path loss exponent is equal to 2, the transmission power is proportional to the value of d^2. By taking node 1 as an example, sending packets to the sink directly consumes a power value of $32d^2$. However, the multi-hop transmission only requires $8d^2$. This finding demonstrates that the power consumption of the multi-hop transmission is a quarter of that for the single-hop transmission. In general, it is concluded that for sensors far from the sink node, the multi-hop transmission can effectively save transmission power for each node.

The power consumption rate consumed by each node is indicated as a blue curve in Fig. 2. With the direct delivery of the packets to the data sink, the four nodes with the largest distance to the sink, identified as 1, 9, 73 and 81, need to expend the greatest amount of power, while the four furthest nodes expend the least amount of power in the multi-hop transmission case. At the same time, it is observed that for the single-hop transmission power condition of the path cluster head (e.g., node 32), the power consumed by the single-hop transmission is the smallest, while the power consumption in the multi-hop transmission case is the largest. An interesting observation is thus made: most of the power consumption in the path cluster head is caused by other transmission nodes instead of its own packet transmission. The other routing cluster heads, including nodes 40 and 42, exhibit similar transmission behavior, in terms of power consumption.

B. PROBLEM STATEMENT

In WSN applications, network lifetime is defined as the number of complete data cycles before the first sensor node runs out of its battery energy. Due to the battery constraints of individual sensor nodes, the lifetime of a WSN is bound by a finite number of data cycles. Ideally, most nodes in the network expire at about the same time. This ensures that very little residual energy is left when the system becomes unmonitored. However, it is a challenging issue to achieve a uniform distribution of energy usage among sensor nodes with improved network lifetime, since sensors with the highest energy usage per data cycle (denoted as hotspot nodes) are bottlenecks to limit the overall network lifetime.

Similar to the network model in [9], a cluster-based WSN can be modeled as follows. It is assumed that all sensor nodes are uniformly distributed in a two-dimensional monitoring area A with a radius of R. There is a static sink with infinite energy, which is located at the center of A. Sensor nodes within a cluster and each cluster head (CH) forward the packets along the established paths, where the CH is rotated with an equal probability in the same cluster. All sensor nodes have the same maximum transmission range r_{max} and the same amount of initial energy E_{init}. It is assumed that $r_{max} > R$, which guarantees that each CH can directly communicate with the sink.

In addition, a shortest path routing protocol can be designed in the sink to compute the shortest path according to the link cost from all sensor nodes to the sink. Thus, a routed spanning tree topology is constructed from the sink to all other sensor nodes. As the spanning tree topology can be reconfigured, it is adaptive to the cost of each link, and the link cost can be varied according to the channel status or other weighting factors. As a result, the topological cost will be updated from each node in the sink and the sink will update the new shortest path.

In the design framework, transmission policies attempt to extend the network lifetime through hybrid multi-hop/single-hop transmission strategies. In the network operation, sensors measure parameters such as temperature, air quality or any other events at the surrounding environment. The gathered data are forwarded to the sink. Let m represent the total number of events due to the direct transmission from node u to the sink or other nodes' packets that are forwarded by u to the sink. It is assumed that q_i is the probability that a sensor detects the ith event among n events during a data cycle and generates f_i amount of packets that are self-generated or received from other nodes. As a result, the packet generation rate in each data cycle for a node u can be expressed as

$$\alpha_u = \sum\nolimits_{i=1}^{m} q_i f_i, \tag{1}$$

For a sensor node u, two policies are opportunistically selected, including the multi-hop and direct transmissions. It is assumed that p_u is the multi-hop transmission probability for node u in terms of a duty cycle for the multi-hop strategy. Therefore, the energy consumption for the multi-hop transmission is $E_M(\alpha_u)$, and the energy consumption for the direct transmission is $E_D(\alpha_u)$. Since the transmission state spends a greater amount of energy than the reception and idle states, only the transmission state is taken into account in order to simplify the power consumption model. Therefore, the average amount of energy consumed by node u per data cycle due to the two different transmission policies, denoted by $E(u)$, can be expressed as

$$\mathrm{E}(u) = p_u[E_M(\alpha_u)] + (1 - p_u)[E_D(\alpha_u)]. \tag{2}$$

As a result, the lifetime of sensor node u is given by

$$L(u) = \frac{E_{init}}{E(u)}, \tag{3}$$

where E_{init} is the initial amount of energy provided to each sensor node. The network lifetime is defined as the time spent from deployment until the drain of each sensor node. Hence, to maximize the network lifetime, we have to maximize the lifetime of the greediest node in the network in terms of the power consumption rate. The lifetime maximization problem can thus be formulated as

$$\max\min L(u) = \min(max\ E(u)). \tag{4}$$

With the same initial amount of energy among nodes, the achievable lifetime for a WSN highly depends on the transmission probability p_u.

III. A PROPOSED SYSTEMATIC DECISION MODEL

To jointly study the design issues of node deployment, routing scheme, traffic pattern, and network energy equilibrium, a systematic decision model is developed. As shown in Fig. 3, The system model consists of four sub-blocks, including

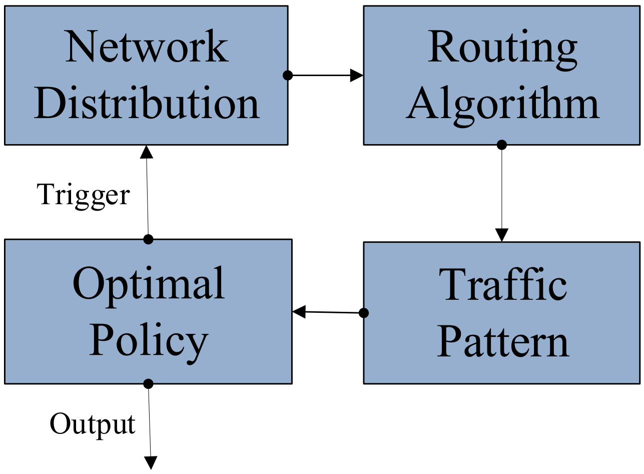

FIGURE 3. A proposed systematic decision model for WSN.

network distribution, routing algorithm, traffic pattern and optimal policy blocks.

In the network distribution block, the network node distributions and various sink positions are generated. The network nodes can be deployed with uniform [17] or random distributions [18] around the sink, where the sink position can be placed in the middle or elsewhere. In the routing algorithm module, the shortest path can be updated according to the varied channel conditions or other weighting factors of each sensor. The varied channel conditions can be classified as either a slow fading or a fast fading channel, and the weighting factor can be defined as the link reliability to calculate the successful packet delivery ratio from the transmitter to the receiver for each data link. In the traffic pattern block, each node can generate packets in a periodic or triggered manner to send the sensing data to the sink. In each time interval T, the optimal policy block triggers the network distribution block to start the systematic decision model. In each cycle, the optimal policy block acquires the information from the network distribution, routing path and traffic pattern blocks to determine the optimization probability in each node for hybrid multi-hop and single-hop transmission, based on the following two design strategies: a power efficiency optimization strategy and a power utilization optimization strategy.

The power efficiency optimization strategy attempts to minimize the overall network power savings in order to improve the energy efficiency of the network. On the contrary, a min-max optimization problem is cast in the power utilization optimization strategy to balance the overall power utilization of nodes and to achieve the maximum network lifetime.

Specifically, the power efficiency optimization strategy achieves the least power consumption for the whole network by determining the probabilities of using the multi-hop or single-hop transmissions at each node. The optimization problem is formulated as

$$\begin{aligned} &\min_{\{p_i\}} \sum\nolimits_{i=1}^{n} \alpha_i(A_i p_i + B_i(1-p_i)), \\ &\text{s.t. } 0 \leq p_i \leq 1, \quad i = 1, \ldots, n. \end{aligned} \tag{5}$$

where n is the number of sensing nodes, A_i is the power consumption value of the node i for transmitting data to the sink with the multi-hop transmission using the shortest path, and B_i is the power consumption value of the node i for transmitting data to the sink with the single-hop transmission. In addition, p_i is the transmission probability of using the multi-hop transmission with the objective of minimizing the overall network power consumption, and α_i is the packet generation rate in each cycle for the node i.

To maximize the network lifetime, the fast drain of the sensor nodes should be avoided with high energy consumption. Therefore, an efficiently routing data packet with the hybrid transmission policy is needed to balance the energy consumption of the network. This goal is achieved by determining the optimal path matrix A to minimize the energy consumption of the greediest sensor nodes, thereby maximizing the network lifetime.

The power utilization optimization strategy is designed to minimize the maximum power consumption among the sensor nodes, enabling us to maximize the power utilization and extend the overall network lifetime. To balance the overall network power consumption and utilization, the multi-hop transmission probability p_i is generated for each node i, and the min-max optimization problem is formulated as follows:

$$\begin{aligned} &\min_{\{p_i\}} \max_{i=1\ldots n} \ [\alpha_i(A_i p_i + B_i(1-p_i))], \\ &\text{s.t. } 0 \leq p_i \leq 1, \quad i = 1, \ldots, n. \end{aligned} \tag{6}$$

The optimization problems in (5) and (6) are linear programming, which can be efficiently solved by using common tools such as CVX [19]. The main computational complexity of the decision system can be divided into two parts. The first part is the forwarding path computation of all transmission nodes, and the second is the calculation of the optimal transmission probability p_i from the power consumption rate of all nodes.

Two methods are designed to realize the systematic decision strategies. One is a centralized method and the other is a cooperative method. The centralized method computes the routing paths and executes the two optimization strategies at the sink node to decide the transmission probability. In each time period, the sink computes the transmission probability p_i of each node, and only the updated information of p_i is appended to the ACK packet from the sink to each node to reduce the network communication overhead. After that, each node uses the multi-hop transmission probability to send its packets, resulting in the minimum power consumption or maximum power utilization.

In the centralized method, the sink node needs to calculate the shortest paths of all pairs and the transmission probabilities for all nodes to the sink. For large-scale WSNs, the computational complexity increases as the network size grows. To balance the computational complexity of the sink, a cooperative method is presented to distribute the routing path computation to each node. Starting from the primary forwarding nodes around the sink, each forwarding node calculates its own shortest path to the sink and then propagates one of its shortest paths to its outward neighbors. Each outward neighbor then uses the received shortest paths to calculate or select the shortest path to the sink. In this way, the generated shortest path is forwarded outwardly in sequence until the most peripheral nodes are reached. In addition, the shortest path tree can be generated at the beginning of the network deployment and only the new path can be updated as the topology changes. Therefore, the communication overhead of the path update is limited along the path, and communication complexity can be reduced to O(*1*) for each sensor.

IV. SIMULATION RESULTS

To evaluate the performance of the systematic decision model, a two-dimensional planar network with a single data sink is considered in the simulation. The network size is 9×9 with a uniform distribution of the cluster heads in the network distribution block. In the routing paths' computations, the Dijkstra algorithm is used to calculate the shortest path for each node to the sink, with various link costs in the routing algorithm block. In regard to the traffic generation rate, each node sends packets to the sink at a variant data rate in the traffic pattern block. For the power efficiency optimization strategy, three performance metrics are evaluated for the first three blocks in Fig. 3: the average power consumption rate distributions for different sink locations, the various link costs in generating the shortest paths, and the power consumption rates for different packet generation rates among the sensor nodes.

In the network distribution block, the impact of various sink locations is studied. With the same traffic rate and link cost, the location of sinks changes from a location near the center node to the outermost node of the network. Fig. 4 shows the average power consumption rate distribution for various sink positions in the power efficiency strategy. Simulation results demonstrate that sink 32 achieves the lowest total power consumption in a computation cycle compared to all other sink nodes, achieving the best total power efficiency. This result is due to the elected sink nodes around the center being able to achieve better power efficiency with shorter routing paths than the sink nodes farther from the center.

In the routing algorithm block, the link costs are updated according to the link reliability, which is defined as the successful packet delivery ratio from the transmitter to the receiver for each data link. The main factor affecting the performance of the packet delivery ratio is the channel status of each data link. With randomly selected links, the channel conditions are simulated to degrade the packet delivery ratio, and the link costs are updated to compute the new shortest routing paths. Based on the power efficiency strategy, Fig. 5 shows the power consumption rate distributions of various link costs and the approximate total power consumption from low channel variation to large channel variation. The low, medium and large channel variations are defined as

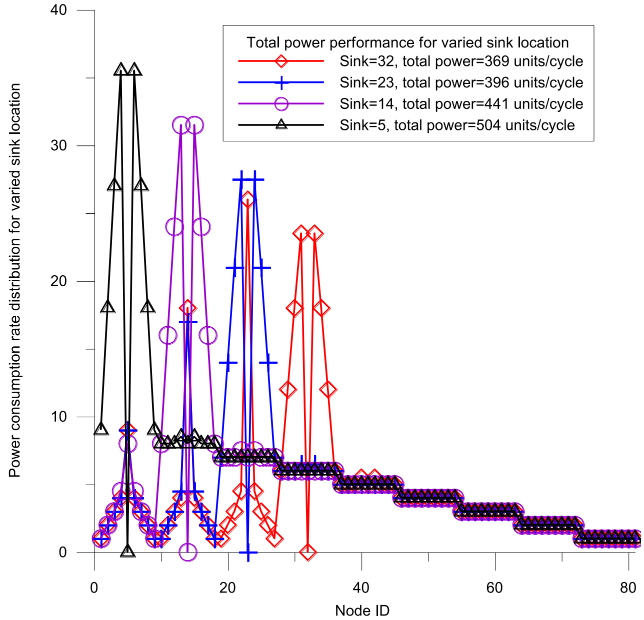

FIGURE 4. Average power consumption distributions for various sink positions in the network distribution block.

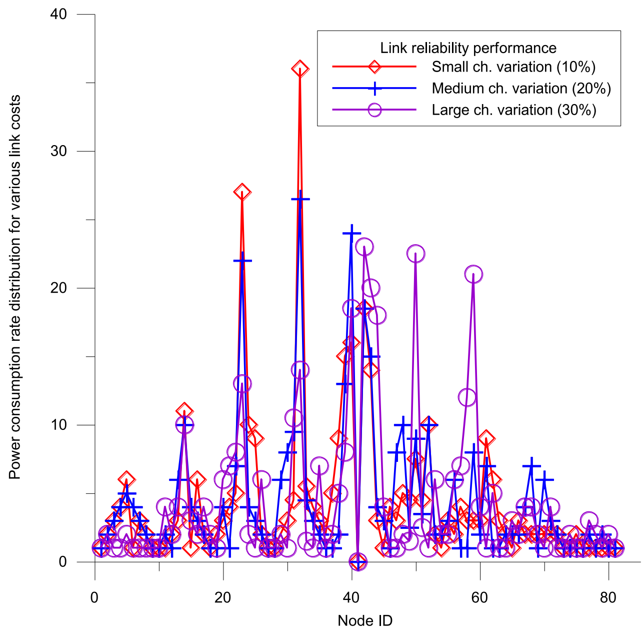

FIGURE 5. Average power consumption rate distributions for various link costs in the routing algorithm block.

total link degradation of approximately 10%, 20%, and 30%, respectively. An interesting phenomenon is found in Fig. 5: the power distribution is more even as the channel variation increases, since the alternative shortest path is updated as the channel of the first shortest path is degraded.

In the traffic generation block, the packet generation rate α_i is assumed to be uniformly distributed for each node i. With the same link cost for the 9×9 network distribution, the packet generation rate can be varied from a uniform

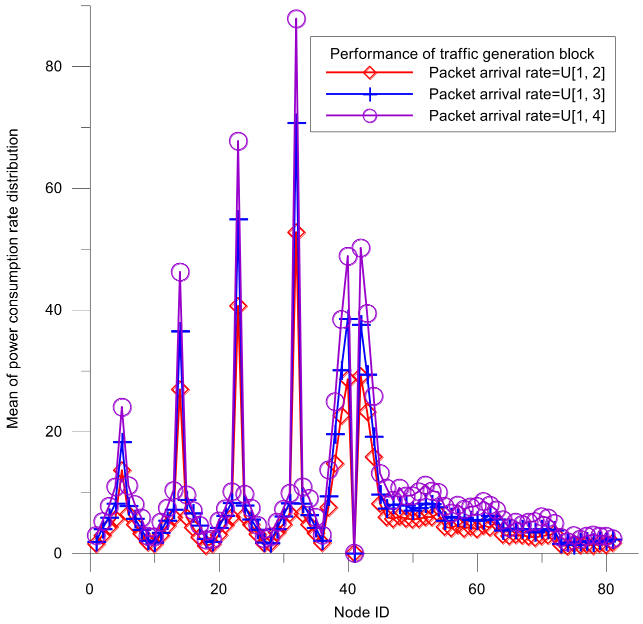

FIGURE 6. **Mean of power consumption distribution rates for various packet arrival rates in the traffic generation block.**

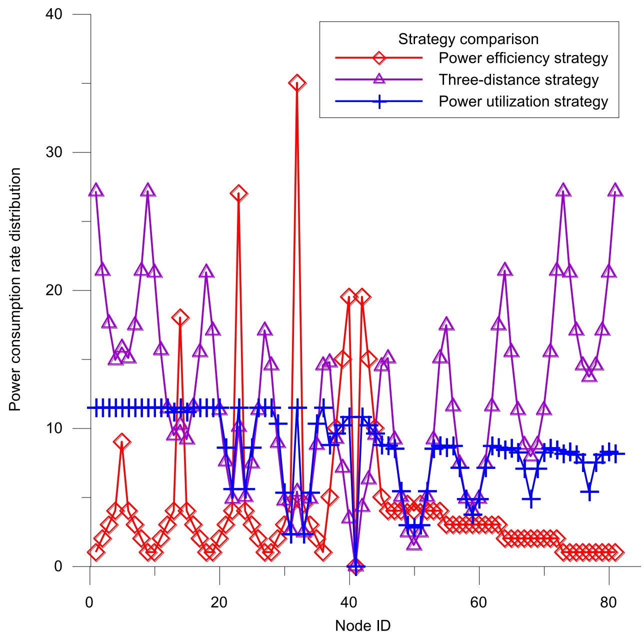

FIGURE 7. **Average power consumption in a transmission cycle of each node for the three strategies.**

distribution U[1, 2] to U[1, 4] in each transmission cycle. Fig. 6 shows the mean value of power consumption distribution rates for various packet generation rates in the traffic generation block. The mean value increases as the packet generation rate increases, since more traffic is produced in the simulated network. The average deviation values for each traffic pattern are 0.68 for U[1, 2], 1.24 for U[1, 3], and 1.61 for U[1, 4], respectively. As a result, the mean and deviation of the power consumption rate is proportional to the increasing amount of traffic.

To evaluate the performances of the two optimization strategies, the Dijkstra algorithm is used to calculate the shortest path for each node to the sink, with the same cost for each link in the routing algorithm block. In regard to the traffic generation rate, each node sends packets to the sink at a periodic constant rate in the traffic pattern block. To achieve the minimal power consumption and extend the overall network lifetime, the two proposed strategies are executed to simulate the performances of the proposed systematic decision model. Three performance metrics are evaluated for various network sizes: the average power consumption rate distribution of each node, the multi-hop transmission probability and the remaining battery capacity of the network when the first depleted node appears.

Fig. 7 shows the average power consumption rate of each node at each cycle for the three decision strategies of the minimization of power consumption, three-distance strategy in [9] and maximization of minimum power consumption among nodes. In the power efficiency optimization strategy, it can be observed that the power consumption rates of most nodes are smaller than those in the power utilization optimization strategy, effectively saving the overall power consumption. However, the power consumption between nodes is concentrated on some specific forwarding paths, especially on the path cluster head. The simulation results show that the power efficiency distribution is similar to that using the multi-hop transmission method in Fig. 2. In addition, when the first node power is depleted, an average of 87% of the battery capacity is not utilized at other nodes. As a result, the remaining battery capacity per node is still very high in the proposed power efficiency strategy, even though the overall power efficiency is better than that with the power utilization strategy.

For the power utilization strategy, power consumption rate distributions among nodes are more balanced than those obtained by the power efficiency strategy, and approximately 36% of the sensor nodes deplete their battery power at the same time. Only an average of 26% of the battery power leaves when a node first exhausts the battery. Therefore, this strategy can effectively improve the remaining battery utilization of each node.

With the transmission combination case of constant hop size with distance d, $2d$, and maximum d for the three-distance strategy [9], the three-distance strategy can achieve better power consumption rate distributions than the power efficiency strategy but less energy equilibrium than the power utilization strategy.

Fig. 8 shows the transmission probability distributions of all nodes in the network with the two proposed strategies. For the power efficiency strategy, it is obvious that the transmission probability is almost equal to one for the nodes far from the sink. Thus, these nodes (e.g., ID 1, 2, 3) choose the multi-hop transmission to save their own electricity but consume the power of the nodes along the forwarding cluster paths. The transmission probability is equal to 0.5 for the

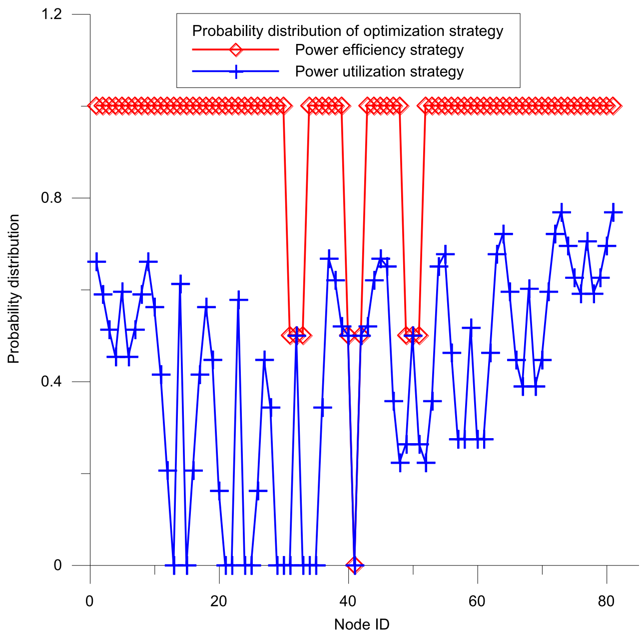

FIGURE 8. Transmission probability of the multi-hop transmission for each node with the two optimization strategies.

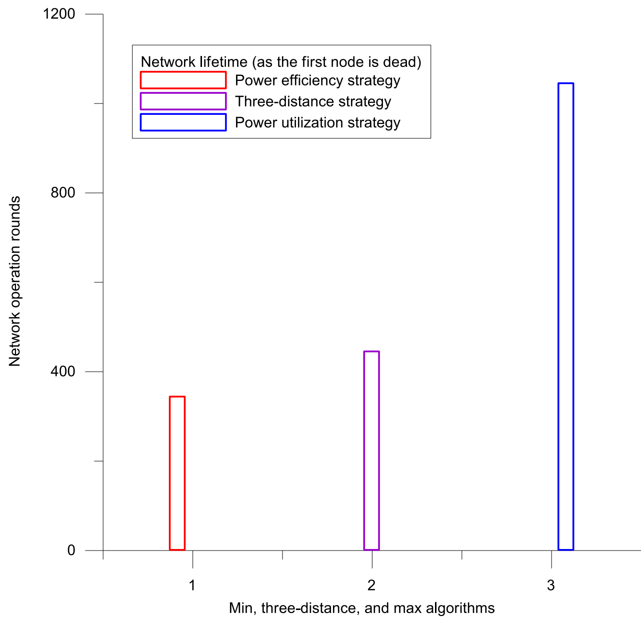

FIGURE 9. Network lifetime for the three optimization strategies.

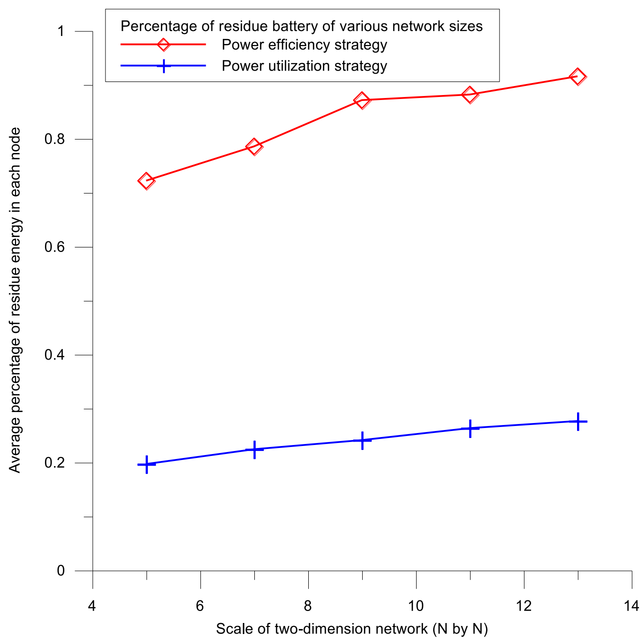

FIGURE 10. Residual percentage of battery power in each node for the two proposed optimization strategies.

nodes closer to the sink, indicating that the data at these nodes can be alternatively transmitted by using either single-hop or multi-hop transmissions. For the power efficiency strategy, it is observed that many nodes with a larger distance to the sink can choose to transmit packets using either multi-hop or single-hop transmissions to mitigate the power consumption of the forwarding nodes along the cluster paths. For the power utilization strategy, with the multi-hop transmission probability in Fig. 8, the power consumption discrepancy of all nodes in Fig. 7 is relatively small, thereby resulting in longer network lifetime.

For the lifetime simulation, the initial amount of the energy at the nodes is set to 0.6 J, and the simulation duration is calculated by rounds. The energy consumption per bit of the transmitting circuit is 50 nJ/bit, and the data packet length is 1000 bits. The sensors with the highest power consumption rate are regarded as the hotspot nodes, which limits the overall network lifetime. As a result, the network lifetime is inversely proportional to the highest power consumption rate in Fig. 7. According to the power consumption rate of the first dead node, the optimal network lifetime achieved by the power utilization strategy is three times larger than that of the power efficiency strategy in Fig. 9. The three-distance strategy achieves better network lifetime performance than the power efficiency strategy but less energy equilibrium than the power utilization strategy. In addition, the power utilization strategy achieves more than twice as much network lifetime as the fixed hop three-distance strategy [9].

Fig. 10 shows the residual percentages of the battery power of the other surviving nodes once there is a node that first exhausts its battery energy over various network sizes, where the network size can be varied from 5×5, 7×7 to 13×13 node distributions. For the power efficiency strategy, the remaining average power percentage is increased from 70% to 92% when the network size is expanded from 5×5 to 13×13. As a result, the larger the network size, the higher the percentage of the remaining battery power. On the other hand, the power utilization strategy makes the power usage of all nodes steadier than the power efficiency strategy and effectively balances the network power utilization as the network size increases. Thus, the power utilization strategy improves the overall network power utilization in terms of the battery capacity by approximately 50% to 60% when compared to the power efficiency strategy for various network sizes.

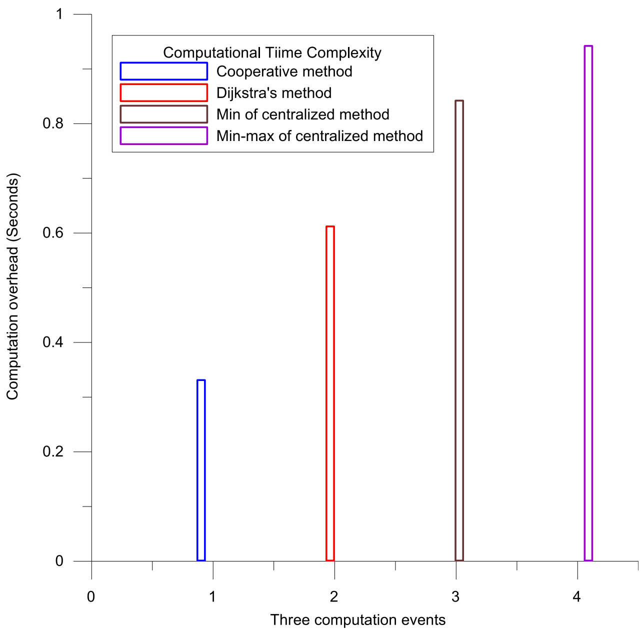

FIGURE 11. Computational time complexity for cooperative method, Dijkstra's method, and the two proposed optimization strategies in the centralized method.

To evaluate the computational time complexity of the two optimal strategies, the algorithm computation time is demonstrated in Fig. 11. Four kinds of computation time are recorded, including the cooperative method, routing paths' determination, the min algorithm execution and the min-max algorithm execution in the centralized method. Regarding the centralized method, the computation time is calculated by the time when the sink determines and sends the shortest paths to all the other sensors. Regarding the computation time of the cooperative method, it is calculated by the time for which all sensor nodes determine their shortest paths. The blue color bar chart represents the cooperative method computation time, the red color bar chart represents the global routing paths' computation time, the brown color represents the computation time of the power efficiency strategy and the purple color represents the computation time of the power utilization strategy in the centralized method. It is found that the power utilization strategy extends the overall network lifetime with slightly additional computation overhead, compared to the power efficiency strategy. In addition, while the cooperative method achieves the least computational time overhead, it introduces more communication overhead than the other three schemes.

V. CONCLUSION

In this paper, two hybrid multi-hop/single-hop opportunistic transmission strategies were proposed to prolong the network lifetime of WSNs. To achieve this goal, a systematic decision model that contains a network distribution block, a routing algorithm block, a traffic pattern block and an optimal policy block was presented to determine the optimal transmission probability of each node. In our systematic decision model, three main conclusions were drawn. First, the traffic load generated by the routing algorithm tends to be aggregated at several paths, which makes hotspot nodes unevenly distributed around the SCA. Second, energy balance probabilities exist between the multi-hop and single-hop network transmissions in each sensor node. Finally, two optimization strategies in the optimal policy block were proposed to minimize the network power efficiency or maximize the network power utilization. Computer simulations show that the power utilization optimization strategy can achieve almost triple network lifetime compared to the power efficiency optimization strategy. Furthermore, the power utilization optimization strategy exhibits superior residual energy utilization to the power efficiency optimization strategy for various network sizes.

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