

# Using a Mobile Vehicle for Road Condition Surveillance by Energy Harvesting Sensor Nodes

Abbas Mehrabi, Kiseon Kim

School of Information and Communications  
Gwangju Institute of Science and Technology  
Gwangju, South Korea

Email: mehrabi@gist.ac.kr , kskim@gist.ac.kr

**Abstract**—In this paper, we introduce the problem of road condition surveillance using a mobile vehicle as a concrete practical application of data collection paradigm on a direct path in energy harvesting wireless sensor networks (EH-WSNs). The application components together with its associated challenges are discussed throughout the paper. An optimization model is introduced for the network throughput maximization problem. In contrast to the previous models, the proposed optimization model considers the effective and heterogeneous duration of sensor's transmission together with the dynamic aspect of energy harvesting over different time intervals. Towards the improvement of the network throughput under a proposed condition, an online centralized algorithm with less complexity is designed. Finally, simulations on both Random and Equal-Distance deployment of sensor nodes are conducted to compare the performance of the proposed algorithm with the previous approaches and to observe the effect of different energy harvesting distributions on the throughput achieved by the algorithm.

**Keywords:** Road Condition Surveillance, Energy Harvesting Sensor Nodes, Data Collection Throughput, NP-Hardness, Online Centralized Algorithm, Energy Harvesting Distribution.

## I. INTRODUCTION

Each year, there are around million road-conditions related crashes causing a huge number of people injured or dead and billion hours delay occurred [3]. The weather condition has a significant impact on most of the accidents which happen on the roads. Therefore, the weather monitoring is essential for safety enhancement and roadway maintenance. The detection of water, ice, fog or light can help to determine the visibility of roads [2]. Therefore, it is essential in surveillance applications to collect data such as temperature or humidity efficiently to improve the road maintenance and enhance the traffic safety.

Using a mobile vehicle as the center of data gathering can reduce the data delivery delay. Furthermore, the one time data forwarding by the sink can increase the reliability of the collected data compared to the multi-stage data collection approaches [1]. Therefore, the focus of the first part of this paper is on using a mobile vehicle in road condition surveillance applications. Fig. 1 shows the collection of road's condition data from one-hop sensor nodes using a mobile vehicle. From the energy harvesting point of view as a potential future development of surveillance applications [2], the unlimited lifetime and continues monitoring service is guaranteed. This is possible by the replenishment of the sensor nodes periodically from the ambient environmental energy resources such as wind, vibration or solar [8]. The contribution of this paper has two folds: First, this work introduces the energy harvesting sensor nodes in the road condition monitoring as a concrete practical application of data collection on a direct path. Second, an efficient optimization model is introduced which in contrast to the previous models considers the dynamic feature of energy harvesting and incorporates the heterogeneous

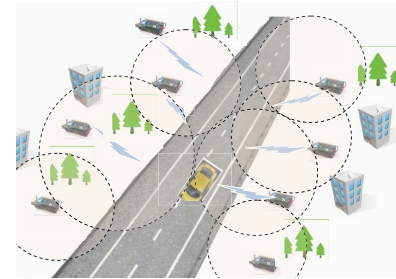


Fig. 1. The mobile vehicle collects the road condition data from one-hop sensor nodes deployed along the road.

duration of sensors' transmission into the problem formulation.

The structure of this paper is organized as follows: In Section 2, the related works are discussed. Section 3 details the road condition surveillance application through the explanation of its components and associated challenges. In Section 4, an optimization model for the problem is introduced and the proposed online centralized algorithm, its complexity and approximation factor are discussed in Section 5. The simulations on different number of sensor nodes are conducted in Section 6 and Section 7 concludes the paper.

## II. RELATED WORKS

The data collection from stationary sensor nodes using the mobile elements and its challenges in conventional WSNs are extensively surveyed in [1]. In conventional sensor networks, sensor nodes have limited power and therefore, the infrastructure and algorithms for data collection should be developed in such a way to preserve the energy of nodes in order to prolong the network lifetime.

On the other side, in energy harvesting sensor networks, the sensor nodes are able to harvest the energy from the ambient energy resources in their surroundings periodically when their energy gives out due to the data transmission [7]. This makes the required infrastructure and algorithms simple since the lifetime constraint is not a deal as long as the nodes are able to recharge themselves.

The data collection using a mobile sink on a direct path in energy harvesting sensor networks is firstly introduced in [4], [5]. In [4], the authors introduce the quality data collection problem by dividing the whole period of one round data collection by sink on the path into several equal-length time slots. In order to achieve the maximum collected data by the sink, they develop a greedy heuristic which allocates each time slot to at most one sensor node in a greedy manner. Similarly, the authors in [5] introduce the maximum data collection problem and due to the intractability of the problem, they propose an approximation algorithm for the problem which works based on an  $\beta$ -approximation algorithm for the single knapsack problem. Although these two works mainly focus on developing heuristics for maximum data collection which has its own contribution to the field, they suffer

from providing a concrete practical application. Furthermore, the data collection throughput achieved by the proposed approaches in these two works can be further improved. As our contributions in this work, we first introduce the road condition surveillance using a mobile vehicle as a concrete practical application for data collection on a path in energy harvesting sensor networks. Then, a generalized optimization model for the network throughput maximization problem is introduced which improves two previous models in [4],[5].

### III. ROAD CONDITION SURVEILLANCE APPLICATION

In the road condition surveillance, the selection of sensor nodes should satisfy the application requirements such as easily portability, low power consumption and low transmission rates. The homogeneous solar-based energy harvesting sensor nodes such as *Helimote* [8] which is built using the *Mica2* platform can be a suitable candidate for deployment along the both sides of the path. They have 512 KB flash memory enough for the surveillance application, a data transmission rate of 40 Kb/Sec and cover the parts of road within the transmission range between 10 to 15 meters. They use the *Lion-MH* embedded battery for storing the harvested energy and are compatible with the IEEE 802.15.4 standard for WAN (Wide Area Networks) with the portability feature. With the homogeneity property, they sense the same amount of temperature or humidity data. However, following the multi-rate communication schema [7], they use different transmission rates at different time slots depending on their geographical location and distances to the road. Following the Fixed Point to Vehicle communication schema, the trajectory of the road is divided into several equal-length time slots and the mobile vehicle traverses the line once few hours per day to collect the sensed data efficiently from the sensor nodes in each time slot.

Each deployed sensor node is stationary during whole one round of data collection and is equipped with a sensing module which is used to sense data such as temperature or humidity from a specific part of the road. In each round of path traversal by the mobile sink, the sensors collect maximum data up to their storage capacity. In this paper, we focus on the type of data which its quantity is vital for the application not the quality. Therefore, the closing nodes may send the similar data to the sink which leads to the increases in network throughput. Although more than one sensor node in each time slot can transmit the sensed data upon the observing of the mobile vehicle in their transmission range, from at most one sensor node the transmitted data is successfully received by the mobile sink. This is due to the channel capacity and the physical interference between the sensor nodes transmitting simultaneously to the sink at each time slot.

The mobile vehicle has a high-power receiver which traverses the road with a constant speed once few hours per day to collect the data from the sensor nodes. Although the high frequency of path traversal by the mobile vehicle may increase the application cost, it can be reduced to some specific periods depending on the application. Furthermore, for the purpose of feasibility of constant speed for the mobile vehicle in real scenarios either when the traffic is high or its speed is low, a specific trajectory on the road is considered for the mobile vehicle.

### IV. THE OPTIMIZATION MODEL

In an energy harvesting wireless sensor network (EH-WSN),  $|V|$  sensor nodes are uniformly deployed along the both sides of the path with fixed length  $L$ . The whole time duration of one round path traversal by the sink is divided into  $|T|$  time slots each equally lasting for  $\tau$  seconds. Denoted by  $t_{rij}$ , the data transmission rate of sensor node  $s_i \in V$  at time slot  $t_j$ , sensor node with total energy budget of  $b_i$  within the current time interval, consumes  $p_{ij}$  amount of power. The transmission power is computed from the path attenuation model,  $p_{ij} = t_{rij} \cdot d^\alpha$ , where  $\alpha$  is the path loss exponent. Due to the movement of sink on the path, the distance of sensor node and sink is accordingly changed at each time slot. For the

sake of simplicity, we assume that  $d$  denotes the average distance of sink to the sensor node  $s_i$  at time slot  $t_j$ . The projected Cartesian Coordinate of sensor node  $s_i$  on  $\mathbb{R}^2$  plane and its transmission range are represented with respectively  $(x_i, y_i)$  and  $r_i$ . The coverage area of each sensor node  $s_i$  has two intersection points with the path on the  $\mathbb{R}^2$  plane when it can partially cover the mobile vehicle on the path at time slot  $t_j$ . The x-coordinate of these two points which we call respectively  $x_{start}$  and  $x_{end}$  with  $x_{start} < x_{end}$  are computed as follows:

$$x_{start} = x_i - \sqrt{r_i^2 - y_i^2}, \quad x_{end} = x_i + \sqrt{r_i^2 - y_i^2}.$$

The constant sink speed during whole of the path is  $v_m$  and for  $\tau$  seconds at each time slot, the mobile sink traverses a corresponding distance  $l = v_m \times \tau$  on the path. Furthermore, for sensor node  $s_i$ , we define  $\tau_{ij}$  to represent the time duration which the mobile vehicle can collect data from the sensor node at time slot  $t_j$ . With the fixed value of  $l$ , the distance per time slot, the quantity  $\tau_{ij}$  is computed as follows:

$$\tau_{ij} = \text{Max}\left\{\frac{\tau}{l} \{ \text{Min}(l \times j, x_{end}) - \text{Max}(l \times (j-1), x_{start}) \}, 0\right\}.$$

We use the widely adopted energy model  $b_i(k) = \min\{b_i(k-1) + h_i(k-1) - c_i(k-1), B_i\}$  where  $b_i(k)$ ,  $h_i(k)$  and  $c_i(k)$  are respectively the energy budget, harvested energy and the power consumption of sensor node  $s_i$  at the beginning of time interval  $k$ .  $B_i(k)$  is the battery capacity of sensor node. Defining the binary variable  $a_{ij}$  to indicate the allocation of time slot  $t_j$  to sensor node  $s_j$ , and the all given values of  $t_{rij}$ , the total volume of data collected by the mobile vehicle during  $|T|$  time slots on the path is defined as  $D_{total} = \sum_{s_i \in V} \sum_{j=1}^{|T|} a_{ij} \cdot t_{rij} \cdot \tau_{ij}$ . Therefore, the Network Throughput Maximization (NTM) problem can be stated as the following Integer Linear Programming (ILP) formulation:

$$\text{Maximize} \quad T_{total} = \frac{D_{total}}{|T| \times \tau} \quad (1)$$

$$\text{Subject to: } a_{ij} \in \{0, 1\}, \forall 1 \leq i \leq |V|, 1 \leq j \leq |T| \quad (2)$$

$$a_{ij} = 0, \quad \forall 1 \leq i \leq |V|, j \notin PT(i) \quad (3)$$

$$\sum_{i=1}^{|V|} a_{ij} \leq 1, \quad 1 \leq j \leq |T| \quad (4)$$

$$\sum_{(k-1)\rho \leq j \leq k\rho} a_{ij} \cdot p_{ij} \cdot \tau_{ij} \leq b_i(k), \quad \forall 1 \leq k \leq |TI| \quad (5)$$

$$c_i(k) = \sum_{(k-1)\rho \leq j \leq k\rho} a_{ij} \cdot p_{ij} \cdot \tau_{ij}, \forall 1 \leq i \leq |V|, 1 \leq k \leq |T| \quad (6)$$

$$b_i(k) = \min\{b_i(k-1) + h_i(k-1) - c_i(k-1), B_i\} \\ \forall 1 \leq i \leq |V|, 1 \leq k \leq |TI| \quad (7)$$

$$0 \leq h_i(k) \leq B_i \quad \forall 1 \leq i \leq |V|, 1 \leq k \leq |T| \quad (8)$$

$$b_i(1) = I_i, \quad 1 \leq i \leq |V| \quad (9)$$

Where  $\rho = \frac{|T|}{|TI|}$  is the number of time slots in each time interval and  $PT(i)$  is used to denote the set of possible time slots at which sensor node  $s_i$  can transmit its data to the mobile vehicle at that time slots. Constraint (3) ensures that time slot  $t_j$  is allocated to sensor node  $s_i$  if the sensor can observe sink during the time slot  $t_j$ . Constraint (4) ensures that at each time slot at most one sensor node transmits data to the mobile sink. Constraint (5) guarantees that the total amount of consumed energy from each sensor node for data transmission in all time slots allocated to it within each time interval does not exceed its energy budget at that time interval. Constraints (6)-(8) describe the energy harvesting model and finally constraint (9) states that the energy budget of sensor node in the first time interval is equal to its initial energy level.

## V. THE ONLINE CENTRALIZED ALGORITHM

In order to improve the data collection throughput compared to the works in [4] and [5], the condition  $l \geq \max(r_i, 1 \leq i \leq |V|)$  is proposed for the distance traveled by sink per time slot. This proposed condition implies that  $|PT(i)| \leq 2$  for each sensor node  $s_i, 1 \leq i \leq |V|$ . In other words, under the proposed condition, each sensor node has maximum two available time slots for data transmission to the mobile sink. Since  $|PT(i)| \leq 2, 1 \leq i \leq |V|$ , different combination of time slots into larger time intervals can be considered. We call each way of combining time slots into larger time intervals as one *Interval Partition*. Due to the correlation between different time intervals, the problem of finding the best time interval is hard. Furthermore, due to the dynamic feature of energy harvesting, sensors have different energy budget at different time intervals making the problem of allocating time slots to sensors considering their energy budget equivalent to the special case of multi-dimensional knapsack problem (MDKP), a well-known NP-Hard problem [6]. Therefore, the NTM problem under the proposed condition is NP-Hard and is harder than MDKP in general.

To cope with the complexity of the problem, we consider a simple interval partitioning which is 2,2, ..., 2 when  $|T|$ , the number of time slots, is even and 2,2, ..., 2,1 when  $|T|$  is odd. An online centralized algorithm called *AdjustmentBased-Allocation* is designed based on this interval partitioning which has been summarized in Algorithm 1. The algorithm is easily scalable to the networks with the large number of sensor nodes. We assume that the trajectory of sink is determined using an accurate navigation system. In the beginning of each time interval, the mobile sink broadcasts a Polling message to acquire some information from sensor nodes about their geographical location, transmission range and transmission rate. The board of this Polling message is adjusted to cover only the sensor nodes in the current time interval. Each sensor node which the mobile vehicle can be in its transmission range while passing the path during the current interval, registers the data transmission process by replying the message with the above-mentioned information. After the reception of all messages from the registered sensor nodes, the mobile sink makes decisions that which two sensor nodes must transmit their sensed data in two consecutive time slots of the current time interval. The procedure of local computation and decision phase comes after the main algorithm.

At the beginning of each time interval, the mobile sink communicates three time in overall with the sensor nodes to recognize two eligible sensor nodes for data transmission. Having  $|V|$  sensor nodes and  $|T|$  time slots, therefore, the message complexity of the proposed algorithm is of order  $O(|T| \cdot |V|)$  in the worst case. Furthermore, finding the two nodes with the maximum profit at two consecutive time slots is performed in  $O(|V|)$  and the profit comparison is done in  $O(1)$ . Therefore, the

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### Algorithm 1: AdjustmentBased-Allocation

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**Inputs:**

$|T|$ : Total number of time slots

$Number\_of\_TI$ : Number of time intervals

**Output:**

Allocation of  $|T|$  time slots to  $|V|$  sensor nodes

**For**( $timeinterval = 1$  to  $Number\_of\_TI$ )

$t_1$  = the first time slot of the current time interval;

$t_2$  = the second time slot of the current time interval;

Mobile vehicle broadcasts **Polling** message;

Each registered sensor node in two time slots  $t_1$  and  $t_2$  replies *message(location, trange, trate)*;

**Run** the local computation and decision phase;

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### Local Computation and Decision Phase

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**For** each registered sensor node  $s_i$  at  $t_1$

**compute**  $Profit[s_i][t_1] = \tau_{it1} \times t_{rit1}$ ;

**For** each registered sensor node  $s_i$  at  $t_2$

**compute**  $Profit[s_i][t_2] = \tau_{it2} \times t_{rit2}$ ;

$s_1-first$  = the sensor node with the first maximum profit in time slot  $t_1$ ;

$s_1-second$  = the sensor node with the second maximum profit in time slot  $t_1$ ;

$s_2-first$  = the sensor node with the first maximum profit in time slot  $t_2$ ;

$s_2-second$  = the sensor node with the second maximum profit in time slot  $t_2$ ;

$e_1$  = the energy consumption of allocating  $t_1$  to  $s_1-first$ ;

$e_2$  = the energy consumption of allocating  $t_2$  to  $s_2-first$ ;

**If**( $s_1-first \neq s_2-first$ )

**Allocate** time slot  $t_1$  to sensor node  $s_1-first$  and time slot  $t_2$  to sensor node  $s_2-first$ ;

**Update** the energy budget of  $s_1-first$  and  $s_2-first$ ;

**Else**

**If**(energy budget of  $s_1-first - e_1 - e_2 \geq 0$ )

**Allocate** both time slots  $t_1$  and  $t_2$  to sensor node  $s_1-first$ ;

**Update** the energy budget of  $s_1-first$ ;

**Else**

**If**( $Profit[s_1-second][t_1] + Profit[s_2-first][t_2] \geq Profit[s_1-first][t_1] + Profit[s_2-second][t_2]$ )

**Allocate**  $t_1$  and  $t_2$  to respectively  $s_1-second$  and  $s_2-first$ ;

**Update** the energy budgets of  $s_1-second$  and  $s_2-first$ ;

**If**( $Profit[s_1-first][t_1] + Profit[s_2-second][t_2] > Profit[s_1-second][t_1] + Profit[s_2-first][t_2]$ )

**Allocate**  $t_1$  and  $t_2$  to respectively  $s_1-first$  and  $s_2-second$ ;

**Update** the energy budgets of  $s_1-first$  and  $s_2-second$ ;

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*AdjustmentBased-Allocation* algorithm has the time complexity of order  $O(|T| \cdot |V|)$  in the worst case. It can be seen theoretically that the proposed algorithm outperforms the greedy-based algorithm *C-Schedule* [6] in term of the data collection throughput with an average improvement of  $529.06 \times \frac{R^5 \cdot \tau^5}{15} Bit$  where  $R$  is the identical transmission range of sensor nodes. Since the greedy algorithm for the MDKP achieves an approximation factor of 2 and the ratio of  $529.06 \times \frac{R^5 \cdot \tau^5}{15}$  to the optimal solution is always  $0 \leq \epsilon \leq 1$ , we conclude that the *AdjustmentBased-Allocation* is an  $(2 - \epsilon)$ -approximation algorithm for the NTM problem.

## VI. EXPERIMENTAL RESULTS

We have implemented the algorithm *AdjustmentBased-Allocation* on different set of deployed nodes in the network and compared its performance with *C-Schedule* [4] and *GAP-Based Approximation* [5] in term of the total collected data by the mobile sink. The algorithms are compared for one round of data collection by the sink on the path. In the simulations, the unit of the total collected data is considered as *KB*. For the simulation purpose, we have used the dataset listed in Table 1 for the system parameters.

In Fig. 2, we have compared the performance of *AdjustmentBased-Allocation* algorithm with both *C-Schedule* and *GAP-Based Approximation* in term of the total volume of collected data under the *Random* deployment of sensor nodes. We assume the initial energy budget from interval [3000Joule, 3500Joule] and 500Joule harvesting at the beginning of each time interval.

TABLE I. THE LIST OF SYSTEM AND ENERGY HARVESTING PARAMETERS AND THEIR CORRESPONDING VALUES USED IN THE SIMULATIONS.

System Parameter	Corresponding Value
Number of Sensor Nodes	2000 ~ 8000
Path length	10 km
Time Slot Period	2 Sec
Distance per Time Slot	15 m
Mobile Vehicle Speed	7.5 m/s
Transmission Range Distribution	[10 m, 15 m]
Transmission Rate Distribution	[60 $\frac{KB}{Sec}$ , 80 $\frac{KB}{Sec}$ ]
Battery Capacity	4000 Joule
Probability of Battery Failure( $P_f$ )	0.05

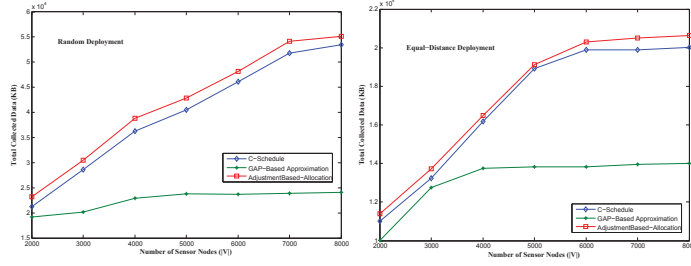


Fig. 2. Comparison between the algo- Fig. 3. Comparison between algorithms rithm under the *Random* deployment. under the *Equal-Distance* deployment.

As we can see from the simulation result, the proposed algorithm outperforms both *C-Schedule* and *GAP-Based Approximation* when the number of sensor nodes increases.

Similarly, we compare three algorithms in term of the total collected data by increasing the number of sensor nodes under the *Equal-Distance* deployment. The comparison result has been demonstrated in Fig. 3. As we can see from this result, the proposed algorithm outperforms the two other approaches under the *Equal-Distance* deployment as well. Furthermore, our experiment with several instances shows that the experimental improvement gap in throughput between two algorithms *AdjustmentBased-Allocation* and *C-Schedule* is at most 10% in average far from the theoretical estimation hence achieving an average of 90% confidence in throughput improvement.

Another observation from both Fig. 2 and Fig. 3 is that the total collected data by the mobile sink under the *Random* deployment is more than the *Equal-Distance* deployment. The reason is that when the sensor nodes are deployed with equal distance on both sides of the path, there is higher probability that a sensor node is eligible for data transmission to the mobile sink in two consecutive time slots than the case when sensors are randomly deployed. As a result, sensors lose their energy more frequently in the case of *Equal-Distance* deployment compared to the *Random* deployment. This leads ultimately to the less amount of collected data by the mobile sink.

The amount of harvested energy from solar resources changes depending on the weather conditions and therefore is not deterministic [9]. However for the sake of simplicity, we have considered two probability density functions (pdf) to stochastically describe the amount of harvested energy by the sensor nodes at the beginning of each time interval. Considering  $h_i(k)$  as a random variable, these two pdfs are *Uniform* and *Gaussian* with the same harvesting mean and variance respectively  $E[h_i(k)] = 500 \text{ Joule}$  and  $Var[h_i(k)] = 135 \text{ Joule}$ . In Fig. 4, we have illustrated the comparison between these two energy harvesting distributions when they are applied into the data collection model. We assume the initial energy budget from the interval [1500 Joule, 1800 Joule]. As we can see from the result, with the same variance, same amount of data is collected by the mobile sink. The reason is that with same variance, the difference in amount of harvested energy at each

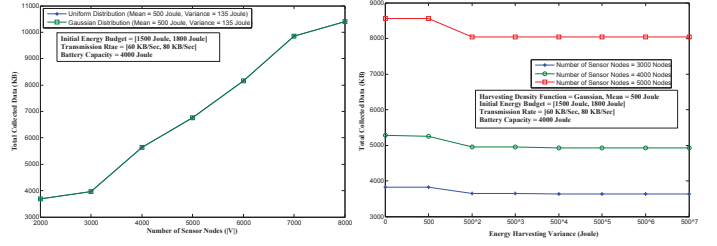


Fig. 4. The effect of same energy Fig. 5. The effect of increase in vari- harvesting variance on the throughput. ance on the throughput.

time interval is negligible compare to the energy budget and power consumption of nodes. Therefore, with the same initial energy, the same volume of data is collected by the mobile sink.

In Fig. 5, we have illustrated the effect of increase in harvesting variance on the throughput when the *Gaussian* pdf is considered. As we can see, by increase in variance the throughput decreases. The reason is that when the variance increases, with the high probability, in most of the time intervals, the amount of harvested energy by nodes is negligible compare to their power consumption. This implies that the amount of collected data by the sink decreases.

## VII. CONCLUDING REMARKS

In this paper, we introduce the road condition surveillance using a mobile vehicle as a concrete practical application of data collection on a path in energy harvesting wireless sensor networks (EH-WSNs). The application components and its challenges are discussed and an optimization model is considered for the network throughput maximization problem which improves the previous models. Toward the improvement of the network throughput with respect to the existing approaches, a simple condition and an online centralized algorithm with low complexity are proposed. The results of simulations confirm the superiority of the proposed algorithm. Furthermore, the simulation results show that with the same energy harvesting distribution, the throughput decreases when the harvesting variance increases.

## REFERENCES

- [1] M. D. Francesco, S. K. Das, G. Anastasi, *Data Collection in Wireless Sensor Networks with Mobile Elements: A Survey*, ACM Transactions on Sensor Networks, vol. 8, no. 1, August 2011.
- [2] S.Y. Cheung, P. Varaiya, *Traffic Surveillance by Wireless Sensor Networks: Final Report*, California PATH Research Report, January 2007.
- [3] A. Bernie, *Implementing an Integrated Road Weather Information System in Minnesota*, PIARC International Winter Road Congress, May 2002.
- [4] X. Ren, and W. Liang, *The use of a mobile sink for quality data collection in energy harvesting sensor networks*, In the Proceedings of IEEE Wireless Communications and Networks Conference(WCNC) 2013.
- [5] X. Ren, W. Liang, W. Xu, *Use of a Mobile Sink for Maximizing Data Collection in Energy Harvesting Sensor Networks*, In the Proceedings of IEEE 42nd International Conference on Parallel Processing, 2013.
- [6] M. Garey, D. Johnson, *Computers and Intractability: A Guid to the Theory of NP-Completeness*, Bell Laboratories Incorporated, 1979.
- [7] R. S. Liu, K. W. Fan, Z. Zheng and P. Sinha, *Perpetual and fair data collection for environmental energy harvesting sensor networks*, IEEE/ACM Transactions on Networking, vol. 19, no. 4, August 2011.
- [8] S. Sudevalayam and P. Kulkarni, *Energy Harvesting Sensor Nodes: Survey and Implications*, IEEE Communications Surveys & Tutorials, Vol. 13, No. 3, 2011.
- [9] V. Raghunathan, A. Kansal, J. Hsu, K.J. Friedman, B.M. Srivastava, *Design Considerations for Solar Energy Harvesting Wireless Embedded Systems*, In the Proceedings of IEEE International Conference on Information Processing in Sensor Networks(IPSAN), 2014.