# An Optimization in Green Energy Harvesting by Using Game Theory Approach for Energy efficient in Wireless Sensor Networks

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***Abstract*: This article studies the sensor activation control for the optimization of green energy utilization in a GEH-WSN. Decentralized operation is considered for the green energy optimization in the EH-WSN. The optimization is achieved in two dimensions: dynamic (activation) mode adaptation and energy balancing in the spatial dimension. In this proposed scheme controls the switching of sensor nodes from active to sleep states (High to Low) and the awakening up of sensor nodes from sleep to active state (Low to High). A utility value is calculated at each node through the utility function and the behavior of the sensor is decided by the utility value of nodes itself and the also by taking into account the utility values of immediate nearby nodes. Sensor nodes in these types of networks have some energy-harvesting mechanism associated with them which can harvest energy from immediate environment such as solar energy, wind energy and vibration energy.***

***Keywords— Active, Green energy-harvesting wireless sensor networks (GEH-WSN), game theory, green energy optimization, High, Low, Node, Sleep state,.***

## I. INTRODUCTION

Green Energy-harvesting technologies are becoming more and more common and advanced with the passage of time. Wireless sensor networks have always suffered a critical issue of limited power supply for the sensor node to work and the advancements in energy-harvesting technologies offer an effective approach to address that issue. Energy harvesting wireless sensor networks has the capability to harvest energy from the immediate environment. Sensor nodes in such networks are equipped with some energy harvesting mechanism through which energy can be harvested [1] from various means such as solar energy, mechanical energy or thermal energy. When working with such energy-harvesting networks, the traditional algorithms of energy optimization no longer serves as an optimal approach because traditional approaches considered battery life to be limited but when the node is harvesting energy from the environment, the scenario is different. Though the nodes have that harvesting capability, the harvesting rate is lower than the consumption rate of energy and also it cannot be guaranteed that energy will be available at all time to be harvested for instance the solar energy will be available at night time. But if proper optimization is applied, these networks have the ability to extend their lifetime indefinitely. In our work we have considered the scenario where there is dense deployment of the sensor nodes so that some nodes can be switched to sleep mode for harvesting of energy and other nodes can keep working to keep the coverage. In this way some nodes will keep harvesting the energy and when some sensor is having low energy, it goes to sleep mode and some other sensor with have higher energy and is in sleep mode, comes back to active mode. To achieve this purpose in a decentralized manner, we have applied the game theory approach. Corresponding to a real world system, a game theory model can be defined and by defining behavior of entities, we can achieve the desirable equilibrium.

## II. OVERVIEW OF GREEN ENERGY HARVESTING WSN

In the GEH-WSN, multiple EHSs are deployed for target monitoring, as shown in Fig. 1. Generally, both the energy generation and target distribution exhibits temporal and spatial diversities. The temporal diversity of target distribution indicates that the target distribution in the network varies in different time slots due to the moving characteristics of targets and probably the joining of new targets. Moreover, targets are randomly distributed in the area; thus, sensors at different locations may experience different target distribution intensities, which reflect the spatial diversity. Besides, green energy generation also possesses both temporal and spatial diversities. For example, solar energy generation depends on many factors such as temperature, sunlight intensity, the geographical location of the solar panel, and so on [7]. Therefore, energy generation by sensors at different locations is different. Moreover, the daily solar energy generation in a given area exhibits temporal dynamics that peak around noon and bottom out during the night. Same as Wind energy is another promising green energy source for powering WSNs, especially in outdoor environments where consistent airflow is available. Can operate day and night, unlike solar, Often used in hybrid systems, potentially high power output in windy conditions, Suitable for remote, windy locations. We can also harvest energy from the vibration by using piezoelectric; this is an interesting and promising method of energy harvesting that can be particularly useful in certain environments. Can harvest energy from ambient vibrations in the environment, no need for external power sources, compact and can be integrated into MEMS devices, suitable for indoor and enclosed environments where solar or wind isn't available.

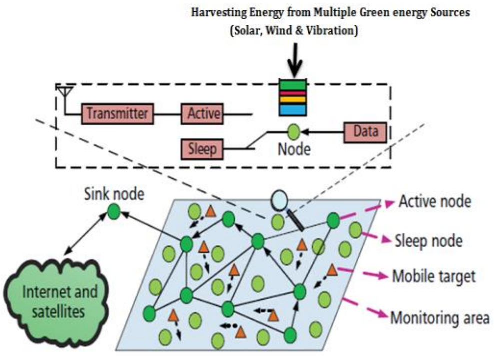


Fig 1: Green Energy Harvesting Wireless Sensor network

## III. GREEN ENERGY HARVESTING OPTIMIZATION IN GEH-WSN

In this we discuss activation based scheduling green energy optimization and challenges of GEH-WSN. Due to the seamless placement of sensors, a target is often covered by multiple sensors. In the traditional battery-operated WSN, optimally turning some of these sensors to sleep mode will extend the lifetime of the network while maintaining complete target coverage. In essence, the energy efficiency is improved and maximum use only by optimizing the energy consumption. However, to improve the energy efficiency in the GEH-WSN, not only energy consumption but also multiple sources GEH should be taken into consideration. In other words, we should minimize the energy consumption and maximize the green energy collection by multiple sources at the same time.

We take an example with three sensors and three targets, as shown in Fig. 2. The node sensing area is the disk centered at the sensor, with the radius equal to the sensing range. A sensor covers a target if the identical distance between the sensor and the target is smaller than or equal to a predefined sensing range [14]. Assume each sensor has two units of energy in storage, and one unit can supply each sensor to be active for one time slot. Thus, if all sensors are active continuously, the network lifetime is two time slots. To prolong the network lifetime, we can permit each sensor to sleep alternately to save energy while ensuring all targets are monitored continuously by at least one sensor. In order to cover all the targets, at least two sensors need to keep active at any time. Therefore, we can divide the sensors into three cover sets: $C1 = \{s1, s2\}$, $C2 = \{s2, s3\}$, $C3 = \{s1, s3\}$, and let each cover set be active for one time slot. This scheme will achieve a longer lifetime (i.e.3 time slots) irrespective of the activation order of the cover sets.

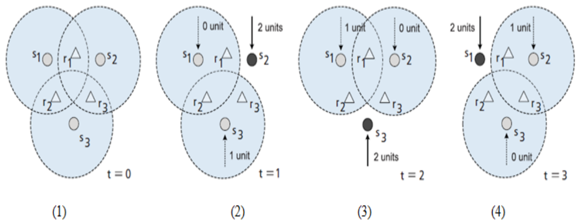


Fig 2: An Example of three Targets R= $\{r_1, r_2, r_3\}$ and three sensor node C= $\{s_1, s_2, s_3\}$

We can derive the optimal activation scheduling scheme as ($C3$, $C1$, $C2$), in Figs. 2. That is, $C3$, $C1$, and $C2$ are active in the first, second, and third time slots, respectively. We can see that each sensor enters sleep state to collect energy when its energy arrival reaches the maximum. Although each sensor consumes two units of energy to activate for two time slots, it also harvests two units of energy from the environment. Therefore, through green energy optimization, not only is the energy consumption minimized, but the green energy collection is also maximized by using multiple sources. Each sensor obtains sustaining supplementation for its energy consumption, which further enhances the energy efficiency and persists the lifetime of the network.

## V. GAME THEORY

Game theory is a mathematical tool which is used to study interactions between self-directed entities. We can define the utility function and the strategy for the sensor node which will in turn decide the overall behavior of the system. For any practical setup, if we wish to apply game theoretic approach, we first need to create a game model of the setup. Game model consists of a set of players, a utility function which maps the parameters of interest to a utility value and a strategy that the players follow. We can change the equilibrium state that a system goes into by changing the game model. For this setup, the set of players is the set of sensor nodes in the GEH-WSN. Utility function is based upon remaining energy of the node, sensed data and the utilities of nearby nodes. There can be many different types of game models. These different game models can be categorized in three main categories, non-cooperative game theory [2], cooperative game theory [3] and repeated game theory [4] which can be mixed together to form further many possible approaches such as evolutionary game theory [5]. In non-cooperative game model as the name suggests, there is no cooperation among the various players. Each player plays to maximize its utility irrespective of actions of other players. Utility function determines the Nash Equilibrium [6] in non - cooperative game theory. Non-cooperative approach reduces the overhead of cooperation because to achieve cooperation between various players, some means of communication are necessary. In cooperative game theory, the players can form a group and cooperate with other players within the group to maximize the utility of the group. These kinds of groups formed are also called an alliance. Rather than working alone, players can decide to work in an alliance aiming for some particular common interest. There can be various means to implement this kind of cooperation among the players. Example of one such approach is the reward mechanism where a node gets some rewards for cooperation. On the contrary there also exist punishment mechanisms where punishment can be given if some player works against the common goal. When the system is complex having many mutually dependent parameters, cooperative game approach is better suited as various priorities can be more accurately modeled into the game model. Repeated game theory is that model in which the player is repeatedly playing the game. It can be cooperative or non-cooperative but the essentials parameter is that each player plays the game repetitively. Thus by using this repetitive approach, the dynamic changes in environment can be handled by the game model as when some change in the system occurs, the decision of the player also changes in accordance with the current state of the system in the next iteration of the game.

Game Model Theory for our System:

The game model that we are using in our approach is of non-cooperative and repetitive type. The set of sensor nodes is the set of players. The utility function is given as

$$U_i^t = \alpha E_i^t + \beta D_i^t - \gamma \sum_{i=1}^{n} U_i^t$$

Where,
$U_i^t$ Utility value of Node i at time t.
$E_i^t$ is energy of node i at time t,
$D_i^t$ is sensed data at node i at time t,
$\alpha$ is normalization factor of energy, $\beta$ is normalization factor for sensed data and $\gamma$ is normalization factor for collective utilities of neighbors.

Above game components are combined with some restrictions for the approach to work effectively. First restriction is that the sensor node will turn itself to sleep mode only if its utility value is lowest among its neighbors.

In accordance with the utility function a low utility value of sensor node indicates that either the sensor node remaining energy is very low or it is lower as compared to other neighboring sensor nodes. And the other restriction is that sensor node re-activates itself only when it has gained some particular amount of utility or some particular amount of time has been elapsed. After a certain utility value gain, it shows that sensor have harvested enough energy and should be activated now. But in case the energy is not available for harvesting for instance solar energy is not available in night, harvest energy from other source from wind energy and vibration energy, we need to activate the sensor node using the time for which it has been in sleep mode so that it can further know about the states of neighboring sensors and make the appropriate decision.

In the utility function, $\alpha E_i^t$ is added because more the available energy to a node, more it can work and does not need to be turned to sleep mode. $\beta D_i^t$ is added as more the data is sensed by a node, more urgent it become to report the arrival of the data. It is for the sake of urgency of monitoring. $\gamma \sum_{i=1}^{n} U_i^t$ is subtracted because more neighbors with good utility means area is being sensed by many neighboring nodes, so it is not very urgent for the node to keep working as other neighbors are doing the work. It signifies a relatively lower need for the sensor node to keep working.

In [7], authors applied the game theory to EH-WSN in association with learning mechanisms to optimize the energy. In their approach the sensor node is not taking into account the state of neighboring nodes. But in our work, we are associating the game theory with some restrictions and creating a neighbor table to store utility values of nearby sensor nodes. Each node creates a neighbor table consisting of entries for n nearest neighbors' utility values. By creating such a table, the node is able to get an idea about the states of immediate neighboring nodes. These n nearest neighbors are decided on the basis of RSSI (Received Signal Strength Indicator) [8, 9]. To minimize the network traffic, each node broadcasts its utility value after some particular intervals of time which follows an AIMD (additive-increase multiplicative-decrease) manner [10]. Any particular node listening to such broadcasts only adds the limited number of nearest neighbors to the neighbor table. The flowchart of the algorithm is as shown in fig 3.

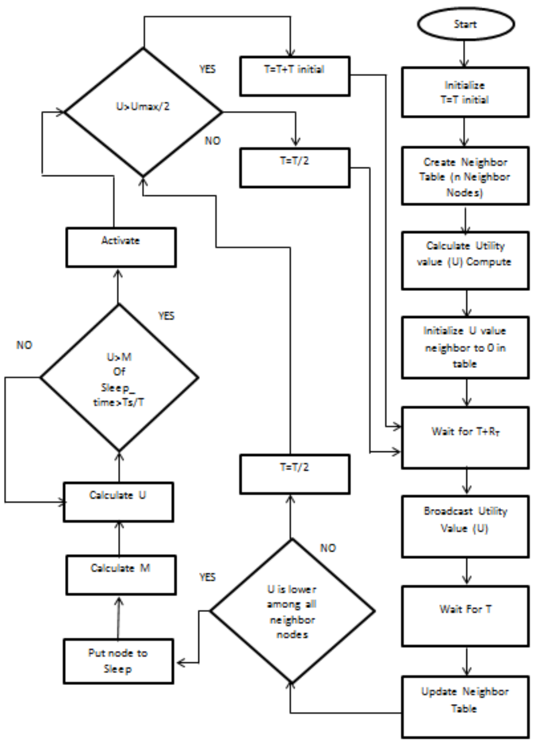


Fig 3: Flowchart of Proposed approach

Here T initial is a predefined constant which denotes the initial amount of time after which a sensor node is supposed to broadcast its utility value. RT is the randomness introduced in time period of broadcasting of utility values to avoid simultaneous broadcasting. TS is also a predefined constant which helps to decide the time duration after which sensor node re-activates. Time period after which the sensor node comes back to active state is computed as TS/T which introduces a relationship between current state of node and time after which it needs to re-activates. And M is the minimum increase in utility value of a particular node after which sensor node will re-activate. These mentioned two factors control the re-activation, if either one of these is satisfied, the sensor node in sleep state comes back to active mode.

Algorithm to be used for the system:

Game Model various functions used is described as follows:

Main ( ) algorithm for game theory energy optimization method

1. Main( )
2. Initialize T = T initial
3. Create_Neighbor_Table(n) // with n neighbor nodes
4. Compute U
5. Initialize U values of neighbors to 0 in neighbor table
6. $R_T$= Random(1,T/10)
7. Compute U
8. Wait for time (T + $R_T$)
9. Broadcast its own U to neighbors
10. Wait for time T
11. Update_Neighbor_Table( )
12. If U0 in neighbor table is lowest among all neighbor nodes

    Put node to SLEEP
    Compute M

while

    Compare M(U,M) == FALSE
    {Do nothing}
    ACTIVATE the node
    Update T(T, U)
    Go to step 6

Else

    Update T(T, U)
    Go to step 6

Compare ( ) function.

```
Compare M (U, M)
{
        if ( U > M ) OR SLEEP_TIME > TS / T
        TRUE
        else
        FALSE
}
```

Neighbor Table Algorithm creation

```
Create_Neighbor_Table(n)
    {
    float Neighbor [n+1] // Create array of size (n+1)
    }
    // The array stores utility values of n neighbors
    // where Neighbor[0] stores utility value and status of node itself
```

update Neighbor Table Algorithm

```
Update_Neighbor_Table( )
    {
        L = list of utility broadcast (UB)
    packets received.
        Sort(L)   // Based upon RSSI of
    neighbors
            // sort using any optimal
        method applicable
        For i = 1 to n
    {
        Neighbor[i]=ExtractMax (L)
    }
    }           //Neighbor[0] contains U
                of node itself, and
                    Neighbor[1] to
                Neighbor[n] are filled
                with U of n nearest
                neighbors.
```

UpdateT( ) function execution.

```
UpdateT(T,U )
    {
If
    U > U MAX / 2
    T = T + T initial
else
    T = T/2
    }
```

## VI EVALUATIONS

The following assumptions have been considered while evaluating our approach.

(1) The sensor nodes in the network are homogenous.

(2) Each sensor node has an energy harvesting mechanism by which it can harvest energy which available from the environment.

(3) Sensor nodes are uniformly distributed in the coverage area.

(4) Each point in targeted area of observation is covered by more than one sensor node for sensing.

As the sensor nodes are energy-harvesting in nature, network lifetime cannot be considered as an evaluation parameter because these GEH-WSNs have the potential of infinite lifetime in terms of energy. So the evaluation parameter we are considering is the amount of data received by the sink within a certain time limit, which is denoted here as the received data utility. This parameter signifies that how much fast the relevant data is sent to the sink.

The change in received data utility as the total number of nodes in the network varies, is demonstrated in figure 4.

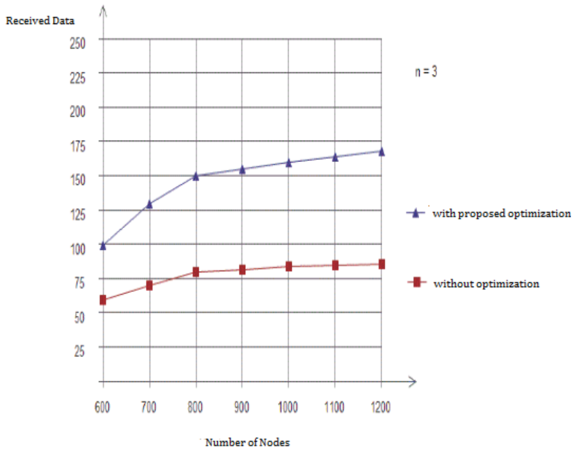


Fig 4: Received Data with and without Optimization

We can see that the received data utility is higher in case when the optimization algorithm is applied on the EH-WSN. When we vary the game model, the behavior of the system also changes. The changes in game model can be made in many ways. We will consider varying the parameters n (number of neighboring nodes in neighbor table), $\beta$ which is the normalization factor for data sensed and $\alpha$ which normalization factor is for remain energy. When we vary the n value, the comparison that a sensor node performs to check if it has the lowest value needs to be done with more number of neighbors. And also the overall sensor nodes that go to sleep state in the network decreases. So a very large number of n reduces the performance of the approach. But also if n is too less then also performance decreases as there will be too much sensors in sleep state. The effect of varying the n on received data utility is shown in figure 5.

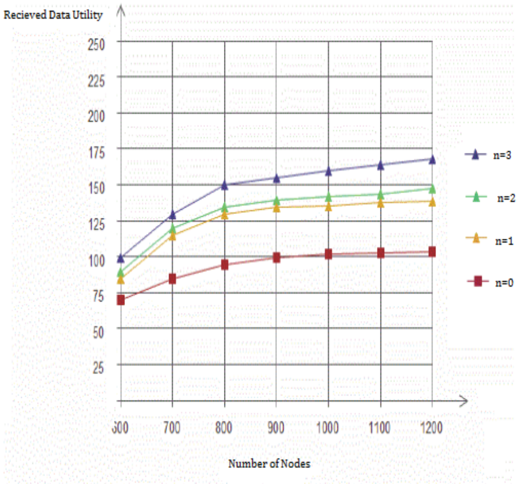


Fig 5: Varying the parameter n

When varying the normalization parameter $\beta$, the behavior changes of the system as shown in the figure 6. When we reduce the $\beta$ parameter, the weight we give to the urgency of reporting the data decreases, so it leads to the lowered received data utility. On the other hand if we reduce the $\alpha$ value, that means the weight of $\beta$ increases, so sensor does not care much about energy. Thus the sensor will keep working even in low energy if it needs to report the data. This situation may lead to some sensors going out of energy and becoming inactive. If there is some mechanism of turning them on again after enough energy has been harvested then they can work after some time but if there is no such mechanism the sensor will keep in off mode which will be really undesirable here our multiple green energy harvesting sources supports not to inactive the system. Here we assume that even if sensor goes out of energy it re-activates after harvesting enough energy. Still the received data utility decreases if we greatly reduce this parameter because sensors in off mode will not sense or send any data and coverage will also be affected. This is shown in figure 7.

Other parameters can also be varied and the effect can be observed. The values of various parameters of the game model depends upon the various parameters and condition of the WSN, such as number of nodes, various priorities of objectives of WSN, environmental conditions etc. So before the game theoretic approach can be applied effectively, it is required to analyze the whole situation and set the parameters according. Each parameter defined in game theory attempts to represent a real world factor. As we vary the game theory parameters the overall system performance also changes. Simulations become very necessary in game theory to analyze the various effects.

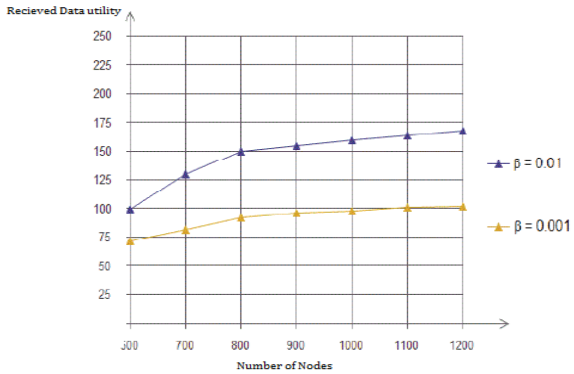


Fig 6: Varying the Parameter $\beta$

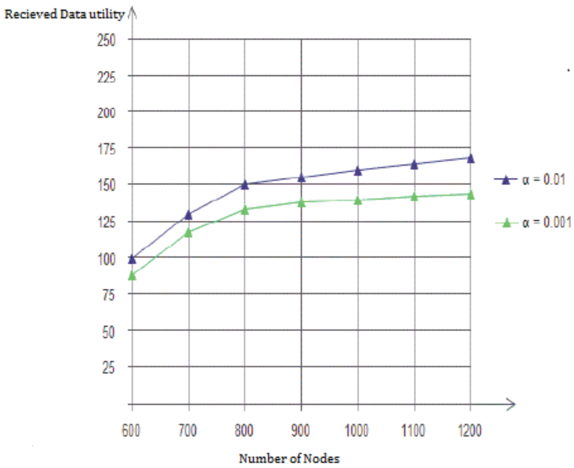


Fig 7: Varying the Parameter $\alpha$

## VII CONCLUSION

Game theory proves itself to be an effective tool for optimization. In this study, the game theoretic approach was combined with some conditions and restrictions to control the behavior of the system and achieve a desired resulting in optimization of the energy of GEH-WSN. The challenge of game theory is to create an appropriate game model before implementing on it to model. We used non-cooperative and repeated kind of game model. Cooperative game models can also be created which can offer more efficiency when there are multiple goals to be achieved such as multiple energy-harvesting sources also use the AI mechanism to update the game theory results.

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