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# A Secure and Energy Efficient Multihop Communication in Wireless Sensor Networks (WSN)

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**Abstract:** In global neural network mainly focuses on the Data transmission power adjustment to minimize the total power consumption and secure data while guaranteeing a target system capacity. However, for the Traffic Scheduling, the dynamic transmission mode is an effective and perfect way to reduce total transmission power in multiuser networks. In this paper, an energy efficient traffic transmission scheme based on Naive Bayesian classification method is proposed which characterizes the phenomenon of convergent or similar users' traffic requests during a certain time window. We discuss Three Strategy, First One Energy Efficiency for Data Transmission and Second Traffic power consumption metrics using Low cost and Finally Secure Data Transmission. We discuss in this article, Data Transmission model is data transmitted particular region of user convergence area, data travelling length of time-window and transmission power consumption. Specifically in each time-window the transmitter analyzes the similarity of users' traffic requests and the similar traffics will be transmitted by multicast mode while the other traffics will be transmitted using unicast mode. To analyze the performance of our proposed article, we establish, an every node will be monitored along with Naïve Bayes Detector model. By using detector we can find the fault data easily and increase the accuracy of the network, our wireless channel conditions and transmitting mode are considered. Our simulation results, such as power reduction ratio, energy efficiency (EE) and secure transmission of the proposed scheme, are developed, from which the quantitative relationship between UCB and the energy conservation can be obtained. Simulation results validate the proposed analysis and demonstrate that our scheme can potentially lead to 35% of energy and above 90% of security compared with the conventional transmission scheme.

**Key words:**

## INTRODUCTION

It has been reported that the information communication technology (ICT) infrastructure leads to of $co_2$ emissions and of worldwide energy, which is expected to double every year. Therefore, green wireless communication is considered as the most promising method for reducing energy consumption to meet the increasing traffic demands. In wireless networks [1], the traffic demands vary in both temporal and spatial domains. A large amount of traffic demands may be generated in small hotspot regions, while only a small amount of traffic demands may be generated in vast non-hotspot regions. In the time dimension, a large number of users may request intensive traffic over the network in peak hours.

**Overview of Networking:** A network is basically all of the components (hardware and software) involved in connecting computers across small and large distances. Networks are used to provide easy access to information, thus increasing productivity for users.

**Energy Conservation:** Mobile ad hoc networks are essentially energy limited networks and are likely to be comprised of heterogeneous nodes with diverse energy constraints. Some mobile devices will have large energy reserves in comparison to others. There exist various energy-aware power-conserving protocols for mobile ad hoc networks. The common objective of these protocols lies in conserving energy as much as possible to prolong the lifetime of the network or extend the lifetime of individual nodes [2].

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Although energy conservation is not a primary concern of HMP, the protocol provides a simple mechanism to conserve energy through its status declaration mechanism. A node with limited energy reserves can declare itself a hotspot by setting its status to YENERGY or RENERGY when its energy reserves are marginally or critically low, respectively. The triggering thresholds are PYELLOW-THRESH and PRED-THRESH. In our current implementation, PYELLOW-THRESH is set to 50% of nodes initial (or maximum) energy reserves and PRED-THRESH is fixed at 1.00 Joule. The latter value represents the amount of energy needed for a node to sustain a flow for approximately 300 packets in most of our simulation sets. However, we note that operators and users are free to set these values according to their own needs, based on the characteristics of the targeted network. A node with energy concerns [3] is acknowledged by neighboring nodes and new route creation through such a node is avoided if possible. On the other hand, a node with critical energy (RENERGY status) immediately relinquishes its role as a router and functions strictly as an end host in order to conserve energy (maximize its lifetime) unless it is identified as the only intermediate node between two communicating end hosts.

**Power Consumption Model and Energy Efficient Technique:** Energy consumption [4] caused by wireless data transmission on smart phones is increasing rapidly with the growing popularity of applications that require network connectivity. This results in shrinking battery life, as the development of battery technology is unable to keep up with the energy demand of applications. While waiting for break throughs in battery technology, we can try and make the networked applications more energy efficient [5]. In order to develop energy-efficient networked applications on smart phones, the developers need to know the factors that affect the energy-efficiency in wireless data transmission and to be able to evaluate the joint effects of these factors on battery life.It have been identified through measurement studies, the joint impact of these factors has not been thoroughly quantified. We still lack models that can accurately estimate the data-transmission-related energy consumption of wireless applications in varying network environments. To remedy the situation, we have built practical power models that utilize traffic characteristics to estimate the energy consumption of heterogeneous data transmission [6]. Our models can be used for power analysis of network applications, as well as for runtime power estimation in energy-aware applications that utilize technologies such as computation offloading or traffic shaping. We base our models on deterministic power modelling where the basic idea is to estimate the energy consumption of hardware components with the help of predefined state machines.

In our case, we have built a state machine that models the standard behaviour of an 802.11 WNI. Since the operating systems on most commercial devices do not expose the durations the WNI spends in each power state, we propose using traffic traces to estimate these durations. The inputs of our models, mainly the traffic statistics such as the burst durations and sizes, are accessible without modifying low-level hardware or software components. While exploring the trade-off between the model accuracy and the granularity of the inputs we find that the burst-level traffic information is enough for power modelling purposes. When high-sampling frequency power meters are not available, burst-level analysis becomes especially interesting as means of reducing the negative impact of the low sampling frequency on the accuracy of model-based energy profiling.

**Literature Review:** The global mobile communication industry is growing rapidly. Today there are already more than 4 billion mobile phone subscribers worldwide, more than half the entire population of the planet. Obviously, this growth is accompanied by an increased energy consumption of mobile networks. Global warming and heightened concerns for the environment of the planet require a special focus on the energy efficiency of these systems.

The EARTH project is a concerted effort to achieve this goal and as part of its objectives, a holistic framework is developed to evaluate and compare the energy efficiency of several design approaches of wireless cellular communication networks [7]. For the quantification of energy savings in wireless networks, the power consumption of the entire system needs to be captured and an appropriate energy efficiency evaluation framework (E3F) is to be defined. The EARTH E3F presented the key levers to facilitate the assessment of the overall energy efficiency of cellular networks over a whole country. The E3F primarily builds on well-established methodology for radio network performance evaluation developed in 3GPP; the most important addendums, introduced to add a sophisticated power model of the base stations (BSs) as well as a large-scale long-term traffic model extension to existing 3GPP traffic scenarios.

**A Energy Efficiency Evaluation Framework (E3F):** The widely accepted state-of-the-art to evaluate the performance of a wireless network is to simulate the relevant aspects of the radio access network (RAN) at system level. The computed results are, e.g. the system throughput measured in bit/s, quality of service (QoS) metrics and fairness in terms of cell-edge user throughput. In order to ensure that the results generated by different RAN system simulation tools are comparable, well defined reference systems and scenarios are specified. This is an outcome of extensive consensus work from standardization bodies and international research projects, such as the EU project Wireless World Initiative New Radio, with partners from academia as well as from industry. The most recent example is the global effort in ITU to evaluate system proposals for compliance with IMT-Advanced requirements.

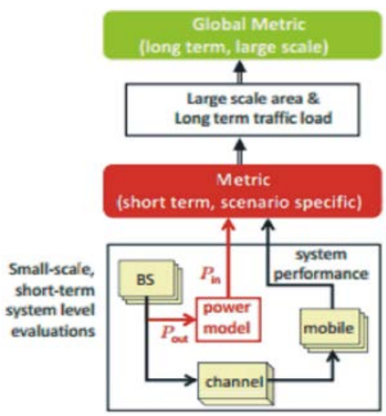



Fig. 2: Earth Energy Efficiency Evaluation Framework

In that direction, the EARTH E3F builds on the 3GPP evaluation framework for LTE over existing performance evaluation frameworks, such that the energy efficiency of the entire network, comprising component, node and network level, over an extended time frame can be quantified. The EARTH E3F identifies the essential building blocks that are necessary for an accurate holistic assessment of energy efficiency enhancements. Although the specific realization of a system level simulation tool largely depends on the specific problem at hand, as well as the chosen software implementation, it is envisaged that for the assessment of combinations of energy efficiency enhancements integrated into one holistic system concept, the E 3F should capture the following aspects:

A sophisticated power model that maps the RF output power radiated at the antenna elements to the total supply power of a BS site. The power model maps the gains on the component level (e.g., an improvement of the energy efficiency of the power amplifiers) to energy savings on the entire network [8].

Long-term traffic models, that describe load fluctuations over a day and complement the statistical short-term traffic models.

Large-scale deployment models of large geographical areas are considered to extend the existing small-scale deployment scenarios.

**Frequency Efficiency Metrics vs Power Consumption Metrics:** In this work, to capture the energy consumption perspective in the analysis, the authors employ the two energy consumption indices:

- Power per area unit, measured in [W/m$^2$];
- Energy per bit, measured in [J/bit].

The reason for arguing for two different metrics instead of only one is that they both are relevant and they provide complementary information about the how efficient the energy use in a network is.

The power per area unit metric is defined as the network average power usage divided by the coverage area of the network, P/A and is measured by the unit [W/m$^2$]. The metric is a measure for the total energy consumption and is closely related to the CO2 emissions and the associated carbon footprint.

**Connectivity and Coverage:** The connectivity of a random network can be described as the probability that an arbitrary pair of nodes is able to exchange information at a specified rate. For example, if this probability is 0.9 for a random selection of a source-destination pair, then one would say that the network is 90 percent connected. The minimum power requirement for wireless network connectivity is intimately connected with percolation thresholds; this formed the basis for many early results. In the simplest case of direct transmission, i.e., single hop communication, the probability of connectivity is simply Pr[SINR > $\beta$], where $\beta$ is the minimum required SINR that is considered acceptable and is a tunable parameter and SINR is the signal-to-interference and noise ratio of a typical link. Note that for a desired rate R in bits per second, $\beta \approx \Gamma(2R - 1)$, where $\Gamma \geq 1$ is the SNR gap from Shannon rate signalling. In many wireless networks of interest, a single hop is all that is required or in fact allowed (e.g., traditional cellular networks).

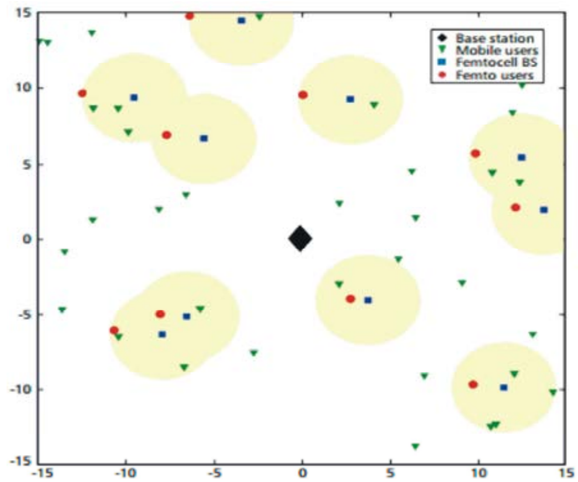



Fig. 3: Node Coverage Regions

**Modelling and Analysis of K-tier Downlink Wireless Networks [9]:** Wireless networks are in a major transition from a carefully planned set of large tower-mounted base-stations (BSs) to an irregular deployment of heterogeneous infrastructure elements that often additionally includes micro, pico and femtocells [10], as well as distributed antennas. In this work, the authors develop a tractable, flexible and accurate model for a downlink consisting of K tiers of randomly located BSs, where each tier may differ in terms of average transmit power, supported data rate and BS density.

Assuming a mobile user connects to the strongest candidate BS, the resulting Signal-to-Interference-plus-Noise-Ratio (SINR) is greater than 1 when in coverage, Rayleigh fading, the authors derive an expression for the probability of coverage (equivalently outage) over the entire network under both open and closed access, which assumes a strikingly simple closed-form in the high SINR regime and is accurate down to -4 dB even under weaker assumptions. For external validation, they compare against an actual LTE network (for tier 1) with the other K - 1 tiers being modelled as independent Poisson Point Processes. In this case as well, the model was accurate to within 1-2 dB. They also derived the average rate achieved by a randomly located mobile and the average load on each tier of BSs. One interesting observation for interference limited open access networks is that at a given SINR, adding more tiers and/or BSs neither increases nor decreases the probability of coverage or outage when all the tiers have the same target-SINR.

Three-Tier Network Architecture

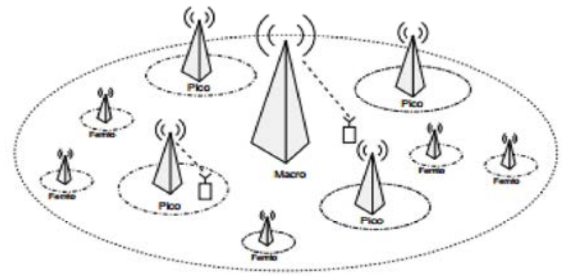



Fig. 4: Illustration of a three tier network utilizing a mix of macro, pico and femtocell BSs. Only a single macro-cell is shown for sake of simplicity.

**Towards Energy-efficient Operation of Base Stations in Wireless Networks [11]:** Energy use of base stations (BSs) in cellular networks has lately become a vital design consideration, due to increased awareness of environmental and economic issues for wireless network operators. This work introduces a range of techniques to reduce energy consumption in BSs, referred to as green cellular networks [12]. In particular, it focuses on presenting details on recent developments from analytical algorithms to practical applications regarding: (i) energy-aware heterogeneous deployment and (ii) joint BS on/off and user association problem [13]. Further, it presents several open problems and other directions including new paradigm and architecture towards green cellular networks.

**Enhancing Spectral-energy Efficiency for Networks: a Users Social Pattern Perspective [14]:** The development of LTE-Advanced and beyond cellular networks is expected to offer considerably higher data rates than the existing 3G networks. Among the many potential technologies in LTE-Advanced systems, users' characteristics and social behaviour have been studied to improve the networks' performance. In this article, the authors presented the concept of user social pattern (USP), which characterized the general user behaviour, pattern and rules of a group of users in a social manner and utilize USP as an optimization basis for network performance enhancement. From large-scale traffic traces collected from current mobile cellular networks, the USP model is evaluated and verified.

Furthermore, to evaluate the potential of spectral efficiency and energy efficiency enhancement based on USP in they established a complete system and link-level

HetNet simulation platform according to 3GPP LTE-A standards. Then, based on the platform, simulations are performed to evaluate the impact of USP on spectral and energy efficiency in an LTE-A network and a USP-based spectral efficiency and energy efficiency enhancement scheme was proposed. Simulation results validate that USP can be used as an effective concept for network performance optimization in an LTE-A system.

**Analysis and Design of Energy Efficient Traffic Transmission Scheme Based on User Convergence Behaviour in Wireless System [15]:** Conventional study of green communication mainly focuses on the transmission power adjustment to minimize the total power consumption while guaranteeing a target system capacity. However, for the energy efficient design the dynamic transmission mode is an effective way to reduce total transmission power in multiuser networks.

**Problem Description:** Large-scale user behaviour can be used as the guidance for deployment, configuration and service control in networks. However, in Neural networks, large-scale user behaviour (in terms of traffic fluctuation in spatial domain) follows in homogeneous distribution, which brings enormous challenges to energy-efficient design of NNs. In Existing work, the Neural of large-scale user behaviour is quantitatively characterized and exploited to study the energy efficiency (EE) in NNs. An optimization problem is formulated for energy-efficient two-tier deployment and configuration [16], where the base station (BS) density, BS transmit power, BS static power and Quality of Service (QoS) are taken into account. We present closed-form formulas that establish the quantitative relationship between large-scale user behaviour and energy-efficient NN configuration.

These results can be used to determine BS density and BS transmit power with the objective of achieving optimal EE. Furthermore, we present three energy-efficient control strategies of micro BSs, including micro BS sleep control, coverage expansion control and coverage shrinking control.

Results validate our theoretical analysis and demonstrate that the proposed control strategies can potentially lead to significant power savings. In Our Proposed, The survival module holds five independent components. Four of them are related to resistance, recognition, recovery and adaptability and the last one is the control component. These properties represent, respectively, the network capability of repelling attacks; detecting attacks and evaluating the extent of damage; restoring disrupted information or functionalities; and quickly incorporating lessons learned from failures and, thus, adapting to emerging Signal and threats [17].

**Proposed System:** In the proposed article a combination of Naive Bayes based neural network to detect the fault rate and secure communication ratio. So we can obtain a network with less data redundancy, energy efficient and accurate data across the network.

Neural Network (NN) is rapidly emerging as the world's most dominant 4G technology, taking mobile broadband to unprecedented performance levels. To meet expectations and predictions for even higher data rates and traffic capacity beyond what is available in current LTE networks a densified infrastructure is needed one. In scenarios where users are highly clustered, using multiple low-output power sites to complement a macro cell providing basic coverage is an attractive solution.

This strategy results in a neural network deployment with two cell layers. They are,

- Low Frequency And Low Power Nodes
- High Frequency And High Power Nodes

The principle can be extended to more than two layers and the concept of multiple layers, is in itself not new; hierarchical cell structures have been considered. The uptake area of a low-power node can be expanded without increasing the output power of the node by adding an offset to the received downlink signal strength in the cell-selection mechanism. In practice, some additional factors such as backhaul capacity should also be included in the cell selection process. Increasing the uptake area of a node is sometimes referred to as range expansion restricting macro-cell transmissions from using the same time-frequency resources as the low-power node, control signalling from the low-power node to the terminal can be protected. Resource partitioning can be implemented in either the frequency domain, by using support for carrier aggregation, or in the time domain [18].

**Frequency-Domain Partitioning:** This method protects downlink control signalling from the low-power node in the range-expansion zone by placing control signalling from the macro and low-power nodes on separate carriers as illustrated in Figure. Assuming transmissions from low-power nodes are time synchronized with the overlying macro, the control signalling on carrier f2 in the range-expansion zone will not be subject to major interference from the macro node. At the same time, through the use of carrier aggregation, data transmissions can still benefit from the full bandwidth of both carriers. The mechanism can be used to coordinate use of data resources. Regardless of the extent of range expansion, frequency-domain partitioning is a natural choice to support NN deployments for operators who already rely on carrier aggregation (CA) to exploit fragmented spectrum; and who have a reasonable number of subscribers using CA-capable terminals in their networks.

**Energy Domain Partitioning:** This method protects the downlink control-signalling from the low-power node by reducing macro transmission activity in certain subframes in the bottom part of Figure. The low-power node is provided with data about the set of protected subframes over the X2 interface and can use this information when scheduling users who are in the range expansion zone. For backward compatibility, the macro node must transmit certain signals, most notably cell-specific reference signals (CRSs) and synchronization signals (PSSs/SSSs), in downlink subframe in the same way. The protected subframes are not completely blank but they are almost blank. Terminals need to apply interference suppression to receive control signalling from the low-power node. Energy domain partitioning can thus be viewed as a terminal-centric approach to achieving excessive range expansion. Support for Energy-domain partitioning for excessive range expansion is incomplete in Rel-10; X2 and RRC signalling are included, whereas interference-suppression receivers are still under discussion for Rel-11. The main argument for implementing Energy domain partitioning is to enable support for excessive range expansion for those operators that do not want to rely on carrier aggregation.

**Energy Domain for Bayesian Method:** The coverage area resulting of integrating the time Window series data transmission is obtained by considering each value of time window series its derivate;

$$\int_{t_k}^{t_{k+1}} y\, dt = y_t(t_{k+1} - t_k)$$

where $y_t$ is the original time window series value. The approximation area is assumed to be its periodical primitive:

$$I_{t_n} = \int^{t_{n+p}} y_t dt = Y_t\Big|_{t_n}^{t_{n+p}}, n = 1, 2, \ldots N.$$

During the learning process, those primitives are calculated as a new input to the NN. The predictor filter attempts to make the area of the forecasted times series equal to the primitive real area predicted. The real area is used in two instances; the first one from the real time series an area is obtained. The H parameter associated of this series is called HA. On the second one, the time series data is forecasted by algorithm, so the H Parameter from this time series is called HS. After the training process is completed, both sequences - {{In}, {Ie}} and $\{\int\{y_n, y_e\}\}$, in accordance with the hypothesis that they should have the same H parameter.

**Bayesian Approach for Tuning the Neural Networks:** A model is most often recognized as Bayesian when a probability distribution is used to describe uncertainty regarding the unknown parameters and when Bayes Theorem is applied. A full Bayesian analysis can lead to the optimal choice among a set of alternative inferences, taking into account all sources of uncertainty in the problem and the consequences of every possible selection. When a rainfall series is being analyzed, it is important to make use of the simplest possible models. Specifically, the number of unknown parameters must be kept at a minimum. For forecasting problems, Bayesian analysis generates point and interval forecasts by combining all the information and sources of uncertainty into a predictive distribution for the future values. It does so with a function that measures the loss to the forecaster that will result from a particular choice of forecasts.

The gamma distribution is chosen for this purpose. When a Bayesian analysis is conducted, inferences about the unknown parameters are derived from the posterior distribution. This is a probability model which describes the knowledge gained after observing a set of data. The application of the regression problem involving the correspond neural network function y(*x,w*) and the data set consisting of N pairs, input vector lx and targets tn (n=1,….,N). Assuming Gaussian noise on the target, the likelihood function takes the form:

$$P(D/w,M) = \left(\frac{\beta}{2\pi}\right)^{N/2} \exp\left\{\frac{-\beta}{2}\sum_{n=1}^{N}\left\|y(x_n;w) - t_n\right\|^2\right\},$$

$$P(w) = \left(2\pi w^2\right)^{-N/2} \exp\left(\frac{|w|^2}{2w^2}\right),$$

assuming that the expected scale of the weights is given by w set by hand. This was carried out considering that the network function f(xn+1,w) is approximately linear with respect to *w* in the vicinity of this mode, in fact, the predictive distribution for yn+1 will be another multivariate Gaussian.

**The Algorithm**

**Step 1: Initialization:** Let t=0, let the users choose their nearest Bss.

**Step 2: BS Optimization:** Based on current $A^{(T)}$, each BS implements a Cluster Head mechanism. (if $A^{(T)}$ denotes Head Node Data Transmission time)

$$A^{(T)} = t_k \int^{t}_{k+1} y\, dt = y_t(t_{k+1} - t_k)$$

**Step 3: User Optimization:** For each user **i** ∴ **N** (**i** no.of User and **N** no.of Nodes)

**Step 3-1: Compute the Best BS:** Compute $BR_i(a^{(t)})$; If $BR_i(a^{(t)})$ != Ø, randomly select

$w^{(t)}_{i} \circledcirc BR_i(a^{(t)})$; otherwise, set $w^{(t)}_{i} = a^{(t)}[i]$ (if BR is Best Route and W weight of Selection Node)

**Step 4: Update Energy:** Shift $w^{(t)}_{i}$ into the front of the Energy;

$$P(D / w, M) = \left(\frac{\beta}{2\pi}\right)^{N/2} \exp\left\{\frac{-\beta}{2}\sum_{n=1}^{N}\left\| y(x_n; w) - t_n \right\|^2\right\},$$

$$P(w) = \left(2\pi w^2\right)^{-N/2} \exp\left(\frac{\left|w\right|^2}{2w^2}\right).$$

if $t \geq M$, shift $w^{(t-M)}_{i}$ out from the end of the Energy

STEP 5: **Determine the Next BS Association:** Uniformly sample the user i's Energy; obtain a BS index as $a^{(t+1)}[i]$

**Step 6: Continue:** If $a^{(t+1)} = a^{(t+1-m)}$ for m = 1, • • •, M, stop.

Otherwise, let t=t+1, go to STEP2).

**Existing Algorithm**

**Power Consumed by Random Selection Method**

- The clusters formed in the random selection method consist of 30, 5, 15 and 50 numbers of nodes as cluster members.
- Power consumption assumed for each receive and transmit is 50 nJ/bit.
- Let us assume a 10 KB message is being sent by each member node to its cluster head (CH) per mS.
- Let us assume that after data compression, energy consumed by a CH to send the data to the Base Station (BS) is 50% of the energy spent to receive the same volume of data from its member nodes.
- The power consumption in the random selection method for cluster head CH04 can be calculated as

Econsume = (ER× Data Packet × number of member nodes) + ET = (ER× Data Packet × number of member nodes) + (ER× Data Packet × number of member nodes)/2

= (50 × 10-9 × 10 × 103 × 50) + ((50 × 10-9 × 10 × 103 × 50)/2) = 37.5 macro J/macro S

**Result and Experimental Setup**

**Performance Metrics:** We evaluate mainly the performance according to the following metrics.

**Throughput and Delay:** Throughput is generally measured as the percentage of successfully transmitted radio-link level frames per unit time. Transmission delay is defined as the interval between the frame arrival time at the MAC layer of a transmitter and the time at which the transmitter realizes that the transmitted frame has been successfully received by the receiver.

**Data Packet Delivery Ratio:** The data packet delivery ratio is the ratio of the number of packets generated at the sources to the number of packets received by the destinations.

**End-to-end delay:** This metric includes not only the delays of data propagation and transfer, but also all possible delays caused by buffering, queuing and retransmitting data packets. Energy Consumption per Packet: It is defined by the total energy consumption divided by the total number of packets received. This metric reflects the energy efficiency for each protocol. Energy efficiency: Energy efficiency can be defined as.

**Energy Efficiency = Total No. Of Bits Transmitted /Total Energy Consumed:** where the total bits transmitted is calculated using application layer data packets only and total energy consumption is the sum of each node's energy consumption during the simulation time. The unit of energy efficiency is bit/Joule and the greater the number of bits per Joule, the better the energy efficiency achieved.

**Results and Comparison:** In Neural Network Bayesian Selection method, the sensor boards of all nodes are in full operation. When a node senses an object, it transmits the sensing information to its cluster head, then, the head forwards the information to the base directly. Cluster heads need to receive messages from its clients, so, the radio boards of the heads are in receiving mode. The radio boards of other nodes are turned off (sleep mode). We know that one of the weaknesses of low power node is that nodes don't always get invitation because there are no cluster head in their zone (called wild nodes). So, in the simulation scenario, I turn on the sensor board of nodes that did enroll in any cluster head. The summary state of nodes is as follow:

**Cluster Heads:**

- Sensor board = Full operation.
- Radio board = Receive.
- CPU board = Sleep, wake up for creating messages only.

**Client Nodes:**

- Sensor board = Full operation.
- Radio board = Sleep, wake up for transmitting only.
- CPU board = Sleep, wake up for creating messages only.

**Wild Nodes:**

- Sensor board= Sleep after 10s of receiving no invitation.
- Radio board = Sleep.
- CPU board = Sleep.

**Power Consumed by Proposed Bayesian Selection Method:**

- The clusters formed in the simulation result consist of 14, 1 5, 16, 24, 26, 28, 31, 33, 37, 46 and 49 numbers of nodes as cluster members because of NN as shows in Figure 9.

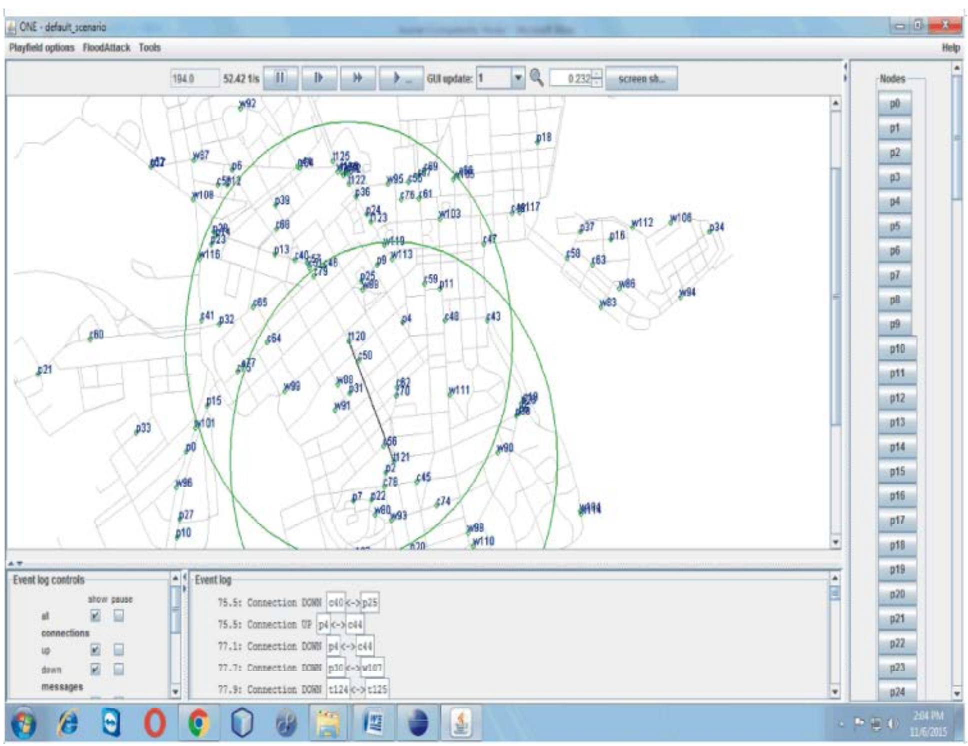



Fig. 9: Head Node Creation

- Same power consumption of 50 nJ/bit is assumed for each receive and transmit functions.
- Let us assume that same 10 KB message is being sent by each member node to its cluster head per mS(macroSeconds).
- Let us Consider Figure 10, Simulation result energy consumed by a CH to send the data to the Base Station is 50% of the energy spent to receive the same volume of data from its member nodes.

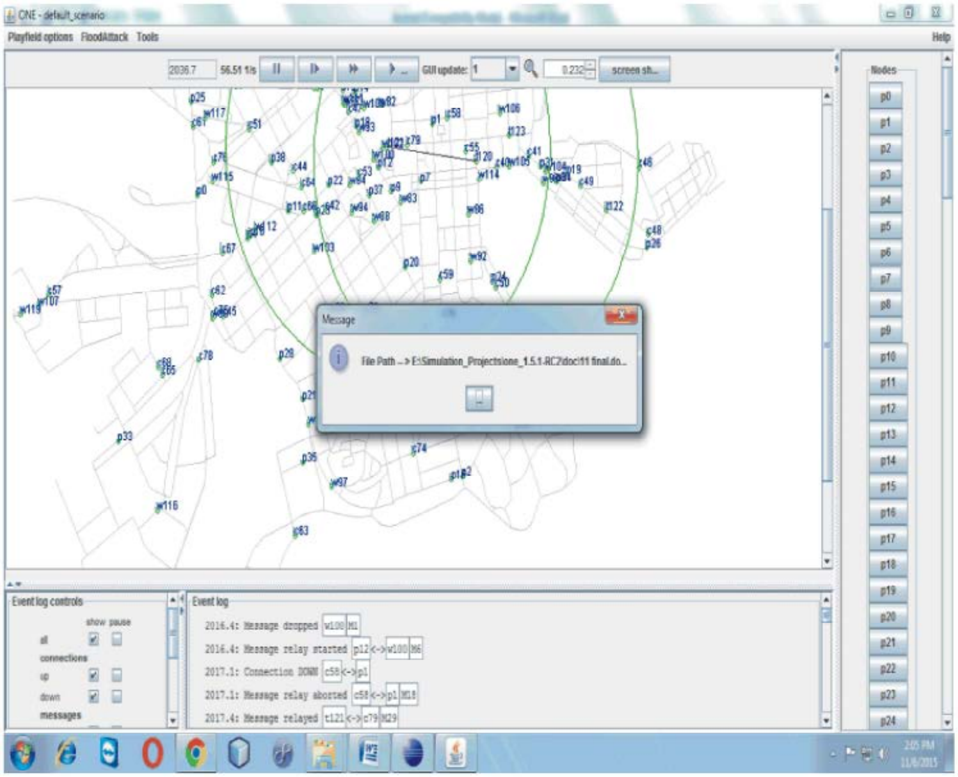
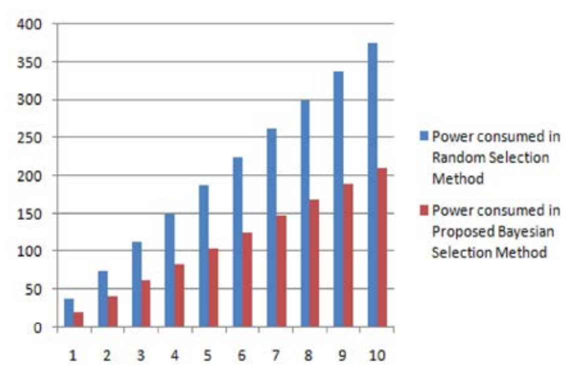


Fig. 10: CH Way Data Transmission

- The power consumption in the NN Bayesian selection method for cluster head CH02 may now be calculated as

Econsume = (ER× Data Packet × number of member nodes) + ET = (ER× Data Packet × number of member nodes) + (ER× Data Packet × number of member nodes)/2 = (50 × 10-9 × 10 × 103 × 28) + ((50 × 10-9 × 10 × 103 × 28)/2) = 21 mJ/mS

We compare the performance of the proposed NN Bayesian algorithm against normal random selection method in terms of energy consumption for sending, as shown in Graph.




## CONCLUSION

There exists an overview for secure and energy efficient data aggregation which is a quite important phase in an effective network. Attack models faced in wireless sensor networks are also mentioned and some suggestions are given to resist against those attacks. In this chapter, we have discussed the security vulnerabilities of data aggregation protocols for sensor networks. We also presented a survey of secure and resilient aggregation protocols for both single-aggregator and hierarchical systems. A number of challenges remain in the area of secure aggregation for sensor networks. Secure tree-based aggregation protocols remain vulnerable to message losses either due to node failure or compromised nodes. The performance and security tradeoffs between resilient tree-based approaches and multi-path approaches such as Attack Resilient Synopsis Diffusion have yet to be explored. The research community is yet to design a secure aggregation protocol for computing holistic aggregates such as Order-statistics and Most Frequent Items. Finally, many data acquisition systems use persistent queries in which nodes periodically send readings to the sink resulting in streams or flows of sensor data [19]. These systems make extensive use of data aggregation. Issues in securing such sensor data streaming applications remain to be investigated. Some recommendations and future works can be summarized as:

- Authenticity, integrity and confidentiality must be provided for a secure network.
- Selecting random nodes to prove trustworthiness of an aggregator can be effective.
- Passive participation must be considered with its security and energy risks.
- Grouping or grading sensor readings may prevent attacks of outsiders. Leaf sensor nodes read data and send only a grade or group information of that data to their aggregator. Since this grouping of sensed data is only known by the nodes inside the network, an outsider can never have an idea about eavesdropped data.
- Accepting certain amount of data in certain time slice can prevent from DoS attacks.
- Tree based aggregator transmission must be chosen instead of direct communication with sink in terms of energy efficiency.
- It is not an adequate evaluation to calculate only direct or indirect trust.

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