# Analytical Modelling of ANCH Clustering Algorithm for WSNs

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***Abstract*—Wireless sensor networks are a popular choice in a vast number of applications, despite their energy constraints, due to their distributed nature, low cost infrastructure deployment and administration. One of the main approaches for addressing the energy consumption and network congestion issues is to organise the sensors in clusters. The number of clusters and also distribution of *Cluster Head*s are essential for energy efficiency and adaptability of clustering approaches. ANCH is a new energy-efficient clustering algorithm proposed recently for wireless sensor networks to prolong network lifetime by uniformly distributing of *Cluster Head*s across the network. In this paper, we propose an analytical method to model the energy consumption of the ANCH algorithm. The results of our extensive simulation study show a reasonable accuracy of the proposed analytical model to predict the energy consumption under different operational conditions. The proposed analytical model reveals a number of implications regarding the effects of different parameters on the energy consumption pattern of the ANCH clustering algorithm.**

***Index Terms*—Wireless Sensor Networks, Clustering, Energy Efficiency, ANCH, Analytical Model.**

## I. INTRODUCTION

Wireless Sensor Network (WSN) is a network of tiny and on-board battery operated sensors with limited power of processing and radio transferring data. They can collect and send their sensed data to a base station for monitoring a remote area and perhaps to send the collected data to a remote centre. WSNs can be employed in different applications, because of their low-cost and adaptable nature, including health-care, emergency response, business, and weather forecasting [1]–[3]. Moreover, WSNs can be used in an ad-hoc manner and in harsh environments in which the attendance of human being is hard or impossible [4], [5].

Energy efficiency is essential for wireless sensor networks lifetime because there is usually no opportunity for a battery replacement or recharging. Therefore, developing energy-efficient algorithms is of higher importance in wireless sensor networks. A large amount of research has been conducted over the past few years to optimise the energy consumption in this area [6]–[8].

Clustering is a widely accepted approach for organising high number of sensors spread over a large area in an ad-hoc manner [9]. This is more useful when we consider that in most cases, neighbouring sensors sense similar data. If each sensor directly sends its data to the base station using long-distance transmission, its energy drains quickly. Moreover, this might also lead to some other issues, such as traffic congestion and data collision.

Appropriate number and size of the clusters is essential for increasing the network lifetime. For a low number of clusters, a large amount of the energy is consumed to send data from Cluster Members (CMs) to Cluster Heads (CHs). On the other hand, if the number of clusters is high, a large number of the CHs will be elected and consequently a large number of nodes will operate using long-distance transmission to communicate with the base station. Therefore, a trade-off should be made between these two factors to optimise energy consumption across the network [10].

Over the past few years, a number of clustering algorithms have been proposed. Hence, it is critical that when proposing a new algorithm, we specify its scope and evaluate it with accurate modelling of the underlying organisation and communication mechanisms. Clearly, after using such models, a comprehensive understanding of the factors that affect the potential performance of a network emerges and this makes it easier to evaluate different algorithms and select the best one for practical implementation. Employing physical experiments is impractical for a large number of configurations and running a network simulator for a large number of configurations needs an unacceptable amount of time. Analytical modelling, in contrast, offers a cost-effective and versatile tool that can help to assess the performance merits of an algorithm [11], [12].

Avoid Near Cluster Head (ANCH) is a new energy efficient clustering algorithm proposed recently for wireless sensor networks to prolong network lifetime by uniformly distributing the CHs [8]. In this paper, an analytical model for predicting the energy consumption of ANCH is proposed. The model details the affecting factors and analyses the energy consumptions under various operational conditions. The accuracy of the proposed model is evaluated using simulation.

The remainder of this paper is organised as follows. In Section II, related work is discussed. The ANCH clustering algorithm is briefly presented in Section III. The proposed analytical model of ANCH and its validation are presented in Section IV and Section V, respectively. Finally, Section VI contains our concluding remarks.

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## II. Related Work

Over the past few years, a number of clustering algorithms for WSNs have been proposed such as Low Energy Adaptive Clustering Hierarchy (LEACH) [6], Hybrid Energy-Efficient Distributed (HEED) [13], and ANCH [8]. One of the most popular clustering algorithms for wireless sensor networks is LEACH. Popularity of LEACH is not only because of its simplicity, but also for the idea of rotating CHs to efficiently balance energy consumption among nodes [6].

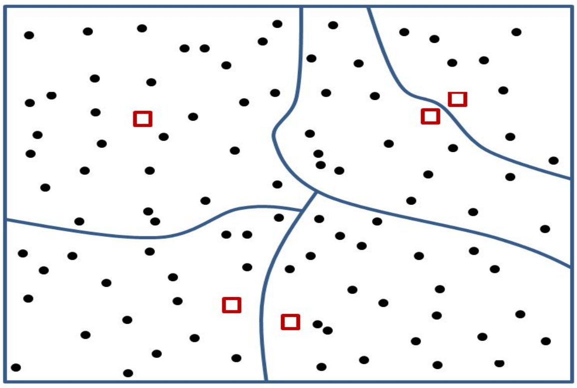

Fig. 1: An example of CHs and CMs arrangement in the LEACH algorithm.

HEED [13] is a distributed clustering algorithm for WSNs which takes into account a mixture of sensors residual energy and communication cost during CH election. In HEED, the transmission power of every node is set to a constant value and each sensor considers other nodes as its neighbouring nodes if they are within its transmission range. Moreover, two neighbouring sensors, which are within the transmission range of each other, are not elected as CH simultaneously, trying to uniformly distribute CHs across the network.

ANCH also, similar to HEED, takes the advantage of uniformly distribution of CHs in order to achieve optimised, or close to, network energy consumption. Nevertheless, it has a few key advantages over HEED. Firstly, the set-up phase overhead of ANCH is much less than that of HEED because HEED executes a procedure to find neighbouring sensors. Also, in this phase, each sensor in HEED executes a complicated iteration including some message passing to select its CH. Secondly, by the end of each iteration in HEED, a node elects itself as a CH if no other CH advertisement has been received. Thus, in many rounds, the number of formed clusters is much more than that of ANCH algorithm where all sensors receive CH advertisement if there exists at least one CH in the network. Finally, ANCH and LEACH are two scalable algorithms both with processing time and message exchange complexity of O(1) and O(N), respectively [14]. Whereas, HEED has O(N) complexity for both processing time and message exchange complexity [15], [16].

In order to design an energy efficient algorithm for wireless sensor networks, it is important to make a trade-off between different parameters involved in a specific application to ensure that the optimum configuration has been applied to maximise network lifetime. In particular, it is quite critical to balance the energy costs of individual nodes in order to obtain the best overall network energy cost. Simulation study of the effects of different parameters on the performance of a network under various network circumstances is difficult because of the time consuming feature of these kinds of tools. Analytical modelling, in contrast, is beneficial as it offers a cost-effective tool to estimate the network energy consumption accurately within an acceptable amount of time. Therefore, in addition to the research on proposing efficient algorithms for wireless sensor networks, a number of studies have also been conducted to develop analytical models [10]–[12], [17], [18].

The first analytical model for the LEACH algorithm has been proposed by Heinzelman *et al.* [17]. In this study, it has been shown that the energy consumption in a network is proportional to the square of transmission distance in clusters. This can be obtained for each sensor using the following expression:

$$E[d_{toCH}^2] = \rho \int_{\theta=0}^{2\pi} \int_{r=0}^{\frac{M}{\sqrt{\pi k}}} r^3 dr d\theta = \frac{M^2}{2k\pi} \qquad (1)$$

where $E[d_{toCH}^2]$ is expected square distance of sensors from their CH, $\rho = \frac{k}{M^2}$ and is called sensors'density, $k$ is the number of clusters, and $M$ is one side of network area.

However, some non-realistic assumptions have been made when developing the model; the area of all clusters are disc-shaped with radius $r$, all clusters are assumed to be formed equally, and also the area of the network is covered by these $k$ non-overlapping clusters.

In [19], Bandyopadhyay and Coyle have proposed a mathematical model for hierarchical clustering algorithms for WSNs. They assumed that the sensors are very simple and all sensors transmit at a fixed power level. Their model analytically suggests the number of CHs at each level of clustering. They conducted a set of experiments to show the optimum number of CHs in different levels of hierarchy in dense networks, with up to 25,000 nodes. Nevertheless, their proposed model is not general enough due to a number of unrealistic assumptions on the fixed power level transmitting ability of nodes.

## III. The ANCH Clustering Algorithm

The proper position of CHs is essential in energy efficiency of clustering algorithms. This has been neglected in the LEACH algorithm and consequently there might be some CHs which are located too close or too far from each other. In either case, some waste of energy might be occurred for data transferring from sensors to the base station.

To overcome this, the ANCH algorithm tries to uniformly distribute CHs across the network as much as possible. To do so, a parameter $d$ is defined as the *closeness* depending on the region size and also network density. If two CHs are found too close to each other in a particular round, closer than $d$, one of them should stand as the CH. Thus once the first CH is selected following normal LEACH procedure, the next potential CH checks its distance from the first CH before advertising itself to other sensors as a CH. If the distance is less than $d$, it cancels its decision to be a new CH in the current round and remains a CH candidate for the future rounds.

Further improvement in ANCH is also obtained by considering the optimum number of CHs through the network. This is because a number of potential CHs might cancel their decision of being a CH due to their close position to other CHs. Therefore, the number of clusters would be less than the optimum number suggested in the LEACH algorithm. This leads to the bigger cluster size and more energy consumption over the intra-cluster transmission.

This issue is addressed in the ANCH algorithm by increasing the threshold $T(n)$ and consequently increasing the number of potential CHs in each round. As a result, in every round more than $p$ percent of sensors will be nominated as CHs, on average, to become closer to the optimum value, $p$, after dropping a number of them because of closeness issue. After setting the new threshold, close to $p$ percent of sensors are eventually selected as the CHs in every round which are more uniformly distributed compared with LEACH. The new threshold, $T'(n)$, in ANCH is defined as follows:

$$T'(n) = T(n) + (1 - T(n)) \times a. \tag{2}$$

$T(n)$ is the threshold value of the LEACH algorithm [6] and $a$, the add-on coefficient, is a constant, whose value depends on network configuration and also on the *closeness* value, $d$. This value plays an essential role in the ANCH algorithm efficiency.

The ANCH algorithm significantly improves network energy consumption and, consequently, prolongs the network lifetime compared with the LEACH algorithm. An example of the positions of CHs and CMs in ANCH is shown in Figure 2. Comparing this arrangement with the one presented in Figure 1 reveals more uniformly distribution of CHs in the ANCH algorithm.

## IV. ANCH Analytical Modelling

In this section, our proposed analytical model for the energy consumption in the ANCH clustering algorithm is presented. Using the model, a comprehensive understanding of the factors affecting the performance of a network emerges. Since a clustering approach is employed in the ANCH algorithm, the total network energy consumption can be derived when the energy consumed by one cluster is calculated.

Let us assume that $N$ sensor nodes are randomly distributed in a M×M area and the number of clusters, on average, is $k$ during the lifetime of the network. As a result, there are $\frac{N}{k}$ sensors, on average, per cluster with $(\frac{N}{k}) - 1$ sensors as CMs and also one node as the CH.

The energy required for a CM to send its data to a CH can be calculated using the following expression [6]:

$$E_{CM} = lE_{elec} + l\epsilon_{amp} d^2_{toCH} \tag{3}$$

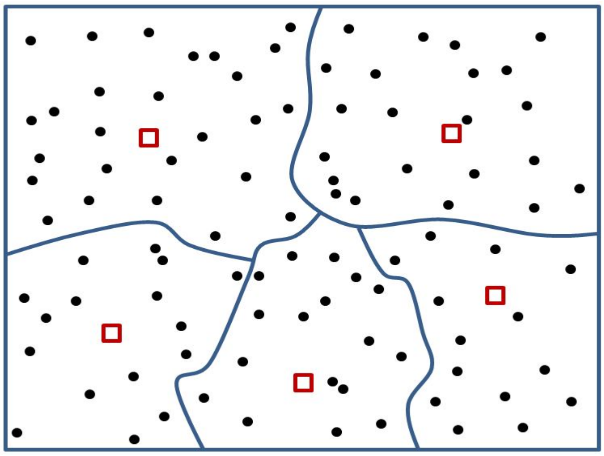

Fig. 2: An example of CHs and CMs arrangement in the ANCH algorithm.

Also, for all nodes in a cluster, this energy can be calculated as follows:

$$E_{Cluster} = lE_{elec}(k-1) + l\epsilon_{amp} E[\sum_{nodes \in Cluster} d^2_{toCH}] \tag{4}$$

where $l$ is the length of messages, $E_{elec}$ is the transmit electronics, $\epsilon_{amp}$ is transmit amplifier, $d_{toCH}$ is the distance between a CM and its CH, and $E[\sum d^2_{toCH}]$ is the expected summation for square distance of CMs from their CH. Except for $E[\sum d^2_{toCH}]$, all other parameters in (4) are known with constant values. Therefore, by calculating $E[\sum d^2_{toCH}]$ we are able to calculate all the energy spent in the network.

$E[\sum d^2_{toCH}]$ can be calculated using the following expression for LEACH [20]:

$$E\left[\sum_{node \in cluster(j)} d^2_{toCH}\right] = 2\pi\lambda_{CM} \times \int_0^\infty r^3 . P\left\{(r,j) \in cluster(j)\right\} dr \tag{5}$$

In (5) and (6), $\lambda_{CH}$ and $\lambda_{CM}$ represent density of the CHs and CMs in the network and are given by $\frac{k}{M^2}$ and $\frac{N-k}{M^2}$, respectively. $P\left\{(r,j) \in cluster(j)\right\}$ is the probability of a sensor node to become member of cluster $j$. The distance between the node and the head of cluster $j$ is also represented by $r$. According to [21], $P\left\{(r,j) \in cluster(j)\right\}$ can be derived from the palm distribution as follows:

$$P\left\{(r,j) \in cluster(j)\right\} = exp\left\{-\lambda_{CH}\pi r^2\right\} \tag{6}$$

In ANCH, the distance between any two CHs is not less than $d$. Each cluster area is divided into two different parts, which are treated separately in our model. The first part is the circular area with the radius of $d/2$ from the CH. All sensors in this area securely belong to that cluster. The second area covers those sensors whose distance from the current CH is more than $d/2$. For the first part, (5) with the probability $P\{(r,j) \in cluster(j)\} = 1$ can be used. Thus, the expected summation for square distance of CMs, located in the first part of the cluster area, from their CH can be obtained using the following expression:

$$E\left[\sum_{node \in cluster(j)} d_{toCH}^2\right] = 2\pi\lambda_{CM}\int_0^{d/2} r^3 dr \qquad (7)$$

On the other hand, all sensors whose distance from other CHs is less than $d/2$ are secure members of other CHs and are not members of the current CH. Thus, $P\{(r,j) \in cluster(j)\} = 0$ for those nodes. Consequently, the value of (5) for those nodes is 0. To calculate the second part of the cluster area, we must subtract the cluster areas whose nodes' distance from a CH is less than $d/2$.

The second part of each cluster area can be calculated by

$$E\left[\sum_{node \in cluster(j)} d_{toCH}^2\right] = 2\pi\lambda_{CM}\int_{R_1}^{\infty} r^3.P\{(r,j) \in cluster(j)\}\, dr \qquad (8)$$

In the above expression, $R_1$ can be calculated as follows

$$\pi R_1^2 = k\pi(\frac{d}{2})^2 \Rightarrow R_1 = (\frac{d}{2})\sqrt{k} \qquad (9)$$

Using (7) and (8), the first and second parts of each cluster area can be merged. Thus, the expected summation of square of each CM from its CH can be obtained from following expression:

$$E\left[\sum_{node \in cluster(j)} d_{toCH}^2\right] = 2\pi\lambda_{CM}. \left[\int_0^{d/2} r^3 dr + \int_{(\frac{d}{2})*\sqrt{k}}^{\infty} r^3.exp\{-\lambda_{CH}\pi r^2\}\, dr\right] \qquad (10)$$

In Figure 3, the inner circle shows the first part of each cluster in which $P\{(r,j) \in cluster(j)\} = 1$. The area between inner and outer circles, demonstrates the first part of other clusters in which $P\{(r,j) \in cluster(j)\} = 0$. The area beyond the outer circle, shows the second part of current cluster in which $P\{(r,j) \in cluster(j)\} = exp\{-\lambda_{CH}\pi r^2\}$.

The accuracy of the proposed analytical model for ANCH is evaluated in the next section.

## V. Model Validation

The accuracy of the described analytical model has been verified by comparing it with simulation results. Extensive validation experiments have been performed for several combinations of cluster size, network dimension, different values of *closeness*, density of sensors in the network, and the number of messages which are sent from CMs to their CHs during the

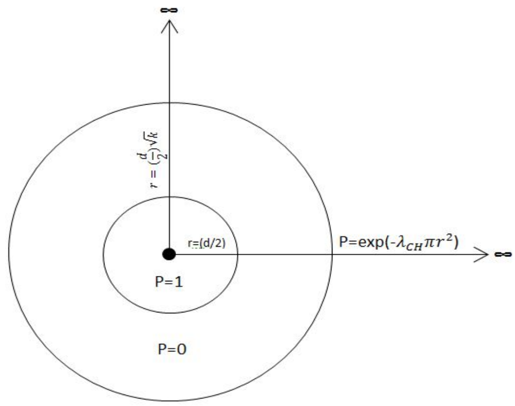


Fig. 3: An example of the first and second parts of cluster areas defined in the analytical model for ANCH.

steady phase, called *MNumbers*. In order to select parameter $a$, different values including $a = 0.02, 0.05, 0.15, 0.25, ..., 0.75$ have been considered and the most effective value has been selected. Each simulation scenario is run for 100 different randomly generated topologies and the average results are presented. In our experiments, the sensors' inner computational procedures do not consume energy: all of their energy used for message passing only. The energy model in all of our experiments is precisely the same as the one employed in [6].

As the first experiment, the effects of varying the number of clusters on the accuracy of our proposed model is compared against the results obtained from simulation. The network area is considered to be 50×50 square metres when base station is 100 metres away from the network's edge. Moreover, $d$ = 15 metres and the initial energy of each node is 10 J. Finally, the number of clusters in this experiment varies from 4 to 15 clusters. The result is presented in Figure 4. In this figure, the horizontal axis shows the number of clusters where the vertical axis represents the total consumed energy. Figure 4 shows the accuracy of our model for three different networks with different number of nodes, N = 50, 100, and 200, when *MNumber* is considered to be 25. 96.3% accuracy in Figure 4 shows that the simulation results closely match those predicted by the analytical model.

In the second experiment, we aim at observing the impact of network size on our analytical model. Different network dimensions from 10 to 100 metres are examined while the value of $d$ is 30% of one dimension. Moreover, the initial energy of each node is 10 J and the number of clusters, $k$, is 5. These are depicted in Figure 5, highlighting that the proposed model on average presents an accuracy of 95.4%. Figure 5 shows the accuracy of our model for three different networks with different number of nodes, N = 50, 100, and 200, when *MNumber* is considered to be 25.

In the third experiment, we aim at observing the impact of *closeness* parameter, $d$, on our analytical model. Different *closeness* values from 5 to 25 metres are examined where

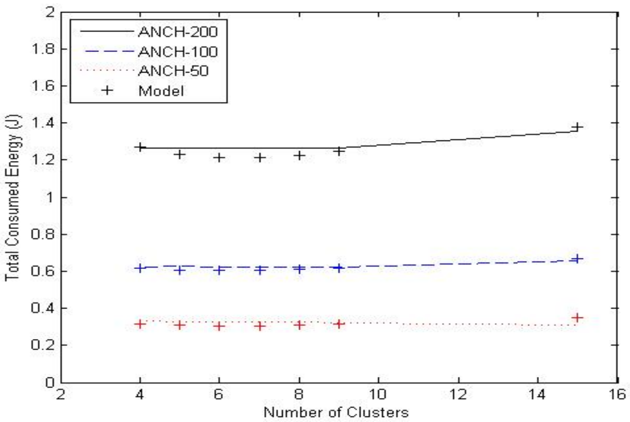


Fig. 4: Accuracy of the model comparing against simulation results varying number of clusters for three networks with different number of nodes, N=50, 100, and 200.

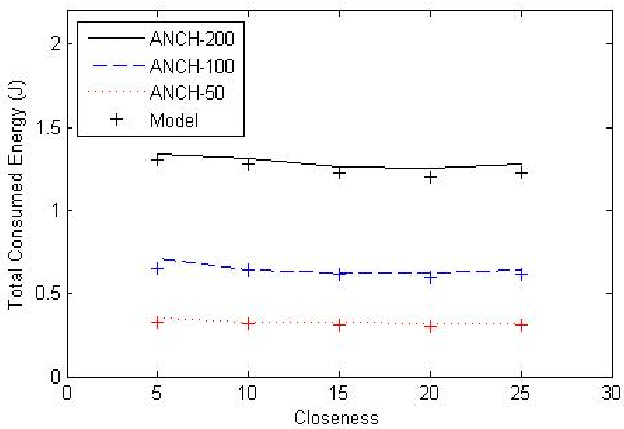


Fig. 6: Accuracy of the model comparing against simulation results varying parameter $d$ for three networks with different number of nodes, N=50, 100, and 200.

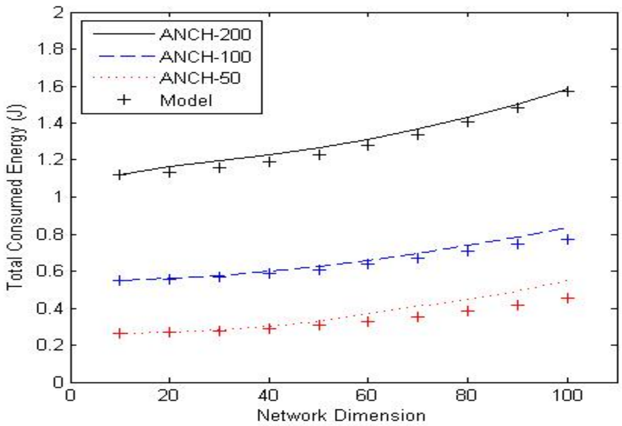


Fig. 5: Accuracy of the model comparing against simulation results varying network dimension for three networks with different number of nodes, N=50, 100, and 200.

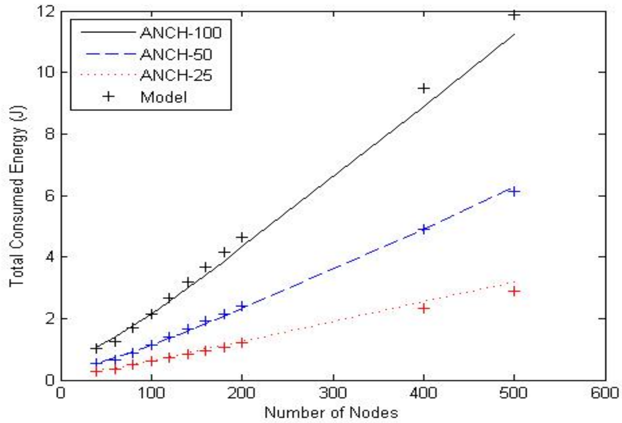


Fig. 7: Accuracy of the model comparing against simulation results for three values of *MNumber*, *MNumber* = 25, 50, and 100 messages per round.

the network area is considered to be 50×50 square metres and base station is 100 metres away from the network's edge. Moreover, the initial energy of each node is 10 J and the number of clusters is 5. This is depicted in Figure 6, highlighting very close agreement between the model and simulation in this figure, 95.8 similarities on average. Figure 6 demonstrates the accuracy of the proposed model for three different networks with different number of nodes, N = 50, 100, and 200, when *MNumber* is considered to be 25.

In the fourth experiment, we aim at observing the impact of network density on our analytical model. In this experiment, different number of sensors, from 40 to 500, are examined. Moreover, the network area is 50×50 square metres when base station is 100 metres away from the network's edge, $d$=15 metres, the initial energy of each node is 10 J, and the number of clusters is 5. The results are presented in Figure 7 for three different configurations, *MNumber* = 25, 50, and 100.

These results show a close agreement, an accuracy of 95.4% on average, between the proposed model and simulation results.

Finally, in the last experiment, we aim at observing the impact of steady phase duration on our analytical model by varying the number of *MNumber* from 5 to 1000 messages per round. The network area is 50×50 square metres when base station is 100 metres away from the network's edge, $d$=15 metres, the initial energy of each node is 10 J, and the number of clusters is 5. In Figure 8, the comparison of the model and simulation results for three different networks with N = 50, 100, and 200 nodes are presented, approving 95.6% accuracy on average.

Overall, our extensive validation study show the credible accuracy of our proposed analytical model to predict the total energy spent by the ANCH algorithm.

Using the proposed model, a number of implications have

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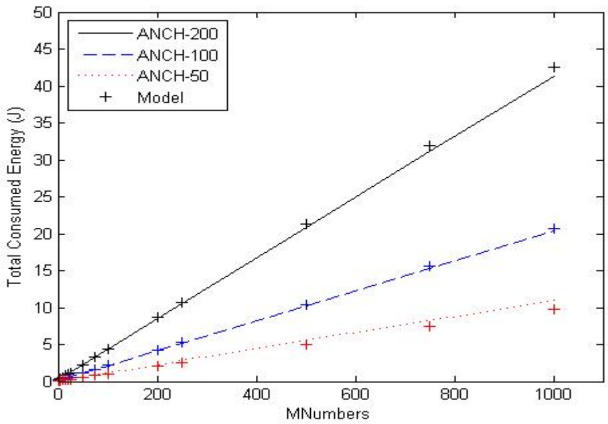


Fig. 8: Accuracy of the model comparing against simulation results for three networks with different number of nodes, N=50, 100, and 200.

been revealed. First, the energy consumed by the ANCH algorithm is almost insensitive to the optimum number of clusters, $k$, proposed by the LEACH algorithm. This is due to the important role of add-on coefficient, $a$, to balance the energy consumption of each cluster. By increasing the value of $k$, the optimum value of $a$ is also increased to protect the network from forming a large number of clusters with smaller number of nodes in each cluster and hence to avoid wasting energy. Respectively, the optimum value of $a$ is also decreased to block the negative effects of smaller number of clusters.

In the same way, the energy consumed by the ANCH algorithm is almost insensitive to *closeness* parameter. This is again due to the balancing role of add-on coefficient, $a$. By increasing the value of *closeness* parameter, the optimum value of $a$ is also increased to increase the number of potential CHs to avoid smaller number of clusters. It also prevents forming large number of clusters when the *closeness* value is decreased.

## VI. Conclusion

ANCH is a distributed energy-efficient clustering algorithm proposed for wireless sensor networks. ANCH prolongs the network lifetime by uniformly distributing of CHs across the network. In this paper, we have presented an analytical model for ANCH to show the effects of different parameters and to predict overall energy consumption under various network conditions. Our extensive validation study has demonstrated a reasonable degree of accuracy achieved by our analytical model compared with the results of a simulation software. The proposed analytical model has also revealed that energy consumption of the ANCH algorithm is almost insensitive to the number of clusters and *closeness* parameter due to the balancing role of add-on coefficient to optimise the total energy consumption of clusters.

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