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Energy efficient organization and modeling of wireless sensor networks

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ABSTRACT

ENERGY EFFICIENT ORGANIZATION AND MODELING OF WIRELESS SENSOR NETWORKS

by
Jin Zhu

With their focus on applications requiring tight coupling with the physical world, as opposed to the personal communication focus of conventional wireless networks, wireless sensor networks pose significantly different design, implementation and deployment challenges. Wireless sensor networks can be used for environmental parameter monitoring, boundary surveillance, target detection and classification, and the facilitation of the decision making process. Multiple sensors provide better monitoring capabilities about parameters that present both spatial and temporal variances, and can deliver valuable inferences about the physical world to the end user.

In this dissertation, the problem of the energy efficient organization and modeling of dynamic wireless sensor networks is investigated and analyzed. First, a connectivity distribution model that characterizes the corresponding sensor connectivity distribution for a multi-hop sensor networking system is introduced. Based on this model, the impact of node connectivity on system reliability is analyzed, and several tradeoffs among various sleeping strategies, node connectivity and power consumption, are evaluated. Motivated by the commonality encountered in the mobile sensor wireless networks, their self-organizing and random nature, and some concepts developed by the continuum theory, a model is introduced that gives a more realistic description of the various processes and their effects on a large-scale topology as the mobile wireless sensor network evolves. Furthermore, the issue of developing an energy-efficient organization and operation of a randomly deployed multi-hop sensor network, by extending the lifetime of the communication critical nodes and as a result the overall network's operation, is considered and studied.

Based on the data-centric characteristic of wireless sensor networks, an efficient Quality of Service (QoS)-constrained data aggregation and processing approach for distributed wireless sensor networks is investigated and analyzed. One of the key features of the proposed approach is that the task QoS requirements are taken into account to determine when and where to perform the aggregation in a distributed fashion, based on the availability of local only information. Data aggregation is performed on the fly at intermediate sensor nodes, while at the same time the end-to-end latency constraints are satisfied. An analytical model to represent the data aggregation and report delivery process in sensor networks, with specific delivery quality requirements in terms of the achievable end-to-end delay and the successful report delivery probability, is also presented. Based on this model, some insights about the impact on the achievable system performance, of the various designs parameters and the tradeoffs involved in the process of data aggregation and the proposed strategy, are gained. Furthermore, a localized adaptive data collection algorithm performed at the source nodes is developed that balances the design tradeoffs of delay, measurement accuracy and buffer overflow, for given QoS requirements. The performance of the proposed approach is analyzed and evaluated, through modeling and simulation, under different data aggregation scenarios and traffic loads. The impact of several design parameters and tradeoffs on various critical network and application related performance metrics, such as energy efficiency, network lifetime, end-to-end latency, and data loss are also evaluated and discussed.

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CHAPTER 1

INTRODUCTION

With the development of the information society, the requirements for detection and monitor-ing of the physical world are becoming more and more complicated and diversified. They trend from single variable to multiple variables, from one point to a plane, from one sensor to a set of sensors, from simple to complex and cooperative. Networking the sensors to empower them with the ability to coordinate on a larger sensing task will revolutionize information gathering and processing in many situations. Networked microsensor technology, seen as one of the most important technologies for the 21st century [1], may provide unprecedented potential in sensing, instrumenting and controlling our world and environment. Networks of sensors can greatly improve environment monitoring for many civil and military applications. Furthermore, many environments may be unsuitable for humans and thus the use of sensors is the only solution; in some places, although accessible, in general it is more effective to place small autonomous sensors than to use humans for collection of data.

By integrating sensing, signal processing, and communications functions, a sensor network provides a natural platform for hierarchical and efficient information processing. It allows information to be processed on different levels of abstraction, ranging from detailed microscopic examination of specific targets to a macroscopic view of the aggregate behavior of targets.

1.1 Wireless Sensor Networks

A distributed sensor network is usually a self-organized system composed of large number of sensor nodes, which are used to measure different parameters that may vary with time and space, and send the corresponding data to a sink or base station for further processing.

Smart sensors can be deployed around buildings, on ground, on bodies, in vehicles, under water even in the air according to different applications. There are far-ranging potential applications of sensor networks, including: (1) system and space monitoring [2]. (2) habitat monitoring [3] [4]. (3) target detection and tracking [5] [6]. (4) biomedical applications [7] [8] [9].

The progress of hardware technology in low-cost, low-power, small-sized processors, transceivers and sensors has facilitated the development of wireless sensor networks. In order to achieve cost-effectiveness and small sensor size, in general the individual sensor nodes present several limitations, such as limited energy and memory resources, small antenna, and limited processing capability. Several experimental sensor nodes and networks have been developed, including Smart Dust mote developed by UC Berkeley [10], WINS (Wireless Integrated Network Sensors) NG (Next-Generation) node by UCLA [11], uAMPS node (micro-Adaptive Multi-domain Power-aware Sensors) developed by MIT [12] and GNOMES node by Rice University [13]. The cutting-edge technologies have been used to lower the cost and power dissipation and minish the node size. For example, the size of Smart Dust mote nodes is comparable with a coin and even envisioned to be small enough to float in the air. Currently a GNOMES node with 2-axes of acceleration sensing costs around $50 without GPS and $80 with GPS component. The cost of sensor nodes is expected to drop (less than $25) along with the advance of semiconductor industry and MEMS technology.

1.2 Sensor Network Architecture

With respect to the communication mechanism adopted, there are three basic architectures of sensor networks, as shown in figure 1.1: direct connected, flat ad hoc or peer-to-peer multi-hop, and cluster-based multi-hop. Because of the fact that the number of sensor nodes is usually large and the transmit range of sensor nodes may be limited due to the battery capacity limitations, in general it is energy-inefficient, and in many cases impossible, for each small sensor to communicate directly with the collector. Thus the direct connected mode is not suitable for large-scale deployed sensor networks.

Multi-hop mode is an apt alternative mainly due to its energy-efficiency considerations. In addition to solving the problems associated with the limited direct transmission range of nodes, multi-hop short-range transmission usually consumes less power than the power required by one large hop transmission for a given pair of source and destination, since in general the average received signal power is inversely proportional to the n-th power of the distance, (usually $2 < n \leq 4$). In a flat ad hoc multi-hop network as shown in figure 1.1(b), some sensor nodes have routing capabilities playing the role of relaying packets besides sensing and sending out their own data. Although this mode is flexible and energy efficient, scalability is still a problem. The nodes closer to the collection and processing center will be primarily used to route data packets from other nodes to the processing center. If the network size is large, these nodes will relay a large number of data and their energy will be exhausted very fast, resulting finally in disconnection of the network.

Cluster-based multi-hop sensor networks attempt to address the scalability issues associated with the flat ad hoc multi-hop networks. In a cluster-based system, sensor nodes form clusters and a cluster-head for each cluster is selected according to some negotiated rules [14]. Sensor nodes only transmit their data to their immediate local cluster-head. In figure 1.1(c), only one level clustering is depicted, however, in general a hierarchical clustering scheme may be used. Local data fusion and classification at cluster heads can be used to reduce the amount of information that must be transmitted to the collection center, thereby reducing the overall energy consumed for transmission. The main disadvantage of this mode of operation is that the communication highly relies on the cluster head thus placing a lot of burden on the higher-level cluster heads and the energy depletion of cluster heads is faster than other nodes. These issues can be addressed through the rotation of the roles of the various nodes.

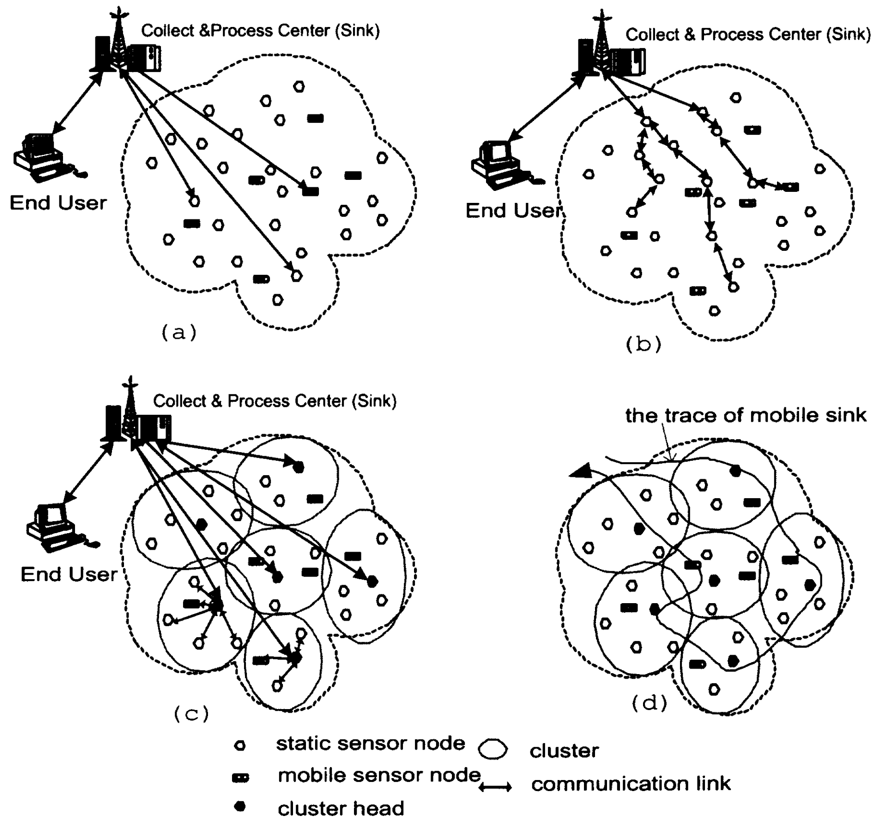

Figure 1.1 Architecture of sensor networks.

1.3 Design Challenges and Motivation

As mentioned before, the sensors are usually used to measure and monitor some parameters that may vary with place and time. Therefore, a large number of sensors is required in order to obtain samples of these parameters at different locations and times. As a result wireless sensor networks are complex systems in which the system behavior involves a large number of individual cooperating sensor nodes. A self-organized wireless sensor network provides the ability to adapt to diverse environment and unforeseeable situations. While the self-organization feature is critical to achieve the wide applicability of sensor networks, it also makes more difficult the modeling and prediction of the system behavior. Modeling, designing and verifying the architecture and organization of a distributed wireless sensor network with such complicated nature requires sophisticated system analysis methods and tools.

With their focus on applications requiring tight coupling with the physical world, as opposed to the personal communication focus of conventional wireless networks, wireless sensor networks pose significantly different design, implementation and deployment challenges. For example, the individual sensor nodes usually have several limitations such as limited energy and memory resources, small antenna size, and weak processing capabilities, due to cost-effective considerations and miniature size requirements. Energy efficiency is closely related to several critical operational aspects of the sensor networks, and therefore is required in all stages of the sensor network design. Several critical operational parameters and processes, such as the network connectivity and the lifetime of the network, need to consider the issues of energy availability and efficiency. In many applications of sensor networks, the data transmission is relative small compared to the Internet or other types of networks, and therefore letting the sensors go to "sleep" mode periodically can help extending the lifetime of a sensor, especially when the traffic is low and the delay constraint is not rigid. However, at the same time, some time-crucial applications such as those in the battlefield, may have very strict performance requirements and the sensor nodes are required to achieve specific Quality of Service (QoS) in data collection and transmission, so that the measurement task can be fulfilled within the corresponding latency and resource requirements. Therefore, the sensor nodes in a distributed sensor network have to collaborate with each other, and as a result, effective information gathering and dissemination strategies need to be deployed.

Although traditional wireless cellular networks are mature and the mobile ad hoc networking technology has been developed, the corresponding architectures and protocols still need to be tailored to the unique features of distributed wireless sensor networks. The behavior and evolvement of a sensor network depends on many system parameters that are tightly related to the corresponding organizations and architecture forms. These parameters include: 1) total number of sensors which indicates the size of a system; 2) density that is related to deployment pattern; 3) connectivity that describes the communication link arrangements and related reliability; 4) sensing coverage range and transmit range (radius) of sensor nodes; 5) power consumption of each unit and energy availability; 6) movement pattern such as speed and direction. Before building and evaluating a sensor network, the communication mechanism and corresponding media access protocols, routing protocols adapting to the self-organized networks, data storage scheme, and data fusion mode (data dissemination/aggregation approaches) have to be designed and the corresponding parameters need to be determined.

1.4 Related Literature Review

Unlike the traditional cellular systems where each mobile needs to have a wireless link to one base station, the situation in multi-hop wireless networks is usually more sophisticated and complicated. It has been shown in [15] that to ensure network connectivity the expected number of nearest neighbors of a transmitter must grow logarithmically with the area of the network. Furthermore, several issues associated with the critical ranges of transmitters for coverage and connectivity purposes are discussed in [16]. In ad hoc wireless networks, the nodes in the network are assumed to cooperate in a decentralized fashion, routing and relaying packets from other nodes, and thus each node should transmit with enough power to guarantee connectivity of the overall network. In [17] the authors determined the critical power at which a node in the network needs to transmit in order to ensure that the network is asymptotically connected with probability one, as the number of nodes in the network goes to infinity. For an one-dimensional network in [18] the authors obtained the exact formula for the probability that the network is connected under the assumption of uniform distribution of nodes in $[0, \pi]$, and extended this result to obtain the upper bound of the connected probability for a two-dimensional network. The connectivity of wireless multi-hop networks with uniformly randomly distributed nodes was investigated in [19], under the assumptions of a free-space radio link model and bi-directional links. For the scenario without border effects, the required transmit ranges to achieve a connected or 2-connected network with high probability (the probability must be close to 1) for homogeneous case were obtained as a function of both the number of nodes and the system area.

As mentioned before, the collaboration between different sensor nodes is mostly realized through multi-hop network architectures due to their energy-efficiency and scalability features [14, 20, 21, 22]. Since in sensor networks the data in the neighboring nodes are considered highly correlated due to the fact that the observed objects in the physical world are correlated, localized data processing and aggregation on the fly may dramatically decrease the amount of information to be transmitted. Therefore, hierarchical infrastructures have been studied to reduce the network traffic, save the energy of sensor nodes, distribute the computation load, and improve the measurement quality in multi-hop sensor networking environments. In these cases, intermediate sensor nodes may be selected to perform data aggregation from the measurement results delivered from different neighboring sensors.

Several recent efforts have noted the importance of data aggregation in wireless sensor networks, and have studied and discussed some of the benefits that can be achieved, by exploiting the features of data correlation [23] and data aggregation [24]. Data aggregation comparison studies have demonstrated the effect of network parameters and the utility of aggregation mechanisms in a wide variety of applications [25, 26]. In [27], an information retrieval protocol, APTEEN, for cluster-based sensor networks that can implement data aggregation, has been presented, while the impact of data aggregation on sensor networks is discussed in [26]. In [28] an SQL-like declarative language for expressing aggregation queries over streaming sensor data is proposed, and it is demonstrated that the intelligent distribution and execution of these aggregation queries in the sensor network can result in significant reductions in communication compared to centralized approaches. Recent work on data aggregation [29], proposed an application independent data aggregation (AIDA) protocol that resides between the media access control layer and network layer. The AIDA module combines network units into a single aggregate outgoing payload to reduce the overhead incurred during channel contention and acknowledgement. Furthermore, since in sensor networks the data in the neighboring nodes are considered highly correlated [23, 30, 31], localized data processing [32, 33, 34] and data aggregation [24,35,36,26] might dramatically decrease the amount of information to be transmitted.

However, although several research works in the literature have discussed the problems of developing efficient routing and data aggregation processes mainly for energy savings or minimization in sensor networks (e.g. [37, 38, 6, 24, 39, 40]), several issues associated with the data aggregation process with the specific objective of meeting the task requirements (i.e. QoS-constrained data aggregation) are not yet well addressed.

1.5 Dissertation Contributions and Outline

This dissertation emphasizes on the energy efficient organization and modeling of dynamic wireless sensor networks. Specifically, in Chapter 2, a connectivity distribution model that characterizes the corresponding sensor connectivity distribution for a multi-hop sensor networking system is presented. Based on this model, some insights are gained about the tradeoffs among the node connectivity, power consumption and data rate [22]. The impact of node connectivity on system reliability, as well as several tradeoffs among various sleeping strategies, power consumption and transmission scenarios, for given connectivity requirements, are also analyzed and evaluated.

Furthermore, since large-scale dynamic sensor networks can be described as time-varying composition of dynamically changing components and entities, additional features such as uncertainty, interaction and collaborations should be considered in the modeling process. Towards that direction, an enhanced model is also developed that gives a more realistic description of the various processes and their effects as the mobile wireless sensor based network evolves [41,42], and facilitates the understanding of the effect of the various events on the large-scale topology of a wireless sensor network. The proposed model stems from the commonality encountered in the mobile sensor wireless networks, their self organizing and random nature, and some concepts developed by the continuum theory [43].

In Chapter 3, the issue of developing an energy-efficient organization and operation of a randomly deployed multi-hop sensor network, by extending the lifetime of the communication critical nodes and as a result the overall network's operation, is considered and analyzed [44].

Motivated by the data-centric characteristic of wireless sensor networks and by the fact that some time-crucial applications may have specific performance requirements, Chapter 4 introduces and investigates an energy-efficient QoS-constrained data aggregation and processing approach for wireless sensor networks [45, 46]. Among the key features of the proposed approach is that the network does not have to be formed into clusters to perform the data aggregation, while the task QoS requirements are taken into account to determine when and where to perform the aggregation in a distributed fashion, based on the availability of local only information. Data aggregation is performed on the fly at intermediate sensor nodes, while at the same time the end-to-end latency constraints are satisfied. Such an approach maintains the flexibility of the network architecture and simplicity in the protocol design, which are essential for the applicability of wireless sensor networks that need to adapt to diverse, unforeseeable and sometimes hostile environments and situations. Furthermore, a localized adaptive data collection algorithm performed at the source nodes is developed that balances the design tradeoffs of delay, measurement accuracy and buffer overflow, for given QoS requirements. The performance of the proposed approach is analyzed and evaluated, through modeling and simulation, under different data aggregation scenarios and traffic loads. The impact of several design parameters and tradeoffs on various critical network and application related performance metrics, such as energy efficiency, network lifetime, end-to-end latency, and data loss are also evaluated and discussed.

Finally Chapter 5 concludes the dissertation by summarizing the main contributions and conclusions of this work, and presenting some current and future open research issues.

CHAPTER 2

MODELING OF WIRELESS SENSOR NETWORKS

The definition and development of models in order to analyze and evaluate sensor networks can help not only to systematically study the network behavior and predict the evolvement of the system, but also direct the deployment and implementation of these networks. This chapter addresses the modeling of sensor networks from the aspect of connectivity.

2.1 Motivation

Connectivity is a fundamental property of wireless networks. In these networks, connectivity relies on the actual physical conditions such as transmit power range, network density and node positions, and provides a good indication of the network status. The in-depth study and modeling of the connectivity distribution facilitates the development of guidelines regarding several processes involved in the design and operation of sensor networks, such as the deployment pattern and density of sensors, communication strategies among individual sensors, distributed information processing algorithms and finally routing and/or information dissemination strategies. For example an algorithm based on multidimensional scaling which uses connectivity information to derive the locations of the nodes in the network, has been proposed in [47].

In this chapter, first a model that characterizes the connectivity distribution in a multi-hop sensor networking system is provided, and based on this model, the energy consumption of a sensor network under periodical sleeping strategies is investigated. Furthermore, based on some concepts developed by the continuum theory [43], a connectivity model is developed that gives a more realistic description of the various processes and their effects as the mobile sensor based network evolves. It provides an analytical

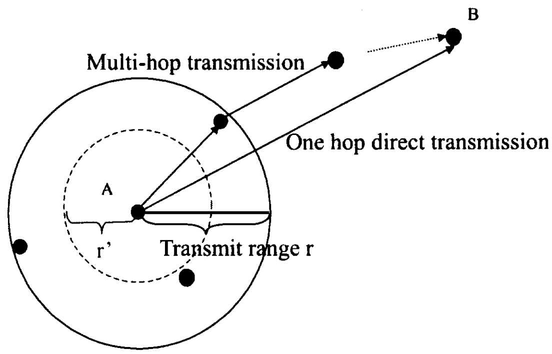

Figure 2.1 Multi-hop vs. direct communications.

approach that describes the dynamics of the network, and facilitates the understanding of the effect of the various events on the large-scale topology of a wireless sensor network.

2.2 Connectivity Distribution of Multi-hop Sensor Networks

Since in general the average received signal power is inversely proportional to the n-th power of the distance (usually $2 \leq n \leq 4$), for a given pair of source and destination the multi-hop short-range transmission consumes less power than the power required by one large hop transmission. However, at the same time due to connectivity and reliability requirements the transmit range can not be reduced arbitrarily. For instance, in Figure. 2.1, if the transmit range (by reducing the corresponding power) of the source node A from r to r' reduces, the number of neighbors of node A reduces as well. The connectivity problem of the whole network is a key part for the network reliability. Here the connectivity of a node is defined as the number of nodes within its transmit range (e.g. neighbors - nodes that can be reached directly in one hop). In this section the connectivity distribution of a node is modeled, and its relation and impact on network reliability, power consumption, transmission data rate are investigated.

2.2.1 System Model and Connectivity Distribution

In the following assume that there are M sensors randomly deployed in an area of A units. Denote by D the density of the active sensors in the area, i.e., $D = \frac{M}{A}$. Let $S = c_i(x_i, y_i), i = 1, 2, \cdots, M$, be the sensor set, where (x_i, y_i) denotes the coordinates of sensor c_i. By denoting with r_i the radius of coverage of any node c_i, the transmit coverage area for each node is $a_i = \pi r_i^2$. Also assume that all transmissions have fixed data rate, all nodes have the same transmit power (that can be adjusted), and that the required transmit power P_T is inversely proportional to the transmit distance between them (i.e. the system is power-limited). Thus all nodes have the same transmit range radius: $r_i = r (i = 1, 2, \cdots, M)$. A small area a within A (where a is a circle plane and $a = \pi r^2$) is randomly selected. Since the sensors are assumed to be randomly deployed, the probability that any node is within the coverage range a is $p = \frac{\pi r^2}{A}$.

Let N be the total number of sensors which are within the range a, then given A, M and a, the probability that there are k sensors within the range a is

$$\Pr[N = k] = C_M^k p^k (1 - p)^{M-k}. \tag{2.1}$$

In a large scale deployment it can be assumed that the transmit range of each sensor is much smaller than the whole coverage area A, i.e. $p = a/A \to 0$, and the total number of sensors is very large, i.e. $M \to \infty$. Since $pM = \pi r^2 D$ is a constant for given r and D, the distribution in (2.1) approaches the Poisson distribution with parameter $\theta = \pi r^2 D$. Therefore, for a given power level, the distribution of the number of neighbors of a node is $\Pr[N = k] = \frac{\theta^k e^{-\theta}}{k!}$, $k = 0, 1, \cdots$, and the probability that the number of neighbors per node is no less than some specific value k, which is determined by the reliability and connectivity requirements, is given by

$$\Pr[N \geq k] = 1 - \Pr[N < k] = 1 - e^{-\theta} \sum_{i=0}^{k-1} \frac{\theta^i}{i!}. \tag{2.2}$$

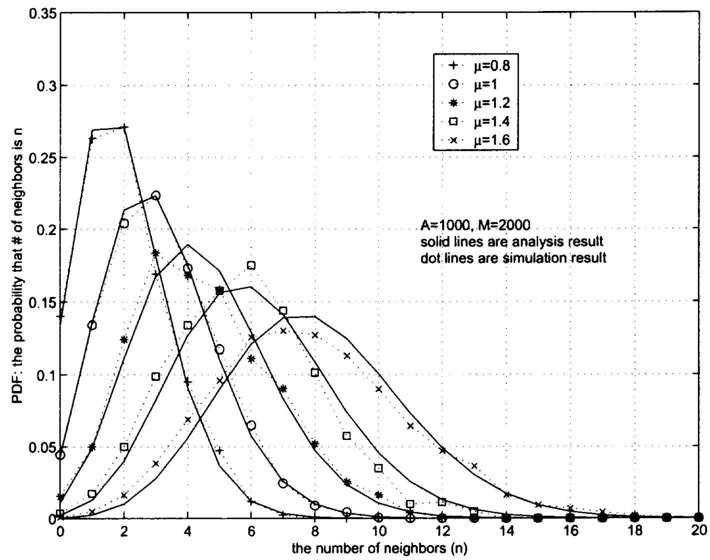

Figure 2.2 Probability density function of the node connectivity.

In the following, some numerical results regarding the node connectivity distribution of a sensor network based on the aforementioned model are presented. For demonstration purposes, a coefficient μ, defined as $\mu = r\sqrt{D}$, is introduced, and a set of curves for different values of μ are shown(since $\theta = \pi\mu^2$, the corresponding distribution depends only on μ). The validity of the proposed analytical model was confirmed via a series of simulation experiments for different scenarios. Specifically in Figures 2.2 and 2.3 the corresponding comparative numerical results for both the analytical study and simulation study are depicted for a system with 2000 sensors randomly deployed in an area of 1000 units, for five different values of μ.

2.2.2 Power Consideration

Utilizing the above model and corresponding figures, the appropriate transmit radius r and the required sensor power level can be determined, according to the required connectivity specifications. For instance, if more than 90% of nodes to have connectivity of at least 2 is required, then $\mu \geq 1.2$ can be selected. Once the appropriate transmit range r is determined,

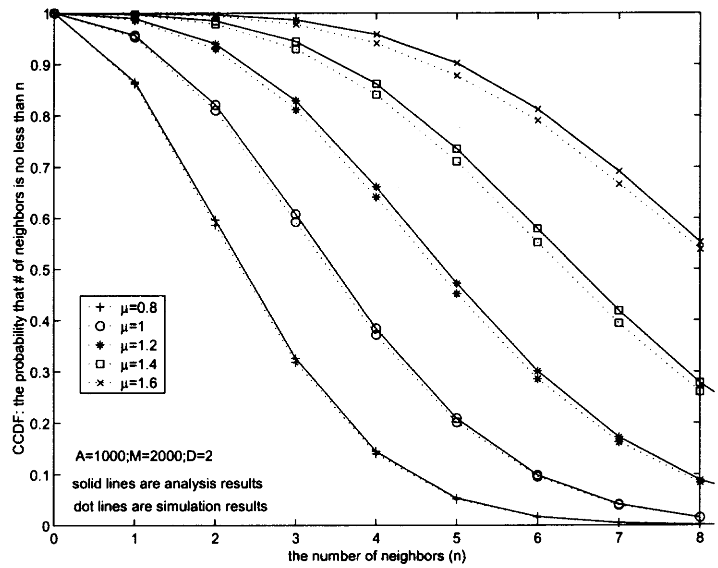

Figure 2.3 Complementary cumulative distribution function of the node connectivity.

then the minimum transmit power level can be adjusted as follows. The average received signal power at distance d can be written as [48]

$$P_R(d)(dB) = P_R(d_0)(dB) + 10n\log(\frac{d_0}{d}) \tag{2.3}$$

where n is the path loss exponent; d_0 is the reference distance that is selected according the propagation environment and the reference path loss can be calculated using the free space path loss formula

$$PL(d_0)(dB) = -10\log(\frac{G_tG_r\lambda^2}{(4\pi)^2d_0^2}) \tag{2.4}$$

where G_t and G_r are the transmit and receiver antenna gains, and λ is the wavelength. Based on (2.3)(2.4) and relation among the average received power $P_R(d)(dB)$, transmit power $P_T(dB)$, and pass loss $PL(d)(dB)$, $P_R(d)(dB) = P_T(dB) - PL(d)(dB)$, the average received power can be expressed as

$$P_R(d)(dB) = P_T(dB) + 10\log(\frac{G_tG_r\lambda^2}{(4\pi)^2d_0^2}) + 10n\log(\frac{d_0}{d}). \tag{2.5}$$

Let the minimum required received signal power (receiver sensitivity for a given system performance (e.g. bit error rate)) be S_{req}, then the minimum required transmit power for the given connectivity requirement is

$$P_T(dB) \geq S_{req}(dB) - 10\log(\frac{G_t G_r \lambda^2}{(4\pi)^2 d_0^2}) - 10n\log(\frac{d_0}{\mu}\sqrt{D}). \tag{2.6}$$

Conversely, given the transmit power and the minimum required receiver power level, the corresponding μ and r can be determined, and furthermore, the connectivity distribution is obtained. Increasing μ, the average connectivity θ increases as well and the system reliability improves, however, the required transmit power also increases; on the other hand, if μ decreases, the required transmit power decreases while at the same time θ decreases and thus the system reliability degrades. Relation (2.6) provides a simple way to quantify this tradeoff between the energy conservation and the system reliability.

2.2.3 Variable Data Rate

In the analysis provided above the problem how to minimize the transmit power via minimizing the transmit range under a specific connectivity requirement is addressed, for a fixed data rate system. However, in the case of flexible data rate transmissions, the data rate can be introduced in the proposed method as another adjustable parameter for the analysis of power and reliability tradeoff. Denote the signal energy per bit by E_b, the bit-rate by R, the noise power spectral density N_0 and the available bandwidth W, according to channel capacity formula [49], the relationship between them is given by

$$\frac{E_b}{N_0} \geq \frac{2^{R/W} - 1}{R/W}. \tag{2.7}$$

Accordingly power efficient modulation schemes can be selected, such as UWB (Ultra Wide Band) communications where small E_b/N_0 suffices to meet the quality of service requirements. Assuming that the required signal energy per bit in order to provide the desired system performance is E_b' with $E_b' \geq (2^{R/W} - 1)(W/R)N_0$, then the minimum required received signal power is $S_{req} = E_b'R$, i.e. S_{req} decreases as the data rate R decreases. Then relation (2.6) that determines the minimum required transmit power for the given connectivity requirement can be modified as follows

$$P_T(dB) \geq (E_b'R)(dB) - 10\log(\frac{G_tG_r\lambda^2}{(4\pi)^2d_0^2}) - 10n\log(\frac{d_0}{\mu}\sqrt{D}). \quad (2.8)$$

In this case the transmit power P_T can still be reduced via reducing the corresponding transmit data rate while the transmit radius r remains unchanged, and therefore, the battery lifetime can be extended while maintaining the connectivity requirement. Similarly the flexible data rate allows the system to easily adjust itself to the various characteristics and specifications. For instance, if the maximum possible transmit power is limited by the system design, its data rate can be reduced in order with the use of the same power to enlarge the corresponding transmit range and increase system reliability and/or minimize the probability of node isolation.

2.2.4 Overall System Connectivity and Reliability

In wireless sensor networks, the communication links between nodes are more likely to fail (than wired links) and as a result the system reliability is an important issue. Furthermore, sensors may be deployed in some unfriendly environments and as a natural result the nodes are more prone to failure. As mentioned before in distributed self-organizing sensor networks [50] [51], sensors usually communicate with each other in a multi-hop ad hoc mode, without the support of centralized base stations. In the previous subsections the node connectivity distribution and its relationship with the transmit power were analyzed and discussed. In this section the relation of the connectivity of the entire network with the node connectivity distribution is investigated. In the following it is assumed that each pair of nodes has the same probability of communicating with each other, and each node can be either source or destination or a relay point. Figure 2.4 presents the statistical results of the

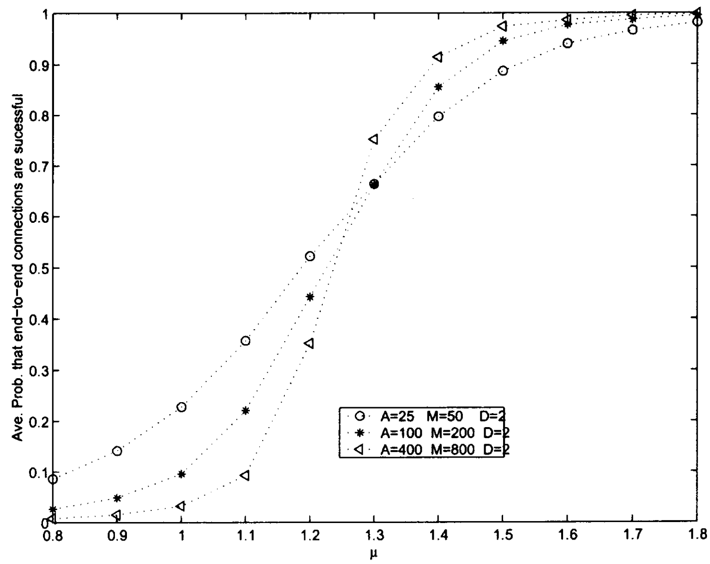

Figure 2.4 End-to-end connections versus node connectivity.

behavior of the end-to-end attempted connections as a function of the node connectivity.

Specifically in Figure 2.4 the horizontal axis (μ) reflects the node connectivity condition (the average connectivity number of a node is $\theta = \pi\mu^2$), while the vertical axis presents the statistical average of the probabilities that the end-to-end connections are successful, which reflects the reliability and accuracy of the entire system. If this probability is equal to 1 then the system is fully connected, i.e. there exist at least one path between each pair of nodes. From Figure 2.4, it can be seen that the end-to-end connection probability increases as μ increases; especially when μ is in the range $[1, 1.5]$, the corresponding increase is very rapid.

2.3 Periodic Sleeping Strategies

As mentioned earlier in sensor networks power/energy conservation is a very important design issue and consideration [52] [53] [54] [55]. In most applications of sensor networks, the data transmission is relative small compared to the Internet or other types of networks, and therefore letting the sensors go to "sleep" mode periodically can help extending

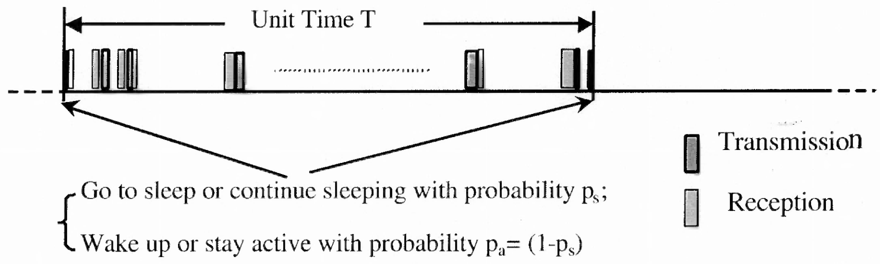

Figure 2.5 Periodical sleeping strategy for sensor nodes.

the lifetime of a sensor, especially when the traffic is low and delay constraint is not rigid. Based on the model and results developed in section 2.2.1, in the following the power/energy consumption problem is studied under both the "sleeping" and "sleepless" scenarios for a given connectivity requirement.

2.3.1 Assumptions and Functioning

In sleepless strategy the nodes only have two energy states: transmission or reception. When there is some data to be transmitted or relayed, the node will be at the transmission state. Otherwise the node will be at the reception state (idle listening or receiving data). It is assumed the idle listening consumes the same power required for receiving data, base on the fact that in some cases the energy consumption in idle listening mode is comparable with that in receiving data. For example, Stemm and Katz [56] measure that the energy consumption ratios in (idle: receive:send) modes are $(1 : 1.05 : 1.4)$ respectively. In the sleeping strategy it is assumed that the sensor nodes will go to sleep periodically (Figure 2.5) with probability p_s (denote by $p_a = 1 - p_s$ the probability of a sensor being active) for every time interval T, and the power consumption during sleeping mode is negligible. In order to keep the same connectivity, the transmit power of each node has to be increased so that the corresponding transmission range can be increased as well.

In the following for simplicity only the power consumed during transmission and reception are considered and the processing power is assumed to be negligible. Let the average transmission time ratio be R_{tx} (i.e. time during transmission over total system runtime) and reception time ratio be R_{rx}(time during reception over total system runtime), where $0 < R_{tx}, R_{rx} < 1$ and $R_{tx} + R_{rx} \leq 1$. Denote by α the ratio between the powers consumed at the transmission and reception states. That is, $P_{rx} = \alpha P_{tx}$ where in realistic cases $0 < \alpha < 1$.

If the total number of nodes in the sensor network is M and the whole coverage of the network is A, then the density of the sensor network in sleepless case is $D = M/A$. For the sleeping strategies since each node goes to sleep with probability p_s, the average number of active nodes is $M_a = M(1 - p_s)$, and the average density of the active sensor nodes is $D_a = D(1 - p_s)$.

It is assumed that a specific connectivity requirement is needed to satisfied in order to avoid nodes isolation and due to reliability consideration. Following the notation introduced in section 2.2.1, if let the transmission range and transmit power for the sleepless case denoted by r and P_T respectively, and the transmit range and transmit power for the sleeping strategy by r' and P'_T, then the parameter of connectivity distribution for the sleepless case is $\theta = \pi r^2 D$, while the corresponding parameter for the sleeping case is $\theta' = (1 - p_s)\pi r'^2 D$. For a system with a given connectivity distribution requirement, if $\theta = \theta'$, then $r' = \sqrt{\frac{1}{1-p_s}}r$, therefore,

$$\frac{P'_T}{P_T} = \frac{PL(r')}{PL(r)} = (\frac{r'}{r})^n = (\sqrt{\frac{1}{1-p_s}})^n = (1 - p_s)^{-n/2}. \tag{2.9}$$

Based on these results, observations and assumptions the average consumed power can easily be obtained for the two different strategies (sleepless and sleeping) as follows.

2.3.2 Average Consumed Power Analysis and Numerical Results

1. *Average consumed power for the sleepless strategy*

As mentioned before in sleepless strategy the nodes only have two states: transmission or receiving. When there is some data to be transmitted or relayed, the node will be at the transmission state. Otherwise the node will be at the receiving state (listening or receiving). In this case $R_{rx} = 1 - R_{tx}$, and the average consumed power can be written as

$$P_{av1} = P_{rx}R_{rx} + P_{tx}R_{tx} = P_{tx}(\alpha(1 - R_{tx}) + R_{tx}). \tag{2.10}$$

2. *Average consumed power for the sleeping strategy*

In this case there will be three states: transmission, reception and sleep. Denote the corresponding consumed power in each stage by: P'_{rx}, P'_{tx}, and P_{sleep}, respectively. In the following, without loss of generality, it is assumed that the power consumption during sleeping is negligible. Therefore, based on the previous relations it is concluded that: $P'_{rx} = P_{rx} = \alpha P_{tx}$, $P'_{tx} = p_a^{-n/2} P_{tx}$ and $P_{sleep} \approx 0$. The corresponding time ratios of a node being in transmission, reception and sleep states are R_{tx}, R_{rx} and R_{sleep} such that $R_{tx} + R_{rx} + R_{sleep} = 1$. Then the average consumed power can be expressed as

$$P_{av2} = P_{tx}[\alpha(1 - R_{tx} - R_{sleep}) + p_a^{-n/2} R_{tx}]. \tag{2.11}$$

If the whole lifetime/runtime of the network is much greater than T, then R_{sleep} is approximately equal to p_s, and

$$P_{av2} \approx P_{tx}[\alpha(p_a - R_{tx}) + p_a^{-n/2} R_{tx}]. \tag{2.12}$$

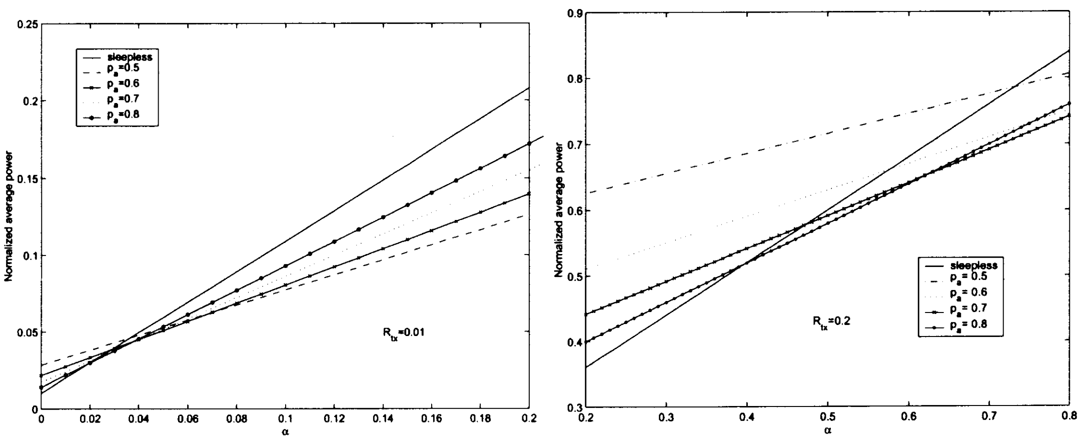

Figure 2.6 Average consumed power as a function of α for various p_a ($R_{tx} = 0.01, 0.2$).

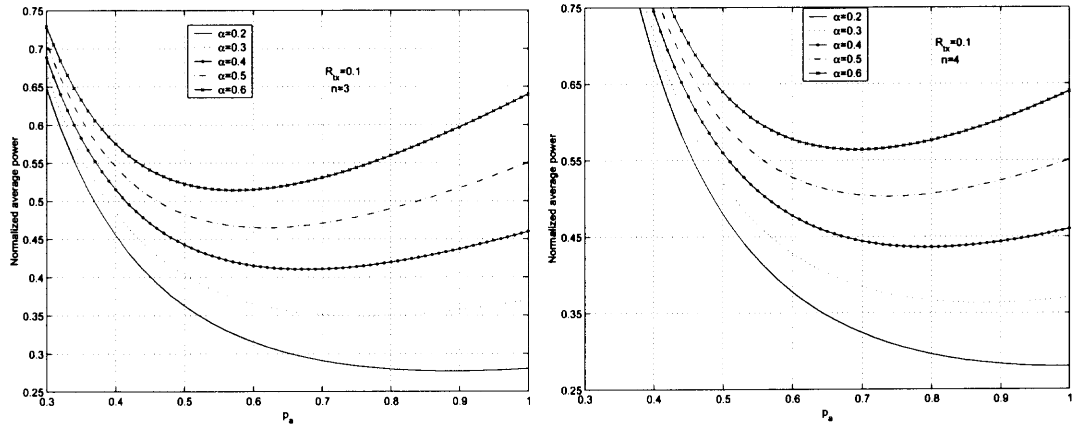

Figure 2.7 Normalized average consumed power as a function of p_a ($R_{tx} = 0.1, n = 3, 4$).

Table 2.1 Optimal p_a for Different Values of Power Ratio α ($R_{tx} = 0.1$)

	α	0.2	0.3	0.4	0.5	0.6
$n = 3$	min. normalized ave. power	0.28	0.35	0.41	0.46	0.51
$n = 3$	optimal p_a	0.89	0.76	0.68	0.62	0.57
$n = 4$	min. normalized ave. power	0.28	0.36	0.44	0.5	0.56
$n = 4$	optimal p_a	1	0.87	0.79	0.74	0.69

Figure 2.6 presents the normalized average consumed power (the powers are normalized by P_{tx} and $n = 3$) as a function of the power ratio parameter α, for the sleepless strategy and various versions of sleeping strategies (the different versions refer to the sleeping/activity probability), for two different cases regarding the transmission time ratio R_{tx}. It can seen that for low transmission ratio (i.e. when traffic is low) there is almost always some benefit from the periodical sleep strategy. For instance, when $R_{tx} = 0.01$, and P_{rx} is greater than $0.04P_{tx}$, the average powers with sleep strategies are significantly lower than the ones for the sleepless case. However, if R_{tx} is relatively large, the results indicate that the power conservation in the sleeping strategies can be obtained only under limited conditions. It can be seen that when R_{tx} is 0.2, the benefit may be gained only for values greater than 0.6. However, for current technologies, the power consumed during reception can be less than half of the power consumed during transmission (e.g. [57]). Figure 2.7 presents the normalized average power versus p_a, for a given power ratio α. It can be seen that the average power consumed decreases as α decreases, and that the optimal p_a corresponding to minimum average power increases as α decreases for the same values of the parameters of R_{tx} and n. The optimal value of the design parameter p_a and the corresponding minimum average consumed power is shown in Table 2.1 for different values of parameter α.

From these results it can be observed that sleeping strategy is in general beneficial when traffic is low, while if the traffic is high, it is beneficial only when α is large. The reason is that when the traffic is low, the node is in reception state for most of time and therefore the conserved power due to the sleeping strategies is much larger than the increase in the transmission power due to the need for increased transmission range (and power) to maintain the pre-specified connectivity requirements. When traffic is high, since the increased transmit power is proportional to R_{tx}, the increased power to keep the same connectivity during transmission due to the density decrease of active nodes is greater than the power conservation due to the use of the sleeping strategy.

2.4 Continuum Theory-based Connectivity Modeling

In this section, in order to provide a more realistic description of the various processes and their effects as the mobile sensor based network evolves, a more complicated model is introduced [41]. The proposed model stems from the commonality encountered in the mobile sensor wireless networks, their self organizing and random nature, and some concepts developed by the continuum theory [43].

The objective of this modeling approach is to create and investigate an extended model of wireless sensor evolution that gives a more realistic description of the local processes, incorporating the addition of new sensors, new links, rewiring of links, etc. In a wireless mobile sensor network such events are tightly coupled with the actual physical events such as node movement, network density, power coverage, energy availability etc. In this section a model with fixed number of nodes is proposed and evaluated under three different scenarios that present several tradeoffs between accuracy and complexity. Specifically the three scenarios are: a) Scenario 1: New links preferentially point to popular nodes, while the more links the node is with, the higher the probability that the node remove a link; b) Scenario 2: New links preferentially are deployed evenly, while the more links the node is with, the higher the probability that the node remove a link; c) Scenario 3: The probability of removing links is relative to the connectivity conditions of the system.

2.4.1 Basic Model

In the following it is assumed that the number N of sensors is constant, that is there are neither new nodes joining the system nor existing nodes leaving the system. It is also assumed that the links are bidirectional. In general one of the following operations is performed at each time-step.

(p1) With probability p ($0 \leq p < 1$), m_1 new links are added ($m_1 \leq N$). It may happen when a node begins to contact other nodes and build new links, or when a node moves within the coverage of another node and would like establish a new link. Randomly select a node as the starting point of the new link; the end point is selected with $Q_1(k_i)$, where $Q_1(k_i)$ denotes the probability that a node i currently associated with k_i links is selected. This process is repeated m_1 times.

(p2) With probability q ($0 \leq q < 1$), m_2 links are rewired ($m_2 \leq m_1$). It will happen when a node find that one or more new links are better than the existing ones for routing or data gathering. For this case, randomly select one node i, and one link l_{ij} that is between node i and node j, then rewire the link to another node $j\prime$, where $j\prime$ is selected with $Q_2(k_i)$ ($Q_2(k_i)$ is similar to $Q_1(k_i)$). This process is repeated m_2 times.

(p3) With probability r ($0 \leq r < 1$), m_3 existing links are deleted ($m_3 \leq m_1$). It may happen when a node finds out that it has too many links or its energy is being depleted faster than its schedule. Select one node i with probability $Q_3(k_i)$, and randomly select one of its links to be released. This process is repeated m_3 times.

(p4) With probability $1 - p - q - r$, no changes occurs in the system.

In this model it is assumed the probabilities $Q_1(k_i)$, $Q_2(k_i)$ and $Q_3(k_i)$ depend only on k_i, i.e. the number of links of node i at a given time. Thus, the probability that a node i changes its connectivity k_i depends only on k_i and the characteristic quantities of the whole network, e.g. parameters p, q, r, N, m_1, m_2, m_3. To analytically estimate the topology changes and the dynamics of the network, it is also assumed that k_i changes continuously, and thus the probabilities $Q_1(k_i)$, $Q_2(k_i)$ and $Q_3(k_i)$ can be interpreted as the rate at which k_i changes. Therefore, the processes (p1)-(p3) described above contribute to k_i , and process (p4) makes no contribution to k_i. Applying the continuum theory [43] [58], the rates at which k_i changes, according to processes (p1)-(p3), are as follows:

(r1) Addition of m_1 new links with probability p

$$\frac{\partial k_i}{\partial t} = \frac{pm_1}{N} + pm_1Q_1(k_i)$$

The first item is due to the random selection of start point of a link, while the second item corresponds to the end point selection which based on probability $Q_1(k_i)$.

(r2) Rewiring of m_2 links with probability q

$$\frac{\partial k_i}{\partial t} = -\frac{qm_2}{N} + qm_2Q_2(k_i)$$

The first item corresponds to the decreasing of the number of links of the node where the link was removed from, and the second item corresponds to the increasing connectivity of the node that the link is reconnected to.

(r3) Removing of m_3 existing links with probability r

$$\frac{\partial k_i}{\partial t} = -rm_3Q_3(k_i) - rm_3A_i$$

where

$$A_i = \sum_{\text{all } k_i \text{ links } l_{ij}} Q_3(k_j)/k_j$$

The first item corresponds to the case that the node itself select to remove one of its links, while the second item corresponds to the decreasing connectivity because other nodes connected with this node select to remove their link with this node.

Since at each time step, all these three processes may have contribution, the change of the connectivity k_i, of a node i is given by the following equation (2.13)

$$\frac{\partial k_i}{\partial t} = pm_1\left[\frac{1}{N} + Q_1(k_i)\right] + qm_2\left[Q_2(k_i) - \frac{1}{N}\right] - rm_3\left[Q_3(k_i) + A_i\right] \tag{2.13}$$

where $Q_1(k_i)$, $Q_2(k_i)$ and $Q_3(k_i)$ denote the probability that a link or a node is selected in process (p1), (p2) and (p3), respectively. The actual values of them depend on the sensor network behavior and organization. In the following the representation of these probabilities for three different scenarios.

2.4.2 Preference on Popular Nodes

Scenario 1: New links preferentially point to popular nodes, while the more links the node is associated with, the higher the probability that the node removes a link

For this scenario, the probabilities $Q_1(k_i)$ and $Q_3(k_i)$ can be expressed as

$$Q_1(k_i) = Q_2(k_i) = \frac{k_i + 1}{\sum_{\text{all node } j}(k_j + 1)} \tag{2.14}$$

and

$$Q_3(k_i) = \frac{k_i}{\sum_{\text{all node } j} k_j} \tag{2.15}$$

Equation (2.14) reflects that the more links the node has, the higher the probability that other nodes selected to point at it. This scenario reflects cases where nodes usually prefer to join a sub-network with more nodes. Usually nodes that belong to relative large networks have more links than other relatively isolated nodes. Equation (2.15) reflects the observation that the nodes with higher connectivity most likely select to decrease their connectivity, in order to reduce the associated overhead and power consumption. As a result it is likely that they may remove one or more of their links. The combination of these behaviors and observations balances the number of links and the power consumption between the various nodes.

Substituting equation (2.15) into the expression of A_i, then

$$A_i = \sum_{\text{all } k_i \text{ links } l_{ij}} \frac{k_j}{\sum_{\text{all node } r} k_r} \cdot \frac{1}{k_j} = \frac{k_i}{\sum_{\text{all node } r} k_r} = Q_3(k_i)$$

Thus, equation (2.13) can be simplified as follows:

$$\begin{aligned} \frac{\partial k_i}{\partial t} &= (pm_1 - qm_2)\frac{1}{N} \\ &+ (pm_1 + qm_2) \cdot \frac{k_i + 1}{\sum_{\text{all node } j} (k_j + 1)} - 2rm_3 \frac{k_i}{\sum_{\text{all node } j} k_j} \end{aligned} \tag{2.16}$$

Let $L(t)$ denote the total number of links in whole network at the time t. Only the processes (p1) and (p3) contribute to $L(t)$, and therefore

$$L(t) = \frac{1}{2} \sum_{\text{all nodes } j} k_j = (pm_1 - rm_3)\, t \tag{2.17}$$

If assume that there are no links at the beginning, i.e. $k_i(1) = 0$, and that in a practical system $k_i(t) \geq 0$ and $L(t) > 0$, then the following condition should be satisfied: $pm_1 > rm_3$. Substituting equation (2.17) into (2.16)

$$\begin{aligned} \frac{\partial k_i}{\partial t} &= \frac{pm_1 + qm_2}{2\,(pm_1 - qm_2)\, t + N} (k_i + 1) \\ &- \frac{rm_3}{pm_1 - rm_3} \cdot \frac{1}{t} k_i + \frac{pm_1 - qm_2}{N} \end{aligned}$$

Furthermore, the connectivity function of a node can be obtained as follows

$$k_i(t)^{f(t)} = \int \left(\frac{a_2}{t + a_1} + a_3 \right) f(t) dt + C$$

where

$$f(t) = \frac{t^{a_4}}{(t + a_1)^{a_2}}; \quad a_1 = \frac{N}{2\,(pm_1 - rm_3)};$$

$$a_2 = \frac{pm_1 + qm_2}{2\,(pm_1 - qm_2)}; a_3 = \frac{pm_1 - qm_2}{N}; a_4 = \frac{rm_3}{pm_1 - rm_3}$$

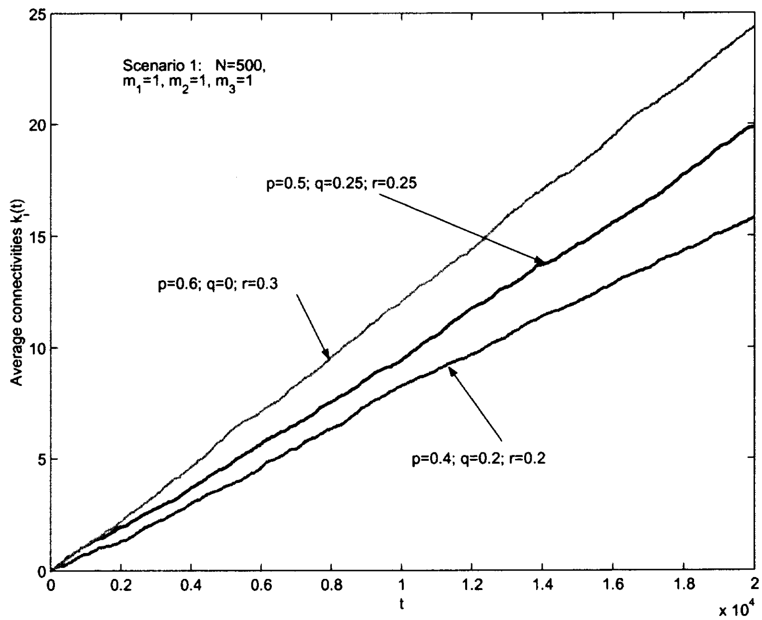

Figure 2.8 Average connectivity evolvement as a function of t for scenario 1.

Constant C can be decided based on the initial condition $k_i(t_0) = n_i$. Since it starts with an isolated system, the initial condition assumed here is $k_i(1) = 0$.

For $t >> a_1$, $k_i(t)$ can be approximated as: $k_i(t) \longrightarrow \frac{t}{a_1}$. Of course in any practical system the number of links is limited by $k_i(t) < N$.

Figure (2.8)–(2.10) present some simulation results regarding the sensor network connectivity for different parameters p, q and r. It can be seen that the results agree with the analytical results obtained above. Specifically from Figure 2.8, it can be seen that the connectivity approximately increases linearly with t, while the slope is proportional to $(pm_1 - rm_3)$ for the same N. In Figure 2.9, the connectivity is rescaled by (a_1/t) and as expected based on the analysis it approaches to 1. The connectivity distribution at different time instances is shown in Figure 2.10. From this Figure it is observed that the mean value of the connectivity distribution approaches to (t/a_1), when t is very large. For example, when $N = 500, p = 0.45, q = 0.25, r = 0.3, m1 = m2 = m3 = 1$ and $t = 100000$, the mean value is around $t/a_1 = 60$.

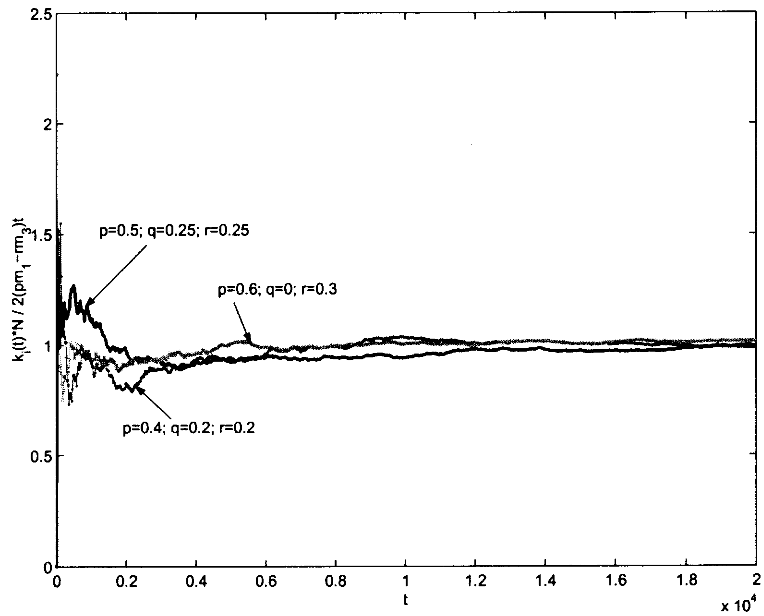

Figure 2.9 Rescaled connectivity by (a_1/t) for scenario 1.

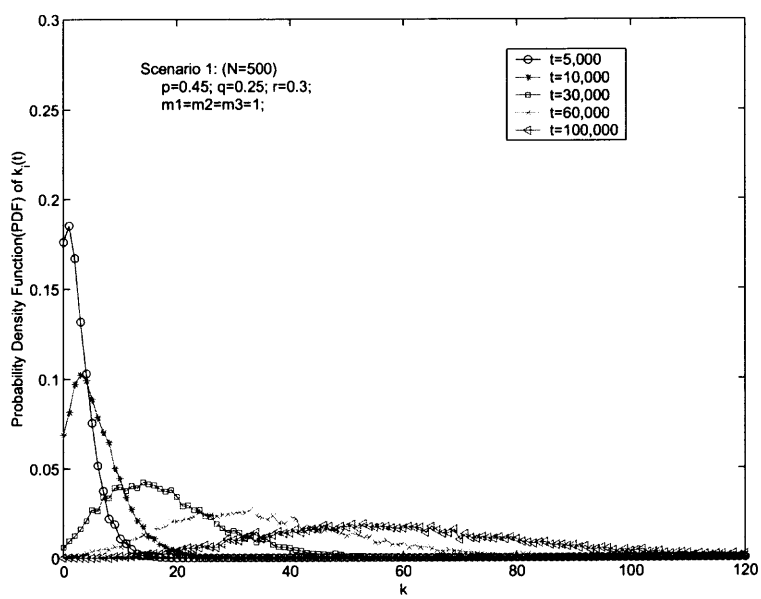

Figure 2.10 Probability density function of the connectivity for scenario 1.

2.4.3 Even Deployment

Scenario 2: New links are preferentially deployed evenly, while the more links the node is associated with, the higher the probability that the node may remove a link.

In this scenario, $Q_3(k_i)$ is the same as in scenario 1 while $Q_1(k_i)$ and $Q_2(k_i)$ are as follows

$$Q_1(k_i) = Q_2(k_i) = \frac{\frac{1}{k_i+1}}{\sum\limits_{\text{all nodes } j} \left(\frac{1}{k_j+1}\right)}$$

From this equation it can be observed that the probability that a node is selected to add a new link is inversely proportional to $(k_i + 1)$, which means that the less links the node has, the higher is the probability that the node adds new links. The reasoning behind such a consideration is that assuming that each node has the same energy and capabilities, if the goal is to maximize the minimum of the life of all node, it would be more appropriate to assign the tasks and organize the network as evenly as possible.

In this case equation (2.13) can be rewritten as

$$\frac{\partial k_i}{\partial t} = (pm_1 - qm_2)\frac{1}{N} + (pm_1 + qm_2)\frac{\frac{1}{k_i+1}}{\sum\limits_{\text{all nodes } j} \left(\frac{1}{k_j+1}\right)} - 2rm_3 \frac{k_i}{\sum\limits_{\text{all node } j} k_j} \tag{2.18}$$

The total number of links still is

$$L(t) = \frac{1}{2} \sum_{\text{all nodes } j} k_j = (pm_1 - rm_3)\, t$$

By making the following approximation

$$\sum_{\text{all nodes } j} \left(\frac{1}{k_j + 1}\right) \approx \sum_{\text{all nodes } j} \frac{1}{E\left[k_j(t)\right] + 1} = \frac{N}{2L(t)/N + 1}$$

Equation (2.18) can be simplified as

$$\frac{\partial k_i}{\partial t} = (pm_1 - qm_2)\frac{1}{N} + (pm_1 + qm_2)\frac{N + 2(pm_1 - rm_3)t}{(k_i + 1)\, N^2} - \frac{rm_3}{pm_1 - rm_3} \cdot \frac{k_i}{t}$$

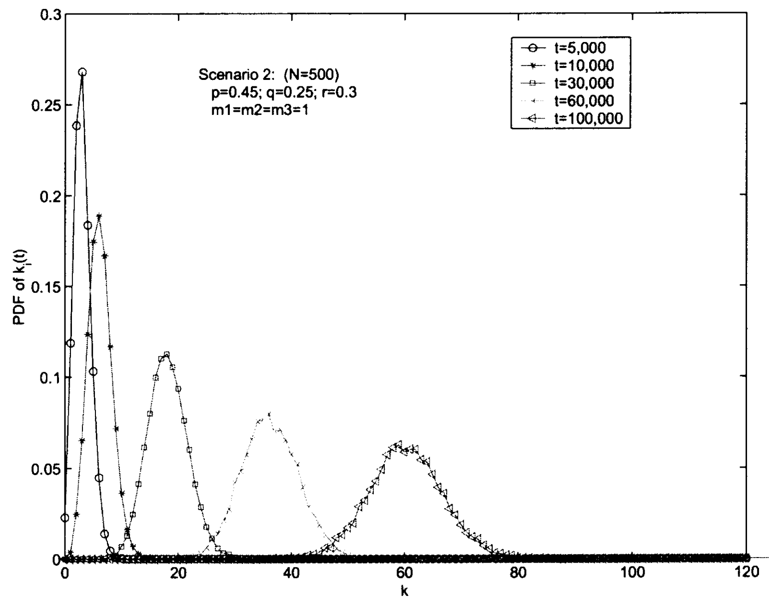

Figure 2.11 Probability density function of the connectivity for scenario 2.

Furthermore, the $k_i(t)$ can be obtained from this differential equation and the corresponding initial conditions. For this scenario, since the links are assigned more evenly, it is expected that all the nodes will approach to the same average number of links. Figure 2.11 shows the evolution of the connectivity distribution. It can be seen that the distributions has mean value (t/a_1), but their variances are much smaller than the corresponding ones in scenario 1. For example, in Figure 2.11, for $t = 100000$ and mean value 60, the k_i of 61 percent of nodes is between 55 to 65, while 99 percent of the nodes have 45 to 75 links.

2.4.4 Removing Links Based on System Connectivity

Scenario 3: The probability of removing links is relative to the connectivity conditions of the overall system.

In this scenario, the same $Q_1(k_i)$ and $Q_2(k_i)$ as in scenario 1 are used, while

$$Q_3(k_i) = \frac{k_i}{\mu N + \sum_{\text{all node } j} k_j} = \frac{k_i}{\mu N + 2L(t)}, \mu > 0.$$

The total number of removed links during t-th unit time can be obtained as follows

$$D(t) = \sum_{i=1}^{N} rm_3 Q_3(k_i) = rm_3 \frac{2L(t)}{\mu N + 2L(t)}$$

The $D(t)$ equals to rm_3 when $\mu = 0$, as in scenario 1 and 2, however, here $D(t)$ is not fixed but depends on the number of existent links at the given time, i.e. $D(t)$ increases as $L(t)$ increases. So the total number of links at t is

$$L(t) = \frac{1}{2} \sum_{\text{all nodes } j} k_j = L(t-1) + pm_1 - D(t-1)$$

Let $\nu = rm_3/pm_1$, $\nu > 0$, then the change of number of links during t-th time interval is

$$\Delta L_t = pm_1 \left[1 - \frac{\nu \cdot 2L(t-1)}{\mu N + 2L(t-1)}\right]$$

(a) $0 < \nu \leq 1$

Since $\lim_{L(t-1) \longrightarrow \infty} \frac{2L(t-1)}{\mu N + 2L(t-1)} = 1$, then $\Delta L_t > pm_1(1-\nu) \geq 0$. It means the $L(t)$ will always increase as t increases until all nodes are connected to each other.

(b) $\nu > 1$

Let $\Delta L_t = 0$, then $L(t-1) = \frac{\mu N}{2(\nu - 1)}$. It can be seen that

$$\begin{aligned} \text{when } L(t-1) &> \frac{\mu N}{2(\nu-1)}, \Delta L_t < 0, L(t) \text{ will decrease;} \\ L(t-1) &< \frac{\mu N}{2(\nu-1)}, \Delta L_t > 0, L(t) \text{ will increase.} \end{aligned}$$

As a result $L(t)$ will approach a dynamic balance at the point $\frac{\mu N}{2(\nu-1)}$. In this case (b) since the system achieves a dynamic balance point, the number of links of each node when t is large approaches

$$2L(t)/N = \mu / (\nu - 1)$$

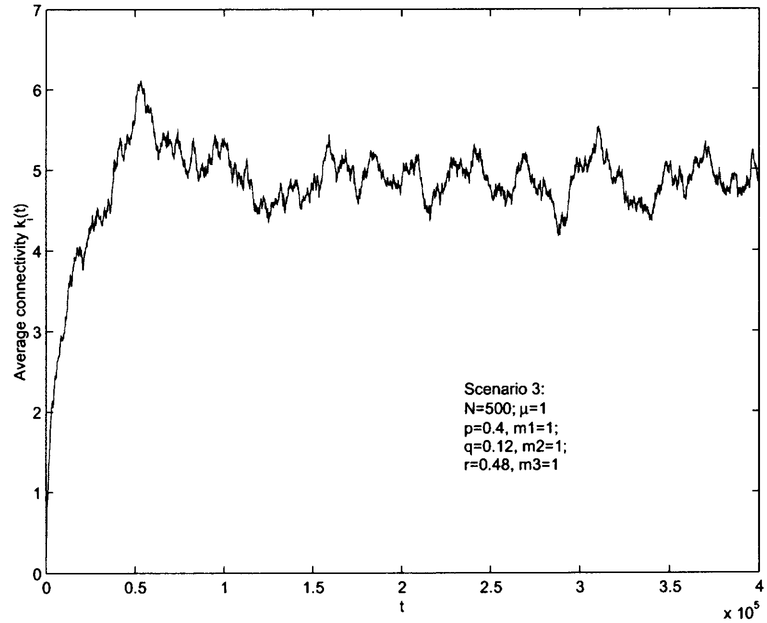

Figure 2.12 Average connectivity evolvement as a function of t for scenario 3.

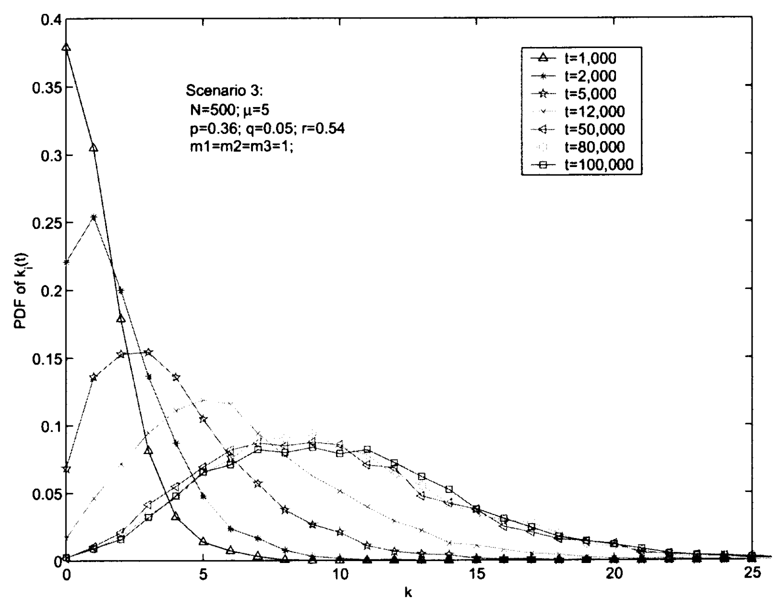

Figure 2.13 Probability density function of the connectivity for scenario 3.

It is expected that the connectivity distribution will achieve a specific distribution with the mean value equal to $\mu/(\nu-1)$ after the transient period. In Figure 2.12, the average connectivity as a function of time is presented, when $\mu = 1$, $\nu = rm_3/pm_1 = 1.2$. In this case the balance point predicted by our analytical model is $\mu/(\nu-1) = 5$. From Figure 2.12, it is observed that based on the obtained simulation results $k_i(t)$ increases rapidly at the beginning and arrives at a dynamic balance $k = 5$ around $t = 100000$, which agree with our analytical model. In Figure 2.13, the corresponding connectivity distribution is provided for $\mu = 5$, $\nu = 1.5$. In this case the predicted balance point is $k = 10$. It can be seen from this Figure that the distribution moves toward the balance point and after the system achieves the balance point, the connectivity distribution with mean value 10 does not change any further.

CHAPTER 3

LIFETIME AND ENERGY-EFFICIENT ORGANIZATION OF MULTI-HOP SENSOR NETWORKS

As we discussed before, the sensor nodes are typically battery operated and have constrained energy resources, therefore the energy-efficiency at various levels (i.e. physical, network layer etc.) is a critical consideration in sensor networks. The goal of various energy-efficiency methods is to extend the lifetime of the network as long as possible.

Networked sensors provide better monitoring capabilities about parameters that present both spatial and temporal variances, and can deliver valuable inferences about the physical world to the end user [59]. In [60], upper bounds on the lifetime of sensor networks were derived and discussed, while in [61] the lifetime of a cluster-based sensor network that provides periodic data is studied. In this chapter the problem of developing an energy efficient operation of a randomly deployed multi-hop sensor network, by extending the lifetime of the communication critical nodes and as a result the overall network's operation lifetime, is considered and analyzed.

3.1 Energy Model

Let us consider a sensor network consisting of N randomly deployed nodes that are used in order to sense, collect and disseminate the data to a collector site for further processing and analysis. Let us also denote by s_i the i-th sensor and by S the corresponding sensor node set $S = \{s_1, s_2, \dots, s_N\}$, where $|S| = N$. The analysis provided here assumes a multi-hop sensor network where all sensors have the same capabilities and can perform the same sensing and communication functions. The energy consumption related parameters at various phases of the network operation are defined as follows:

- E_0 : the initial energy/total energy of a sensor node.

- $E_{b,sense}$: the energy needed to sense a bit. It depends on the power dissipation of the sensors and corresponding A/D circuits and in the following is assumed equal to ε_s.

- $E_{b,Rx}$: the energy needed to receive a bit. It accounts for the power dissipation of the receiver electronics, and in the following is assumed to be equal to ε_{rx}.

- $E_{b,Tx}$: the energy needed to transmit a bit. It can be divided into two parts: the transmitter electronics energy dissipation $E_{b,txe}$ that is similar to $E_{b,Rx}$, and the RF transmit power $E_{b,RF}$ that is related to the transmission distance d. If the path loss exponent is n, then $E_{b,Tx} = E_{b,txe} + E_{b,RF} = \varepsilon_{tx} + \varepsilon_{rf}(\frac{d}{d_0})^n$, where ε_{rf} is the energy consumed to transmit a bit to the reference distance d_0.

- $E_{b,process}$: the energy consumed per bit for data processing, such as aggregation, and special functions required to relay data (other than receiving and transmitting data). Let us denote by γ the data aggregation ratio. For the end nodes that do not relay data from other nodes, γ is equal to 1 since there is no aggregation. The energy per bit for aggregation is a function of γ, that is: $E_{b,process} = \varepsilon_p + \varepsilon_a f(\gamma)$, where $f(\gamma) = 0$ when $\gamma = 1$.

In this model multi-hop communication is adopted, and therefore a sensor node can generate data or relay data from other nodes. Denote by $\lambda_{org,i}$ and $\lambda_{re,i}$ (packets per unit time) the corresponding rates of the traffic originally generated and the traffic relayed by s_i, and it is assumed that the packet length is L bits. It should be noted that multi-path transmission which has been used in ad hoc networks to achieve energy efficient routing and load balance, is not appropriate for the scenarios under consideration here. The main reason is that in sensor networks the data collected by some neighboring nodes may exhibit certain degree of correlation. Furthermore, in order to achieve efficient data fusion and dissemination techniques, preliminary data processing may take place at some intermediate nodes. Based on these assumptions and definitions, the power dissipation of node s_i can be expressed as:

$$\begin{aligned} P_i &= E_{b,sense}\lambda_{org,i}L + E_{b,Rx}\lambda_{re,i}L + (\lambda_{org,i} \\ &\quad +\lambda_{re,i})E_{b,process}L + (\lambda_{org,i} + \lambda_{re,i})\gamma E_{b,Tx}L \\ &= E_{b,i}(d,\gamma)\alpha_i L \end{aligned} \tag{3.1}$$

where $E_{b,i}(d,\gamma) = \varepsilon_s + \varepsilon_{tx} + \varepsilon_p + \varepsilon_{rf}(\frac{d}{d_0})^n\gamma + \varepsilon_a f(\gamma)$ and $\alpha_i = \lambda_{org,i} + \lambda_{re,i}[\varepsilon_{rx} + \varepsilon_{tx} + \varepsilon_p + \varepsilon_{rf}(\frac{d}{d_0})^n\gamma + \varepsilon_a f(\gamma)]/E_{b,i}(d,\gamma)$.

3.2 Lifetime Definition

Depending on the sensor network topology and the corresponding applications, several definitions of the network lifetime have been reported in the literature. Some of them define the network lifetime as the time interval from the point that the sensor network starts its operation until the point that the sensing coverage falls below than a pre-specified threshold, or until the point that the number of active nodes is less than a pre-specified threshold. It should be noted here that the main objective of energy efficient organizations and power conservation policies in large-scale sensor networks, is to extend the network lifetime as long as possible. Therefore in this chapter the network lifetime is defined as the time interval from the point that the sensor network starts its operation until the point that loss of communication to the collector site by all sensor nodes occurs.

3.3 Node Lifetime

Before proceeding with the calculation and estimation of the sensor network lifetime, the lifetime of individual sensor nodes is studied first. Since the expected lifetime of a sensor node depends on the traffic model, in the following two scenarios are considered: (1) periodical traffic. This scenario may occur for instance when the sensor nodes measure periodically various environment parameters (such as temperature, pressure, etc.) and sent

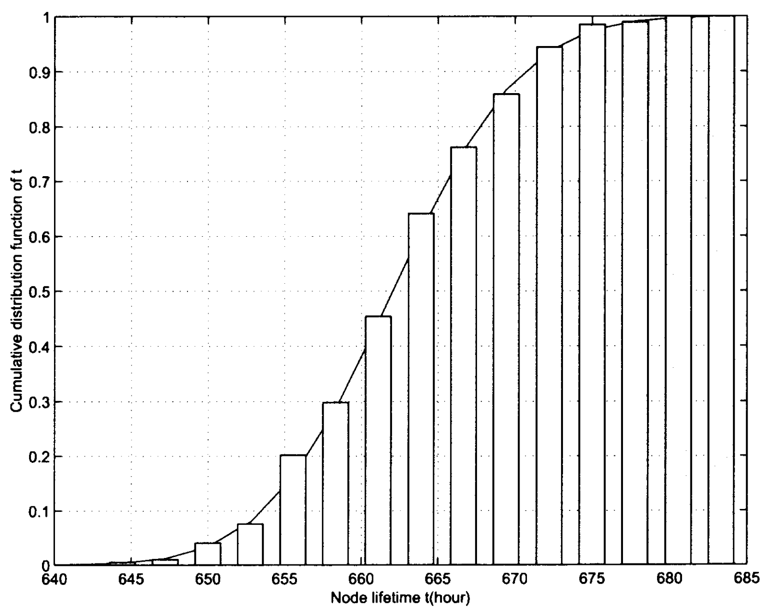

Figure 3.1 Cumulative distribution function of the node lifetime.

the data back to a central site for further analysis. In this case it is assumed that there is a steady flow of data from sensors to the collector, and the lifetime ti of sensor node s_i is $t_i = E_0/P_i$. (2) In the second scenario the packet origination process is assumed to form a Poisson process. Furthermore, it is assumed that the packet arrivals at a relay node from other nodes still follow Poisson processes, i.e. the traffic originally generated by sensor node s_i and the relay traffic at node s_i are Poisson processes of rate $\lambda_{org,i}$ and $\lambda_{re,i}$, respectively. Then it can be shown that the lifetime of sensor node s_i is described by Gamma distribution as follows:

$$f(t_i) = \begin{cases} \alpha_i e^{-\alpha_i t_i} \frac{(\alpha_i t_i)^{n-1}}{(n-1)!}, & t_i > 0 \\ 0, & else \end{cases} \tag{3.2}$$

where $n = \lfloor E_0/E_{b,i}(d,\gamma)L \rfloor$ and α_i is as defined before in relation (3.1). The expected value of lifetime is $E(t_i) = E_0/P_i$ and the standard deviation is $STD(t_i) = n^{1/2}/\alpha_i = \sqrt{E_0/P_i\alpha_i}$. In Figure 3.1, the cumulative distribution function of a node lifetime is given for the following scenario: the original packet arrival rate is 5 packets/hour, the relayed traffic is 10 packets/hour; ε_{tx} and ε_{tx} are 50nJ/bit; ε_p and ε_s are 20nJ/bit; packet length is 32 bytes; E_0 is $6 \times 10^3 mJ$. The solid line corresponds to the analytical results while the statistical results of 200 simulations are indicated by the histogram.

3.4 Critical Nodes and Energy-efficient Organization

In most of the cases the operation of the sensor network is completely disrupted if and only if all of the nodes that can directly communicate with the collector site (e.g. one-hop communication from the collector site) "expire", and as a result the lifetime of these nodes is more critical to the network lifetime.

Let G be the set of sensors that can communicate directly with the collector and that all traffic has to be transmitted to the data process center through one of the members of this node set. Therefore: $G = \{s_i | d_i < r, s_i \in S\}$, where d_i is the distance between node s_i and the collector, and r is the maximum transmission range of a node. It is easy to conclude that the lifetime of set G determines the lifetime of the network. Furthermore, it should be noted that the lifetime of set G depends not only on the traffic generated by these nodes, but on the traffic generated by other nodes outside G, since they are used as relay nodes for the latter traffic as well. In a large-scale sensor network with hundreds or thousands of nodes, the small low cost sensor nodes, due to hardware and cost constraints, have limited transmission range which is in general considerably less than the diameter of the whole network. Therefore in general it can be expected and assumed that $|G|$ is much smaller than the total number of nodes N.

Since the lifetime of set G determined the lifetime of the whole network, the objective is to minimize the energy consumption at the critical nodes $s_i \in G$. The basic idea here is let other nodes outside G transmit data as far as possible within their transmission range to save energy needed to relay the data at critical nodes. The reason is that while the traffic that goes through these nodes is considerably less compared to the traffic of the nodes $s_i \in G$ and the lifetimes of these nodes do not directly affect the network lifetime as defined here.

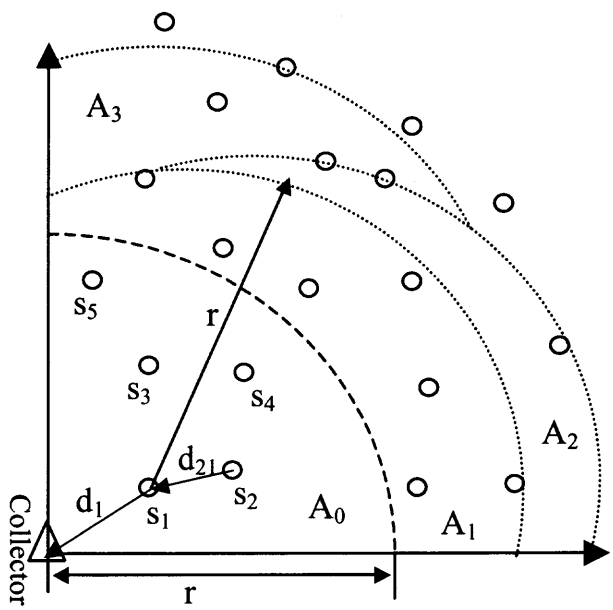

Figure 3.2 An example of the sensor network used to estimate network lifetime.

3.5 Network Lifetime

Without loss of generality, it is assumed that the distances between the sensor nodes of set G and the collector site are arranged in increasing order, i.e. $G = \{s_1, s_2, \ldots s_M\}, d_1 \leq d_2 \leq \ldots \leq d_M$. In Figure 3.2, an example of the topology and scenario under consideration is presented, where $G = \{s_1, s_2, s_3, s_4, s_5\}$. Only the first quadrant is depicted here and the collector is assumed to be located at the origin of the coordinates. In the remaining for simplicity let the aggregation rate γ be 1.

Assuming that the total energy in each node is the same and fixed, the problem of extending the lifetime of a node can be converted to the problem of minimizing the total energy used to transmit each bit. It is considered that each node in set G first selects the route that consumes the least energy to transmit a bit to the collector site, and then based on that, the traffic can be determined that should be sent through these nodes. Let v_i be the optimum route for node $s_i \in G$ and e_i be the corresponding energy required to transmit a bit from s_i to the collector. The energy needed to transmit a bit from a node to the collector can be divided into two parts: the transmit energy that is related to the transmission distance, and the consumed power for relay processing if packets need to be relayed. Let ε_{re} be the additional energy required at each hop due to the need for relaying (this element includes only the energy for sensing and processing): $\varepsilon_{re} = E_{b,Rx} + E_{b,process}$. Then e_i can be determined according to the following procedure, which is executed in the same order indicated in the ordered set G:

(1) Node s_1: since it is the nearest node to the collector, it is optimum to transmit data directly to collector, i.e. $v_1 : s_1 \rightarrow c$, where c denotes the collector. For any packets received by or originated at $s_1, e_1 = \varepsilon_{tx} + \varepsilon_{rf}(d_1/d_0)^n$.

(2) Node $s_i, 2 \leq i \leq M$: There are i possible choices: direct communication to the collector ($s_i \rightarrow c$) or via the intermediate nodes $s_j(s_i \rightarrow s_j, v_j)$ for all $j < i$. Then $e_i = \min_{all\ j,\, j<i} \{\varepsilon_{tx} + \varepsilon_{rf}(\frac{d_i}{d_0})^n, (\varepsilon_{tx} + \varepsilon_{rf}(\frac{d_{ij}}{d_0})^n) + \varepsilon_{re} + e_j\}$, where d_{ij} is the distance from s_i to s_j. The corresponding route is denoted by v_i.

It is easy to see that $e_1 \leq e_2 \leq ... \leq e_M$ because $d_1 \leq d_2 \leq \ldots \leq d_M$. In each node s_j belonging to G the traffic is composed by three different parts: traffic generated by itself, which in the following is assumed to be the same for all nodes and equal to λ_s, traffic received from other nodes that belong to G which is denoted by $\lambda_{v,i}$, and traffic received from nodes outside G that are not able to communicate directly with the collector site, which is denoted by $\lambda_{r,i}$. As explained before, all the data received or originated at node s_i ($s_i \in G$) will be transmitted to collector via the route v_i. Therefore it should be determined which part of traffic outside G will be relayed to each node $s_i \in G$. Since the maximum transmission range of nodes is limited, only a certain restricted number of nodes are able to communicate with a given node $s_i \in G$. For instance the nodes within the transmission range of s_1 but outside G can transmit data to s_1. Let A_0 denote the area where nodes are able to communicate with the collector and A_i denote the area that is within the transmission range of node s_i ($s_i \in G$) but outside $A_j, j < i$. Since $e_1 \leq e_2 \leq ... \leq e_M$, as much traffic as possible should be assigned to s_1 , then to s_2,...and finally to s_M. It follows that node s_i should relay all traffic from A_i. Based on the assumptions that the sensor nodes are uniformly distributed in the area, the total traffic in A_i is given as follows:

$$\lambda_{r,i} = \frac{A_i}{\sum_{j=1}^{|G|} A_j}(|S| - |G|)\lambda_s.$$

Then λ_i, the traffic at s_i, can be determined in terms of the selected routes $\{v_i\}$: $\lambda_M = \lambda_s + \lambda_{r,M}$ and $\lambda_i = \lambda_s + \lambda_{r,i} + \sum_{s_{jx}=s_i,\, j>i} \lambda_j$ for $s_i \in G$, where s_{jx} denotes the next to s_j node in route v_j. Therefore the energy consumed by the critical nodes $s_i \in G$ is minimized at the possible cost of increasing the energy consumption at other nodes, since the nodes outside G transmit data as far as possible within their transmission range. However the lifetimes of these nodes do not directly affect the network lifetime as defined here, while the traffic that goes through these nodes is considerably less compared to the traffic of the nodes $s_i \in G$. Based on this argument and relation (3.1) the expected lifetime of each node can be obtained as:

$$E(t_i) = E_0/[\lambda_s \varepsilon_s + (\lambda_i - \lambda_s)\varepsilon_{re} + \lambda_i(\varepsilon_{tx} + \varepsilon_{rf}(\tfrac{d_{i,ix}}{d_0})^n)] \tag{3.3}$$

Assuming that the energy consumed to transmit a packet is much smaller than the total energy of a node, as expected in any realistic case, i.e. the number of packets that a node is able to transmit is quite large, then, relatively to the expected value, the deviation of t_i will be quite small and the probability that the lifetime approximates the expected value is high. With reference to Figure 3.1, the expected node lifetime is 662 hours and the probability that the lifetime is in the range of $[649, 675]$ and $[643, 681]$ hours are 0.955 and 0.997, respectively.

In order to calculate the total expected lifetime T of set G, an iterative process is employed. Specifically it starts with all the nodes in set G and at every iteration the expected lifetime of the set is calculated as described above. Then the node with the minimum expected lifetime is eliminated and the same process is applied again for the remaining nodes. With reference to the notation introduced earlier in this chapter, the iterative process of calculating the expected lifetime T of set G, based on t_i at different phases can be summarized as follows: $T = \sum_{k=0}^{M-1} \min_{s_i \in G_k} [E(t_i)]$, where $G_0 = G$, and $G_k = G_{k-1} - \{s_j | E(t_j) = \min_{s_i \in G_{k-1}} [E(t_i)]\}$, $k = 1, 2, \ldots (M-1)$.

CHAPTER 4

ADAPTIVE QOS-CONSTRAINED DATA AGGREGATION AND PROCESSING IN DISTRIBUTED SENSOR NETWORKS

Although several research works in the literature have discussed the problems of developing efficient routing and data aggregation processes mainly for energy savings/minimization in sensor networks, several issues associated with the data aggregation process with the specific objective of meeting the task requirements (i.e. QoS-constrained data aggregation) are not yet well addressed. Given the fact that many sensing tasks present some strict reporting quality requirements (e.g., in a time critical application an obsolete sensor report that may exceed a given time threshold is discarded), development of efficient and feasible strategies that perform data aggregation in a distributed manner and with energy efficiency, in order to meet various quality requirements such as end-to-end latency and measurement accuracy, is of high research and practical importance.

4.1 Objective

Therefore, in this chapter the data gathering and aggregation process in a distributed, multi-hop sensor network under specific QoS constraints is studied. For a sensor network, the data collection and dissemination is basically divided into two parts: the original data collection at the end nodes (i.e. source nodes) and the data transmission from the source nodes to the collector center through the intermediate nodes. The end nodes are the ones that are responsible for performing the actual measurements and for the collection of the required samples, while the intermediate nodes receive, process and forward samples originated from other nodes to the collector center.

Since in a distributed multi-hop sensor network the resulting end-to-end QoS heavily depends on the actual system conditions, traffic load, and the actions taken by each intermediate node, in the following the emphasis is placed on the operations performed at the intermediate sensor nodes. Therefore, this chapter first presents and analyzes a QoS-constrained Data Aggregation and Processing approach (Q-DAP) that is performed at the intermediate nodes in a totally distributed fashion. Each intermediate sensor node determines independently whether or not to perform data aggregation randomly with some specific probability that is precalculated according to the resource conditions and the specific task requirements. One of the main principles of the proposed scheme is that the network does not need to be formed into clusters to perform the data aggregation, while the task QoS requirements are taken into account to determine when and where to perform the aggregation in a distributed fashion, based on the availability of local only information. Furthermore, taking into account that each sensor operates autonomously and without any central control, a Localized Adaptive Data Collection and Aggregation (LADCA) approach for the end nodes is also proposed. The objective is to balance the tradeoffs among energy-efficiency, delay requirement, accuracy and buffer overflow probability. It provides a method of adjusting measurement accuracy related parameters at the source nodes, in order to allow the system to adapt to the changing conditions.

It should be noted that in the literature the study of QoS guarantee in sensor networks is usually focused on the routing protocols tailored to meet the requirements (e.g. [24, 37, 62,63]), while in this chapter the emphasis is placed on the study of localized data collection and aggregation strategies that should be implemented at each individual sensor node in a distributed fashion, which is complementary to the applied QoS routing protocols, and can enhance the capability of QoS guarantee in sensor networks.

4.2 QoS-constrained Data Aggregation and Processing (Q-DAP) at Intermediate Nodes

The proposed Q-DAP approach aggregates data on the fly at intermediate sensor nodes, while satisfying the latency and measurement quality constraints with energy-efficiency. One of the main principles of the proposed schemes is that the network does not need to be formed into clusters to perform the data aggregation, while the task QoS requirements are taken into account to determine when and where to perform the aggregation in a distributed fashion, based on the availability of local only information.

In the following it is assumed that when a sensor node receives a packet or message from its neighbor, it is able to either perform local processing and aggregation or just forward (relay) it, according to the QoS requirements of the corresponding applications. Here the procedure that a sensor node locally generates and/or processes a measurement packet in which new data may be aggregated is referred to as reporting, while the corresponding new/updated packet is referred to as a report.

4.2.1 Q-DAP Approach

The operation of the Q-DAP approach can be described as follows. When a sensor node receives a report from its neighbor, it first determines whether or not it would perform data aggregation on the report. The following different cases may occur. a) If the delay constraint can be satisfied, the sensor node defers the report for a fixed time interval τ with probability γ, during which the node processes and aggregates any reports that arrive, and generates a new report before transmitting it to the next hop. With probability of $(1-\gamma)$ the sensor node will directly try to forward the report without introducing any deferred period. b) If the delay constraint can be satisfied only if the report is not deferred, the sensor node simply tries to forward this report to the next hop. c) If the delay constraint cannot be satisfied in any case, the sensor node will discard the report, to avoid further wasting of any additional resources.

In this chapter, the considered end-to-end QoS constraint is the end-to-end latency requirement D of a report, that may aggregate other data or reports along its path from the source to the collector center. If the report is delivered to the collector center within the given latency constraint D after its initial generation, it will be considered as a successful delivery. At intermediate nodes, the delay from the origination of a report to the intermediately receiving of the report is checked, and the report will be discarded if the delay is larger than the requirement D. The actual procedure of performing this check and making the appropriate decision is an implementation specific issue. For instance, assuming that the nodes can be synchronized, time stamps can be added in the packets and the intermediate nodes can calculate the delay between the current time and the time when the packets are generated, and then compare this delay with the delay constraint to determine whether to discard or forward the packet. Alternatively a time to live field, with an initial value equal to each packet's delay requirement can be used, which will be reduced appropriately as the packet is forwarded through other nodes towards the collector center.

It should be also noted that at a sensor node, for a received report, in addition to the possible deferred period τ, there is some additional waiting time caused by the transmission of the previous report at the node. The relation between these delays depends actually on the traffic load and system conditions, and is linked to the performance of the data aggregation process. The energy-efficiency that is achieved via aggregation during the deferred periods along the transmission path, is mainly due to the traffic reduction that is achieved by the data aggregation. In some cases under light load the end-to-end delay may increase due to the introduction of the deferred period τ, since some packets that otherwise could have been transmitted, may have to wait for the aggregation. However, as the traffic load increases, in a system without data aggregation the network becomes congested and the waiting time at each node becomes the dominant factor. Since in principle the waiting time is significantly affected by the network load, performing data aggregation and thus reducing the network traffic load, will result in reduction of the end-to-end delay in the sensor network. In the proposed algorithm, γ and τ are configurable system parameters, and their actual impact on the achievable system performance is analyzed and studied in detail later in this chapter.

4.2.2 Data Aggregation Modeling

It is assumed that by using proper routing mechanisms, each report goes through each node only once, and nodes always forward the report to other nodes that are closer to the collector center. Therefore, assuming that l nodes are visited from the source node to the collector center, denote the set of these sensor nodes as $G_l = \{s_1, s_2, ..., s_l\}$. Without loss of generality it is also assumed that the distances between the sensor nodes and the collector site are arranged in decreasing order, i.e., $d_1 > d_2 > ... > d_l$, where d_i is the distance between node s_i and the collector center.

Let us also denote by $t_i^{(R)}$ the reporting time at node s_i which includes the time period for data aggregation, by $t_i^{(F)}$ the forwarding time at node s_i to next node s_{i+1} which accounts for the transmission time including the potential retransmission time due to channel contention (this time is related to the report length, the bandwidth and the communication success probability), and by $t_i^{(P)}$ the propagation time from node s_i to next node s_{i+1} which depends on the distance between the two nodes. Time periods $t_i^{(R)}$, $t_i^{(F)}$ and $t_i^{(P)}$ are random variables and in the following their corresponding probability density functions (pdf) are denoted by $f_i^{(R)}(t)$, $f_i^{(F)}(t)$ and $f_i^{(P)}(t)$, respectively. Let us denote by t_i the time interval between the point that node s_i receives a report to the point that this report is delivered to node s_{i+1}. If node s_i does not perform data aggregation the corresponding time interval is $t_i^{(F)} + t_i^{(P)}$; otherwise, the time interval is $t_i^{(R)} + t_i^{(F)} + t_i^{(P)}, i \geq 1$, i.e.,

$$t_i = \begin{cases} t_i^{(R)} + t_i^{(F)} + t_i^{(P)}, & \text{with reporting} \\ t_i^{(F)} + t_i^{(P)}, & \text{without reporting,} \end{cases}$$

and its pdf is denoted by $f_i(t)$. Under the assumption that a sensor node performs reporting with probability γ, then

$$\begin{aligned} f_i(t) &= f_i\,(t|\text{with reporting})\,\gamma \\ &\quad + f_i\,(t|\text{without reporting})\,(1-\gamma). \end{aligned}$$

Let us also assume that the time periods are independent of each other, and denote by $F_i^{(R)}(s)$, $F_i^{(F)}(s)$ and $F_i^{(P)}(s)$ the Laplace transforms of $f_i^{(R)}(t)$, $f_i^{(F)}(t)$ and $f_i^{(P)}(t)$, respectively. Applying the Laplace transform to $f_i(t)$, then

$$\begin{aligned} F_i(s) &= E[e^{-st_i}] = \int_0^{\infty} f_i(t)e^{-st}dt \\ &= F_i^{(F)}(s) \cdot F_i^{(P)}(s) \cdot \left[\gamma F_i^{(R)}(s) + (1-\gamma)\right]. \end{aligned} \tag{4.1}$$

In the following, first assume that no reports will be discarded due to the delay constraint, and obtain the end-to-end delay distribution, which can be used to obtain the probability P_{succ} that the report is delivered to the collector center within the delay constraint D. Then the probability that the report is discarded due to unsatisfactory end-to-end delay performance can be obtained as $(1 - P_{succ})$. Denote the end-to-end delay of a report by $T_L = \sum_{i=1}^{L} t_i$ and its corresponding pdf by $f_{T_L}(t)$, where the random variable L is the number of hops that are involved in the transmission of a report from the source node to the collector center (including the source node). Thus, the Laplace transform of $f_{T_L}(t)$, denoted by $F_{T_L}(s)$, is given by

$$\begin{aligned} F_{T_L}(s) &= E[e^{-s(t_1+t_2+\ldots+t_L)}] \\ &= \sum_{l=1}^{N} E[e^{-sT_L}|L=l]\Pr[L=l] \\ &= \sum_{l=1}^{N} p_L(l) \prod_{i=1}^{l} F_i(s), \end{aligned} \tag{4.2}$$

where $p_L(l)$ is the probability mass function of L, where the random variable L represents the number of hops that are involved in the transmission of the report from the source node to the collector center (including the source node). The pdf of T_L can be obtained by using the inverse Laplace transform of $F_{T_L}(s)$, i.e.,

$$\begin{aligned} f_{T_L}(t) &= \mathcal{L}^{-1}\{F_{T_L}(s)\} \\ &= \sum_{l=1}^{N} p_L(l)\mathcal{L}^{-1}\left\{\prod_{i=1}^{l} F_i(s)\right\}. \end{aligned} \tag{4.3}$$

When $f_{T_L}(t)$ is obtained, the successful probability P_{succ} that a report can reach the collector center within the delay constraint D is given by

$$P_{succ} = P[T_L \leq D] = \int_0^D f_{T_L}(t)dt. \tag{4.4}$$

4.2.3 End-to-End Delay Distribution Under Poisson Report Arrivals

In this subsection, it is assumed that the report arrival at each sensor node follows Poisson process with arrival rate λ, therefore, the report interarrival time X is exponentially distributed, i.e., $p_X(t) = \lambda e^{-\lambda t}, t \geq 0$. Also assume that $t_i^{(F)}$ and $t_i^{(P)}$ are exponentially distributed with parameter λ_1 and λ_2, respectively. In the sequel the node index of $t_i^{(R)}$, $t_i^{(F)}$ and $t_i^{(P)}$ are suppressed for notational convenience. There are two possible operations (cases) to handle a report at a sensor node: case 1: directly forward the report without using a deferred period (this happens with probability $1 - \gamma$); and case 2: wait for a deferred period τ to perform aggregation (this happens with probability γ). In the following the delay distribution is studied by analyzing these two different cases.

Case 1 A sensor node does not use a deferred period τ to perform data aggregation.

In this case, when a report arrives, if the system is idle, there is no waiting time for the report to be forwarded; otherwise, it has to wait for the previous report to finish its transmission and therefore some additional waiting time is introduced. Denote by p_1 the probability that upon its arrival a report finds that another report is still in transmission, then

$$P[t^{(R)} \leq t] = P[t^{(R)} \leq t|\, idle](1 - p_1) + P[t^{(R)} \leq t|busy]p_1,$$

where

$$p_1 = \int_0^\infty P[t^{(F)} > x]p_X(x)dx = \int_0^\infty e^{-\lambda_1 x}\lambda e^{-\lambda x}dx = \frac{\lambda}{\lambda_1 + \lambda}.$$

Since

$$\begin{aligned} P[t^{(R)} &> t|busy] = P[t^{(R)} > t|t^{(F)} > X] = \int_0^\infty P[t^{(R)} > t|t^{(F)} > x]p_X(x)dx \\ &= \int_0^\infty P[t^{(F)} > t + x|t^{(F)} > x]p_X(x)dx = \int_0^\infty P[t^{(F)} > t]p_X(x)dx = e^{-\lambda_1 t} \end{aligned}$$

and $P[t^{(R)} \le t|\ idle] = 1$, then

$$P[t^{(R)} \le t] = \begin{cases} 0, & t < 0 \\ (1 - p_1) + p_1 \left[1 - e^{-\lambda_1 t}\right] & t \ge 0. \end{cases}$$

Therefore, the corresponding pdf is given by

$$f^{(R)}(t) = (1 - p_1)\delta(t) + p_1\lambda_1 e^{-\lambda_1 t}u(t). \qquad \text{(without deferred period)} \qquad (4.5)$$

Case 2 A sensor node uses deferred period τ to perform data aggregation.

In this case, when a report after the deferred period τ finds the system idle, the waiting time is 0; otherwise it has to wait for the end of the transmission of the previous report. Let us denote by p_2 the probability that after deferred period τ, a report finds the previous report still in transmission, then

$$p_2 \equiv P[\text{busy after deferred period } \tau] = \frac{\lambda}{\lambda_1 + \lambda} e^{-\lambda_1 \tau}.$$

Similar to case (1),

$$P[t^{(R)} > t|\text{busy after deferred period } \tau] = P[t^{(R)} > t|t^{(F)} > X + \tau] = e^{-\lambda_1 (t-\tau)}.$$

Therefore, the distribution function of the reporting (which includes the waiting time) is given by

$$P[t^{(R)} \le t] = \begin{cases} 0, & t < \tau \\ (1 - p_2) + p_2 \left[1 - e^{-\lambda_1 (t-\tau)}\right] & t \ge \tau, \end{cases}$$

and the pdf is

$$f^{(R)}(t) = (1-p_2)\delta(t-\tau) + p_2\lambda_1 e^{-\lambda_1(t-\tau)}u(t-\tau) \qquad \text{(with deferred period } \tau\text{).} \tag{4.6}$$

Since in the proposed Q-DAP approach a node chooses to defer for a period τ with probability γ, the Laplace transform of $f_i(t)$ can be obtained as follows

$$\begin{aligned} F_i(s) &= (1-\gamma)\frac{\lambda_1\lambda_2}{(s+\lambda_1)(s+\lambda_2)}\left[(1-p_1)+p_1\frac{\lambda_1}{(s+\lambda_1)}\right] \\ &\quad +\gamma\frac{\lambda_1\lambda_2}{(s+\lambda_1)(s+\lambda_2)}\left[(1-p_2)+p_2\frac{\lambda_1}{(s+\lambda_1)}\right]e^{-s\tau} \\ &= \frac{B_1+B_4\cdot e^{-s\tau}}{(s+\lambda_1)(s+\lambda_2)} + \frac{B_2+B_3\cdot e^{-s\tau}}{(s+\lambda_1)^2(s+\lambda_2)}, \end{aligned} \tag{4.7}$$

where

$$\begin{aligned} B_1 &= (1-\gamma)(1-p_1)\lambda_1\lambda_2, \quad B_4 = \gamma(1-p_2)\lambda_1\lambda_2\,, \\ B_2 &= (1-\gamma)p_1\lambda_1^2\lambda_2, \quad B_3 = \gamma p_2\lambda_1^2\lambda_2. \end{aligned}$$

Thus, the Laplace transform of the pdf of the end-to-end delay for l-hop transmission is

$$\begin{aligned} \prod_{i=1}^{l} F_i(s) &= \left(\frac{B_2+B_3\cdot e^{-s\tau}}{(s+\lambda_1)^2(s+\lambda_2)} + \frac{B_1+B_4\cdot e^{-s\tau}}{(s+\lambda_1)(s+\lambda_2)}\right)^l \\ &= \sum_{k=0}^{l}\binom{l}{k}\frac{(B_2+B_3\cdot e^{-s\tau})^k(B_1+B_4\cdot e^{-s\tau})^{l-k}}{(s+\lambda_1)^{l+k}(s+\lambda_2)^l} \\ &= \sum_{k=0}^{l}\binom{l}{k}\sum_{h=0}^{k}\binom{k}{h}\sum_{n=0}^{l-k}\binom{l-k}{n}\frac{B_1^{l-k-n}B_4^nB_2^{k-h}B_3^he^{-s\tau(n+h)}}{(s+\lambda_1)^{l+k}(s+\lambda_2)^l} \end{aligned} \tag{4.8}$$

Using the partial fraction decomposition [64], (4.8) can be rewritten as

$$\begin{aligned} \prod_{i=1}^{l} F_i(s) &= \sum_{k=0}^{l}\binom{l}{k}\sum_{h=0}^{k}\binom{k}{h}\sum_{n=0}^{l-k}\binom{l-k}{n}B_1^{l-k-n}B_4^nB_2^{k-h}B_3^h\,\cdot \\ &\quad e^{-s\tau(n+h)}\left[\sum_{j=0}^{l+k-1}\frac{A_{1j}}{(s+\lambda_1)^{l+k-j}} + \sum_{j=0}^{l-1}\frac{A_{2j}}{(s+\lambda_2)^{l-j}}\right]. \end{aligned}$$

where

$$A_{1j} = (-1)^j \binom{l+j-1}{j} \frac{1}{(\lambda_2 - \lambda_1)^{l+j}},$$

$$A_{2j} = (-1)^j \binom{l+k+j-1}{j} \frac{1}{(\lambda_1 - \lambda_2)^{l+k+j}}$$

Therefore, the pdf of the end-to-end delay when the number of hops is l can be obtained by taking the inverse Laplace transform of (4.8).

$$\begin{aligned} F_{T_l}(t) &\equiv \mathcal{L}^{-1}\left\{\prod_{i=1}^{l} F_i(s)\right\} \\ &= \sum_{k=0}^{l} \binom{l}{k} \sum_{n=0}^{l-k} \binom{l-k}{n} B_1^{l-k-n} B_4^n \sum_{h=0}^{k} \binom{k}{h} B_2^{k-h} B_3^h \cdot \\ &\quad \left[\sum_{j=0}^{l+k-1} \frac{A_{1j}(t-\tau(n+h))^{l+k-j-1}}{(l+k-j-1)!} e^{-\lambda_1(t-\tau(h+n))} \right. \\ &\quad \left. + \sum_{j=0}^{l-1} \frac{A_{2j}(t-\tau(n+h))^{l-j-1}}{(l-j-1)!} e^{-\lambda_2(t-\tau(h+n))} \right] u(t-\tau(n+h)). \end{aligned} \tag{4.9}$$

From (4.9) the pdf of T_L can be obtained

$$f_{T_L}(t) = \sum_{l=1}^{N} p_L(l) F_{T_l}(t). \tag{4.10}$$

In this subsection, the pdf of T_L is derived under the assumption that the report arrival process is Poisson, while $t_i^{(F)}$ and $t_i^{(P)}$ are exponentially distributed. However, it is difficult to obtain an analytical expression for P_{succ} in practice, since the distribution of T_L is generally unknown. In the next subsection the lower-bound of the probability P_{succ} is investigated.

4.2.4 Lower Bound on P_{succ}

The end-to-end delay of an independent report that meets the delay constraint and passes through l hops can be represented by

$$T_l = \sum_{i=1}^{l} t_i^{(R)} + \sum_{i=1}^{l} t_i^{(F)} + \sum_{i=1}^{l} t_i^{(P)} \leq D, \tag{4.11}$$

where in general $t_i^{(F)}$ can be upper-bounded based on the largest report length and the corresponding data rate of the sensor network, and $t_i^{(P)}$ can be upper-bounded by the range of the sensor network and the longest distance between two sensor nodes. Thus, D can be decomposed as

$$D = D_r(l) + D_f(l) + D_p(l), \tag{4.12}$$

where $D_r(l)$, $D_f(l)$, and $D_p(l)$ are the upper bounds on the end-to-end reporting time, forwarding time and propagation time, respectively, when the report needs to be delivered to the collector center using l hops. As a result, in our study the constraint that needs to be satisfied regarding the reporting time can be represented as

$$\sum_{i=1}^{l} t_i^{(R)} \leq D_r(l). \tag{4.13}$$

Noted that $t_i^{(R)}$ is a function of τ and γ, and (4.13) provides a worst-case bound on the reporting time under the constraint (4.11). Therefore, the lower bound on the probability $p_{succ}(l)$ that a specific independent report is delivered to the collector center within the end-to-end constraint, when the distance between the source node and the collector center is l hops, is lower-bounded by

$$p_{succ}(l) = P[S_L(t) < D | L = l] \geq P(\sum_{i=1}^{l} t_i^{(R)} \leq D_r(l)). \tag{4.14}$$

Thus the probability of success P_{succ} under delay constraint (4.11) is lower-bounded by

$$P_{succ} = \sum_{l=1}^{N} p_L(l) p_{succ}(l) \geq \sum_{l=1}^{N} p_L(l) P(\sum_{i=1}^{l} t_i^{(R)} \leq D_r(l)). \tag{4.15}$$

Note that (4.15) provides a lower bound to the probability of a successful report delivery within the QoS constraint for sensor networks with and without data aggregation schemes. When $\gamma = 0$, P_{succ} is reduced to the probability of a successful delivery in a sensor network without any data aggregation scheme, in which each received report will be forwarded as is (without any deferred period). Since the QoS routing algorithm deployed in the sensor network is independent of the proposed Q-DAP approach, it can be assumed that if there is no data aggregation scheme deployed in the sensor network, the report can be delivered to the collector center within its end-to-end delay constraint D, through the use of the deployed routing algorithm. Otherwise the sensor node will not participate in the specific measurement task. That is, assuming $P_{succ,non-aggregation} = 1$. Furthermore, it is assumed that under the Q-DAP approach, the generated reports will follow the same path as in the case without data aggregation.

In the Q-DAP approach, if data aggregation is not performed at node i, the reporting time $t_i^{(R)} = 0$ while if data aggregation is performed with probability γ, $t_i^{(R)} = \tau$. It is clear that the longest delay that a report may experience due to data aggregation is $l\tau$, when the number of hops between the source to the collector center is l. If $l\tau \leq D_r(l)$, the end-to-end delay can be guaranteed even if at each node data aggregation is performed, i.e., $\gamma = 1$. Thus $p_{succ}(l) = 1$ when $l\tau \leq D_r(l)$. When $l\tau > D_r(l)$, if all the intermediate nodes perform data aggregation and reporting with a deferred period τ, the end-to-end delay of a report may exceed the delay constraint. The maximum number of data aggregation and reporting that can be performed to guarantee the delay constraint, determined by the upper bound on the reporting time $D_r(l)$, is given by

$$C(l) = \lfloor \frac{D_r(l)}{\tau} \rfloor. \tag{4.16}$$

That is, the lower bound of P_{succ} is equal to the probability that a report experiences at most $C(l)$ times of data aggregations and reporting along its path. Therefore, the probability

$p_{succ}(l)$ is lower-bounded by

$$p_{succ}(l) \geq p_{succ}^{(LB)}(l) \triangleq \begin{cases} \sum\limits_{k=0}^{C(l)} \binom{l}{k}\gamma^k(1-\gamma)^{l-k}, & C(l) < l \\ 1, & C(l) \geq l. \end{cases} \tag{4.17}$$

Consequently, the probability of success P_{succ} under delay constraint is lower-bounded by

$$P_{succ} \geq P_{succ}^{(LB)} \triangleq \sum_{l=1}^{N} p_L(l)p_{succ}^{(LB)}(l). \tag{4.18}$$

4.2.5 Numerical Results and Discussions

In the remaining of this section, based on the developed models, the impact of parameters γ and τ on the data aggregation model and the performance of Q-DAP algorithm is studied. Among the objectives is to identify the various trade-offs that these parameters present, in order to provide guidelines to choose the appropriate values of these design parameters that achieve the desired performance. In the following, let us consider a sensor network where the sensor nodes are uniformly distributed in a disk area with radius R, and each node has a fixed limited transmission range r, as shown in Figure 4.1. It is assume that each node always transmits a report as far as possible within its transmitting range. Therefore, the maximum number of hops is $M = \lceil \frac{R}{r} \rceil$. If the total number of sensor nodes N is large, the probability $p_L(l)$ can be approximated by

$$p_L(l) = \begin{cases} \frac{2l-1}{M^2}, & 1 \leq l \leq M \\ 0, & l > M. \end{cases} \tag{4.19}$$

Let us assume the report arrival process at each sensor node follows Poisson distribution with rate λ.

In the first numerical example presented here, our objective is to demonstrate how the lower bound approximation of P_{succ}, given by (4.18), is affected by different values of γ and τ. Specifically, Figure 4.2 shows the lower bound $P_{succ}^{(LB)}$ for different values of γ and τ, for the case with $\lambda = 20$, $M = 20$, and $D_r(l) = 2$ seconds. It can be seen from this figure

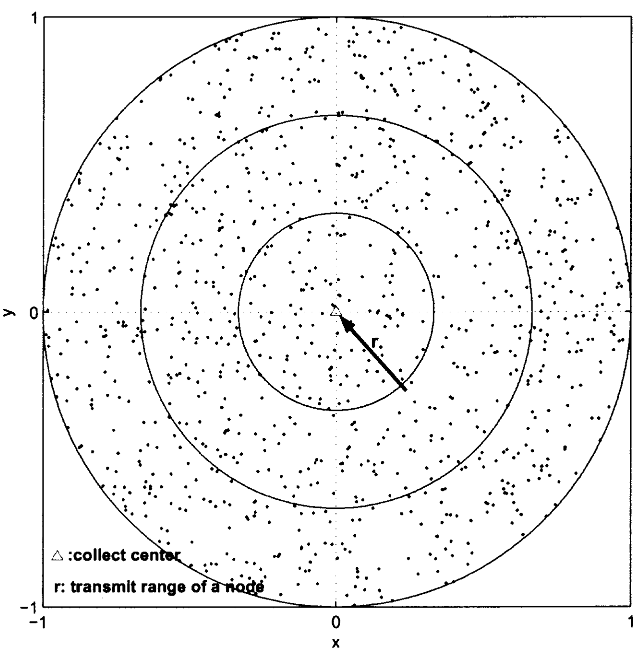

Figure 4.1 A sensor network with uniformly distributed nodes.

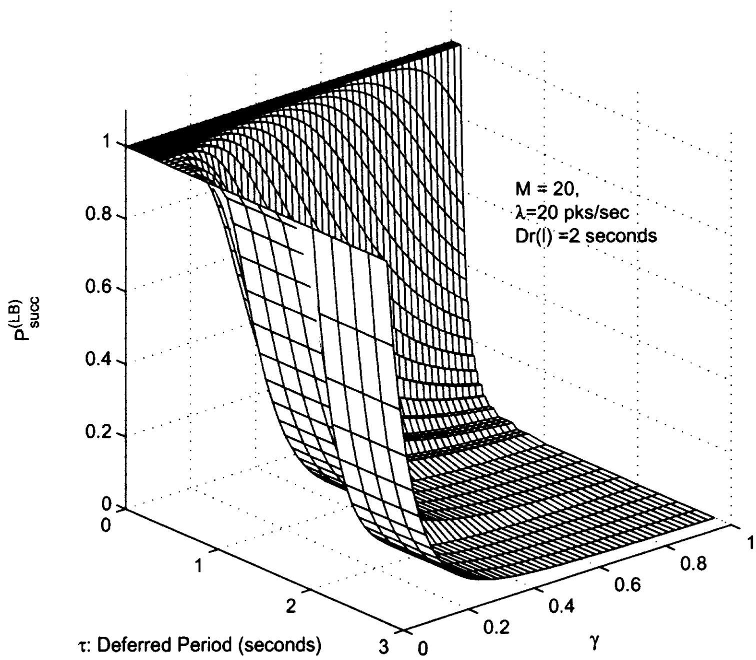

Figure 4.2 Probability of successful report delivery as a function of γ and τ.

that $P_{succ}^{(LB)}$ decreases with γ and τ, since larger values of γ will result in more frequent data aggregation and reporting during the delivery of the report, and larger values of τ will increase the end-to-end delay. As these values both increase, there is higher probability that the end-to-end delay is larger than the constraint, which results in the decrease of P_{succ}.

As shown before, expression (4.18) provides a simple lower bound on the successful report delivery probability P_{succ}. In the following the relation between this lower bound approximation and the actual value of P_{succ} is discussed and evaluated. In Figure 4.3 the curves of the corresponding probabilities are plotted as functions of the deferred period τ, for a sensor network with $M = 10$, $\lambda = 20$, and $\gamma = 0.5$. In this figure the lower bound approximation $P_{succ}^{(LB)}$ is obtained by using (4.17) and (4.18), and the actual P_{succ} is obtained from (4.4) and (4.10) for Poisson report arrivals. In this figure four different curves are plotted, which represent the corresponding probabilities for delay constraints $D = 4$ and $D = 2$ seconds respectively. Correspondingly in the lower bound calculation, it is assumed [1] that $D_r(l) = 3.4$ and $D_r(l) = 1.4$. The results in Figure 4.3 demonstrate that, in general smaller D will result in lower P_{succ}, while the lower bound approximation demonstrates similar trend with the actual performance of P_{succ}. Based on these results it can be concluded that $P_{succ}^{(LB)}$ provides an accurate lower bound approximation of the probability of successful report delivery for all values of τ.

As can be seen from the above discussions, for a given sensor network with specific delay requirement D, P_{succ} depends on parameters τ, γ and the arrival rate λ. From Figures 4.2 and 4.3 it becomes clear that in order to meet the required quality objectives, there are many different choices for parameters τ and γ, while λ is determined by the nature of the measurement task. Furthermore, it can be noted that if a report is deferred at a node for the time period τ, while no other reports arrive during that period, and as a result

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[1] Since in the calculation of P_{succ} using results in section 4.2.3, $\lambda_1 = 80$ and $\lambda_2 = 10000$, and almost all packets spend less than 0.6 time units for the transmission and propagation through their delivery from the source to the collector center. Thus in the corresponding lower bound approximation, parameters $D_r(l) = 3.4$ and $D_r(l) = 1.4$ are used.

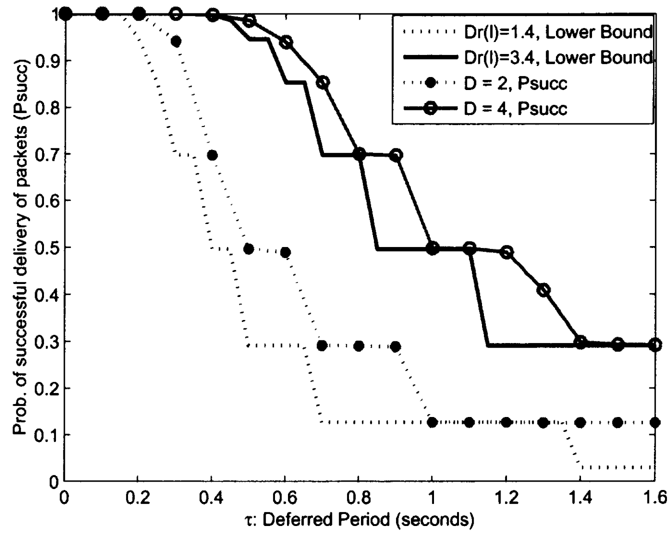


Figure 4.3 Lower bound approximation of P_{succ} ($P_{succ}^{(LB)}$) and actual P_{succ} for $\gamma = 0.5$ and different delay constraints D, as a function of deferred period τ.

no aggregation is actually performed, benefits can not be gained from such an approach, although P_{succ} decreases. In order to enhance the efficiency of the Q-DAP algorithm and maximize its benefits, when determining the optimal τ and γ, P_{succ} can be specified as a QoS requirement of the task or application, together with the delay constraint D. Then the objective function can be to maximize P_{agg}, the probability that a node determines to perform data aggregation and the data aggregation occurs during the deferred period τ. The optimal values of τ and γ can be determined by

$$(\tau_{opt}, \gamma_{opt}) = \arg \max_{P_{succ} \geq P_{req}} (P_{agg}) . \tag{4.20}$$

where P_{req} is the minimum required probability of successful report delivery to the collector center within the end-to-end delay requirement D. When the report arrival process follows Poisson distribution with rate λ, the probability that there is at least one report arrival during the deferred period τ is $1 - e^{-\lambda\tau}$. In this case, the probability that data aggregation occurs during the deferred period τ is given by

$$P_{agg} = \gamma \left(1 - e^{-\lambda\tau}\right). \tag{4.21}$$

Figure 4.4 shows the lower bound $P_{succ}^{(LB)}$, and P_{agg}, for different combinations of τ and γ under the assumption of Poisson report arrivals with $\lambda = 20$. From this figure it is observed that there is a tradeoff between P_{agg} and the probability of successful report delivery, since they follow opposite trends with the change of τ. That is, as τ increases, P_{agg} increases as well - which means that more data will be aggregated in a single report and therefore energy savings will be achieved - while, on the other hand, the probability of successful report delivery decreases. Therefore, if P_{req} is known, the set of (τ, γ) can be selected that can provide the maximum P_{agg}, while the resulting $P_{succ}^{(LB)} \geq P_{req}$. Since $\gamma \in [0, 1]$, from (4.21), P_{agg} has to satisfy $P_{agg} \leq 1 - e^{-\lambda\tau}$. It can be observed that P_{agg} approaches γ and is insensitive to τ for large values of τ. Finally although the objective function considered in this study is the maximization of P_{agg} so that aggregation efficiency can be maximized, other objective functions, such as the maximization of the number of reports aggregated, can be considered, depending on the metrics of interest.

It should be noted that the objective and contribution of the proposed approach and the corresponding models introduced here, is two fold. On one hand, for a system with given design parameters, such as the deferred period τ and the aggregation probability γ, based on the models and the strategies developed, various performance metrics, such as the expected successful report delivery probability and the expected end-to-end measurement delay, can be evaluated. More importantly, on the other hand, given some specific QoS requirements (such as measurement end-to-end delay constraint and successful report delivery probability requirement) imposed by the task/application under consideration, the proposed approach can be used to accordingly adjust the design parameters τ and γ, in order to fulfill the required QoS and achieve the desired objective (e.g. maximize number of reports aggregated, reduce communications overhead, achieve significant energy savings,

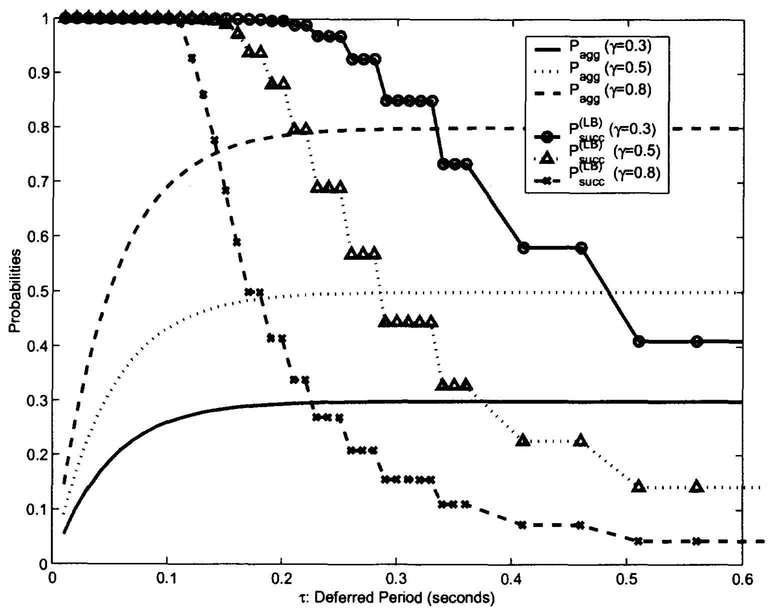


Figure 4.4 The relationship between $P_{succ}^{(LB)}$ and P_{agg}.

extend the sensor network operational lifetime etc.)

4.3 QoS-constrained Data Collection and Aggregation at the End Nodes

It is known and documented in the literature that transmitting or receiving a bit is much more expensive than processing a bit in local CPU [65]. For instance, in Sensoria sensors and Berkeley motes, the ratio of energy consumption for communication and computation is in the range of 1000-10000 [66]. Hence in order to maximize the sensor network lifetime it is expected that the sensor network architecture will converge towards a localized and adaptive approach. In section 4.2 data aggregation at intermediate nodes has been used as an effective way to improve energy efficiency, and its impact on wireless sensor networks has been investigated. However, the process of data collection at end nodes and the impact of this process on energy-efficiency and latency has not yet been exploited. In this section, taking into account that each sensor operates autonomously and without any central control, an adaptive localized algorithm for the data collection and aggregation at the end nodes is introduced, with the objective of balancing the tradeoffs among energy-efficiency, delay requirement, accuracy and buffer overflow probability.

In a sensor network, whenever the sensor nodes measure some environmental variables, the analog signals have to be converted to digital through A/D components, before their transmission. For instance 10-16 bits analog-to-digital conversion can be executed [2, 67]. The sampling rate depends on the bandwidth of the sensed signals and the accuracy requirements. After the sample is collected, the sensor node has to determine when to transmit the data and how frequently the data should be transmitted. It can be easily argued that it is not cost efficient (both from energy and communication point of view) to transmit each sample individually. Compared with the one or two bytes of data for each sample, the corresponding overhead could be very high. For instance, with 26 bytes of the MAC layer header of IEEE802.11, the overhead is over 90%. Therefore, aggregating multiple samples before a transmission occurs can result in significant energy savings. On the other hand the limitation of the buffer size at the individual nodes and the task delay constraints pose different and contradicting design requirements and challenges.

The goal of this section is to investigate and analyze the tradeoffs among several parameters that are involved in the data collocation process, such as delay, energy efficiency, accuracy and buffer overflow. Specifically, a flexible weighted cost function is defined first to balance the tradeoffs of delay, accuracy and energy-efficiency in the data collection process in sensor networks. Furthermore, a localized adaptive algorithm is proposed that balances the afore mentioned design tradeoffs for given QoS requirements at the end nodes. The proposed algorithm provides a method of adjusting the measurement accuracy related parameters at the source nodes based on the communication conditions, as they are observed and interpreted through local only information, in order to allow the system to adapt to the changing conditions.

4.3.1 System Model

The procedure adopted here in order to collect the appropriate samples is described as follows. One sample is collected every T_Δ unit times. However, if at some point the change of the sensed signal is beyond a predefined threshold θ_Δ, a sample is also collected independent of the time. It is also assumed that a sensor node will collect and save a total number of N_s samples before it originates a packet transmission to disseminate this information to the appropriate destination. Based on this data collection procedure the measurement quality or accuracy is determined by parameters θ_Δ and T_Δ. It should be noted that for energy efficiency purposes multiple samples are collected and aggregated together in a single packet.

Intuitively, it can be argued that there is a tradeoff among the various parameters and performance metrics involved in this scenario, such as: N_s, T_Δ, θ_Δ, delay, energy efficiency, and node buffer size. Specifically as N_s or T_Δ increase, the energy efficiency of the data collection and transmission increases, while the corresponding delay and buffer size requirements at each sensor increase as well. On the other hand the accuracy of the collected data increases as θ_Δ and T_Δ decrease. Therefore, an adaptive algorithm that realizes the data collection process by taking into account the system conditions and the task related quality of service requirements (in terms of accuracy, delay, etc.) can be summarized as follows. The initial values of parameters N_s, T_Δ and θ_Δ are first determined according to the delay requirements, the desired accuracy, and certain other criteria. Then based on the communication conditions, as they are expressed and represented by some local measurements (e.g. observed data departure rate μ_e), these parameters may be adjusted according to some desired objectives. One such objective is to adjust the parameters so that the expected probability of buffer overflow is lower than some pre-specified overflow threshold $P_{of,th}$. Figure 4.5 depicts a block diagram that represents this adaptive algorithm for a sensor node.

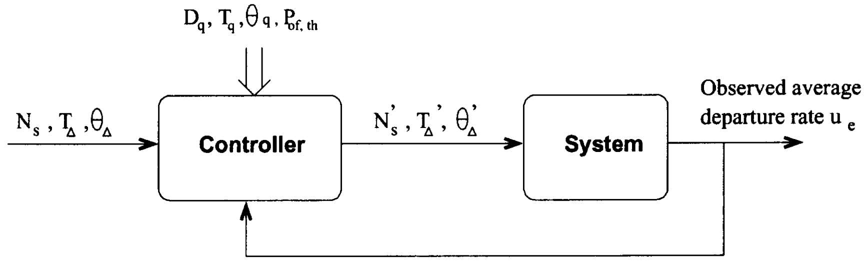


Figure 4.5 Block diagram of adaptive collecting algorithm.

4.3.2 Flexible Cost Function

In order to balance the tradeoffs between the various elements of the data collection process, a general cost function is considered and defined as the summation of the costs of the different elements involved in the overall data collection process, for a given data collection policy π:

$$C_\pi = C(\text{delay}) + C(\text{accuracy}) + C(\text{energy}) + C(\text{others}).$$

The optimal collection policy is selected to minimize the corresponding cost. Weight coefficients can be assigned to control the impact of each part on the total cost. Here the cost components of the delay, accuracy and energy are considered, and will be evaluated quantitatively by utilizing the model provided in section 4.3.1.

Delay

Let us denote by T the time interval from the point that a sample is collected till the point that this sample is successfully transmitted out of the sensor node. If D_q denotes the corresponding average delay requirement, then we need: $E(T) \leq D_q$. The cost of delay is defined as

$$C(\text{delay}) = w_1 \frac{E(T)}{D_q}, \tag{4.22}$$

where w_1 is the weight coefficient of delay. Using the ratio between the average delay and the delay constraint, the QoS requirement (delay) can be taken into account, while at the same time eliminating the effect of the delay units.

Delay T can be divided into two parts. Let T_{ct} be the time interval required to collect N_s samples in order to generate a packet, and T_{st} be the time interval from the point that a packet is ready for transmission till the point that is actually transmitted successfully. Then $T = T_{ct} + T_{st}$. The expected delay $E(T)$ can be obtained when the two delay components are evaluated, respectively.

T_{ct} depends on the sample arrival patterns. Based on the system model described in the previous section, the sample arrival process consists of two components: a periodic arrival process with rate $\frac{1}{T_\Delta}$, and a non-deterministic arrival process which depends on threshold θ_Δ. In the following it is assumed that the latter follows a Poisson distribution with rate $\lambda_s(\theta_\Delta)$. Denoting the random variable of the interarrival time between two consecutive samples as Y, we obtain the probability density function (pdf) of the interarrival time Y as follows:

$$\begin{aligned} f_Y(y) &= [(1-p_s)/T_\Delta + \lambda_s - (1-p_s)\lambda_s y/T_\Delta]\, e^{-\lambda_s y} \cdot \\ &\quad [u(y) - u(y - T_\Delta)] + p_s e^{-\lambda T_\Delta} \delta(y - T_\Delta), \end{aligned} \tag{4.23}$$

where $p_s = \frac{1}{1+\lambda_s T_\Delta}$. Thus we can obtain

$$E(T_{ct}) = \frac{N_s - 1}{2} E(Y) = \frac{(N_s - 1)\, T_\Delta}{2\,(1 + T_\Delta \lambda_s)}. \tag{4.24}$$

T_{st} includes the possible queueing delay as well as the transmission time. In order to obtain T_{st} we need to calculate the queueing delay and take into account the characteristics and behavior of the adopted MAC protocol. The calculation of $E(T_{st})$ is shown for a simplified scenario later in this chapter.

Accuracy

According to the system model, the measurement quality or accuracy is determined by parameters θ_Δ and T_Δ. Let us denote by θ_q and T_q the desired accuracy. That is: $\theta_\Delta \leq \theta_q$

and $T_\Delta \leq T_q$. The cost component of the accuracy is defined as

$$C(\text{accuracy}) = w_2(\frac{\theta_\Delta}{\theta_q} + \frac{T_\Delta}{T_q}). \tag{4.25}$$

Here we also use the ratio between the accuracy parameters and the desired accuracy, in order to take into account the impact of the task requirements on the collection policy.

Energy

It has been argued that in wireless sensor networks the communication dominates the energy consumption. Therefore, here it is assumed that the energy consumption for computation is negligible, and only the energy consumption for data transmission is considered. The energy-efficiency coefficient β_{ef} is defined as :

$$\beta_{ef} = \frac{\text{Energy used to transmit payload}}{\text{Total energy used to transmit both payload and overhead}}, \tag{4.26}$$

In order to evaluate the degree of energy-efficiency, in the cost component that corresponds to the energy, the ratio between the energy consumed to transmit the overhead and that used to transmit the data (payload) is used, other than the absolute value of the energy consumption to transmit a bit. Therefore, the cost of energy is defined as:

$$C(\text{energy}) = w_3 \frac{1 - \beta_{ef}}{\beta_{ef}}. \tag{4.27}$$

Assuming that the average overhead of data packets is L_{ov} bits and the size of a sample is b bits, the energy coefficient is obtained as: $\beta_{ef} = \frac{bN_s}{bN_s + L_{ov}}$. The overhead as defined here includes the control packets and the headers of the data packets. Furthermore, the value of L_{ov} also depends on the retransmission probability and the implementation of the MAC protocol.

4.3.3 Overall Cost and Parameter Optimization

Based on the above discussion and definitions the cost of a data collection policy $C_{\pi(N_s,T_\Delta,\theta_\Delta)}$ is defined as:

$$C_{\pi(N_s,T_\Delta,\theta_\Delta)} = w_1\frac{E(T)}{D_q} + w_2(\frac{\theta_\Delta}{\theta_q} + \frac{T_\Delta}{T_q}) + w_3\frac{1-\beta_{ef}}{\beta_{ef}} \tag{4.28}$$

where w_i, $i = 1,..,3$ are the weights of delay, accuracy (measured by θ_Δ and T_Δ) and energy-efficiency.

Then the optimal values of parameters N_s, T_Δ and θ_Δ can be selected to minimize the above weighted cost, as follows:

$$(N_{s0}, T_{\Delta 0}, \theta_{\Delta 0}) = \arg\min C_{\pi(N_s,T_\Delta,\theta_\Delta)} \tag{4.29}$$

$$E(T) \leq D_q,\ N_s \leq B_{sz}/2b \tag{4.30}$$

$$\theta_\Delta \leq \theta_q,\ T_\Delta \leq T_q \tag{4.31}$$

$$\lambda_s(\theta_\Delta) + 1/T_\Delta < R/b \tag{4.32}$$

where B_{sz} is the buffer size for storing the collected data.

In the following an instance is provided on the optimization of the corresponding parameters. First $E(T_{st})$ will be evaluated. For demonstration purposes first it is assumed that the probability of buffer overflow is very small and therefore the system can be treated as a system with infinite buffer. Later on the buffer size is taken into consideration as well. Since there are two patterns of sample arrivals, one periodic with rate $\frac{1}{T_\Delta}$ and one Poisson with rate λ_s, the system can be viewed as a combination of an $D/G/1$ and an $M/G/1$ system. Thus the average queueing delay $E(W)$ is given by

$$E(W) = p_s E(W_D) + (1-p_s)E(W_M),$$

where W_D and W_M are the corresponding queueing delays of the $D/G/1$ and $M/G/1$ systems, respectively. The service time depends on the transmission rate and the probability of collisions, while the queueing delay can be obtained when the average service time and the second moment of service time are given. Under the assumption that at the beginning no collision occurs and the service time depends only on the transmission rate, denoted by R (bits per unit time), the average data departure rate μ is constant for given N_s, L_{ov} and b:

$$\mu = \frac{N_s R}{bN_s + L_{ov}} \text{ samples/unit time} \tag{4.33}$$

In this case, the average queueing time can be easily obtained. Furthermore:

$$E(T_{st}) = \frac{T_\Delta}{2\,(1 + T_\Delta \lambda_s)} \frac{\lambda_s^2}{\mu\,(\mu - \lambda_s)} + \frac{1}{\mu} \tag{4.34}$$

From (4.33), the data departure rate has to satisfy $\mu < \frac{R}{b}$ and $\lim_{N \longrightarrow \infty} \mu = \frac{R}{b}$, and thus an upperbound of N_s is obtained

$$N_s < 2\left(\frac{1}{T_\Delta} + \lambda_s\right)\left(D_q - \frac{b}{R}\right) - \frac{\lambda_s^2 b^2}{R\,(R - \lambda_s b)}. \tag{4.35}$$

It can be shown that $\lambda_s \propto \frac{1}{\theta_\Delta}$. Therefore, let

$$\lambda_s = \frac{\alpha}{\theta_\Delta}, \alpha > 0. \tag{4.36}$$

For a stable system, $\mu > \lambda_s + \frac{1}{T_\Delta}$ is required, and therefore a lowerbound of N_s can be obtained as follows:

$$N_s > \frac{L_{ov}}{R/\left(\frac{\alpha}{\theta_\Delta} + \frac{1}{T_\Delta}\right) - b}. \tag{4.37}$$

Thus the selection of N_s has to satisfy (4.30), (4.35) and (4.37). In this case relation (4.28) can be expressed as:

$$\begin{aligned} C_{\pi(N_s, T_\Delta, \theta_\Delta)} &= \frac{w_1}{D_q}\left[\frac{T_\Delta}{2\,(1 + T_\Delta \lambda_s)}\left(N_s - 1 + \frac{\lambda_s^2}{\mu\,(\mu - \lambda_s)}\right)\right. \\ &\quad \left. + \frac{1}{\mu}\right] + w_2\left(\frac{\theta_\Delta}{\theta_q} + \frac{T_\Delta}{T_q}\right) + w_3 \frac{L_{ov}}{bN_s}. \end{aligned}$$

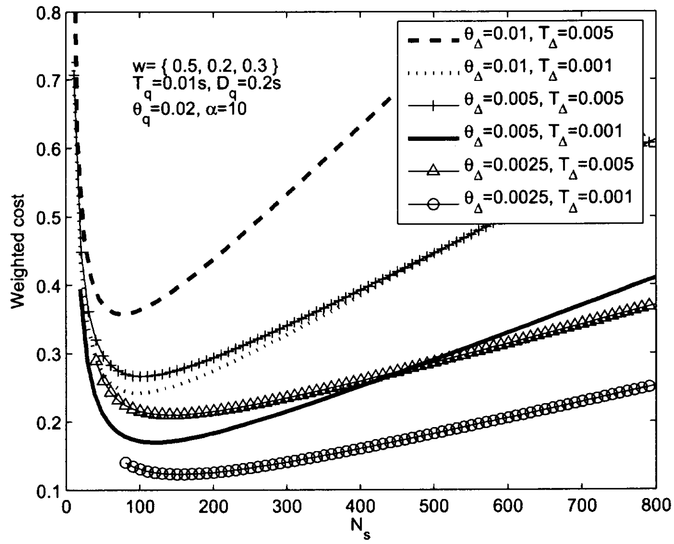


Figure 4.6 Cost as a function of N_s for different T_Δ and θ_Δ values.

In Figure 4.6, the data collection process cost is depicted as a function of N_s for different values of T_Δ and θ_Δ. The corresponding tradeoffs among the various parameters involved in the overall process can also be seen and evaluated by this figure. For a given set of T_Δ and θ_Δ the optimal value of N_s can be identified. For example, given $w = \{0.5, 0.2, 0.3\}$, $b = 16$ bits, $L_{ov} = 320$ bits, $R = 1e5$ bps, $D_q = 0.2$s, $T_q = 0.01$s, $\theta_q = 0.02$ and $\alpha = 10$, the optimal parameters can be selected as $\theta_\Delta = 0.0026$, $T_\Delta = 0.0006$ and $N_s = 182$.

4.3.4 Adaptive Data Collection

When the initial values of parameters (N_s, T_Δ and θ_Δ) are determined as explained above, the sensing nodes will collect data using these parameters. The actual data departure rate is lower than the ideal value μ, since collisions may occur under realistic scenarios (when the network load increases or the channel conditions deteriorate). When the data departure rate decreases, the probability of buffer overflow will increase. The tradeoff that arises here is that we can lower the buffer overflow probability by decreasing the provided accuracy of the sensed variables. By letting μ_e be the actual departure rate, the probability of overflow is:

$$P_{of} = 1 - \frac{\mu_e}{\frac{\alpha}{\theta_\Delta} + \frac{1}{T_\Delta}}.$$

If we denote by $P_{of,\,th}$ the buffer overflow threshold, i.e. $P_{of} \leq P_{of,\,th}$, then an adaptive data collection algorithm, based only on local information, can be described as follows:

- A sensor node periodically checks its current P_{of};
- If $P_{of} > P_{of,\,th}$, increase θ_Δ and T_Δ so that $P_{of} = P_{of,\,th}$ and $\min C^p_{\pi(N_s,T_\Delta,\theta_\Delta)}$;
- If $P_{of} < \eta_1 P_{of,\,th}$, decrease θ_Δ and T_Δ so that $P_{of} = \eta_2 P_{of,\,th}$, $0 < \eta_1 \leq \eta_2 \leq 1$ and $\min C^p_{\pi(N_s,T_\Delta,\theta_\Delta)}$.

Since sensor nodes have only limited computation capabilities, an alternative method to optimize the cost function periodically is to use the initial N_s and find suboptimal values for T_Δ and θ_Δ that satisfy the above requirements of P_{of}.

4.4 Performance Evaluation

In this section the overall performance of the proposed quality-driven data aggregation approach in multi-hop sensor networks is evaluated through modeling and simulation. First, the achievable performance in terms of the end-to-end delay and overall network energy savings is evaluated, under different data aggregation scenarios and traffic loads. Then the impact of several design parameters and tradeoffs on various critical network and application related performance metrics, such as the energy efficiency, network lifetime, end-to-end latency, are also evaluated and discussed. Finally, the impact of LADCA algorithm on the data loss due to the buffer overflow at the end nodes is evaluated as well.

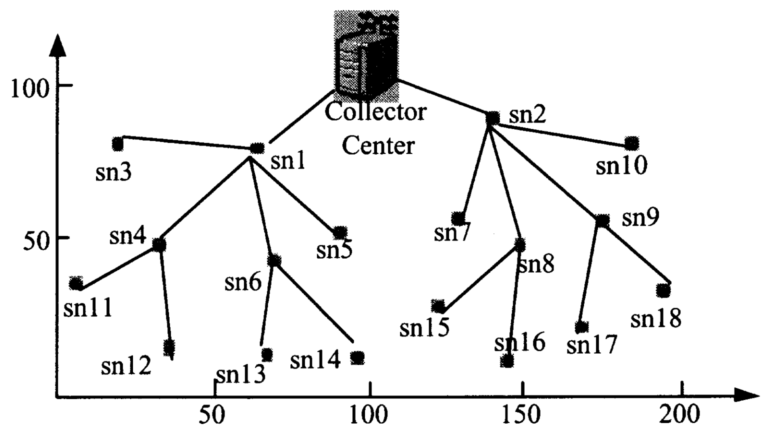


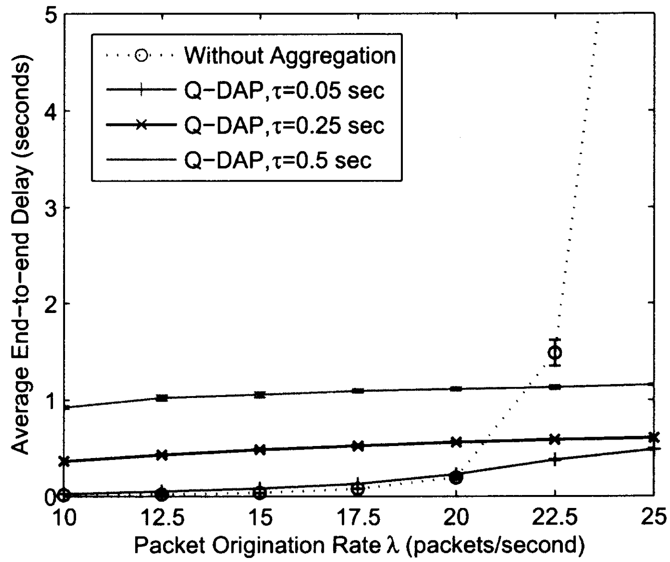
Figure 4.7 The reference multi-hop sensor network for simulations.

4.4.1 Assumptions and Network Reference Topology

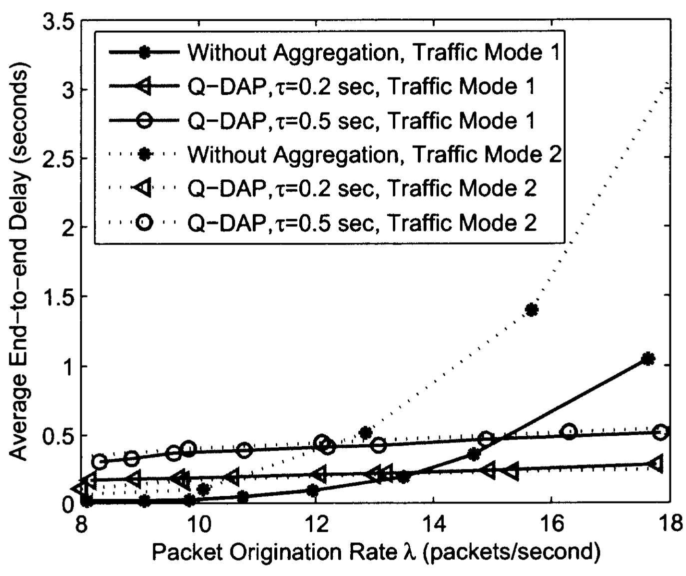
Throughout this study a sensor network consisting of 18 nodes and one collector center, distributed in an $100m \times 200m$ area as shown in Figure 4.7, is considered. In order to better focus on the study of the impact of the Q-DAP approach on the end-to-end delay and the network energy consumption, we assume that the routing paths are predetermined during the whole network operation. The corresponding routes from the individual sensor nodes towards the collector center are identified by the edges between the various nodes as shown in Figure 4.7. The transmission range of each node is assumed to be 50 meters. When a node begins to transmit, all the neighbors within its transmission range will receive the signal, which is considered as interference for a node if the packet is not destined for it. The media access control (MAC) protocol adapted here is CSMA/CA. Rts/Cts messages are exchanged before a data packet is transmitted if the length of the data packets is more than 64 bytes, otherwise the data packet is transmitted without Rts/Cts exchange. The corresponding power consumption of a node under idle/listen, receiving and transmitting modes is assumed to be 1mW, 10mW and 36mW, respectively [57]. Furthermore, we assume that the data transmission rate is 1Mbps. Let us also denote by β the aggregation coefficient, which represents the ratio of the new report length after aggregation and reporting, to the total length of all the received packets/reports before aggregation. i.e., $\beta = \frac{\text{length of packet after aggregation}}{\text{total length of original packets}}$ and $0 < \beta \leq 1$.

4.4.2 End-to-End Delay

In this subsection, we compare the end-to-end delay of the sensor network under the Q-DAP approach with the corresponding results obtained by a system that does not perform any data aggregation. In the following, for demonstration purposes, we assume that the packet length is exponentially distributed with mean 100 bytes, and the aggregation coefficient is considered to be 0.9. In order to compare the achievable delays under different scenarios, we first set the delay constraint D to a very large number, so that there are no packets discarded at the intermediate nodes due to the delay constraint. The corresponding average end-to-end delays, for two different data generation processes at each node, are shown in Figure 4.8. Specifically, in Figure 4.8(a) the data generation at each node follows a Poisson process with rate λ, while in Figure 4.8(b), the data generation follows an ON-OFF bursty process where packets are only generated while the process is in the ON state. For the ON-OFF case we consider two different traffic modes. For traffic mode 1, the duration for which the process stays in the ON and OFF states follows exponential distribution with mean 2 and 8, respectively, while for traffic mode 2, the duration for ON state is uniformly distributed between 1 and 50 and the duration for OFF state is exponentially distributed with mean 50 seconds. It can be seen from these figures that without data aggregation, the delay increases exponentially with the increase of the network load (indicated by λ), while under the Q-DAP approach, the delay increases at a much slower rate, since performing data aggregation reduces the network traffic load significantly. When the network load is light, the delay introduced by the Q-DAP strategy is the dominant factor, due to the fact that the sensor node introduces a deferred period of τ to perform the data aggregation, while the corresponding waiting time at each node is negligible. Therefore, in this case, the delay in the sensor network under the Q-DAP



(a)



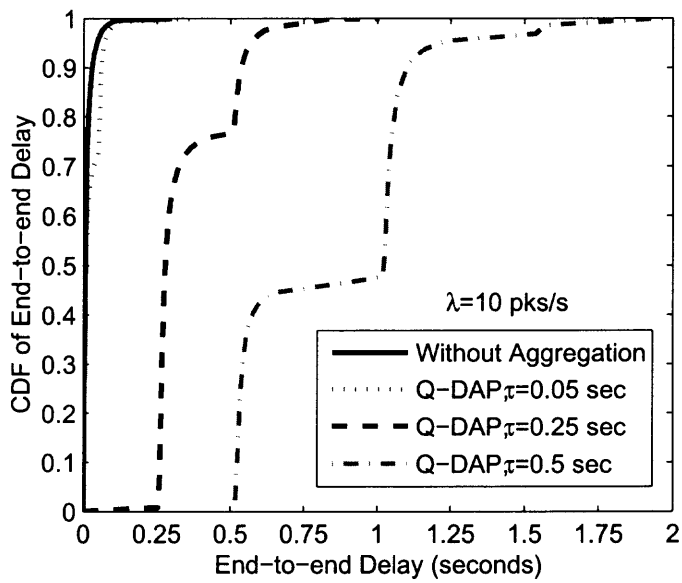
(b)

Figure 4.8 Average end-to-end delay as a function of λ. (a) Poisson packet arrival ($\gamma = 1$). (b) Burst packet arrival ($\gamma = 0.9$).

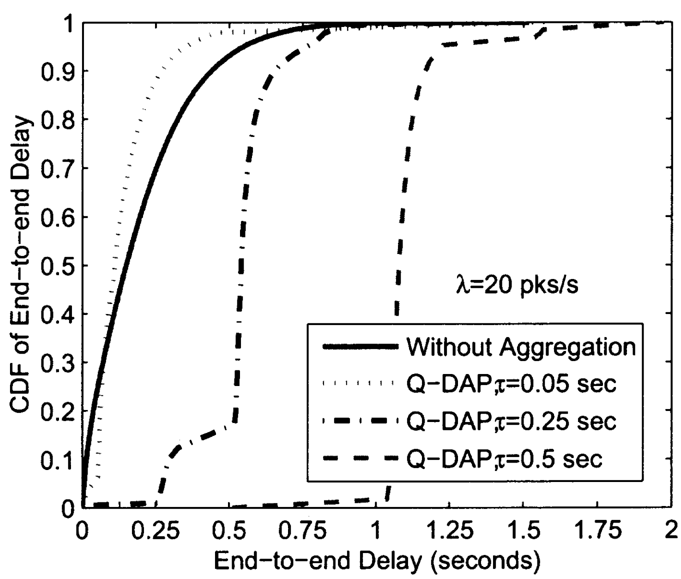
approach is larger than the one that can be achieved by a system without aggregation. However, when the network load increases, the waiting time at each node becomes the dominant factor (as compared to τ). Therefore, since the waiting time is significantly affected by the network load, performing data aggregation can reduce the network traffic load and therefore result in the reduction of the end-to-end delay in the sensor network. Therefore, as we can observe from Figure 4.8, for heavy traffic loads the average end-to-end delay under the Q-DAP is significantly lower than the corresponding delay of a system without any data aggregation.

In Figure 4.9 the corresponding cumulative distribution functions (CDF) of the end-to-end delay are shown for $\lambda = 10$ pks/s and $\lambda = 20$ pks/s. This can be used to estimate the successful report delivery for a system with the delay constraint comparable to the end-to-end delay. For instance, based on this, we can choose a delay constraint of $D = 0.6$ seconds for the system with deferred period $\tau = 0.25$ seconds, and a delay constraint of $D = 1.1$ seconds for $\tau = 0.5$ seconds, and then perform experiments in order to obtain the probability of successful packet delivery and actual packet dropping probability P_{drop}, due to the imposed delay constraint.

The corresponding results are shown in Figure 4.10. For comparison purposes only, we also present the probabilities that the packets arrive at the collector center within a certain end-to-end delay equivalent to the corresponding delay constraints imposed by the Q-DAP, under a strategy that performs data aggregation (similar to Q-DAP) without discarding packets at the intermediate nodes due to any delay constraints (in the following graph we refer to these cases as no-packet-drop). As we expected, the successful packet delivery probability of the system with delay constraint $D = 0.6$ and $D = 1.1$ seconds is better than the estimated probability under the strategy that does not discard any packets due to the delay constraints. This happens because the packets that can not satisfy the imposed delay constraint have been discarded at the intermediate nodes, and therefore the overall traffic has been reduced. Furthermore, as can be observed by this figure, the successful



(a)



(b)

Figure 4.9 Cumulative Distribution Function (CDF) of the end-to-end delay. (a) $\lambda = 10$ packets/second. (b) $\lambda = 20$ packets/second.

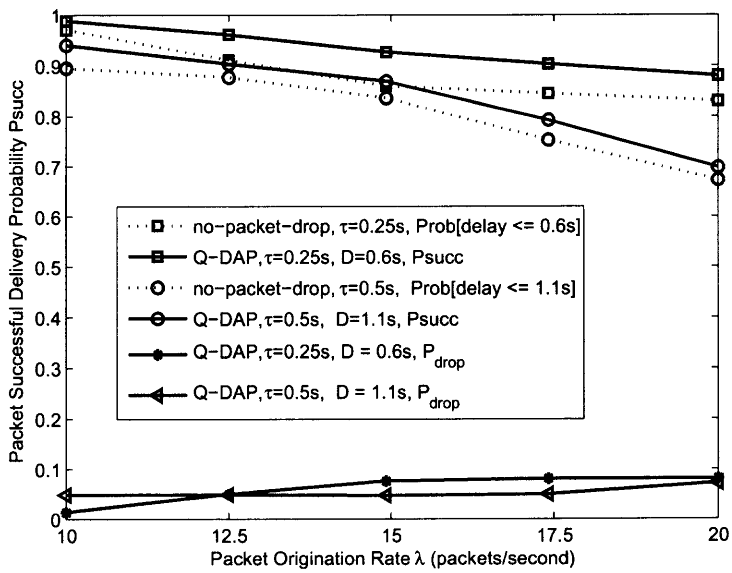


Figure 4.10 Probability of successful packet delivery for different delay constraints.

packet delivery probability increases as τ decreases, however, as we see later this happens at the cost of higher energy consumption.

4.4.3 Energy Efficiency

Since the energy consumption for communications is usually considered as the dominant factor compared to that for data processing [66], the proposed Q-DAP approach will result in lower energy consumption and thus extend the lifetime of the sensor network, due to the resulting reduced communication traffic that is achieved by the data aggregation. Throughout this experiment, the energy consumption for the local data processing and aggregation is set to 0.1 nJ/bit. Figure 4.11 depicts the total energy consumption in the sensor network under four different scenarios. The first one corresponds to the system where no aggregation is performed, while the other three scenarios correspond to implementations of the Q-DAP approach with different deferred period τ. As can be seen from this figure, the Q-DAP approach outperforms the system without data aggregation, and achieves significant energy savings in the sensor network. For instance, when $\lambda = 20$

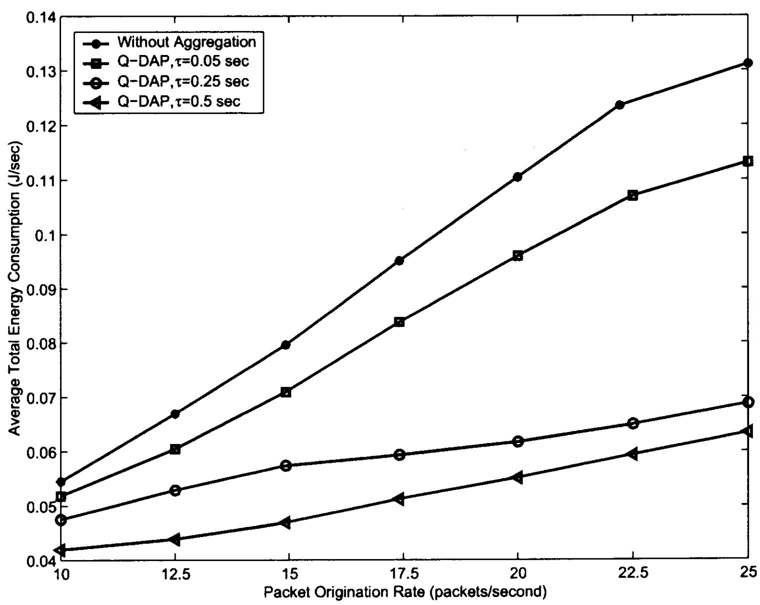


Figure 4.11 Average total energy consumption under various traffic conditions ($\gamma = 1$).

packets/second, the Q-DAP system with $\gamma = 1$ and $\tau = 0.5$ seconds can save around 50% of the total consumed energy when compared to the system without any data aggregation. Furthermore, it can be also observed from this figure that the energy consumption decreases as τ increases, since when τ increases the average number of packets that can be used for data aggregation increases as well (even for the same traffic load λ).

4.4.4 Critical Nodes and Network Lifetime

In a sensor network with large number of small low cost sensor nodes, due to hardware and cost constraints, there exist several limitations on the sensor node transmission range and available energy capacity. In most of the cases the operation of the sensor network is completely disrupted, if and only if all the nodes that can directly communicate with the collector center (e.g. one-hop communication from the collector center) "expire", and as a result the lifetime of these nodes is more critical to the network lifetime [22]. In the following we refer to these nodes as critical nodes. Here we define the network lifetime as the time interval from the point that the sensor network starts its operation until the point

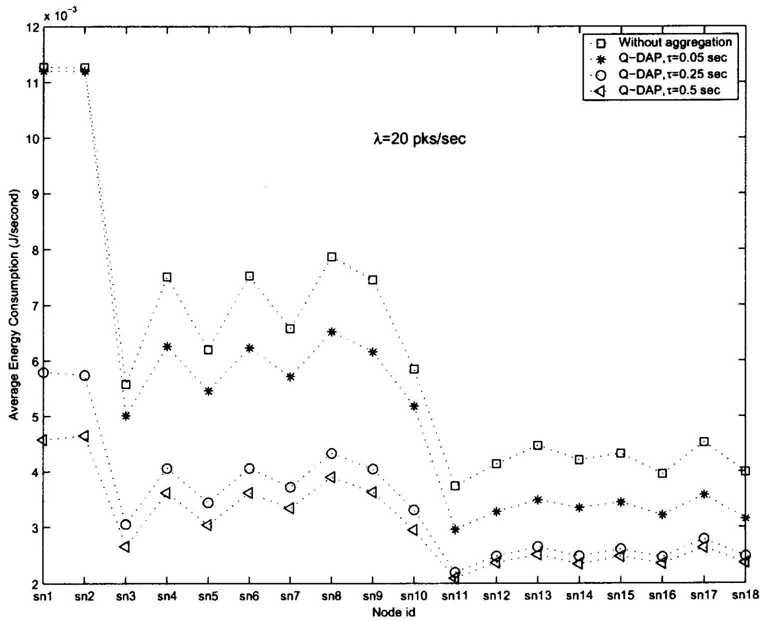


Figure 4.12 Energy consumption rate at each node for λ= 20 packets/second.

where loss of communication to the collector site by all sensor nodes occurs.

With reference to the network topology of Figure 4.7, only nodes $sn1$ and $sn2$ can communicate directly with the collector center, and therefore they are the critical nodes. In this case, according to the definition of the network lifetime presented above, the network lifetime of the reference network equals the maximum lifetime of nodes $sn1$ and $sn2$. The corresponding results regarding the energy consumption of all the sensor nodes, for $\lambda = 20$ packets/second and different values of τ, are shown in Figure 4.12. As it is expected, the energy consumption rates of sensor nodes $sn1$ and $sn2$ are significantly larger than the rest (almost twice the rate of the other nodes).

In order to study the impact of the deferred time τ on the network lifetime, we performed several experiments which correspond to different values of parameter τ, as shown in Table 4.1. Case $\tau = 0$ represents the system without any data aggregation. Specifically, Table 4.1 presents the network lifetime (normalized by the lifetime of a system without any data aggregation for $\lambda = 10$ packets/second) and the corresponding

Table 4.1 Network Lifetime for Different Values of τ

τ (sec.)	Lifetime		delay(sec.)	
	$\lambda = 10$	$\lambda = 20$	$\lambda = 10$	$\lambda = 20$
0	1	0.470	0.009	0.195
0.05	1.097	0.473	0.033	0.196
0.25	1.260	0.922	0.346	0.538
0.5	1.499	1.157	0.834	1.099
1	1.880	1.221	2.093	2.201
2	1.975	1.247	4.296	4.325

average end-to-end delays, under two different traffic loads ($\lambda = 10$ packets/second and $\lambda = 20$ packets/second), for different configurations of parameter τ. From the results presented in this table, we observe that the network lifetime increases as the deferred period τ increases. This happens because the average number of packets that can be used to perform data aggregation increases with τ as well, therefore resulting in reduced communication traffic. We also notice that there exists some value of τ above which the network lifetime increases very slowly as τ increases. For the cases under consideration here, this value is about $\tau = 1$ second for $\lambda = 10$ packets/second and $\tau = 0.5$ second for $\lambda = 20$ packets/second. Furthermore, it can be seen that the average end-to-end delay increases significantly with the increase of τ, and as can be concluded from the results that were presented in Figure 4.10, the larger the parameter τ, the higher the probability that a packet may not be delivered within the delay constraint. Therefore, large values of τ will mainly benefit those tasks with loose delay constraints, while the proper value of τ should be identified so that the lifetime of a network can be extended and most of the packets will be delivered to the collector center within the imposed delay constraint.

The network lifetime may be even further extended by allowing different nodes to

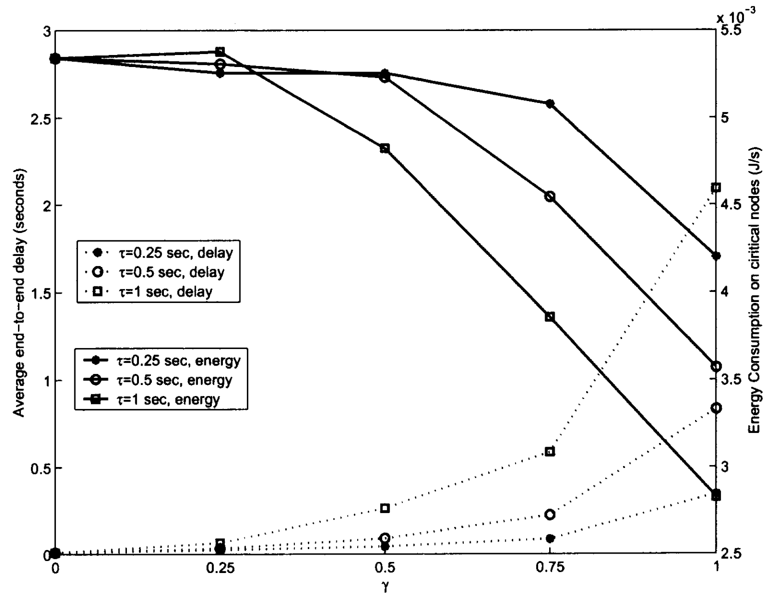


Figure 4.13 Average end-to-end delay and energy consumption for different values of τ.

have different deferred periods. For example, for $\lambda = 20$ packets/second, if we let τ of nodes $sn1$ and $sn2$ be 0, τ of nodes $sn4$, $sn6$, $sn8$ and $sn9$ be 0.5 seconds and τ of the rest of the nodes be 0.25 seconds, the resulting network lifetime is 0.9854, which is longer than the lifetime (0.922) of a system with $\tau = 0.25$ for all nodes, while at the same time it achieves smaller average end-to-end delay (0.35 seconds) than the corresponding delay (0.538 seconds) of the system with $\tau = 0.25$ for all the nodes. The optimal τ configuration depends on the network topology and the traffic pattern and load, and it is part of our current research work.

4.4.5 The Impact of γ

In Figure 4.13, the energy consumption and average end-to-end delay as a function of parameter γ are shown, for $\lambda = 10$ packets/second, $\beta = 0.9$ and $\tau = 0.25$, 0.5 and 1 second, respectively. The results for $\gamma = 0$ correspond to the case that no data aggregation is performed. It can be seen from this figure that as γ increases, the system consumes less energy during the same operation period, while at the same time the average delay increases. So there is also a tradeoff between energy consumption and end-to-end delay. Therefore, the γ provides another adjustable factor for the appropriate design according to the system design requirements and available resources.

4.4.6 Buffer Overflow and Energy Efficiency at End Nodes

In this subsection, the impact of LADCA on the data loss due to the buffer overflow at the end nodes is evaluated and discussed. The data transmission rate is assumed to be $1Mbps$, each sample is 16 bits (i.e. $R = 1\ Mbps$ and $b = 16$), while the buffer size for collected samples is $B_{sz} = 256\ kbits$. For demonstration purposes in the following experiment the sample collection requirements are set to: $T_q = 0.01$, $\theta_q = 0.02$, $\alpha = 10$, $D_q = 0.2$ second. The simulation for each scenario lasts for 1800 seconds, while each simulation scenario is repeated 5 independent times (i.e. each run starts with a different random number seed) and statistical averages are calculated. The initial accuracy related system parameters are selected as $T_\Delta = 0.0005$ and $\theta_\Delta = 0.001$. Figure 4.14 presents the average data loss ratio due to buffer overflow, as a function of the total number of samples N_s that are collected before a packet is generated at the source (end-node), under the proposed adaptive collection algorithm. The results are shown for two different buffer overflow requirements: $P_{of,th} = 0.1, 0.05$.

For comparison purposes the corresponding data loss ratio for a strategy without such adaptation capabilities is also depicted (we refer to this strategy as "without adjustment" strategy). It can be seen by this figure that through the adaptive method introduced by the LADCA approach, the buffer overflow is well controlled and the corresponding data loss due to buffer overflow decreases significantly. Therefore, when the sensor network traffic and conditions change (i.e the network load increases or the channel conditions deteriorate), each end node via the proposed localized adaptive collection approach will attempt to readjust the corresponding measurement related parameters based on the interpretation of local information (e.g. P_{of} and μ_e), in order to balance the tradeoffs between

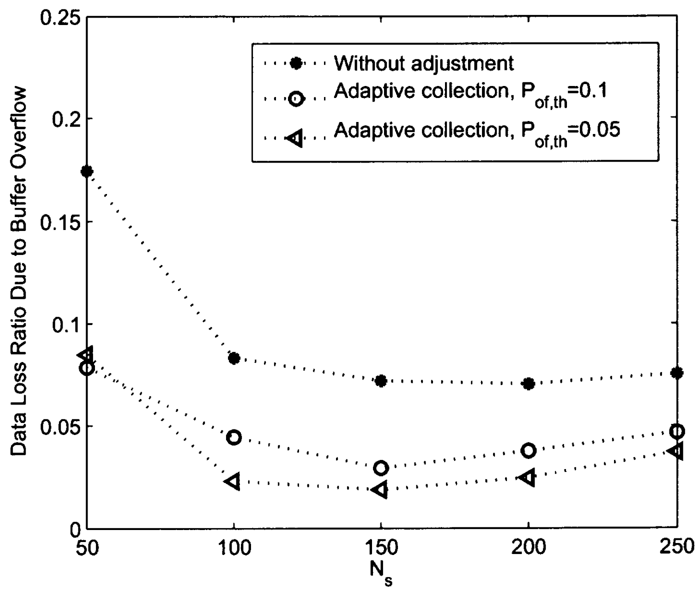


Figure 4.14 Data loss ratio at the end nodes as a function of the number N_s of the aggregated samples.

delay and accuracy, and thus decrease/mimimize the actual data loss.

Furthermore, we observe from this figure that the data loss decreases when the value of N_s increases and after some point the data loss increases as N_s increase both under the adaptive adjustment and the "without adjustment" strategy. This happens because when N_s is small, as the number of collected samples that are aggregated in a single packet for transmission increases, the traffic load injected in the network by each end node as well as the corresponding communication overhead decrease. Therefore, when the network load is heavy the congestion can be reduced and the achievable throughput may improve. However, as N_s keeps increasing the decrease of the overhead becomes slower, while when N_s becomes large the dropped data increases as well once buffer overflow occurs.

4.5 Concluding Remarks

This chapter introduced and analyzed an efficient QoS-constrained data aggregation and processing approach for distributed wireless sensor networks. The proposed approach consists of: a) a QoS-driven data aggregation algorithm (Q-DAP) that aggregates data on the fly at the intermediate nodes in a distributed fashion, therefore reducing the traffic load and the consumed communication energy while at the same time satisfying the latency and measurement quality constraints; and b) an adaptive localized algorithm (LADCA) for the data collection and aggregation at the end nodes, that balances the design tradeoffs of delay, measurement accuracy and buffer overflow, and provides a method of adjusting the measurement accuracy related parameters at the source nodes.

An in-depth evaluation of the proposed approach, under different data aggregation scenarios and traffic loads, was performed via modeling and simulation, and the corresponding numerical results demonstrated the significant performance improvements that can be achieved, in terms of several critical operational metrics, such as energy efficiency, improved network lifetime, reduced traffic load, end-to-end delay etc. In conclusion given some specific QoS requirements imposed by the task/application under consideration, the proposed approach can be used to accordingly adjust the design parameters τ and γ at the intermediate nodes, as well as the measurement accuracy related parameters at the end nodes, in order to fulfill the required QoS, while at the same time achieve significant energy savings and extend the sensor network operational lifetime.

CHAPTER 5

CONCLUSIONS

5.1 Summary and Contributions

It is envisioned that a mobile sensor based communications and processing infrastructure will significantly enhance and facilitate the data gathering, information-based detection, prevention, and response processes, under several scenarios and applications. Networking a set of sensors to empower them with the ability to coordinate on a larger sensing task will revolutionize information gathering and processing in many situations. A certain set of applications require that sensor nodes collectively form an ad hoc distributed processing network and provide information about the environment they monitor. Due to hardware, energy, cost and other physical constraints, sensor-based networks present various design, implementation and deployment challenges. In this dissertation, several issues associated with the energy efficient organization and modeling of dynamic wireless sensor networks were investigated.

Specifically, in Chapter 2, we investigated the design tradeoffs between the connectivity, reliability and power/energy efficiency in wireless ad hoc sensor networks. We first proposed and developed a model to obtain the connectivity distribution for a power limited sensor networking system. Based on this model we investigated the qualitative and quantitative relations between the various involved design parameters and tradeoffs, and studied their impact on the overall system connectivity and reliability. Furthermore, since most of the wireless sensors have limited power resources as they are usually battery-operated, we investigated the power/energy savings that can be obtained by the introduction and use of periodical sleeping strategies. The corresponding numerical results demonstrated and confirmed that if the traffic is low, there is almost always some benefit from the periodical sleeping in all the realistic systems; however if traffic is high, the power conservation could be obtained only under limited conditions, since in order to keep some pre-specified connectivity requirements, the power consumed during transmission increases faster than the power savings due to the use of the sleeping strategy.

Furthermore, since large-scale dynamic sensor networks can be described as time-varying composition of dynamically changing components and entities, additional features such as uncertainty, interaction and collaborations should be considered in the modeling process. Towards that direction, in Chapter 2 we proposed and developed a model that gives a more realistic description of the various processes and their effects as the mobile wireless sensor network evolves. The proposed model stems from the commonality encountered in the mobile sensor wireless networks, their self organizing and random nature, and some concepts developed by the continuum theory. Based on this analytical model we investigated the corresponding connectivity distribution of the sensor network for different scenarios regarding the way that various links are added, rewired or removed. The proposed model and obtained results, facilitate the understanding of the effect of the various events on the large-scale topology in wireless sensor networks.

In Chapter 3, the energy-efficient organization of a randomly deployed multi-hop sensor network was considered, and an analytical model to estimate and evaluate the node and network lifetime was provided. Based on this, a procedure for the creation of an energy efficient sensor network organization, that attempts to extend the lifetime of the communication critical nodes, and as a result the overall network's operation lifetime, is also provided.

In order to meet and fulfil the various task requirements, individual sensor nodes in a distributed sensor network, have to collaborate with each other, and as a result, effective information gathering and dissemination strategies need to be deployed. In order to address this problem, in Chapter 4 of this dissertation, a QoS-constrained data aggregation and processing (Q-DAP) approach was introduced. The proposed method aggregates data on the fly at intermediate sensor nodes, while satisfying the latency and measurement quality constraints with energy efficiency. One of the main features of the proposed approach is that the task QoS requirements are taken into account to determine when and where to perform the aggregation in a distributed fashion. Furthermore, an analytical statistical model was introduced, to represent the data aggregation and report delivery process in sensor networks, with specific delivery quality requirements in terms of the achievable end-to-end delay and the successful report delivery probability. Based on this model some insight is gained about the impact on the achievable system performance, of the various design parameters and the tradeoffs involved in the process of data aggregation and the Q-DAP strategy. Furthermore, a localized adaptive data collection and aggregation (LADCA) approach used at the source nodes was developed. Specifically, a flexible weighted cost function was defined first to balance the tradeoffs of delay, accuracy and energy-efficiency in the data collection process in sensor networks. A localized adaptive algorithm was proposed that balances the afore mentioned design tradeoffs for given QoS requirements at the end nodes. The proposed algorithm provides a method of adjusting the measurement accuracy related parameters at the source nodes based on the communication conditions, as they are observed and interpreted through local only information, in order to allow the system to adapt to the changing conditions. Furthermore the simulation results presented in this dissertation demonstrated the effectiveness and efficiency of the proposed approaches, in terms of the network energy savings and the achievable end-to-end delay.

5.2 Future Work

It should be noted that the proposed QoS-constrained Data Aggregation and Processing (Q-DAP) approach is evaluated here for a fixed sensor network. However, since this is an adaptive QoS-oriented data aggregation method, it is expected that combined with the appropriate routing mechanism, it would be ideal for deployment in sensor networks with dynamic configuration. Extending it to support dynamic and mobile environments, by allowing the dynamic adjustment of several operational parameters such as the deferred period and the aggregation probability, is part of our current and future research.

Furthermore, additional energy efficiency may also be achieved by considering multiple node energy states based on the relaxation phenomena of the batteries and other possible battery renewal modes (e.g. for solar batteries). For instance, the proposed Q-DAP approach can be combined with adaptive topology configurations by introducing another state for the sensors, namely the relaxation state. In this case, depending on its energy levels an active sensor node is assumed to be in one of the following two states at a given instant: normal state and relaxation state. In the normal state, a sensor node will participate in the process of forwarding and/or aggregating data from other nodes (as explained before), in addition to transmitting its own data; while in the relaxation state it only transmits data generated by itself, in order to reduce its power consumption. Periodically each sensor may check its energy level. When its energy level is beyond a certain threshold, the sensor node remains in the normal state, otherwise it switches to the relaxation state. When its energy is replenished a sensor node will switch back to the normal state. Each sensor node may also notify its neighbors about its decisions regarding its current state. The thresholds of the energy levels that determine the sensor node states can be pre-set in the sensor nodes or broadcasted by the collector center. These values may also be adjusted dynamically during the network operation. For instance, the current discharge rate [68] can be used to determine whether or not a node should go into the relaxation state. Alternatively, neighboring sensors can also dynamically adjust the corresponding thresholds to extend the network lifetime.

Finally, the relationship among the aggregation coefficient, data correlation and packet concatenation, as well as its corresponding impact on the performance of the proposed approach needs to be further investigated and evaluated. The degree of data aggregation and its relation to the data aggregation coefficient is closely related to the corresponding savings that can be achieved due to both the MAC overhead reduction and the corresponding payload savings of packets with correlated data. It should be noted that a frame aggregation scheme is one of the possible components considered in the future 802.11n MAC, where a transmitting station may concatenate multiple packets into a single frame thus reducing the corresponding overheads. The optimization of the MAC overhead, that depends on several related timers and thresholds, based on the aggregation coefficient is a very interesting issue of high research and practical importance.

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