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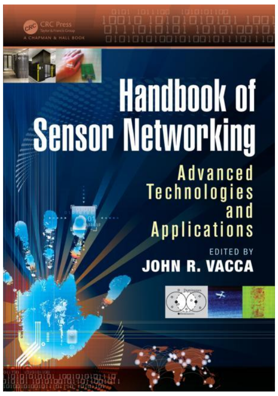

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Advanced Technologies and Applications

John R. Vacca

In-Network Processing in Wireless Sensor Networks

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4

In-Network Processing in Wireless Sensor Networks

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4.1 Introduction

During the past decade, wireless sensor networks (WSNs) have been widely used in many applications, including environment monitoring, homeland security, industrial control, and disaster alarm. The community has been doing extensive research on different areas of this field, including embedded system design, communication protocol design, and in-network processing (INP) method. Different from traditional computer networks, WSNs are highly resource and environment constrained. Each sensor has a limited power capacity, a small memory, and a short transmission range. Due to all these constraints and other application-specific constraints, how to make sensors smartly use their resource, especially their energy, becomes a key challenge for research in WSN.

To solve this challenge, different INP methods have been proposed to improve energy efficiency and data delivery performance by reducing network traffic load and thus channel contention. Over the past years, many INP protocols have been proposed for query processing [8,44,45,63] and data collection [18,19,33,41,65].

In this chapter, we conduct a comprehensive survey on INP in WSN. We categorize INP protocols into two categories: application-dependent INP, that is, data aggregation and data fusion, and application-independent INP, that is, packet packing and network coding. We review representative protocols of each INP in WSN. Before we end this chapter, we also point out some open research challenges.

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4.2 Application-Dependent INP

When designing INP protocols for WSN, researchers and engineers usually need to design customized INP functions and modules that fit requirements of targeting applications. These INPs are called *application-dependent INP*. In the following sections, we introduce the two most classic application-dependent INPs, data aggregation and data fusion.

4.2.1 Data Aggregation

Data aggregation is the most common INP method in multihop WSNs. Figure 4.1 shows an example of data aggregation. Instead of sending value v_1 through v_5 to the root node T, nodes F and G send the mean value they received from the last hop, respectively, to the sink. In this way, the data traffic in the network is reduced while the sink still receives useful data.

There are lots of literatures on data aggregation in WSN. Most of the early data aggregation research place energy efficiency as their main concern. Different protocols are proposed to increase the energy efficiency for different network architectures. Later on, quality of service (QoS) metrics in data aggregation have also drawn interests of the community, especially for end-to-end delivery latency. In the following, we discuss representative data aggregation protocols that focus on energy efficiency and latency, respectively.

4.2.1.1 Energy Efficiency

Chandrakasan et al. [6] first proposed a low-energy adaptive clustering hierarchy (LEACH) protocol for cluster-based WSN. In LEACH, the whole network is divided into several small clusters, each of which has a node functioning as a cluster head. Data within a cluster are collected by nodes in the cluster and transmitted to the head node. Nodes in the same cluster take turns to work as a cluster head. After the head node collects all the data, it aggregates all the data and sends the aggregated data to the sink.

Although LEACH improves the energy efficiency of the whole sensor network, it uses some strong assumptions that limit its development to real-world applications. LEACH assumes that each node has the same power level and collects data all at a fixed frequency, but in real-world applications, sensors' energy level may vary, and the data collection frequency is arbitrary. Some other cluster-based data aggregation protocols have also been proposed to overcome these drawbacks [2,24,66]. However, all these protocols are designed for the case when there is only one hop from the cluster head to the sink.

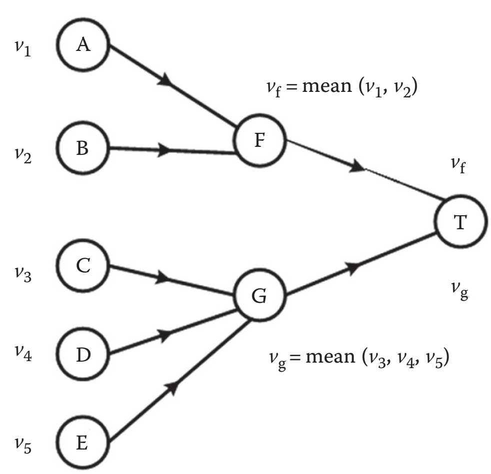

FIGURE 4.1 An example of data aggregations.

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Besides cluster-based data aggregation, chain-based data aggregation protocols are also studied. A chain-based aggregation protocol called power-efficient gathering in sensor information systems (PEGASIS) is proposed in [40]. PEGASIS has each node only communicate with its closest neighbor during the transmission to the base station, which means the data are aggregated hop by hop. Two modified versions of PEGASIS are also proposed in [40], both of which aim to combine the idea of clustering with chain-based data aggregation. According to simulation results, PEGASIS can achieve 100%–200% better energy efficiency than LEACH. Nevertheless, both PEGASIS and its modified versions assume that each node has a global knowledge of all nodes in the network. And the delay to transmit data from the end of the chain to the sink may be very large, especially when the network size is large, even though the authors adopt CDMA technique to allow simultaneous transmissions.

Both cluster-based and chain-based data aggregation protocols organize the aggregation structure into a special tree, that is, a cluster tree or a chain. Therefore, designing data aggregation tree in WSNs becomes general focus in the data aggregation area. Ding et al. [9] designed an energy-aware distributed heuristic (EADAT) algorithm to construct a data aggregation tree in WSN. EADAT makes sensors choose their role in the whole tree based on their residual energy.

Tan and Körpeoğlu [49] propose another data aggregation tree construction algorithm called power-efficient data-gathering and aggregation protocol (PEDAP) based on minimum spanning tree. Although PEDAP achieves a better energy efficiency compared with EADAT, it assumes that each node has the global position knowledge of the whole network, which makes its communication overhead too high for general WSN.

There are also many other references talking about how to build data aggregation tree with different metrics [18,42]. Lu et al. [42] proposed a medium access control (MAC) protocol with data aggregation tree construction. Nodes in the tree take turns to be active and asleep. By doing this, not only can the energy efficiency be improved, but also the channel collision problem is alleviated.

Fan et al. [18] studied the scalability issue in data aggregation protocol design. The authors point out that maintaining the whole data aggregation tree structure in large-scale networks is resource and time consuming. To make data aggregation protocol scalable, the proposed protocol [18] first constructs several small shortest path trees as data aggregation trees. Then the root node of each small tree dynamically decides how to forward and further aggregate the aggregated data to the sink. In this way, the whole protocol becomes scalable, and the energy of nodes can be fully utilized since only several small tree structures need to be recorded and updated.

Another designing metric that is often used when designing data aggregation protocols is the network lifetime. In WSN, there is not a general definition for network lifetime. Currently, the most widely used definition is to define the network lifetime to be the time when the first node/the first fraction of nodes in the network run out of its/their energy. Some works have been done aiming to maximize the network lifetime of WSN with data aggregation [10,28,62].

Kalpakis et al. [28] designed an approximate algorithm to solve the maximum lifetime data gathering (MLDA) problem. The authors divide time into multiple time units and build a relaxed network flow model on this problem. Based on this model, data aggregation tree is constructed and updated. To make the whole algorithm scalable, a cluster-based MLDA problem is modeled and solved. The proposed model is compared with PEGASIS [40] using simulation. Results show that the network lifetime is significantly prolonged by the proposed MLDA-based protocol.

Xue et al. [62] modeled the problem of maximizing network lifetime in WSN as a multicommodity flow problem, in which a commodity represents the data generated from a sensor node and delivered to the sink. They designed an approximate algorithm with an approximation ratio of $1 - \varepsilon$ for any $\varepsilon > 0$. Based on this centralized algorithm, they further designed a distributed data aggregation algorithm. Simulation results show that the distributed algorithm has a much better performance on both energy efficiency and network lifetime than the minimum energy routing (MinEnergy) algorithm, whose goal is to minimize the energy consumption for each data unit routed through the network.

4.2.1.2 Latency

Yu et al. [68] studied the energy-latency trade-off for data gathering in WSN. Although this chapter still uses energy efficiency as the objective function, the authors put hard latency constraints on the problem definition. This research assumes that the data aggregation structure has already been built. In each data collection round, each nonroot node generates one piece of data, and every piece of data should be sent to the base station within its latency constraint. During the transmission, data from different sources can be aggregated such that only aggregated data need to be transmitted to the sink. The objective is to find a transmission and aggregation scheme for the whole data aggregation tree in each data collection round, such that the total energy consumption is minimized and every data is sent to the sink without violating the latency constraint. The authors build a nonlinear programming model for this problem and solve it using a numerical algorithm. Then a pseudopolynomial time approximation centralized algorithm based on dynamic programming is designed for this model. Furthermore, the authors implement an online distributed algorithm to adaptively control the transmission and aggregation policy of each node. It adopts a feedback control scheme to make nodes transmit faster if there are data violating the latency constraint. The proposed protocol is evaluated in simulation. Numerical results show that the distributed protocol can give a good approximated performance compared with the numerical algorithm and the dynamic programming centralized algorithm in terms of energy consumption. In the meantime, its adaptivity is also demonstrated through simulation.

As a starting chapter on the energy-latency trade-off in data aggregation, this chapter gives a good approximate algorithm to solve the problem modeled in this chapter. However, the problem definition is relatively simple since in each instance, only one data is generated at one source in each round. And the proposed distributed algorithm requires the cooperation from MAC layer protocols to minimize the interferences between nodes.

Becchetti et al. [3] systematically studied the complexity of latency-constrained data aggregation scheduling problem in WSN under different models. Different from [68], this chapter studies the complexity of latency-constrained data aggregation scheduling problem on different aggregation structures and different traffic patterns. Instead of minimizing the total energy consumption, the authors define two different objective functions. The first one is to minimize the total expected number of transmissions (ETX) given that each link has a constant ETX regardless of packet size, and the second one is to minimize the maximal total ETX in one node. This chapter proves that when the data aggregation structure is a tree, the whole problem is nondeterministic polynomial time (NP)-hard for both two objective functions with a reduction from the boolean satisfiability (SAT) problem. However, both problems are proved to be 2-approximative. The authors also give a polynomial dynamic programming algorithm to solve the problem with the first objective function in a chain data aggregation structure. Besides, this chapter also proposes a simple aggregation algorithm that evenly divides the spare waiting time for aggregation at different intermediate nodes along the transmission path. The authors analyze the competitive ratio of this algorithm and the upper bound for the competitive ratio of all possible algorithms for this problem on different aggregation structures.

The chapter mentioned earlier gives a complete theoretical analysis on the complexity of latency-constrained data aggregation in WSN, which builds a good theory foundation for the latency-guaranteed data aggregation research. The drawbacks of this chapter, however, are the following: (1) it does not evaluate the proposed simple packing scheme on either simulation or experiment and (2) the competitive ratio and the bounds have too many parameters, which make the ratio highly depend on specific data aggregation structures.

As a continuous work [3], Oswald et al. [47] proposed another approximate algorithm for the latency-constrained data aggregation problem. Instead of using energy efficiency as the objective function, this chapter defines the objective function to minimize the transmission cost. The authors define energy cost functions for energy consumption on transmissions and delay cost functions for nodes to hold data for further aggregation opportunity. The transmission cost is defined as the sum of energy cost and the delay cost. The chapter proposes an approximate algorithm to solve this problem. They derive a

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competitive ratio ($h(c)$) of this algorithm for tree structure, where h is the tree's height and c is the transmission cost per edge, and a competitive ratio $\Theta(\min(\sqrt{h}, c))$ for chain structure. Both these two ratios are proved to be tight since the upper bound of the competitive ratio is proved to be at least $\Omega(\min(h, c))$. This chapter only focuses on theoretical analysis and does not give simulation or experiment evaluation for the proposed algorithm [3]. And the importance of this chapter is weakened because the objective function is not defined objectively. It would be more appropriate to define the objective function to be minimizing energy consumption.

Latency-constrained data aggregation is also studied in vehicular ad hoc networks (VANETs). Yu et al. [67] proposed a data aggregation protocol called CatchUp for data aggregation in VANETs. CatchUp dynamically controls the data forwarding delay in VANETs so that data can be fully aggregated during the transmission with an allowable delay. Different from data aggregation in WSN, where all data have the same base station as the destination, data aggregation model used in this chapter is described as follows. Each vehicle would broadcast its sensed data to every other vehicle in the network. CatchUp defines a rewards function for each node in the network to decide what action to take to have a maximal reward. The energy efficiency and latency constraint are not directly shown in the problem definition [47]. And CatchUp uses a local heuristic algorithm for each node to make decisions, which can only provide soft local latency guarantee.

Ye et al. [64] give a more systematical solution on local latency-constrained rewards maximizing algorithm [67]. This chapter models the problem on a single node in a WSN using data aggregation. In this chapter, the authors build a semi-Markov chain decision-making model for each node. The impact of latency constraint of data is defined as a negative-exponential rewards function. With the help of some important characteristics of semi-Markov chain, the chapter shows that once the statistics of the data arrival and the availability of the channel satisfy certain conditions, there exist optimal control-limit-type policies that are easy to implement in practice. In the case when the condition of the existence of optimal transmitting and waiting policy is not satisfied, the chapter provides two learning algorithms to solve a finite-state approximation model of the decision problem. Simulation results show that under two data aggregation schemes, the fixed aggregation scheme (FIX) scheme and on-demand aggregation scheme (OD) that are designed [23], both the optimal transmitting and waiting policy control algorithm and two approximate learning algorithms could effectively reduce the energy consumption while the data delay is guaranteed in a low value. Although it does not pose any hard latency constraint on the semi-Markov chain model, the fast decrease property of negative-exponential rewards function ensures that holding data for a long time for further data aggregation opportunities will not happen in the proposed algorithms.

4.2.2 Data Fusion

Data fusion is a collaborative signal processing technique that is widely used in distributed systems to enable the cooperation among multiple devices with limited sensing capability [56]. This technique has been widely studied for decades. Due to the limited sensing capability, the limited energy capacity, and the application background of WSN, data fusion has a wide application prospect in WSN applications.

Though it has a similar definition with data aggregation, data fusion is a more general technique that is more close to the application layer in WSN. In data aggregation, data from different sources are simply aggregated or compressed at some intermediate node so that the whole traffic in the network is reduced. On the contrary, in data fusion, not only are data aggregated or compressed, but also they are processed along the transmission to the sink to provide guarantee for data accuracy. Each individual sensor in the whole network can play the role as a decider. In other words, with data fusion technique, WSN can work as a distributed detection and decision-making system. Figure 4.2 gives a demonstration on how data fusion can be utilized in WSNs. In this network, nodes F and G each serves as a distributed fusion center and makes their own decision based on the information they received. And they only need to send their decisions d_F and d_G to the root node T.

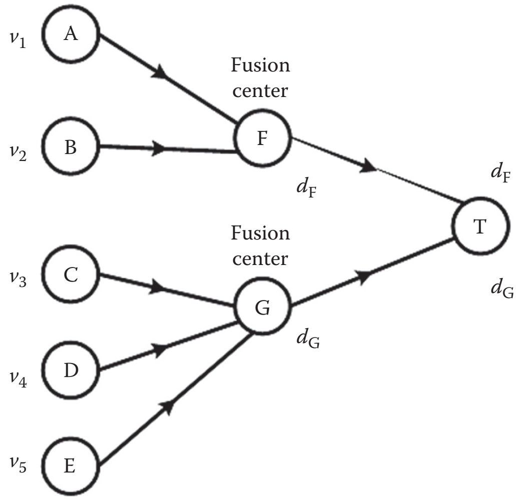

FIGURE 4.2 An example of data fusion.

Different data fusion architectures and systems are designed to fully use the limited resources in each sensor and in the meantime to guarantee the data accuracy. In the following, several representative works on data fusion in WSN are reviewed.

Thomopoulus et al. [55] studied the optimal data fusion in the sense of the Neyman–Pearson (N–P) test in a centralized fusion center. In the whole system, each sensor independently executes an N–P test and sends the decision result of the test back to the sink instead of sending the raw data. After receiving all decision results, the sink makes a final decision and adjusts the threshold of the whole test based on the final decision. This is an early work on data fusion in sensor networks. The whole system is built on sensor networks with powerful sensor, which does not take energy efficiency into account.

Niu et al. [46] proposed a distributed detection protocol in WSN [55]. In the proposed protocol, each sensor also individually and independently runs a hypothesis test and only sends the test result back to the sink. Consideration exists for the spatial correlation of data sensed by different sensors. The authors reach the conclusion that if the number of sensors is sufficiently large, the proposed fusion rule can provide a very good system level detection performance, in the absence of the knowledge of local sensors' performances and at low signal-to-noise ratio (SNR). Though the authors mention that sending only decisions from sensors to the sink could reduce the traffic in the networks, they do not formally take energy efficiency into account, either.

These two chapter are early work on applying data fusion into WSN, and they mainly focus on the data accuracy provided by fusing distributed decision value together. Energy efficiency is not the main design objective in these protocols, but only a by-product.

Clouqueur et al. [7] systematically compared the performance of distributed detection systems in WSN using value-based data fusion and decision-based data fusion. In value-based data fusion, raw data are directly sent back to the sink, and the sink fuses all raw data, abandons the outliers, and makes the final fusion. In decision-based data fusion, the chapter adopts a similar way [46,55], which sends back only decision calculated by each individual sensor to the sink. The authors conduct simulations to compare the performance of these two fusion schemes with robustness as the main metric. Results show that when the proportion of failed sensors in the whole network increases, decision-based fusion outperforms value-based fusion by providing a lower false decision probability, a lower power consumption, and a higher packet delivery probability.

Even though Clouqueur et al. [7] studied the energy efficiency of both value-based and decision-based data fusion in WSN, the authors do not discuss how to further reduce the traffic in WSN by

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allowing data fusion in sensors. Kumar et al. [33] developed an architectural framework, DFuse, for distributed data fusion in WSN. There are two main components in the framework of DFuse. First, a fusion API is implemented so that the system can afford the development of complex sensor fusion applications. Second, the authors propose a heuristic algorithm to decide which set of sensors can play the role of fusion center. The idea of fusion center is similar as the cluster head in data aggregation. Not only does the fusion center is aware of the energy efficiency of the whole network, but also it helps distributed fusion operation in the network. The performance of DFuse is evaluated via simulation. Results show that DFuse can make sensor consume energy in an efficient way. The simulation also analyzes the latency caused by data fusion, but no bound of latency can be guaranteed in DFuse. Furthermore, although the evaluation studies the impact of different energy cost functions on DFuse, it does not talk about the impact of DFuse on different fusion applications.

Duarte and Hu [17] propose a distance-based decision fusion scheme for the collaborative target detection and classification of moving vehicles using acoustic spectral features. The authors design a new scheme to use the distance between the target and the sensor as a parameter to select sensors that can give a reliable detection result to participate decision fusion. This scheme makes use of an intuition that sensors far from the target will have a lower probability of making correct classification decisions. Therefore, only sensors close to the target can participate the target detection and classification. In this way, the communications within WSN is reduced so that energy efficiency is achieved. Simulation results show that the accuracy of target detection and classification is guaranteed and the energy efficiency is improved. Though data accuracy is guaranteed, the proposed scheme does not take other QoS requirements, for example, reliability and delay, into account.

Tan et al. [50] developed an analytical framework to study the real-time surveillance performance of large-scale WSN that is designed based on collaborative data fusion schemes. The authors define a delay metric called α-delay that is defined as the delay of detecting an intruder subject to the false alarm rate bound by α. The road map of this chapter is as follows: compared with intruder detection systems in WSN without data fusion, fusion-based systems require a smaller network density to achieve a false alarm rate α. Network density will further affect the end-to-end latency in WSN. Therefore, to achieve minimal α-delay, the ratio of network density of WSN with data fusion scheme and without data fusion scheme has an asymptotic tight bound of $\Theta(\mathrm{SNR}/Q^{-1}(\alpha))$, where Q^{-1} is the inverse function of the complementary cumulative distribution function of the standard normal distribution. Simulations with realistic settings show that data fusion can reduce the network density by about 60% compared with the a general disc model without fusion while detecting any intruder within one detection period at a false alarm rate lower than 2% and guaranteeing that the detection delay is minimal.

Tan et al. [51,52] studied the calibration problem for fusion-based sensor networks. The authors propose an adaptive system-level calibration approach for sensor networks that employed collaborative data fusion for event/target detection. This calibration approach adopts a feedback control loop to adaptively mitigate the impact of physical uncertainties on the environment and the dynamics of the physical event/target of interest. The authors prove the stability and convergence of the proposed feedback control scheme. A routing algorithm for fusion-based sensor networks is also designed to minimize the impact of dynamics on fusion-based WSNs. Experiment and simulation results show that the proposed calibration system is able to maintain optimal detection performance under the presence of system and environmental dynamics.

Under the similar sensor measurement and data fusion model [51,52], Tan et al. [53,54] proposed a two-tier system level calibration approach for fusion-based sensor networks. The whole system is composed of two tiers. In the first tier, each sensor learns its local sensing model using in-place measurements and only transmits model parameters to the fusion cluster head. In the second tier, the fusion cluster head calibrates each sensor's model to a common sensing model. Using this two-tier approach, the communication overhead from sensors to fusion head is significantly decreased. A linear regression algorithm is proposed for first-tier local sensor model learning. And another algorithm is designed to calibrate biased local sensing models and maximize the system detection probability. The authors evaluate the performance of this two-tier system using both experiment and simulation. Results show that the proposed approach can significantly improve the detection performance of sensor networks under different realistic settings.

4.3 Application-Independent INP

Besides data aggregation, there are also INP methods that do not require customized functions depending on specific applications in WSN. These methods are called *application-independent INP*. In this section, we introduce two most representative application-independent INPs in sensor networks, packet packing and network coding, and survey their recent research progress.

4.3.1 Packet Packing

Different from data aggregation, which aggregates spatial- or temporal-related packets into a packet while the size of the aggregated packet remains the same, packet packing technique simply puts information elements in packets together regardless of the correlation of packets. The length of the packed packet equals to the header plus the length of all information elements. Figure 4.3 gives an example on how packet packing works. Different from Figures 4.1 and 4.2, where data aggregation and data fusion sent aggregated/processed value to the sink, packet packing only assembles short packets into longer ones, for example, node F putting packets p_1 and p_2 together. In this way, nodes F and G can also send less number of packets to T such that the efficiency of the whole sensor network can be improved.

As a special INP method, packet packing has also been studied for WSN as well as general wireless and wired networks. In the following, we investigate the same representative ones. Jain et al. [27] studied the benefits of packet packing in ad hoc wireless networks under IEEE 802.11b standard. The authors point out that 802.11b networks have a high header overhead, which takes up a lot of bandwidth. They alleviate this high overhead by allowing a small delay on packets during the transmission so that intermediate nodes can pack different small packets into a larger packet before forwarding it to the next hop. In their protocol, they preconfigure a maximum aggregation delay to keep each packet wait at intermediate nodes for a while so that packets can be packed together. Based on both experiments on a wireless test bed and simulations on NS-2, their protocol can provide a significant improvement on network capacity compared with wireless networks without using packet packing. However, there are some drawbacks on this predefined waiting time. The end-to-end latency cannot be guaranteed. Meanwhile, by waiting at a fixed time at each intermediate node, a packet may lose the opportunity to pack more other packets at some certain nodes.

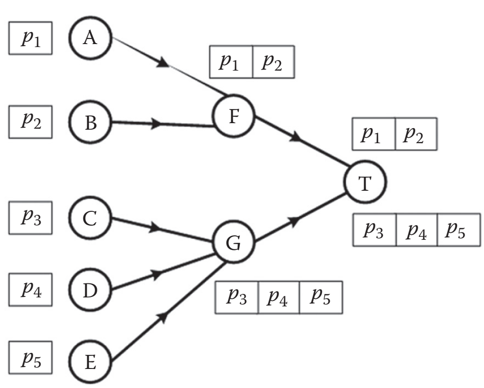

FIGURE 4.3 An example of packet packing.

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Other work [27] also looks at the throughput gains by applying packet packing into MAC protocol design [36,38,43]. Li et al. [36] proposed an adaptive QoS-aware frame concatenation mechanism (AQCM) to control how long a packet should wait at an intermediate node. The AQCM is mainly designed for multimedia applications in multirate wireless ad hoc networks. AQCM controls the waiting time of every packet by detecting whether the required flow rate is satisfied and whether there is congestion in local traffic. The simulation results show that AQCM can achieve a desirable performance on multimedia multirate wireless ad hoc networks. However, AQCM only provides soft QoS guarantee.

Li et al. [38] and Lu et al. [43] use a packet packing to design a MAC protocol in ultra-wideband networks (UWBNs) and high-speed wireless local area networks (WLANs), respectively. Both of them adopt an opportunistic scheme to do packet packing. Using this scheme, the end-to-end delay of data flows is to some extent improved. But packets will still lose an opportunity to get further packed [27].

Kliazovich and Granelli [31] designed an internet protocol (IP) level packet packing scheme in WLANs. The authors categorize IP layer packets into two groups, with low priority and high priority, respectively. Packets in different groups cannot be packed. By this way, packets with high priority, that is, small delay constraints, will be packed and transmitted first. This scheme is easy to implement. Both experiment and simulation results show that the throughput can be improved using this grouping scheme compared with no packing scheme and the delay constraint can be satisfied. Though this packing strategy is easy and direct, the drawback of this scheme is that not only will packets lose packing opportunity but also the latency constraint can still be violated if packets in the same group have different latency constraints.

Then, Saket and Navet [48] studied packet packing in single-hop controller area networks (CANs) with a finite packet size. It gives a heuristic greedy algorithm that packs small packets into a single frame as many as possible. Different from the other authors [27,36,38,43], this chapter studies the impact of finite packet size on packet packing.

He et al. [23] developed a novel adaptive application-independent data aggregation (AIDA) protocol to provide soft latency guarantee for packet packing in WSN. AIDA is designed to be an independent layer between network layer and MAC layer. Packets can be packed in this layer under different packing schemes. The authors propose three different packing schemes. The first one is called fixed aggregation scheme (FIX), where AIDA packs a fixed number of network units into each AIDA payload. To ensure that network units do not wait an indefinite amount of time before being sent, a time-out threshold is predefined in the system. The second scheme is called on-demand (OD) scheme, which adopts an opportunistic packing policy. OD puts the real-time guarantee as the top concern. Packets at the same sensor can only be packed when the MAC layer is not available for transmission. In FIX scheme, the system can only provide a soft latency guarantee, and packets will lose opportunities to get further packed. In OD scheme, hard latency constraints are guaranteed, but packets have less opportunity to get packed than in FIX, which can increase energy consumption. To balance the energy efficiency and the latency requirement, the authors propose the third scheme called dynamic feedback (DYN) scheme. DYN implements a combination of OD scheme and FIX scheme where the number of packets packed in one sensor is adjusted dynamically via a feedback control from the output. In the case of low network traffic, DYN will default to the OD mechanism delivering packets to the MAC transmission queue as soon as they are ready. As network traffic builds up and the contention delays transmission, the feedback loop adjusts the threshold of number of packets that can be packed together to allow a greater degree of packing prior to sending. Simulation results indicate that DYN outperforms OD and FIX by providing a lower-average end-to-end delay, especially in heavy-load traffic. Nonetheless, the proposed DYN scheme has overreaction or underreaction on the change of MAC delay, which cannot provide hard latency guarantee for each single packet.

Dong et al. [13] studied the dynamic packet length control (DPLC) in sensor networks. The authors show that the length of packet can significantly affect the delivery performance in WSN. Therefore, this chapter proposed DPLC, a dynamic packet length adaption scheme with a lightweight and accurate data-plane link estimation component. DPLC adaptively aggregated smaller packets into a larger one or fragments larger packets into smaller ones based on the physical channel conditions and interferences. Experiments on a 20-node test bed under a light traffic pattern showed that DPLC results in a 13% reduction in transmission overhead and a 41.8% reduction in energy consumption compared with collection tree protocol (CTP).

Xiang et al. [57,58] studied the joint optimization between packet packing and the latency of data delivery. They provide a comprehensive computational complexity analysis on this scheduling problem in sensor networks. The authors proved the strong NP-hardness of this problem via a reduction from SAT problem. They also show that certain special packing constraints make this problem polynomial solvable. Based on the complexity analysis, the authors designed a distributed, online protocol named tPack to make packing decisions to maximize the local utility of packet packing at each node. Experiment results on the NetEye test bed show that tPack is able to provide at least a reduction of 70% transmission cost in various heavy traffic patterns in a 120-node dense topology.

4.3.2 Network Coding

Network coding (NC) is first proposed for wired networks [1]. By mixing packets at intermediate nodes during the transmission, the bandwidth can be saved, and therefore, the throughput of the whole network can be significantly improved. During the past years, network coding has been one of the most popular research topics in computer networks. Different coding schemes are designed, categorized into linear network coding and nonlinear network coding. Compared with linear network coding, nonlinear network coding has been reported to outperform linear coding in several studies [15,16,34,35]. And there are multisource network coding problems for which nonlinear coding has a general better performance on throughput [16]. Nevertheless, according to the an analysis [37], linear network coding can provide a performance close to the best possible throughput, while only requiring a relatively low complexity, compared with the high complexity of nonlinear coding.

Due to the broadcast nature in wireless communication, each intermediate node can receive redundant packets during the transmission in wireless networks. Network coding is one of the best choices to make use of these redundancies. By mixing redundant packets together and forwarding the mixed packet, the throughput of wireless networks can be further improved. It is shown that linear coding functions can be designed randomly and independently at each node. Ho et al. [25,26] proposed a coding technique called random linear coding (RLC). Since RLC can be easily implemented in a distributed manner and it has a low complexity, it is widely used in wireless networks.

In sensor networks, network coding has been mainly applied in three scenarios, NC-based opportunistic routing, code dissemination, and NC-based network protection. In the following, we will introduce representative network coding protocols of these application scenarios.

4.3.2.1 NC-Based Opportunistic Routing

Opportunistic routing is proposed [4] with the protocol ExOR and has drawn the community's interests. Since opportunistic routing also makes use of the broadcast property in wireless communication, researchers have been working on the hybrid architecture of network coding and opportunistic routing in wireless networks.

Katti et al. [30] proposed COPE, a new architecture for wireless mesh networks. It is the first network coding that is implemented with the current network stack seamlessly. In the design of COPE, only interflow network coding is concerned. COPE adopts an opportunistic coding scheme, which does not delay packets' transmissions for further coding opportunity. According to the theoretical analysis, not only can network coding bring significant improvement on throughput, but also the MAC layer protocol can also improve the network throughput when it is combined with coding technique. COPE is implemented on a 20-node wireless network test bed. Experiment results show that COPE can increase the throughput of wireless mesh networks without modifying routing or higher layers.

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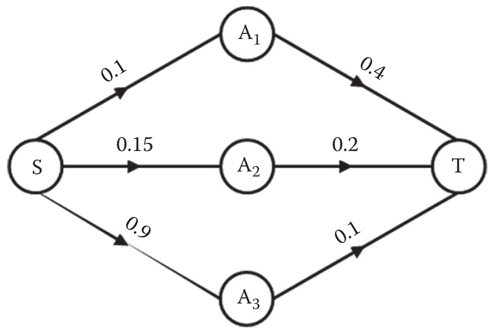

FIGURE 4.4 An example for NC-based opportunistic routing.

With continuous research [4,30], Chachulski et al. [5] combined intraflow RLC and the opportunistic routing protocol in [4] together to develop a new routing protocol called a MAC-independent opportunistic routing protocol (MORE) in wireless mesh networks. Figure 4.4 gives an example of intraflow NC-based opportunistic routing. Different from traditional shortest single path routing, where node S can only choose node A_3 as next hop, NC-based opportunistic routing makes use of all one-hop neighbor of node S, that is, nodes A_1–A_3. In this way, the routing diversity is fully utilized such that the network throughput can be improved. The contribution of MORE is multidimensional. First, it makes use of the broadcast property of wireless communication to improve the network throughput without modifying the existing MAC layer, that is, 802.11. Second, it adopts RLC for intraflow network coding. RLC has a low complexity and is easy to implement in a distributed system. Therefore, the network throughput is further improved. Third, both the memory overhead and the header overhead are bounded within a reasonable range. MORE is also evaluated in a 20-node test bed [4], and it outperforms ExOR in both unicast and multicast traffic flow with a higher throughput.

To further improve the throughput of wireless networks, Lin et al. [39] made use of hop-by-hop ACK and sliding window to allow different segments of packets to be transmitted in the network concurrently (CodeOR). However, it still adopts off-line ETX metric to decide how many coded packets to transmit to ensure the end-to-end decodability. To be adaptive to the dynamic of wireless links, Koutsonikolas et al. [32] designed a cumulative coded ACK (CCACK) scheme to allow nodes to notifying their upstream nodes that they have received enough coded packets in a simple and low overhead way. The throughput of CCACK is shown to be 45% better than that of MORE. The CCACK scheme gives a good solution to the problem *when should a sender stop broadcasting*. However, CCACK's major objective is to minimize the broadcast cost at each sender/forwarder. This approach cannot give a global minimization on transmission cost for NC-based opportunistic routing. Furthermore, CCACK requires a high memory space and a relatively complex computation process, which is not suitable for resource-constrained sensor networks.

Xiang et al. [59,60] studied the minimal cost NC-based routing problem in WSNs. The authors proposed the first mathematical framework on analytically measuring the cost of NC-based routing. They designed a greedy algorithm that can minimize the transmission cost of NC-based routing and prove its optimality. It is also shown in this work that the transmission cost of NC-based routing is upper bounded by the cost of shortest single path routing and that the shortest single path is not always chosen into the minimal cost forwarding set, as shown in Figure 4.5. Figure 4.5 has the same topology as Figure 4.4. In this example, the shortest path is $S \rightarrow A_3 \rightarrow T$, while the minimal cost NC-based routing braid is $S \rightarrow \{A_1, A_2\} \rightarrow T$. The authors proposed energy-efficient network-coding-based routing protocol (EENCR), an energy-efficient network coding-based routing protocol, which contains a distributed implementation of the greedy algorithm. Experiment results from the NetEye test bed demonstrated that EENCR significantly outperforms CTP, MORE, and CodeOR in terms of delivery reliability, delivery cost, and goodput. This work shows the routing diversity of wireless communication requires adaptively utilization in order to provide efficient and reliable service in WSNs.

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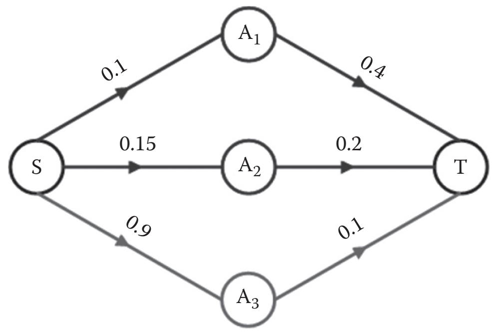

FIGURE 4.5 Minimal cost NC-based routing versus shortest path routing.

4.3.2.2 Code Dissemination and Reprogramming

Hagedorn et al. [22] proposed Rateless Deluge, the first WSN code reprogramming protocol that utilizes network coding. The use of network coding can effectively eliminate the need of feedback information about which packets need to be retransmitted and hence effectively increase the efficiency of code dissemination and reprogramming. Experiment results on Tmote Sky motes in both single-hop and multihop networks demonstrate that Rateless Deluge can significantly save the communication overhead in both data and control plan, that is, 15%–30% and 50%–80% than regular Deluge protocol, respectively.

Dong et al. [12] presented an analytical mathematical framework to analyze the performance of code/bulk data dissemination protocols in WSNs. This framework considers topology information, impact of contention, and pipelining. The authors compared the analytical results of this framework and simulation results in both square structures and linear structures. Results show that this mathematical framework fits accurately with the simulation results and much better than the analytical approach used in Deluge.

Dong et al. [11] studied the reprogramming problem in sensor networks and proposed ReXOR, a lightweight and density-aware reprogramming protocol for WSN. ReXOR uses XOR coding technique in the retransmission phase to reduce the transmission cost. The authors analyzed the advantage of ReXOR over Deluge in sparse and lossy network and its advantage over Rateless Deluge in dense network. ReXOR utilizes both the advantage of general network coding in reducing transmission cost and the near-zero decoding delay in XOR coding. In sparse and lossy network, ReXOR adaptively increases the interpage waiting time to improve the coding opportunity while in dense networks; the interpage time can be controlled to reduce transmission cost and propagation delay. Experiment results show that ReXOR has a much lower code dissemination completion time than both Deluge and Rateless Deluge in both sparse and dense grid topologies. In the meantime, it has a significant lower data traffic than both Deluge protocols, which is desirable in resource-constrained sensor networks.

Gao et al. [20,21] proposed a multithreaded design for network coding-based data dissemination. The protocol, MT-Deluge, separates the coding and radio operations into two threads. In the coding thread, an incremental decoding algorithm is proposed to shorten the waiting delay of radio thread. When the incremental decoding algorithm is executed, a packet-level thread synchronization mechanism is adopted to provide precise synchronization between multiple threads. When this algorithm is not being executed, a state-level thread synchronization mechanism would be enough. Experiment results in multihop line topology, multihop grid topology, and single-hop clique topology show that MT-Deluge can reduce the dissemination delay significantly in multihop topologies while single-thread dissemination topology such as Rateless Deluge is enough in single-hop topologies.

Dong et al. [14] proposed an efficient code dissemination protocol (ECD), an efficient code dissemination protocol in sensor networks. Leveraging the results [13], ECD supports configurable packet sizes, which improve the transmission efficiency in terms of transmission cost. ECD designs an accurate sender selection algorithm to mitigate the collision between transmissions. It also employs a simple

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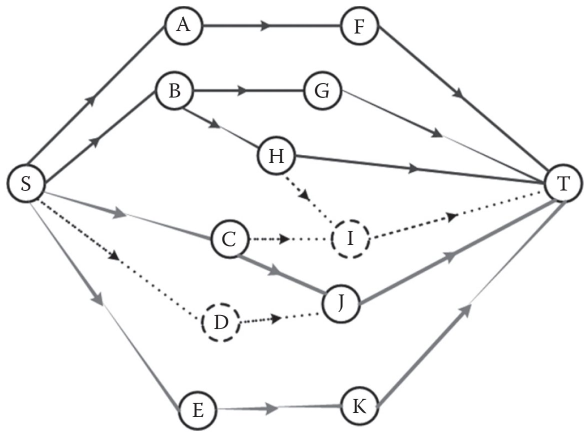

FIGURE 4.6 An example of node-disjoint NC-based braids.

impact-based backoff timer design to reduce the time spent in coordinating the transmissions of eligible senders. Experiment results show that ECD provides a better performance than Deluge and MNP, two classic code dissemination protocols, in terms of both data traffic and completion time. Results also demonstrate the impact of sender selection in code dissemination. Plus, network coding technique used in designing Rateless Deluge and ReXOR [11] can also be applied into ECD design and implementation.

4.3.2.3 NC-Based Network Protection

Kamra et al.'s [29] work is the first work to put resiliency as the major concern for network coding in WSN. The authors propose Growth Codes, a new class of network coding particularly suited to sensor networks where data collection is distributed. Unlike previous coding schemes, Growth Codes employs a dynamically changing codeword degree scheme that delivers data at a much faster rate to network data sinks. Furthermore, the coding algorithm is designed such that the sink is able to decode a substantial number of the received coded packets at any stage. Simulations in TOSSIM and experiments show that Growth Codes provide a high reliability in WSN where nodes are highly prone to failures.

Xiang et al. [61] studied the proactive NC-based protection problem to provide resiliency against transient network failures in sensor networks. The approach utilized in this work is to construct two node-disjoint braids to provide 1 + 1 protection. In Figure 4.6, for example, two node-disjoint braids marked in red and blue are constructed to deliver two copies of data from S to T. Different from constructing two node disjoints with minimal total cost, which is polynomial solvable, it is shown to be NP-hard to construct two node-disjoint network coding routing braids with minimal total cost in this work. The authors design a heuristic algorithm alternatively assigning nodes into two braids. Based on this algorithm, the authors designed ProNCP protocol and evaluated its performance on the NetEye test bed. Results show that ProNCP provides stable performance with close to 100% reliability under different transient failure models.

4.4 Research Challenges

From the previous discussion, we can find that, in resource-constrained wireless networks, INP effectively enhances messaging efficiency by reducing network traffic load. Nonetheless, most of the study of INP in wireless and sensor networks has ignored the issue of providing hard QoS such as the timeliness, reliability, and resiliency of data delivery when controlling the temporal and spatial data flow in networks. Therefore, how to provide QoS guarantee for INP in WSN is still a new area where only some preliminary works have been done. In this section, we point out some open issues and research challenges in this field.

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4.4.1 Systematic Modeling and Complexity Analysis

Because QoS constraints are added to INP protocol design for WSN, the problem formulation will be different from that in existing research on energy-efficient INP design for traditional WSN and wireless networks. Some authors [64] have proposed some simple modeling frameworks for QoS-aware data aggregation protocol design based on semi–Markov chain. Nonetheless, frameworks like these are used for specific QoS constraints, such as reliability and latency, and only for data aggregation. And we still lack a general modeling framework across different QoS constraints and different INP methods to push the research on this area. Other authors [57,58] give an interval graph model for the latency-constrained packet packing problem, which may also apply to general QoS-aware INP scheduling problem in sensor networks. Still, other authors [60] propose the first mathematical framework on computing the transmission cost of NC-based routing and an optimal NC-based routing algorithm. But a more robust modeling framework for general INP methods is still needed.

Besides modeling issues, complexity analysis is also of great importance in this area. Complexity of problems may change due to the joining of new QoS constraints. Some QoS constraints may make the new problem easier, especially in a chain network [3,57,58], while some constraints may make the new problem even NP-hard to approximate [3,61]. A complete complexity analysis on QoS-aware INP problem will provide a guideline on how people can design and implement efficient approximate algorithm for sensor networks.

4.4.2 Joint Optimization of QoS and WSN-Specific INP

Existing work on QoS-aware INP design mainly consider how to provide service in WSN with guaranteed latency and reliability. Although in mission-critical real-time WSN these two metrics are the most important ones, there are other QoS metrics unexplored, for example, interactivity. Besides the aforementioned INP methods, there are also other WSN-specific INP methods including different degrees of data compression and local data filtering. Different INP methods in WSN will lead to different trade-offs among different QoS metrics. These trade-offs tend to be application specific. Studying the joint optimization on QoS and these new INP methods can provide support in the close-loop control in modern WSN.

4.4.3 Cooperation of Different INP Methods in WSN

The community has started to study the trade-off between QoS and single INP method in WSN. Some work [5,30,45] also proposes whole system architectures that cooperate INP with existing network protocol stack. However, how to apply different INP methods together in one system is still an open area. A simple example will show that this approach can further improve the system performance. Suppose intraflow coding is adopted in wireless networks. After a node did intraflow network coding for a few packets, it can further pack these coded packets together using packet packing method. In this way, the total ETX can be further reduced. Since INP methods all aim to reduce the traffic load in WSN, studying the cooperation between different INP methods is a promising direction to provide QoS-guaranteed performance for WSN. However, characteristics and major concerns of different INP methods can make the cooperation complex. For example, data fusion mainly aims to guarantee the data accuracy while data aggregation mainly considers how to minimize energy consumption. Thus, it is a challenging task to balance these two goals.

4.4.4 Theoretical Foundations of Algorithm Design

The research on QoS-aware INP design in WSN is still a developing area. Due to the different characteristic between WSN and other wireless networks, traditional network optimization theory is not enough to provide mathematical tools for this area. For example, traditional network flow perspective

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mainly studied the static network flow model under which the conservation law always holds. Xiang et al. [60,61] studied the nonadditive network coding-based routing flow problem, showing that under NC-based routing pattern, the conservation law of network flow does not always hold. This shed lights for future research on QoS-assured INP data flow control in modern WSN.

4.5 Summary

After the past decade of active research and field trials, WSNs have started penetrating into many areas of science, engineering, and our daily life. They are also envisioned to be an integral part of cyber-physical systems such as those for alternative energy, transportation, and health care. However, most sensor nodes are highly resource constrained in terms of energy and computational capability. For resource-constrained WSN, INP improves energy efficiency and data delivery performance using light-weight and local computation to reduce network traffic load and thus channel contention. Over the past years, many INP methods have been proposed for query processing and general data collection. In this chapter, we introduce different INP methods in WSN, including data aggregation, packet packing, and network coding. By presenting the basic idea and discussing representative protocols of each category, we give a comprehensive tutorial on INP in WSNs.

In other words, in this chapter, we have presented a comprehensive survey of INP methods in WSN. INP techniques are adopted in WSN with the main goal of minimizing energy consumption. Different INP protocols are investigated in this chapter. We also point out some possible research directions in this area. With both the quick development of modern WSN and its wide use in cyber-physical systems, it is expected that INP continues to play an important role in modern WSN. Therefore, studying how to design QoS-aware INP protocols in WSN is a challenging and an important area for future research.

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