Joint Optimization for Wireless Sensor Networks in Critical Infrastructures

by

©Mohamed Said Elsersy

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Abstract

Energy optimization represents one of the main goals in wireless sensor network design where a typical sensor node has usually operated by making use of the battery with limited-capacity. In this thesis, the following main problems are addressed: first, the joint optimization of the energy consumption and the delay for conventional wireless sensor networks is presented. Second, the joint optimization of the information quality and energy consumption of the wireless sensor networks based structural health monitoring is outlined. Finally, the multi-objectives optimization of the former problem under several constraints is shown. In the first main problem, the following points are presented: we introduce a joint multi-objective optimization formulation for both energy and delay for most sensor nodes in various applications. Then, we present the Karush-Kuhn-Tucker analysis to demonstrate the optimal solution for each formulation. We introduce a method of determining the knee on the Pareto front curve, which meets the network designer interest for focusing on more practical solutions. The sensor node placement optimization has a significant role in wireless sensor networks, especially in structural health monitoring. In the second main problem of this work, the existing work optimizes the node placement and routing separately (by performing routing after carrying out the node placement). However, this approach does not guarantee the optimality of the overall solution. A joint optimization of sensor placement, routing, and flow assignment is introduced and is solved using mixed-integer programming modelling. In the third main problem of this study, we revisit the placement problem in wireless sensor networks of structural health monitor-

ing by using multi-objective optimization. Furthermore, we take into consideration more constraints that were not taken into account before. This includes the maximum capacity per link and the node-disjoint routing. Since maximum capacity constraint is essential to study the data delivery over limited-capacity wireless links, node-disjoint routing is necessary to achieve load balancing and longer wireless sensor networks lifetime. We list the results of the previous problems, and then we evaluate the corresponding results.

To the soul of my parents ...

To my wife and my daughters, Nada, Zeina and Lina ...

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Co-Authorship Statement

I, Mohamed Said Elsersy, hold a principal author status for all the manuscript chapters (Chapter 2 - 6) in this dissertation. However, each manuscript is co-authored by my supervisor, whose contributions have facilitated the development of this work as described below.

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   I was the primary author and with my supervisor contributed to the idea, its formulation and development, and refinement of the presentation.

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Mohamed Elsersy Date

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List of Abbreviations and Symbols

AODV	Ad-Hoc On-Demand Distance Vector
CH	Cluster Head
DEAP	Delay Energy-Aware routing Algorithm
EARQ	Efficient and Reliable Routing
EEHCA	Energy-Efficient Hierarchical Clustering Algorithm
FAR	Flow Augmentation Routing Algorithm
GA	Genetic Algorithms
GAF	Geographic Adaptive Fidelity Algorithm
GEAR	Geographic and Energy Aware Routing Algorithm
GeRaF	Geographic Random Forwarding Routing Algorithm
GEDIR	Geographic Distance Routing Algorithm
GOAFR	Greedy Other Adaptive Face Routing Algorithm
GPS	Global Positioning System
HGR	Hybrid Geographical Routing Algorithm
HEED	Hybrid Energy-Efficient Distributed Clustering
HPAR	Hierarical Power Aware Routing
KKT	Karush Kuhn Tucker
LEACH	Low-Energy Adaptive Clustering Hierarchy
LAPC	Latency Sensitive Power Control

LAR	Location Aided Routing Algorithm
MIP	Mixed-Integer Programming
MOGA	Multi-objective Optimization Genetic Algorithm
MOPT	Multi-objective Optimization
MLR	Maximum Lifetime Routing Algorithm
MNL	Minimum Network Lifetime
PAGER	Partial-partition Avoiding Geographic Routing
PEGASIS	Power Efficient Gathering in Sensor Information Systems
PF	Pareto Front
QoS	Quality of Service
SPEED	Spatio Temporal Routing Algorithm
SPIN	Sensor Protocol for information via Negotiation
TEEN	Threshold sensitive Energy-Efficient sensor Network Algorithm
TTDD	Two Tier Data Dissemination routing Algorithm
WSNs	Wireless Sensor Networks

$\mathbf{A}$	The incidence matrix.
$\mathbf{b}$	The total data traffic generated.
$b_{l,l'}$	The total data traffic generated by node l intended for node l' measured in (packets/second).
$\mathbf{C}$	The link incidence matrix through the link.
$\mathfrak{C}$	The coordinates matrix of the sensor nodes.
C_l	The capacity of the link.
$\mathbf{d}$	The distance matrix for each link.
d_{ij}	The distance between sensor node i and sensor node j.
D_{max}	The acceptable delay set by the user or the application requirement.

$E_t(x_k)$	The transmission energy function for x_k.
$E_r(x_k)$	The reception energy function for x_k.
$e_t(ij)$	The transmission energy on link $i - j$.
$e_r(ji)$	The reception energy on link $j - i$.
$E_t(i)$	The transmission energy consumed by sensor node i.
$E_r(i)$	The reception energy consumed by sensor node i.
$E_{total}(\mathbf{S}, \mathbf{x})$	The total energy consumption by all nodes.
E_{init}	The initial energy of the sensor node.
$\mathbf{F}_{i,j}$	The set of paths that include link (i, j).
k	The number of paths for each l, l' pair.
$\mathbf{L}$	The set representing the pair of nodes connected by a link (i, j).
M	The number of all potential locations.
N	The number of sensor locations are selected.
n^b	The number of bits per packet.
$\mathbf{P_{l,l'}}$	The set of k paths for l, l' pair.
$\mathbf{Q}$	The Fisher information matrix.
q_{ij}	The capacity of the link (i, j).
$\mathbf{R}$	The covariance matrix.
r_c	The maximum transmission distance.
$\mathbf{S}$	The set of location indicator.
$\mathbf{S}_{temp}$	The temporary sensor location indicators set.
s_i	The link indicator for sensor node i.
s_j	The link indicator for sensor node j.
T	The network lifetime.
T_i	The lifetime of a node i.
$\mathbf{x}$	The matrix that shows the number of flows per link.

x_{ij} — The link indicator from sensor node i to sensor node j.

χ — The average flow of traffic (packets per second).

x_k — The average flow of traffic (packets per second) on a path k.

$\mathbf{Y}$ — The expected flow in a link.

$y_{i,j}$ — The expected flow from a source i to a destination j.

LATIN SYMBOLS

α — The first coefficient of the equation for the fitted curve.

β — The first coefficient of the exponent of the equation for the fitted curve.

γ — The second coefficient of the equation for the fitted curve.

δ_{Mk} — The measured vibrations collected by the Mth sensor for the kth mode shape.

θ — The second coefficient of the exponent of the equation for the fitted curve.

ϵ_{amp} — The power amplifier energy cost per bit per m^2.

ϵ_r — The reception energy cost per bit.

ϵ_t — The transmission energy cost per bit.

ϵ_{ij}^t — The energy consumption coefficients for transmission per second per bit of the link (i, j).

ϵ_{ij}^r — The energy consumption coefficients for reception per second per bit of the link (i, j).

$\mathbf{\Phi}$ — The mode shape matrix.

$\phi_{i,j}(y_{i,j})$ — The delay in the link (i, j) with the expected flow in the link $y_{i,j}$.

$\Psi_{i,j}$ — The overall delay value of the link (i, j).

Ψ — The normalized sensor information quality.

α	The path loss exponent.
$\mho$	The information quality to the total energy consumption ratio.
$\mho_{norm}$	The normalized information quality to the total energy consumption ratio.
ω	The weighting factor.
ω^*	The optimal weighting factor.

Chapter 1

Introduction

1.1 Research Motivation

Wireless sensor networks (WSNs) play an important role in both civilian and military applications [1]. WSNs have resource-limited nodes, hence, optimization for the available resources is needed to achieve the highest performance and the existing resources need to be well utilized.

Numerous studies have been devoted to designing routing for WSNs. These studies include energy-efficient algorithms [2–4], delay-efficient algorithms [5, 6] and location-aware algorithms [7–11]. However, these studies lack the comprehensive understanding of WSNs node limitations and application requirements. Most of these investigations require previous information to be known before making the routing decision. Since this requirement can not be met, routing for WSNs is the point of interest. This motivates us to develop a joint placement, routing and flow assignment for the case of the structural health monitoring (SHM) using WSNs.

A typical sensor node is usually powered by a limited-capacity source. Consequently, energy optimization represents the main goal in WSNs design where collected data needs to be delivered within a certain limit and with a definite quality. In this thesis, we aim to enhance the performance of WSNs, by optimizing the utilization of available resources. We formulate and solve the optimization problem jointly subject to additional constraints.

1.2 Research Objective

In this thesis, the following problems are addressed in separate chapters in manuscript style: First, the joint optimization of the energy consumption and delay for a conventional WSNs is presented. Second, the joint optimization of the information quality and energy consumption for the WSNs based structural health monitoring is outlined. Finally, the multi-objectives optimization of the former problem under several constraints is shown. Motivated by the promising preliminary results obtained in single objective formulation WSNs, we extend the problem formulations to the multi-objective formulation WSNs to further limit the amount of flow to neighbouring nodes while taking into consideration the node-disjoint and flow assignment.

In the first problem, the following points are presented: First, we introduce a joint multi-objective optimization formulation for both energy and delay for most sensor nodes in various applications. Second, we present the Karush-Kuhn-Tucker analysis to demonstrate the optimal solution for each formulation. Third, based on the multi-objective optimization formulation, we introduce a method for determining the knee on the Pareto front curve, which meets the network designer interest for focusing on more practical solutions. Lastly, we calculate the optimal weighting factor for both objectives which allows the network designer balance their mutual interaction between the two objectives. This technique helps network designers increase the simplification of the design process.

A joint routing and flow assignment hybrid geographical routing is proposed. In the proposed algorithm, we use the progressive distance and angle directionality to choose the best route and determine the optimal flow which is considered a novel distributed algorithm. A near-optimal flow for diverse network sizes is achieved by the proposed algorithm under the evaluated network metrics. Hence, the implementation of the proposed algorithm is suitable for the limited-resource sensor node due to the reduced complexity. Several network metrics will be evaluated; the simulation will be conducted to complement and to extend the results.

In the second main problem of this work, joint optimization of sensor placement, routing, and flow assignment is introduced and solved using mixed-integer programming modelling. Sensor node placement optimization has a significant role in WSNs, especially in structural health monitoring. Since sensor node placement affects the routing, optimization should be done for the node placement and routing jointly. Existing work optimizes the node placement and routing separately (by performing routing after carrying out the node placement). However, this approach does not guarantee the optimality of the overall solution.

Finding an optimal solution for this joint problem is too complex. Hence, a near-optimal solution is obtained using genetic algorithms with reduced complexity. Moreover, a heuristic algorithm for joint routing and flow assignment with placement is proposed using the effective independence model, which optimizes the information quality and energy consumption for efficient communication. Last but not least, the results are presented in a nine-floor building to compare the three proposed algorithms with the heuristic algorithm introduced. The numerical results show the efficiency of the proposed algorithms and the trade-off between the effectiveness and complexity. After we have addressed this problem using a single objective to minimize the energy consumption, we consider another approach to solving the designated problem.

In the third main problem of this research work, we revisit the placement problem in WSNs for SHM. We apply the multi-objective approach for minimizing the energy consumption and maximize the information quality simultaneously. Furthermore, we take into consideration more constraints that were not taken into account before. This includes the maximum capacity per link and the node-disjoint routing. Whereas the maximum capacity constraint needs to be studied to investigate the packet delivery over wireless links, node-disjoint routing is necessary to achieve load balancing among possible paths. We outline the detailed results for the previous problems and evaluates the performance of the corresponding outcome.

1.3 The Knowledge Gap

After the revision of the previous work in [2–11], the following is a list of holes that exist in the literature that needs to be filled in a better way. The research problem can be divided into the following subproblems:

(a) Achieving an optimal flow that provides communication in WSNs that works in an efficient manner with low delay and satisfies the flow rate constraint while optimizes the network metrics. An optimization algorithm should be chosen to bring up optimal routes with the shortest delay at low cost. This problem is essential as the delay is one of the main constraints in certain WSN applications. The problem has to be represented as a multi-objective optimization in order to introduce the flexibility for the network designer and solved using the chosen optimization tool.

(b) Finding an optimal flow for WSNs that provides an energy-efficient manner with the information quality required to be up to a certain value. Moreover, the optimization algorithm needs to be well-presented enough to guide the path selection. For this reason, the situation has to be formulated as an optimization problem to be enlightened using selected solvers. The problem formulation also needs to be well-presented in order to achieve the optimal solution.

(c) Providing a simple and efficient routing algorithm for WSNs based SHM, which takes into consideration information quality issues and satisfies different constraints. Routing algorithm that minimizes the energy consumption and maximizes the information quality is needed. Increasing the number of parameters for the routing decision can be prohibitive for the resource-limited sensor node. The multi-objective optimization is needed to give the flexibility of focusing on one objective more than the other.

1.4 Thesis Outline

The remainder of the thesis is organized as follows: A classification of WSNs and the literature survey of the previous work is shown in Chapter 2. A joint optimization routing and delay for WSNs is presented in Chapter 3. The proposed system model for WSNs based SHM with the related results is explained in Chapter 4, the multi-objective optimization model is used for solving the research problem with the corresponding results is shown in Chapter 5 with the associated heuristic routing algorithm for WSNs based SHM. Overall conclusions are drawn and the future work contributions are presented in Chapter 6.

In Chapter 2, we present a comprehensive survey of the existing routing algorithms, together with the highlights of the classification of these routing algorithms. We also provide a taxonomy of different routing algorithms and outline the fundamental components and challenges associated with routing algorithms. Moreover, the design requirements of routing algorithms for WSNs are discussed to provide an insight into the objectives of routing algorithms. We compare existing routing algorithms and lay the groundwork for further research.

Most of the proposed routing algorithms are designed to be energy-efficient algorithms while delay caused by these flows has not been taken into account. In Chapter 3, end-to-end delay is mathematically formulated and a sub-optimal routing algorithm to minimize the delay is proposed. In this chapter, the problem is formulated assuming that the average delay follows the Poisson arrival process.

In Chapter 4, we present a new and detailed analytical model for calculating the flow traffic in WSNs-based SHM. Routing in SHM introduces a new aspect to the typical joint optimization in SHM networks. To the best of our knowledge, there is no analytical model which can jointly optimize the information quality and the energy consumption in a WSN based SHM. Optimizing the routing in such system helps to provide important insights into designing efficient routing algorithms (the assumption introduced in Chapter 4 is improved, using the mathematical analysis based on the multi-objective formulation as outlined in Chapter 5).

The model of the joint optimization is employed in Chapters 4 and 5 to add the node-disjoint routing into our optimization. We propose the algorithm by combining placement, optimal routing, and flow control in Chapter 4. After the proposed algorithm in Chapter 4, a sub-optimal routing is introduced due to the following reasons; (1) the energy consumption is decoupled from the information quality and (2) a sub-optimal approach is employed in the node placement and node's flow are selected for each link.

In Chapter 5, we obtain the optimal solution by formulating the problem as a large-scale mixed integer linear programming optimization problem. To solve the optimization problem, we also propose a solution based on the branch and bound algorithm. In order to reduce the computational complexity of the optimal solution, we propose a near-optimal joint placement and routing algorithm in Chapter 5. In the near-optimal algorithm, we solve the problem by decoupling the optimal energy consumption and information quality from the optimal placement.

In Chapter 6, we summarize the contributions presented in this dissertation and discuss several potential extensions to this work in our future work section.

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Chapter 2

Routing Algorithms for Wireless Sensor Networks based Structural Health Monitoring

2.1 Abstract

The building blocks of WSNs are the sensor nodes. Each node is deployed randomly or manually to collect readings about chosen attributes of an environment with access limitations such as in harsh environments [1]. All collected data need to be reported to the central node, called a sink, which is intended to manipulate the collected readings. In order to reach the sink, traffic can be sent directly or through intermediate nodes by a number of hops. The frequency of readings and reporting is application dependent.
This work focuses on WSNs as a special kind of ad-hoc network. These networks are subject to difficulties that have raised a number of research issues including deployment [12, 13], sensing [14, 15], decision making [16] and routing [1, 17, 18].

The development of routing for WSNs needs to address many challenges such as high computational overhead for processing data and prior knowledge requirements about the route. These challenges need to be handled during the process of routing algorithm design.
An overview of the WSNs is outlined in Section 2.2. Existing routing algorithms for WSNs are surveyed in Section 2.3.

2.2 Overview of Wireless Sensor Networks

WSNs consist of tiny, spatially scattered, autonomous devices or nodes equipped with several sensors that cooperatively monitor physical or environmental attributes and communicate wirelessly between each other. These attributes can be temperature, lighting, sound, vibration, pressure or motion depending on the application. Attributes of the WSNs also introduce special design requirements for the selected communication algorithm. The nature of WSNs as resource-constrained networks demands a communication algorithm that is optimized and customizable in terms of average end-to-end delay, energy consumption and memory size. WSNs have the potential to be an integral part of many applications. Examples include environmental monitoring and conservation, manufacturing, asset tracking, transportation, automation and health care [1].
The main goal for WSNs, which consist of mainly battery-powered nodes, is to prolong the lifetime of the network as it senses information and delivers it to the sink. As the main power source in WSNs, batteries cannot be replaced due to cost, or the hostility or remotivity of the environment. Therefore, the design, implementation and operation of WSNs require the integration of many disciplines. Unlike other networks, WSNs promise to connect end-users directly to the physical world in order

to provide information that is precisely determined in time and space according to the user's demands.

WSNs are application-specific, which means that one algorithm in one application can be more efficient than another algorithm in a different application. WSNs applications range from small-room temperature monitoring, to the monitoring of large areas such as airports. Since sensor nodes are usually small in size and low in cost [19], they are assumed to have low processing power and limited memory. However, a major problem for WSNs is the limited energy that sensor nodes have when powered by portable batteries, as these nodes are unattended and most are unable to receive energy from external sources.

The transmission and reception of bits consume over 50% of the energy in WSNs [20]. The minimization of transmission energy in WSNs has been studied in [21]. Energy consumption can be reduced by shortening the distance between source and sink, which can be translated to cutting down the number of hops under the assumption of fixed transmission range. However, it may be more energy-efficient to send data directly to the sink when the path loss increases with the increase in the number of hops.

In most applications, the sensed data should be as accurate as possible to ensure suitable decision making. Moreover, the sensed data should reach the sink in a timely manner. Some applications require guaranteed data delivery while other applications can tolerate the presence of faulty sensors while remaining functional [22]. Energy and delay are two important design parameters in WSNs. Energy-efficient algorithms achieve longer network lifetime but suffer from high delay, while QoS supported algorithms offer a lower delay at the cost of faster energy depletion. Therefore, a trade-off between energy and delay is needed for extending the lifetime of WSNs while satisfying the traffic requirements.

WSNs started to be running with a battery. This was preferred because of the reduction of size and associated cost in addition to helping with mobility. After a while the proposed power source acts as a burden in the WSNs functionality. The lifetime of the network is limited to the battery size and how its energy is depleted. The usage of the WSNs was limited to certain applications.

2.3 Existing Routing Algorithms for Wireless Sensor Networks

Node deployment in WSNs can be done in two ways, either randomly or manually. When node deployment is done in a random fashion, the nodes in the network form a wireless ad-hoc structure. Thus, the routing algorithms deployed in the network have to self-learn the topology information and dynamically forward data through an energy-efficient operation. When node deployment is done manually, the routes for transmitting data can be calculated optimally using an off-line algorithm to achieve some goals of lifetime maximization. In other words, the routes can be predefined. However, in case of the topology changes due to node/link failures, dynamic routing schemes are still necessary in manually deployed WSNs.

A survey on routing algorithms for WSNs is introduced in [1, 17, 18, 23, 24]. With the introduction of WSNs to new applications, QoS metrics are needed to be optimized [25–28]. A new category of WSNs routing algorithm are introduced where delay efficiency is the key design issue. Some examples of delay-efficient WSNs can be found in [5, 6]. As sensor nodes are equipped with a location finding device or can apply some kind of localization technique, the node location is used to guide the routing process. Location-aware routing algorithms are introduced such as [7–11].

Cross layer routing algorithms are introduced in [29–32] that use MOPT to optimize the routing decision.

An approach to get the benefits of the energy-efficient routing algorithms and delay efficiency imposed by the new user/applications requirement raises the need for energy and delay efficient routing algorithms. Some of these algorithms were introduced in [33–35]. Applying the idea of location-aware routing algorithms to achieve a balance between energy efficiency and delay efficiency is introduced in [36].

Energy-efficient algorithms are introduced in Section 2.3.1. They focus on minimizing the energy consumption in a node in order to extend the network lifetime, which is defined as the time till the first node runs out of energy. This is followed by a survey of algorithms, which try to make use of the node's location as well as the location of its neighbours in order to choose the next hop. These algorithms are called location-aware algorithms and are highlighted in Section 2.3.2. Because the type of traffic travelling through the WSNs can be data, audio or video, more focus is directed towards QoS metrics. This is achieved by presenting algorithms which accommodate such traffic. Delay-efficient algorithms are discussed in Section 2.3.3. Finally, MOPT routing algorithms are introduced in Section 2.3.4.

2.3.1 Energy-Efficient Algorithms

This section focuses on energy-efficient algorithms that choose the next hop for routing data in a way to maximize network lifetime [15, 24, 37]. Multiple studies propose techniques to reduce energy consumption in WSNs as in [38]. Flat-based energy-efficient routing algorithm is proposed in [39] where each node is assumed to be a base station. Each sensor node is flooded with information by its neighbours whether it is requested or not, so that the data availability is increased. Although queries in flat-based routing can be received faster than other routing, energy consumption depends on the traffic pattern instead of being uniform in each node. Moreover, the use of data flooding causes a high collision overhead and the reception of unnecessary or redundant data. Also, data aggregation is processed through nodes on the multihop path, which increases the overhead in these nodes. Routing here can be made optimal, but with added complexity. Thus, flooding is inefficient in terms of balanced energy consumption and memory management.

Flat-based energy-efficient routing algorithms provide routes based on a flat topology. This causes scalability problems as well as increased congestion among all nodes closer to the sink. Distributed aggregation mechanisms are necessary to decrease the information content flowing in each part of the network. Also, they suffer from data overload close to the sink as density increases. The nodes which are located near the sink route more information than nodes in other parts of the network. On the other hand, hierarchical routing algorithms maximize network lifetime by forcing high-power nodes to process and send data to the sink, leaving the low-power nodes to sense the environment. The network is divided into clusters, so a cluster head (CH) is chosen whose task is to compress the data and send it to the sink. Clustering ensures fair sharing of tasks among sensor nodes in the network, which reduces overhead on low-power nodes. However, data redundancy in the nodes cannot be prevented, creating the problem of uncertainty in routing data to the destination. CH loses energy faster, and thus, energy dissipation of the network cannot be controlled [40].

To solve problems associated with a flat-based approach, hierarchical or cluster-based routing techniques [41, 42] such as low-energy adaptive clustering hierarchy (LEACH) [3], energy-efficient hierarchical clustering algorithm (EEHCA) [2], and hierarchical power aware routing (HPAR) [43] have been proposed. LEACH [3] is based on the idea of an iterative randomized selection of CH in order to distribute the load of CH among nodes, hence extending the lifetime of the network. EEHCA is a hierarchical routing algorithm with reduced complexity presented in [2]. It uses a weighted function in order to achieve better performance, but still needs an iterative calculation to choose the next hop. HPAR [43], the last hierarchical algorithm, introduces lower memory requirements, but still suffers from additional calculation in the building of clusters. All these algorithms try to extend the network lifetime. The energy efficient routing to come to the foreground such as LEACH [3] and some other energy efficient algorithms are based on the iterative approaches such as [4]. All these algorithms were centralized and assumed to be run offline and fed to nodes. The need for a distributed routing algorithm that can be implemented on the sensor node drives the trend for the simplified node-based routing algorithms such as [1, 17, 18, 23, 24].

Power efficient gathering in sensor information systems (PEGASIS) proposed in [4] employs node localization. PEGASIS makes use of a minimal-energy consumption rule to determine whether to transmit data directly from one node to another or to relay it via a different node. This technique can minimize energy consumption; however, it fails if the node density is low.

Chang et al. propose an approach in [44]. An approach that employs maximum-lifetime routing (MLR) is introduced in [44]. Energy consumption is distributed fairly and practically. The sensor nodes adjust their power levels while selecting routes to optimize their overall performance. MLR achieves the best performance in terms of network lifetime. However, its computational complexity is high. It attempts to reduce the cost of data flooding instead of finding the most efficient path towards the destination.

Flow augmentation routing (FAR), which is nearly optimal in terms of maximizing network lifetime, is considered in [44]. However, its computational complexity is high. It attempts to reduce the cost of data flooding instead of finding the most efficient path towards the destination. In addition, its QoS metrics are lower than the traditional techniques such as ad-hoc on demand vector routing (AODV) [45].

A combination of randomized clustering and energy-level awareness is proposed in [46]. Hybrid energy-efficient distributed clustering (HEED) achieves a better energy consumption per cluster than LEACH [3] but ends up being more complicated than LEACH. Latency sensitive power control (LAPC) [47] is a power-control routing algorithm designed to reduce communication delays by adapting the transmission power to the work load. LAPC is not concerned with packet deadlines and only reduces communication delays in a best effort fashion.

Energy-efficient algorithms, in general, provide scalability in the network by limiting most of the communication inside the clusters formed. Consequently, the traffic generated in the network can be limited in CHs. This enables large-scale networks to be deployed without traffic overhead in certain parts of the networks. Moreover, dynamic clustering mechanisms result in better energy efficiency compared to flat topology algorithms. In event-based WSNs, where the nodes are mostly passive, most of the sensors can be put to sleep with the help of the CHs. Furthermore, most of the information and sophisticated functions are passed to a small number of CHs and the rest of the nodes perform simple tasks. This improves the overall network lifetime.

Despite their advantages, energy-efficient algorithms significantly rely on CH and face robustness issues such as failure of the CHs. Moreover, cluster formation requires additional signaling which increases the overhead in case of frequent changes. As a result, the trade-off between increased energy consumption of the CHs and the overhead in cluster formation needs to be considered for efficient operation.

Furthermore, communication inside the cluster is still a major challenge for many energy-efficient algorithms. Generally, CHs are assumed to directly communicate with the sink using high transmission power. This limits the applicability of these algorithms for large-scale networks, where single-hop communication with the sink is infeasible. Energy-efficient algorithms mechanisms are generally required in multihop communication. To make energy-efficient algorithms [4, 48] robust to changes and routing decision locally made, location-aware algorithms are presented in Section 2.3.2 that help make the decision distributed.

2.3.2 Location-Aware Algorithms

Routing can be achieved by using the location of the nodes as retrieved from a device such as global positioning system (GPS) receiver or by applying a localization algorithm. These are called location-aware routing algorithms. In such routing algorithms, nodes know their actual or relative positions with respect to a reference point and share this information with their neighbour nodes for routing processes [7, 49–52].

Most of the location-aware routing algorithms use directed routing, which can overcome the redundancy problem of the energy-efficient algorithms and reduce energy consumption by requiring low memory and complexity [7]. Location-aware routing techniques have been researched for ad-hoc networks for a long time [50]. They employ the geographical location of the nodes to route information from one node to another. One challenge with these techniques is to determine the location of the sensor nodes. Employing GPS to all the nodes in a large sensor network is costly and power hungry; however, a number of solutions have been presented [53]. An example would be the employment of reference points transmitting periodic beacon signals in which the nodes can localize themselves [10].

In [8], a location-aware routing algorithms, geographical adaptive fidelity (GAF), has been proposed where the network is divided into fixed zones. For a certain period of time, a portion of the nodes in the zone sleeps while the rest of the nodes perform the routing tasks on their behalf. Although this technique is location-based, it is similar to the hierarchical technique. It cannot overcome most of the problems faced in the hierarchical approaches, but the selection of nodes is simpler and more efficient than the hierarchical technique.

Geographic distance routing algorithm (GEDIR) [54] solves this problem by forwarding a packet to a neighbour that is the shortest distance from the sink instead of computing the total cost. However, it fails when a data packet crosses the same path twice in succession. Moreover, a node often selects the same neighbour causing higher energy consumption in some selective nodes and gets trapped in void regions.

Geographic and energy aware routing (GEAR) [9] uses directional routing to overcome the data redundancy and collision problem associated with the previous approaches. The nodes in the network calculate the lowest cost of sending data to the sink and forward data according to the calculated route. GEAR imposes computational overhead on the nodes as they try to estimate the total energy requirement for several paths.

Greedy other adaptive face routing algorithm (GOAFR) [55] uses both the greedy approach and face routing. The greedy approach forwards data to the nearest neighbour. Whenever a local minimum occurs, it sends the data back through the same route to the best face of the graph that has the lowest distance from the destination. The routing of data from source to destination is ensured by this technique; however, it cannot reduce the cost of routing since it increases as the network size increases.

Although location-aware routing algorithms try to be scalable and energy-efficient, they are subject to a dead-end problem where no more nodes make better progress to the sink. Partial-partition avoiding geographic routing (PAGER) [11] addresses this problem efficiently by identifying the danger zones, dividing the graph accordingly and providing directions to each node based on the division. Thus, PAGER relieves nodes from memorizing paths. However, it only routes data along the perimeter of the obstacle rather than finding an efficient path.

Location-aware routing algorithms exploit local position information for routing decisions. Instead of routing tables that are explicitly constructed, neighborhood information is implicitly inferred from the physical placement of nodes. This results in scalable routing algorithms. Moreover, location-aware routing algorithms have low complexity since the next hops can be selected based on local information.

On the other hand, the performance of location-aware routing depends on accurate knowledge of the location. The error in location detection can cause an error in routing. For example, sensor nodes are prone to failure and may be deployed in a hostile environment. If the GPS or location device is damaged, sensor nodes that depend on the device are rendered useless. In addition, the memory cost for the GPS may be expensive for some applications. Also, the power consumption and size of the GPS may not be appropriate if sensor nodes are operated by batteries and deployed in thousands.

Although location-aware algorithms are robust to changes, they do not match fast delivery constraints as location-aware algorithms are needed to be updated every interval. Energy-efficient algorithms that were discussed previously did not investigate the possibility of having time-sensitive traffic. In Section 2.3.3, a number of algorithms are introduced, which discuss how to accommodate the new type of traffic.

2.3.3 Delay-Efficient Algorithms

Routing algorithms designed to offer better results regarding QoS parameters are called delay-efficient algorithms [56]. Delay-efficient algorithms in WSNs have several applications including real-time target tracking in battle environments and emergent event triggering in environment monitoring applications such as tsunami alert. Consider an environment where monitoring, locating, detecting and identifying an event is crucial. In order to identify such an event, imaging and/or video sensors should be employed. After locating and detecting the event, those sensors can be turned on to capture an image of the target every time interval and to send it to the base station. Environment monitoring requires a real-time data exchange between sensors and destination in order to make proper decisions. However, real-time multimedia require a certain bandwidth with a minimum acceptable delay and jitter. In that case, a routing algorithm is needed in order to guarantee the delivery of data within specified time limits.

Threshold sensitive energy-efficient sensor network algorithm (TEEN) proposed that hierarchical clustering allows CH to impose a constraint when sensors report their sensed data according to two thresholds; a hard threshold that checks when to send the aggregated data in CH and a soft threshold that decides when to broadcast a small change in the value of the sensed attribute [57].

The two tier data dissemination routing algorithm (TTDD), proposed in [58], is a location-based technique for mobile sinks where data from the source is flooded to the local nodes in a cell in a grid structure. TTDD, however, does not work for mobile sources because high flooding is needed. Sensor algorithms for information via negotiation (SPIN) [6] is a resource-aware algorithm that is able to calculate the energy consumption required to compute, send, and receive data over the network. Thus, it can make informed decisions for efficient use of their own resources; however, its complexity is high.

An algorithm named SPEED is proposed in [5]. SPEED ensures a desired delivery speed via a combination of feedback control. It achieves real-time communication, however, it considers delay as a function of distance.

Heo et al. proposed a routing algorithm for WSNs, especially with industrial applications energy-aware routing for real-time communication (EARQ) [59]. EARQ provides real-time, reliable delivery of a packet, while considering energy awareness. In EARQ, a node estimates the energy cost, delay and reliability of a path to the sink node, based only on information from neighbouring nodes. However, it cannot be applied to all kinds of WSNs.

Delay-efficient routing algorithms consider metrics in addition to energy consumption for constructing routes. This provides additional capabilities to WSNs where more sophisticated applications can be developed. However, providing additional guarantees increases the cost in terms of energy consumption and hence, network lifetime. The trade-off between these additional capabilities and their costs should be carefully tailored to the requirements of the application.

In addition to the previous features, its QoS metrics are lower than traditional techniques. While routing is built on heuristic, optimization requires fixed inputs and well defined formulation. Routing algorithms are needed to keep the routing decision distributed by letting each node decide the next hop.

2.3.4 MOPT Routing Algorithms

Several studies have investigated combining energy consumption with other objectives in WSNs such as in [60–64]. Multi-objective optimization (MOPT) is usually used when balancing two contradicting variables. In WSNs, MOPT is needed when

WSNs design needs to match energy and delay requirements. In WSNs, energy optimization is a challenging issue since maximizing the network lifetime must be achieved without interrupting the flow of information. Delay optimization is also an important issue, especially when more delay-sensitive traffic is encountered in specific WSNs applications. Also, energy and delay optimization in WSNs have been the subject of several studies in order to find a possible set of solutions. Various WSNs applications, from environmental monitoring to smart environments, are discussed in [1, 18]. Routing optimization is used to calculate the optimal flow which prolongs the lifetime of the network. However, it is complicated for a large sized network.

A selected MOPT problem is considered in [60] with delay and energy objectives. An optimal set for the first relay is found where energy, delay and robustness are considered. Robustness is defined as the probability that a message will arrive successfully at the destination with a delay lower than the desired end-to-end delay, and with a number of hops lower than the hop limit. Another MOPT problem is presented in [63], where transmission energy and network geometry optimization are considered.

Madan and Lall [65] propose a cross-layer algorithm that works in the three lower layers of the communication stack. It is a partial and a distributed algorithm which aims to maximize network lifetime. They consider a single, stationary sink in this case. They expand their work in [31, 32] to maximize the lifetime of the network by employing optimization of transmission power, rate and link schedule. In these algorithms, Madan et al. introduce only the theoretical formulation of the optimal performance and no practical implementation or comparison of the required computational power to the existing node capabilities.

A cross-layer strategy to explore trade-off between energy efficiency and packet timeliness is shown in [66] through transmission power allocation and routing path selection schemes. In this article, optimization problem formulation fails to consider the network designers point of view. They fail to find the weighting factor for different objectives. A weighting factor reflects how each objective is affected by changes in other objectives. These complicated cross-layer algorithms push the limited resources of the node, resulting in NP-hardness.

To avoid NP-hardness of the combinatorial optimization problem of cross-layer design, a heuristic algorithm is proposed in [67] that follows the greedy approach towards energy efficient communication. A synergy between the physical and the medium access control layers is introduced to achieve efficient energy minimization. In this case, MOPT is used to ensure network connectivity and coverage above a certain level [33]. The utility maximization framework is applied in [68] to optimize the performance of WSNs.

An iterative algorithm for obtaining an optimal solution is introduced in [64] based on the upper network lifetime bound for a specific network topology. The complexity of the distributed algorithm is $O(N^4)$ where N is the number of nodes. The duty cycle is tuned dynamically based on network conditions to achieve the desired end-to-end delay [69]. The authors in [69] introduce a MOPT formulation for two objectives and find a set of possible solutions. They fail to study the effect of the objectives on each other.

Delay-energy aware routing algorithm (DEAP) is introduced for heterogeneous wireless sensor networks in [70], but it lacks MOPT formulation. A MOPT formulation for the sensor deployment problem. The solution is found using the genetic algorithms (GAs), which generates a set of optimal solutions in a single run and within a reasonable time. The designer then selects the best solution to fulfill the objectives [71]. The delay performance with in-network aggregation is introduced in [72].

The analytical results obtained show that with a small network the results are near-optimal. However, results for large networks have yet to be uncovered.

Decision thresholds for distributed detection using MOPT is introduced in [34], where probability of error and energy consumption are the objectives. In this case, WSNs applications, such as flood detection and military monitoring, develop more events per time unit [27]. A trade-off index is introduced and coefficients are tuned to produce better probability of error. Asymptotic analysis of transmission energy and delay is introduced in [73]. All these studies optimize two objectives at a time but fail to relate the objectives to each other and miss the understanding of the encountered complexity.

Chen et al. introduce hybrid geographic routing (HGR) [74]. HGR is a routing algorithm that combines both distance and direction-based strategies in one cost function. The cost function is used in order to find the trade-off between energy consumption and end-to-end delay. In HGR, packet delivery decisions are made locally and the state of a node is independent of the number of nodes in the network. However, each node must calculate its distance and direction to each other node in addition to deciding the weighting factor of the cost function. All these calculations are complex for the sensor node's capability. Also, deciding the weighting factor is not an easy task and requires a lot of feedback among nodes.

Most up-to-date research on MOPT has focused on finding the optimal solution. A spectrum allocation optimization is used to maximize fairness and spectrum utilization in [75]. A MOPT function compromising between probability of error and energy consumption is introduced in [76]. A distributed decision scheme that achieves minimum reporting delay with the power consumption constraint is shown in [77]. Some other QoS-supported routing algorithms are found in [78]. All these QoS supported algorithms require a large computational power that can quickly deplete a portable battery. Moreover, they are not able to accommodate different kinds of nodes.

Several WSNs applications are discussed in [80] that highlight the need for the

Table 2.1: The routing algorithms classification

Algorithm Category	Examples
Energy-Efficient algorithms	LEACH [3], EEHCA [2], HPAR [43], FAR [44], PEGASIS [4].
Location-Aware algorithms	GAF [8], GEAR [9], GEDIR [54], GeRaF [79], GOAFR [55], LAR [50], PAGER [11].
Delay-Efficient algorithms	TTDD [58], TEEN [57], SPIN [6], SPEED [5], EARQ [59], HEED [46].
MOPT algorithms	Cross layer [31, 32, 65], DEAP [70], HGR [74].

joint optimization of energy and delay. Energy optimization has been a salient concern for minimizing energy consumption and must be carried out without violating the data delivery constraint. Delay optimization is a substantial objective where fast-delivery of traffic is desired such as health care monitoring.

A solution that optimizes the design objectives is required where all considered constraints are satisfied. The conversion of the various objectives into a single one is done using either the weighted sum method or ϵ-constraint method [81]. The obtained solution reflects a trade-off between the objectives.

A single-objective function can be optimized by the ϵ-constraint method by representing all other objectives as constraints. Although this simple paradigm usually helps to achieve an acceptable result, multiple runs are required to achieve the optimal Pareto Front (PF). The PF is defined as the collection of all potential solutions, therefore, it is hard to obtain the best solution focusing on one objective without encountering at least one poor objective. There are a number of drawbacks associated with this method as the found solution will depend along the relative values of the weights specified. A non-dominated solution is the one which none of the objective functions can be improved in value without degrading some of the other objective values. Moreover, non-dominated solutions cannot be differentiated by this method. Only the convex part of the PF solution can be found, because the change in the formulation includes a linearization, which indicates the susceptibility of the results to the PF shape.

Existing research focuses on energy consumption and delay minimization in order to get a faster, energy-efficient delivery of the data [17]. Although some works on energy and delay minimization are introduced in [32, 65, 74], they fail to account for the necessities of the designer into account. Optimization results need to be detailed to specify the route for forwarding traffic between nodes. The algorithm should run within a linear time to match the sensor node's computation capability. Furthermore, the solution should achieve lower delay than the boundaries imposed by the WSNs application.

A cost function, including energy and delay, is optimized while delivering data to the sink. An energy and delay trade-off presents the constrained optimization problem formulation to satisfy the description of the WSNs. Optimization should meet the QoS requirements and maintain the lowest energy consumption. In addition, optimization should be scalable to large-scale network.

In [65], Madan and Lall introduce a cross-layer algorithm that operates on the lowest layers of the open system interconnection (OSI) communication model. A distributed algorithm is presented in order to maximize the network lifetime. A theoretical formulation of optimal performance is also introduced, but lacks the practical implementation to match the available computational power or the node facilities. In [32], the authors optimize the link schedule and the flow rate, as well as transmit power. They then extend their work to include the network lifetime maximization.

HGR algorithm is introduced in [74] which combines distance and direction-based methods in a composite equation for route selection. HGR enhances routing to be energy-efficient and matches delay requirements. Packet routing selection is locally made in HGR where each node is independent from others in the network. Therefore, each sensor node should calculate the distance and direction parameters as well as select the designated weighting factor. Only routing is decided since no flow assignment is determined. All the overall HGR calculations are above the limit of the sensor node's capabilities. Moreover, the weighting factor choice is difficult as the feedback between nodes is needed. A trade-off between packet timeliness and energy efficiency is demonstrated in [66] as authors presented a cross-layer policy for routing algorithm and transmission power allocation.

All optimization formulation problems presented in the reviewed literature fail to take the WSNs designers' perspective into account. An optimal weighting factor is still missing for a multi-objective solution. The perfect balance of objective weights indicates the influence of a change in one objective on the other. To achieve efficient energy minimization, a cooperation between layers is presented in [33] where the physical and medium access control functions are coordinated. Network connectivity and coverage optimization find solutions above a certain threshold. The cross-layer algorithms are complicated and pressure the sensor node's limited resources, resulting in NP-hardness [33].

To escape NP-hardness, a sub-optimal algorithm is introduced in [67] that attempts to have an energy-efficient communication which employs the greedy approach based on some heuristics. Framework using utility maximization is introduced in [68] to enhance the WSNs functionality. None of the works discussed so far try to find an equation for fitting a curve on the PF curve in order to offer a series of solutions.

Several studies have investigated combining energy consumption with other objectives in WSNs, such as [60, 63, 64, 69]. A MOPT problem with energy and delay objectives is considered in [60]. Robustness is the probability of success for a message arrival at its destination within the acceptable delay and the hop count limit. Energy, delay, and robustness are the considered objectives in [60] in order to find a Pareto optimal set for the relay selection problem. An additional MOPT problem is presented in [63] where optimization is considered for the geometry of the network and transmit energy.

An iterative algorithm is introduced in [64] for optimizing the routing based on the network lifetime upper bound for certain networks. Their distributed method complexity is bound by $O(N^4)$ where N is the number of nodes. In [69], to achieve the target delay, the sensor node's duty cycle is dynamically adjusted according to the network conditions. A two-objective expression is introduced to find the PF possible solution. However, the authors fail to show the effect of each objective on the other.

WSNs real-time applications such as military monitoring and flood detection are developing more events per time unit [27]. Due to the increased number of events, works such as [34] focuses on energy consumption and error probability are the two objectives optimized using distributed detection where decision thresholds are found. Coefficients are tuned, and a trade-off indicator is introduced to lower probability of error results. The authors in [73] then present an analysis of transmission energy and delay using an asymptotic method. All studies reviewed optimize two objectives simultaneously, on the other hand, authors do not investigate the relationship between the two objectives. Furthermore, they fail to evaluate the encountered complexity.

One of the existing algorithms shown in [44] uses maximum lifetime routing (MLR) algorithm, which optimizes the flow transmission through a cost function built based on the energy level in both the sender and receiver. MLR distributes energy consumption fairly before each node reports its residual energy level and decides the routes that would optimize their overall performance. Other existing algorithms take network conditions such as environmental design parameters into consideration.

In [70], a routing algorithm is introduced for heterogeneous WSNs which is taking energy and delay into consideration, but no MOPT formulation is given. A solution to the sensor deployment problem presented in [82], which generates a set of Pareto optimal solutions within a limited run-time. This solution is based on a MOGA implementation, however, [71] presents the best solution in terms of fulfilling the objective. In-network aggregation delay optimization introduced in [72] demonstrates that the analytical results obtained are near-optimal for a small network size. However, the literature has not yet covered large-scale networks.

Recent research on MOPT focusing on the PF curve can be found in [75–77]. Spectrum allocation optimization is presented in [75] to maximize spectrum utilization and fairness. Energy consumption and the probability of error are formulated as a MOPT function in [76]. Lastly, a distributed algorithm shown in [77] achieves minimum delay in reporting data under the energy consumption constraint.

In location-based routing, sensor nodes are addressed by their positions. The distance is estimated between neighbouring nodes on the basis of received signal strength indicator (RSSI). By exchanging such RSSI information between neighbours, neighbouring nodes can obtain their relative coordinates. Instead of that, the node's location may be available directly using a low power GPS receiver equipped with the nodes [7]. Location-based routing requires lower computational complexity and smaller memory size because they save no redundant data much like flat-based routing demonstrated in [6].

Unlike hierarchical routing shown in [2, 3, 5, 32, 44, 58, 65, 83]. The purpose of these algorithms is to compute a flow that minimizes the energy consumption as in [32], maximizes the lifetime of a network as in [3, 44, 65] and minimizes the average delay as in [5,58]. Most of the existing algorithms factor in the distances among the sensor nodes when determining the next hop to find the route to forward data towards its destination.

The routing algorithm needs to be energy-efficient, QoS-aware and preferably distributed. Node capability must be taken into consideration and should accommodate different application requirements [18]. When more parameters are added to the cost function of the routing algorithm, the routing decision becomes too complex for the sensor node. Finding a suitable routing algorithm that is application-independent is still an open research topic [18].

Using the node's location information, the routing algorithm limits data flooding in the network. Such nodes become aware of their neighbours' location by exchanging information obtained from the GPS module embedded in some sensor nodes or by using a localization method. Location information leads to faster discovery with lower traffic flowing through the network [51].

FAR algorithm is introduced in [44] and associates a cost value to each link according to the following function:

$$cost_{ij} = (e^{t}_{ij})^{\pi_1} \underline{E}_i^{-\pi_2} {E_{\Delta}}_i^{\pi_3} + (e^{r}_{ji})^{\pi_1} \underline{E}_j^{-\pi_2} {E_{\Delta}}_j^{\pi_3}, \tag{2.1}$$

where e^t_{ij}, e^r_{ji} is the transmission and reception energy consumption on link $i - j$, respectively; $\underline{E}_i, \underline{E}_j$ is the residual energy of node i and j, respectively; $E_{\Delta i}, E_{\Delta j}$ represents the initial energy of node i and j, respectively; (π_1, π_2, π_3) are the arbitrary exponents which are employed to modify the weighting of each parameter

in the associated mapping. FA has the best performance at $\pi_1 = 1$ regardless of the values assigned to both π_2 and π_3. FAR with $\pi_1 = 1$ achieves better performance compared with other combinations of the exponent vector [44, 84], however, the memory requirement for most techniques is excessive [7]. FAR achieves a near-optimal network lifetime, however, the embedded computational complexity is high. FA decreases the data flooding instead of picking out the best route to the sink yet it gives lower QoS metrics than traditional algorithms such as AODV algorithm presented in [45].
Location-based routing is surveyed in [7]. Moreover, path selection using the angular directionality is presented in [36]. The approach in [36] uses the node's coordinates to decide how to forward the data to other nodes. That algorithm calculates the deviation angle between the sensor node and the sink. The calculated angle is compared with predefined threshold values, and the decision of either forwarding data to a one of the neighbouring nodes or sent to the sink directly is made by the node. Angle directionality is employed in order to send the data on a route as close to the direct communication.

2.4 Existing Work for SHM Using WSNs

In WSNs for SHM, nodes are deployed in selected locations to gather data reflecting the structural state. To guarantee the the effectiveness of the WSNs, the sensor node placement is required to be energy-efficient and with high information quality. Recently, the sensor placement optimization for WSNs for SHM has been studied in [27, 43, 64, 85–91].
In [43], Li et al. design an algorithm to find the optimal locations for sensor nodes, taking both network connectivity and civil engineering requirements such as cover-

age of critical locations in the structure into consideration. Sensor placement ensures the optimization of the Fisher information matrix (FIM) for the placement location indicator quality and energy consumption.Fisher information essentially describes the amount of information data provide about an unknown parameter.

Sensor node placement algorithm using the effective independence method (SPEM) is a placement algorithm based on sorting sensor locations according to the FIM results. SPEM excludes the nodes with the least contribution. The authors in [27] introduce a power-aware sensor placement algorithm using the effective independence method (p-SPEM) algorithm for the placement optimization. The algorithm is based on a local search between all possible locations selected by SPEM. p-SPEM takes the following inputs: a vibration pattern of the structure called the mode shape, the number of candidate locations (M) given by the civil engineering placement criteria, the number of sensor nodes to be placed (N) and the assumptions related to the routing. The p-SPEM algorithm outputs the set of the selected sensor nodes out from the set of candidate locations. The output set is chosen to optimize FIM and satisfy the constraints.

The authors in [27] show that the placement optimization problem is NP-hard. They use a heuristic iterative algorithm that decouples the structure monitoring and network requirements. The complexity of the placement algorithm is reduced from $O(N^M)$ to $O(N^4M)$ by using this heuristic technique. In [88], the authors develop a benchmark for SPEM in MATLAB. This benchmark implements the sensor placement algorithm for SHM, while SPEM in [88] used both synthetic and real data models for evaluation.

The authors in [91] find the minimum number of sensors required to reconstruct the mode shapes for SHM. They investigate the optimal placement of accelerometer sensors to achieve acceptable FIM for a structure. The resulting sensor node placement algorithm is used in conjunction with the extension of Shannon's theorem to the spatial domain. The steps for sensor placement are as follows: First, the algorithm selects the highest mode shape to be measured. Then, it estimates the wavelength for that mode and place a sensor node for each value of the mode shape. Lastly, it places two additional sensors within half the wavelength span, with each sensor at one-sixth of the wavelength spacing from each node.

The authors in [86] present an evaluation of sensor placement for WSNs that use large amounts of prior information. The placement algorithm of the selected nodes gives minimum energy consumption and maximum sensing coverage while capturing most of the available information. The energy efficiency, sensing coverage and operational lifetime of WSNs are improved in [86], but the algorithm is impractical for real structures as it has high computational complexity. The authors in [87] introduce an energy-efficient placement algorithm based on GAs, which has sufficient coverage. The two objectives in [87] take sensor coverage and system lifetime into consideration. The simulation results indicate an improvement in performance in terms of coverage and system lifetime. However, an extremely vast increase in the number of generations in GAs is needed.

An added objective in [85] includes fault tolerance in sensor placement optimization. The authors take a heterogeneous WSNs for SHM that has three types of nodes. These types of nodes are resource-rich nodes, resource-constrained nodes, and redundant nodes. Furthermore, the algorithm in [85] adds these nodes to enable the fault tolerance ability of the network. They present a three-phase sensor placement (TPSP) approach to obtain the sensor node positions. Phase 1 looks for a near-optimal location for resource-rich nodes. Phase 2 finds the optimal location for resource-constrained nodes while ensuring connectivity. Phase 3 places redundant nodes to mitigate a sensor failure situation. The optimization of the placement in [85] aims at achieving the following objectives: satisfying the networking demands, maintaining reliable and low-complex placement, and reducing the chance of failures in WSNs.

The authors in [90] consider a sensor placement algorithm based on GAs to optimize the SHM for bridge constructions. They present an algorithm for maximizing the system lifetime by employing network coding in sensor placement optimization for linear network topologies to match the structure type. When sensors are placed along the length of the bridge, optimization aims at minimizing the failure in the link connectivity and maximizing the lifetime of the network. Both packet relay and network coding are key factors for routing collected data packets between two sink nodes positioned at each end of the bridge. The mathematical analysis in [90] shows that their algorithm saves energy, prolongs the system lifetime and removes bottlenecks in the networks. While work in [90] is useful, it lacks numerical results to support their claims.

In [64], Zussman et al. study energy-efficient routing in emergency sensor networks by using an iterative algorithm. Their objective is to maximize the network lifetime and the flow bounded by the possible node's data rate. Their algorithm complexity is $O(N^4)$, where N is the number of nodes in the network. This work shows the need for a low complexity heuristic algorithm to deal with the special characteristics of WSNs.

In [89], the authors formulate the sensor placement optimization problem with the following objectives to be optimized: coverage, energy consumption, and connectivity. The conversion of multiple objectives into a single objective uses the decomposition approach. The authors then compare the performance of their algorithm with other evolutionary algorithms.

Building WSNs for SHM requires an optimal placement of sensor nodes as well as efficient routing. All placement algorithms in the studied literature perform routing after selecting the sensor node locations. These approaches do not guarantee the optimality of the entire solution in terms of achieving the optimization problem objectives such as minimizing energy consumption and maximizing information quality.

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Chapter 3

Joint Routing and Flow Assignment Hybrid Geographical Routing in Wireless Sensor Networks

3.1 Abstract

Energy optimization represents the main goal in wireless sensor networks design where a typical sensor node has usually operates by making use of battery with limited-capacity. The sensor's collected data has to be delivered within a specific delay limit which shows the need of delay optimization. The joint optimization of the energy consumption and delay for a conventional wireless sensor networks is presented. In this problem, the following points are presented: First, we introduce a joint multi-objective optimization formulation for both energy and delay for most sensor nodes in various applications. Second, we present the Karush-Kuhn-Tucker

analysis to demonstrate the optimal solution for each formulation. Third, based on the multi-objective optimization formulation, we introduce a method for determining the knee on the Pareto front curve, which meets the network designer interest for focusing on more practical solutions. Lastly, we calculate the optimal weighting factor for both objectives which allows the network designer balance their mutual interaction between the two objectives. This technique helps network designers increase the simplification of the design process. A joint routing and flow assignment hybrid geographical routing is proposed. In the proposed algorithm, we use the progressive distance and angle directionality to choose the best route and determine the optimal flow which is considered a novel distributed algorithm. A near-optimal flow for diverse network sizes is achieved by the proposed algorithm under the evaluated network metrics. Hence, the implementation of the proposed algorithm is suitable for the limited-resource sensor node due to the reduced complexity. Several network metrics will be evaluated; the simulation will be conducted to complement and to extend the results.

3.2 Introduction

Energy optimization is an essential design goal in WSNs, as sensor nodes are equipped with a limited-capacity battery. The data gathered from the sensing field needs to be delivered within an acceptable delay limit which highlights the necessity of delay optimization. In this chapter, we make the following contributions: First, we introduce a joint MOPT formulation for both energy and delay for monitoring and tracking applications. Second, we present the Karush-Kuhn-Tucker (KKT) analysis to demonstrate the optimal solution for each formulation. Third, based on the MOPT formulation, we introduce the development and testing of knee determination on the PF curve, which meets the network designer interest for resilience while limitings the design solutions. Lastly, we calculate the optimal weighting factor for both objectives, and the proposed trade-off allows the WSN designer various solutions for their mutual interaction. This technique helps network designers to simplify the design process. A novel distributed algorithm called joint routing and flow assignment hybrid geographical routing (JFA-HGR) is proposed that uses the progressive distance and angle directionality to choose the best route and determine the optimal flow. The proposed algorithm achieves near-optimal flow for diverse network sizes for different metrics. Hence, the proposed algorithm implementation is possible along the sensor node due to the reduced complexity. The simulation conducted complements and extends the results, allowing several network metrics to be evaluated.

Optimization plays a significant role in the WSNs design. In the optimization procedure, multiple and equally opposing objectives must be met. MOPT finds the optimal solution from a set of possible solutions that optimize all objectives. However, all possible solutions may be needed by the WSN designer at the same time. MOPT is more difficult to solve compared to single objective optimization, therefore, the MOPT problem is converted into a single objective problem using the weighted sum method [1]. A weighting factor attached to each objective can indicate the preferences of the network designer before merging them into a unified expression that can be solved by an optimization method applying only a single-objective.

PF is the collection of all potential solutions, therefore the best solution focusing on one objective is impossible to obtain without encountering at least one poor objective. These reviewed works overlook the knee on the PF is which the designer's area of interest that makes the movement in one objective produce a reduction on the other objective. As a result, we introduce an extension to finding knee on the

PF for the joint optimization of energy and delay in WSN.

Hybrid geographic routing (HGR) algorithm is introduced in [2] which combines distance and direction-based methods in a composite equation for route selection. A heuristic algorithm is introduced to compute the best routes employing the node's coordinates to minimize energy consumption and delay with low computational complexity. FA algorithm is introduced in [3]. To overcome the exorbitant memory requirement problem of previous algorithms, several algorithms try to minimize the energy consumption. In this chapter, a location-based routing algorithm that employs a criterion using the angle of deviation for forwarding data is proposed.

Energy is optimized with a delay constraint and delay is minimized under an initial energy constraint. Both found solutions do not guarantee the optimality of the energy and delay together. In this chapter, the following contributions are introduced:

- We formulate a joint optimization of energy and delay for WSNs.
- We find the generated PF from MOPT that jointly optimizes both the energy and delay.
- We calculate the knee region on the fitted PF curve where the optimal solutions exist. However, the weighting factor given to each component in the MOPT is unknown.
- We develop a technique for finding the optimal weighting factor. Thereafter, the weighting factor is found to help the network designer choose the optimal solution.
- We propose a heuristic algorithm for jointly providing the flow assignment and routing as an extension based on an existing algorithm introduced in [2].

The rest of this chapter is arranged as the following: the problem description and the system model, as well as the energy, delay and joint MOPT models, are presented in

Section 3.3; the proposed algorithms are explained in Section 3.4; simulation results for energy, delay and joint MOPT model are presented in Section 3.5; finally, The conclusion of the chapter is found in Section 3.6.

3.3 Problem Description and System Model

In WSNs, the main goal is to deliver traffic to the sink in an optimized fashion with low delay, using limited available energy. Sensor nodes are usually equipped with nonchargeable batteries and deployed in limited access environments. These limitations contribute to the problem of energy optimization, a common design concern in WSNs [32].

In our work, energy consumption is reduced by data flow minimization in each link while the node's information generation rate is satisfied. This should be done with the capacity constraint taken into consideration as it imposes limited capacity links all around the network.

The selection of a route depends on the traffic flow at any given time in the link. Formulation of the link delay is modeled so that the delay increases proportionally with the flow passing at this link. The data flow is divided among different network links in the optimization problem to balance the flow between links and reduce delay efficiently. Hence, a joint of energy consumption and network delay optimization is proposed.

3.3.1 Model Assumptions

The WSNs model used in [8] is based on the following assumptions:

- There are N sensor nodes, which are uniformly distributed within the area of interest.

- One or more source nodes exist with only one sink node whereby the source nodes generate data flow destined for the sink.
- The remaining nodes act as intermediary nodes that generate no more traffic.
- Sensor nodes are stationary with equal capabilities regarding communication and signal processing.
- Sensor nodes are battery-powered, which means they are energy constrained.
- Their initial energy is fixed and power control is enabled so they can adapt their transmission power to the distance of the next hop.

3.3.2 Energy Model

The notations used here are much like those found in [37] include the following: the link set $\mathbb{L}$ consists of many links from a source i to a destination j represented by a link $(i-j) \in \mathbb{L}$. q_{ij} is the capacity for the link $(i-j)$, which indicates the upper limit of the number of packets that can be transferred through that link per time unit. In the network, a sensor node can act either as a source or intermediary router passing traffic to the next hop or the sink, where traffic is delivered. A path is the group of consecutive links meeting with the source-destination pair. There are up to k possible paths for each $l-l'$ pair. The number of all paths is defined in $P_{l-l'}$ where $(l-l') \in \mathbb{L}$. The average traffic going through a link is measured at a packet per second and is represented by the flow. Therefore, the flow x_k indicates the amount of flow for a particular path k.

The total data traffic generated by the node l for a given $(l-l')$ pair, which is used by the node l', is represented by $b_{l-l'}$. Routing decision is defined as determining a route from l to l' to allocate the traffic to each path linking the pair. $A_{(l-l')_k}$ is the path indicator for the $l - l'$ pair which is shown as follows:

$$A_{(l-l')_k} = \begin{cases} 1 & \text{if} \qquad k \in \mathbf{P}_{l-l'}, \\ 0 & \text{otherwise}, \end{cases} \tag{3.1}$$

where $\mathbf{P}_{l-l'}$ is the set of all the paths for $l - l'$ pair. The flow equality constraint is given as:

$$\mathbf{A}\mathbf{x} = \mathbf{b}, \tag{3.2}$$

where the path incidence matrix is $\mathbf{A} \in \mathbb{R}^{m \times n}$, $\mathbf{x}$ is the flow matrix and $\mathbf{b}$ is the information generation rate. Meanwhile, the link incidence matrix $\mathbf{C}$ contains the elements such as $(c_{ij})_k$ which is given by:

$$(c_{ij})_k = \begin{cases} 1 & \text{if} \qquad k \in \mathbf{F}_{ij}, \\ 0 & \text{otherwise}, \end{cases} \tag{3.3}$$

where $\mathbf{F}_{ij}$ is defined as the set of paths that include link (i, j). The flow through the link is the sum of all flows passing through that link. The flow constraint is given in matrix form as follows:

$$\mathbf{Y} = \mathbf{C}\mathbf{x}, \tag{3.4}$$

where $\mathbf{Y}$ is the matrix representing the flow in each path.

To send a number of data packets between nodes, one of the nodes needs to expend energy. Energy will also be consumed when the node receives data packets from other nodes. The energy consumed through transmission is a function of the separating distance between the two nodes and the amount of the data to be sent. In terms of reception, the energy is a function of the data flow, since the distance does not play any role on the receiver side. Let y_{ij} be the flow in a link $i - j$ where $E_r(y_{ji})$ is the reception energy function. The transmission energy function is

$E_t(y_{ij})$. $E_t(y_{ij})$, is a function of the distance between the source and the sink. The total energy consumed through a link $i - j$ is $E(y_{ij})$ and is given by the following:

$$\begin{aligned} E(y_{ij}) = & \quad E_t(y_{ij}) + E_r(y_{ji}) \\ = & \quad (\epsilon_t + \epsilon_{amp} d_{ij}^2) y_{ij} + \epsilon_r y_{ji}, \end{aligned} \tag{3.5}$$

where ϵ_{amp} is the transmit amplifier coefficient, since radio parameters ϵ_t and ϵ_r are the energy consumption coefficients per second per bit for transmitter and receiver, respectively. The total energy per node is given by

$$E_{total}(\mathbf{x}) = \mathbf{1}_N^T E_i(\mathbf{x}), \tag{3.6}$$

where $\mathbf{1}_N$ is the sum vector of size $1 * N$ having all N elements equal to one, $E_i(\mathbf{x})$ is the total energy consumption for node i. The main use of this sum vector is to find the sum of the elements in $E_i(\mathbf{x})$.

The energy optimization formulation is expressed as follows:

$$\begin{aligned} & \underset{\mathbf{x}}{\text{Minimize}} && E_{total}(\mathbf{x}) \\ & Subject \quad to: && \\ & (c1): && \mathbf{Ax} = \mathbf{b}, \\ & (c2): && \mathbf{Cx} \leq \mathbf{Q}, \\ & (c3): && E_{total}(\mathbf{x}) \leq E_{\Delta}, \\ & (c4): && \Psi(\mathbf{x}) \leq D_{max}, \\ & (c5): && \mathbf{x} \geq 0. \end{aligned} \tag{3.7}$$

The optimization problem's constraints address traffic, capacity, delay and flow. The formulation has the following constraints: (c1) imposes that the total traffic from each node is equal to the data sources generation rate $\mathbf{b}$ in all nodes, (c2) guarantees that the flow rate for each link should not exceed the upper limit of the link capacity $\mathbf{Q}$, (c3) ensures that the consumed energy is lower than the initial energy E_{Δ} of each node, (c4) imposes that the delay, $\Psi(\mathbf{x})$ presented in Eq. (3.8), is less than the maximum delay limit set by user and application requirements for the whole network $D_{\max}$, and (c5) ensures that the flow rate is always positive.

3.3.3 Delay Model

In the WSNs design process, delay becomes an important objective for applications such as fire detection and tsunami alert [32] where traffic needs to be reported with minimum delay. The source node delay consists of the following components: the data acquisition sensing time, the processing time, the transmission time, the waiting time in the queue for the received data and the propagation time, which is the time taken to cross the physical media and is deeply dependent on the characteristics of the link. In addition, for a wireless media, the propagation time depends on the source-destination distance. Compared to the other components the propagation delay is negligible as the encountered distance between nodes in WSNs is commonly short. In this chapter, the transmission time and queuing time are the only components considered to represent the end-to-end delay as they are the most dominating ones. The delay will increase as the traffic on the link approaches the magnitude of the capacity. When this occurs, the link qualifies as congested.

The delay can be determined by the defining level of congestion in each link such as the method used in the $M/M/1$ queuing model as in [37]. The optimization problem can be formulated when the delay is defined as a convex function [37]. Suppose link $(i-j)$ has a capacity of q_{ij} such that the expected flow in the link, x_{ij} is bounded by the assigned capacity. The delay will be longer when the traffic reaches link capacity and the link becomes congested. The flow through a link divided by the link maximum capacity is assumed to be proxy to the average delay experienced by all the packets in the network. The network's total delay is the sum of all delays measured across all links. In any given path, the delay is assumed to be summable over the traversed links to obtain an overall delay value expressed as:

$$\begin{aligned} \Psi(\mathbf{x}) = & \quad \textstyle\sum_{i,j} \phi(x_{ij}) \\ = & \quad \textstyle\sum_{i,j} \frac{c_{ij}x_{ij}}{(q_{ij}-c_{ij}x_{ij})} + \sigma c_{ij}x_{ij}, \end{aligned} \tag{3.8}$$

where $\phi(x_{ij})$ is a result of the queue at the sending end of the link. $\sigma c_{ij}x_{ij}$ is the sum of the processing delay through the link. The constrained optimization problem formulation of the delay is given as follows:

$$\begin{aligned} & \underset{\mathbf{x}}{\text{Minimize}} \qquad \Psi(\mathbf{x}) \\ & \textit{Subject} \quad \textit{to}: \ \ (c1) \quad \textit{to} \quad (c5). \end{aligned} \tag{3.9}$$

The problem solvability relies on having a high enough capacity for the network links. The objective function shown in Eq. (3.9), is convex since it is a weighted sum of linear functions. Also, it is convex due to being differentiable on $\mathbf{x}$ [38]. The proof of convexity of the delay component is performed by checking if the Hessian is positive semi-definite. The Hessian of the delay component is given as follows:

$$H = 2x_{ij}(q_{ij} - x_{ij})^{-3} + x_{ij}(q_{ij} - x_{ij})^{-2}. \tag{3.10}$$

Although the delay function is nonlinear on $\mathbf{x}$, its Hessian is a positive, semi-definite for all values of $\mathbf{x} > 0$, which still makes the objective function convex as shown in [37].

3.3.4 Multi-Objective Optimization (MOPT) Model

MOPT model provides trade-offs among energy consumption and an end-to-end delay. The joint energy and delay optimization problem is represented as follows:

$$\begin{aligned} \underset{\mathbf{x}}{\text{Minimize}} \quad & E_{total}(\mathbf{x}) \\ \underset{\mathbf{x}}{\text{Minimize}} \quad & \Psi(\mathbf{x}) \\ Subject \quad to: \quad & (c1) \quad to \quad (c5). \end{aligned} \tag{3.11}$$

In this model, there are two objectives optimized. The first objective is the energy minimization intended to exploit of the node's battery efficiently while the second objective is the delay minimization for fast delivery of the data. These two objectives are opposing each other and each objective is assigned a weight based on its importance.

3.4 The Proposed Algorithms

In this section, we list the proposed algorithms first, the KKT optimality condition in Section 3.4.1. Second, the MOGA algorithm is used to find a near-optimal solution in Section 3.4.2 and finally a heuristic algorithm based on HGR is presented in Section 3.4.3.

3.4.1 Karush-Kuhn-Tucker (KKT) Analysis

In the addressed energy minimization problem under a delay constraint, the Lagrangian multipliers for the objective function for energy are as follows:

$$\begin{aligned}
L_e(x, \Gamma, \lambda) = & \quad (\epsilon_r \mathbf{C}^T \mathbf{x} + \\
& (\epsilon_t + \epsilon_{amp} \mathbf{d}) \mathbf{C} \mathbf{x}) + \\
\Gamma_1 (\mathbf{A}\mathbf{x} - \mathbf{b}) + \lambda_1 (\mathbf{C}\mathbf{x} - \mathbf{Q}) + & \\
\lambda_2 (\epsilon_r \mathbf{C}^T \mathbf{x} + & \\
(\epsilon_t + \epsilon_{amp} \mathbf{d}) \mathbf{C} \mathbf{x} - E_\Delta) + & \\
\lambda_3 (\Psi_\mathbf{x} - D_{max}), & \qquad (3.12)
\end{aligned}$$

where $\Psi_\mathbf{x}$ represents the maximum overall delay for any given path in the network. Based on the Lagrangian function, the equations of the associated multipliers is as follows:

$$
\begin{aligned}
\frac{\partial L_e(x,\Gamma,\lambda)}{\partial \mathbf{x}} &= & \epsilon_r \mathbf{C}^T + & \\
& & (\epsilon_t + \epsilon_{amp}\mathbf{d})\mathbf{C} + & \\
& & \Gamma_1 \mathbf{A} + \lambda_1 \mathbf{C} + & \\
& & \lambda_2(\epsilon_r \mathbf{C}^T + & \\
& & (\epsilon_t + \epsilon_{amp}\mathbf{d})\mathbf{C}) & \\
& & + \lambda_3 \Psi'_{\mathbf{x}} & = 0 \\
\frac{\partial L_e(x,\Gamma,\lambda)}{\partial \Gamma_1} &= & \mathbf{Ax} - \mathbf{b} & = 0 \\
\frac{\partial L_e(x,\Gamma,\lambda)}{\partial \lambda_1} &= & \mathbf{Cx} - \mathbf{Q} & = 0 \\
\frac{\partial L_e(x,\Gamma,\lambda)}{\partial \lambda_2} &= & \epsilon_r \mathbf{C}^T \mathbf{x} + & \\
& & +(\epsilon_t + & \\
& & \epsilon_{amp}\mathbf{d})\mathbf{Cx} & \\
& & -E_{\Delta} & = 0 \\
\frac{\partial L_e(x,\Gamma,\lambda)}{\partial \lambda_3} &= & \Psi_{\mathbf{x}} - D_{max} & = 0, \qquad (3.13)
\end{aligned}
$$

where $\Psi'_{\mathbf{x}}$ is the first derivative of the delay component with respect to $\mathbf{x}$.

In the case of $\vec{x}$ as a vector of two variables, the x_1, x_2 are the data flow on each link. Similarly, let $a_{11}, a_{12}, a_{21}, a_{22}$ represent whether a link exists or not between nodes. In addition, b_1, b_2 are the information generation rates for each source. Meanwhile, $c_{11}, c_{12}, c_{21}, c_{22}$ represent links in each path. The values q_1, q_2 are the capacity for each link. When the system of equations is solved on the element level, the optimal flow for minimizing energy $\vec{x_e^*}$ is as follows: In the addressed delay minimization problem under an energy constraint, the Lagrangian multipliers for the objective function of delay with the energy constraint are as follows:

$$\begin{aligned} L_d(x,\Gamma,\lambda) = \Psi_{\mathbf{x}} + \Gamma_1(\mathbf{Ax}-\mathbf{b}) + \lambda_1(\mathbf{Cx}-\mathbf{Q}) \\ +\lambda_2(\epsilon_r\mathbf{C}^T\mathbf{x} + (\epsilon_t + \epsilon_{amp}\mathbf{d})\mathbf{Cx} \\ -E_\Delta) + \lambda_3(\Psi_{\mathbf{x}} - D_{max}). \end{aligned} \tag{3.14}$$

The equation of the associated Lagrangian is as follows:

$$\begin{aligned} \frac{\partial L_d(x,\Gamma,\lambda)}{\partial x} &= & \Psi'_{\mathbf{x}} & \\ && +\Gamma_1\mathbf{A} & \\ && +\lambda_1\mathbf{C} & \\ && +\lambda_2(\epsilon_r\mathbf{C}^T & \\ && +\epsilon_t\mathbf{C} & \\ && +\epsilon_{amp}\mathbf{Cd}) & \\ && +\lambda_3\Psi'_{\mathbf{x}} & = 0 \\ \frac{\partial L_d(x,\Gamma,\lambda)}{\partial \Gamma_1} &= & \mathbf{Ax}-\mathbf{b} & = 0 \\ \frac{\partial L_d(x,\Gamma,\lambda)}{\partial \lambda_1} &= & \mathbf{Cx}-\mathbf{Q} & = 0 \\ \frac{\partial L_d(x,\Gamma,\lambda)}{\partial \lambda_2} &= & \epsilon_r\mathbf{C}^T\mathbf{x}+ & \\ && (\epsilon_t+ & \\ && \epsilon_{amp}\mathbf{d})\mathbf{Cx} & \\ && -E_\Delta & = 0 \\ \frac{\partial L_d(x,\Gamma,\lambda)}{\partial \lambda_3} &= & \Psi_{\mathbf{x}} - D_{max} & = 0. \end{aligned} \tag{3.15}$$

Solving the system of equations for a small-scale results in finding the values of the optimal solution x_d^* with the unknown variables $\vec{x_d^*}, \Gamma_1, \lambda_1, \lambda_2, \lambda_3$.
The Lagrangian multipliers of the joint energy and delay minimization problem under its constraint using MOPT with the weighted sum method for the energy and delay objective function are as follows:

$$
\begin{aligned}
L_{e,d}(x, \Gamma, \lambda) = \omega \Psi_{\mathbf{x}} + (1-\omega)(\epsilon_r \mathbf{C}^T \mathbf{x} + \\
(\epsilon_t + \epsilon_{amp} \mathbf{d}) \mathbf{C} \mathbf{x}) + \\
\Gamma_1 (\mathbf{A}\mathbf{x} - \mathbf{b}) + \\
\lambda_1 (\mathbf{C}\mathbf{x} - \mathbf{Q}) + \\
\lambda_2 (\epsilon_r \mathbf{C}^T \mathbf{x} + \\
(\epsilon_t + \epsilon_{amp} \mathbf{d}) \mathbf{C}\mathbf{x} - E_{\Delta}) + \\
\lambda_3 (\Psi_{\mathbf{x}} - D_{max}).
\end{aligned}
\tag{3.16}
$$

The equations of the associated Lagrangian is as follows:

$$\begin{aligned}
\frac{\partial L_{e,d}(\mathbf{x},\Gamma,\lambda)}{\partial x} &= & \omega\Psi'_{\mathbf{x}}+ & \\
& & (1-\omega)(\epsilon_r \mathbf{C}^T\mathbf{x}+ & \\
& & (\epsilon_t+\epsilon_{amp}\mathbf{d})\mathbf{C}\mathbf{x})+ & \\
& & \Gamma_1 A+\lambda_1\mathbf{C}+ & \\
& & \lambda_2(\epsilon_r\mathbf{C}^T+ & \\
& & \epsilon_t\mathbf{C}+ & \\
& & \epsilon_{amp}\mathbf{C}\mathbf{d})+ & \\
& & \lambda_3\Psi'_{\mathbf{x}} & = 0 \\
\frac{\partial L_{e,d}(\mathbf{x},\Gamma,\lambda)}{\partial \Gamma_1} &= & \mathbf{A}\mathbf{x}-\mathbf{b} & = 0 \\
\frac{\partial L_{e,d}(\mathbf{x},\Gamma,\lambda)}{\partial \lambda_1} &= & \mathbf{C}\mathbf{x}-\mathbf{Q} & = 0 \\
\frac{\partial L_{e,d}(\mathbf{x},\Gamma,\lambda)}{\partial \lambda_2} &= & \epsilon_r\mathbf{C}^T\mathbf{x}+ & \\
& & (\epsilon_t+\epsilon_{amp}\mathbf{d})\mathbf{C}\mathbf{x} & \\
& & -\mathrm{E}_{\Delta} & = 0 \\
\frac{\partial L_{e,d}(\mathbf{x},\Gamma,\lambda)}{\partial \lambda_3} &= & \Psi_{\mathbf{x}}-D_{max} & = 0.
\end{aligned} \tag{3.17}$$

From the previous equations, $\vec{x^*_{e+d}}$, Γ_1, λ_1, λ_2, λ_3 can be found, therefore, optimal flow for minimizing both energy and delay can be calculated.

3.4.2 Multi-objective Optimization Using Genetic Algorithms (MOGA)

The optimal solution found numerically in the previous section is too complex for the sensor node capability; therefore, a simpler sub-optimal approach is needed. In the following, MOGA is used as an ace of the heuristic approach for obtaining a sub-optimal result. MOGA is an efficient heuristic search technique, which starts with a population of available chromosomes. Each chromosome represents a solution for the specified problem. Each solution is evaluated through the fitness function to demonstrate the solution's suitability. Two solutions are selected according to their fitness values to generate a newer offspring solution through the crossover operation. The generated solutions share some features taken from each selected solution.

A closed form solution is difficult to achieve even for WSNs on a large-scale, nevertheless, the study of the mathematical paradigm is necessary to read the following physical parameters: the information generation rate for each node, the initial energy, the delay limit, and the capacity attributed to each link. These parameters clarify the convexity of the problem.

After the new formulation that jointly minimize the energy and delay through the multi-objective optimization, a sub-optimal solution based on artificial intelligence approach of MOGA is introduced. MOGA is compared to the MOPT-based routing and flow assignment using the optimality conditions of KKT. The solution with the lowest fitness is less likely to be selected.

A population of potential solutions is produced by the selection of the best solution from the current generation. The selection process is repeated until the stopping criteria are reached. With the proper tuning of the MOGA parameters, the population will converge to a near-optimal solution of the current problem [39]. MOGA is an optimization tool explained in [1] that solves MOPT problems. This is an attractive tool because of its ability to search partially ordered search space for several alternative trade-offs. Additionally, MOGA can track several solutions simultaneously via its population.

3.4.3 The Proposed Joint Flow Assignment- Hybrid Geographical Routing (JFA-HGR) Algorithm

The communication among nodes is determined after the optimization problem has been formalized. While the optimized solution taken from different solvers minimizes the energy and delay, a full practical routing algorithm is still needed to choose the next hop and decide the flow in each link. In this chapter, a novel, location-based routing algorithm is proposed that minimizes the energy consumption and delay with reduced complexity and increased network lifetime.

HGR [2] uses the following equation to decide the best route:

$$\rho_i = \alpha(\mu_i/r_c)^2 + (1-\alpha)(1-|\theta_i|/90)^2, \quad \alpha \in [0,1], \tag{3.18}$$

where ρ_i is the route preference for node i, θ_i is the deviation angle from the direct path, μ_i is the progressive distance towards the sink, r_c is the transmission range, and α is the weighting factor in the route selection composite metric. To decide the flow amount on a specific link the following equation is used

$$x_{ij} = \eta_i[(\theta_{total} - \theta_i)/\theta_{total}], \tag{3.19}$$

where x_{ij} is the flow going through the link $i-j$, η_i is the information generation rate of node i. θ_{total} is the sum of all angles for nodes inside the arc of $|\theta_i| \leq \theta_{th}$, let ρ_{max} be the maximum route preference and θ_{th} is the threshold angle, whereas, ρ_{max} and θ_{th} be the design parameters.

Contrasting with other algorithms, the HGR algorithm employs angle directionality with the node's coordinates of the sensor nodes that calculate the best route with the lowest computational complexity. The sensor network has many-to-one traffic patterns, which means many of the sources forward their traffic to the sink node. We propose a joint flow assignment - hybrid geographical routing (JFA-HGR) algorithm. The routing decision is based on location information collected from the neighbouring nodes and the sink. The proposed routing algorithm avoids the route discovery, establishment, and maintenance phases that take place in other routing algorithms.

A new joint flow assignment based on HGR is proposed. Algorithm 1 demonstrates the JFA-HGR pseudo-code. The proposed algorithm fits into the many-to-one traffic pattern of WSNs with its consideration of the sink direction, where θ_i is embedded inside the node that contains the forwarding decision. The node can then make decisions for itself based on the location information of its neighbours. In addition to the routing, the flow assignment is determined to optimize the network objectives.

Algorithm 1 **Joint Flow Assignment- Hybrid Geographical Routing (JFA-HGR)**

Inputs N is the number of nodes and node locations.
Compute ρ_i by Eq. (3.18) for N sensors.
while true **do**
    Compute flow assignment x_{ij} on link $i - j$ according to Eq. (3.19);
    if $\rho_i \leq \rho_{max}$ **then**
        Calculate the total energy consumption E_{total}.
    else Calculate the best routes **Break**
    end if
end while
Outputs The selected route and the flow assigned x_{ij} for each link.

3.5 Numerical Results

This section elaborates on how the optimization results are obtained in Section 3.5.1. MOGA results are presented in Section 3.5.2. In Section 3.5.3 introduction to the simulation environment and its configuration. In this section, simulation results that evaluate the proposed algorithm are shown. With the platform used in the simulation is explained and metrics are calculated. Performance of each metrics is analyzed in a separate section with the detailed discussion of these results.

3.5.1 Optimization Results

In this section, we demonstrate the optimization environment, energy results, delay results and MOPT results. We implement all these algorithms to find optimal location-based routing algorithms: energy results, delay results and MOPT results where both energy and delay are combined to generate MOPT results. MOPT is executed and compared to existing routing algorithms, and thus, the optimal solution found under the given settings.

Optimization Environment

The simulation experiments are implemented in MATLAB on the Windows XP operating system running on a IBM computer with an Intel Xeon processor and a 2 GB memory. Test cases are available for 5, 7, 16, 20, 30, and 50 node networks. The network area is 100 m $\times$ 100 m. All source nodes have 6 Mbps information generation rate as in [40]. In all case studies, the link capacity is set to be 10 Mb at maximum. Initial energy in each node varies from 1 to 100 joules. The acceptable delay is limited to 20 msec up to 400 msec. Both the energy coefficient ϵ_t and ϵ_r are equal to 50 nJ/bit and ϵ_{amp} is equal to 100 pJ/bit/m$^2 according to 1001$[29].

Energy Results

The energy results listed in columns 1 to 4 in Table 3.1 are generated under an upper delay bound, which is the maximum acceptable delay assigned. The energy for different network sizes is determined using the constrained optimization toolbox in MATLAB, which runs using the interior point method algorithm [41].

The performance of the network is calculated in terms of energy consumption under different delay limits. Results show the metrics for the amount of energy required to achieve lower delay limits for different network sizes. To address larger networks, they need to be simulated to obtain the required energy. The run-time is also recorded for each network case study to judge the optimization complexity.

As shown in Table 3.1, the energy efficiency is higher with lower delay limits. Energy supplied is set to 100 J which corresponds to a higher required energy beyond the available one. This makes the solution with these restrictions infeasible for the parameters given. The acceptable maximum delay bound is set to 20, 32, 100, 200, and 400 msec, which are the acceptable delay limits for highly interactive applications such as voice applications [42].

Delay Results

The delay results listed in columns 5 to 7 in Table 3.1 show the average end-to-end delay to investigate additional available energy effects on performance. The performance of the network case study is characterized under an upper energy bound. This bound represents the initial energy stored in each node in the network.

The delay for different network sizes is determined using the *fmincon* function in MATLAB [43]. As expected, the run-time increases as the size of the network increases. The analytical results in Section 3.3.3 are useful to provide an approximation of the effect of

Table 3.1: Energy and delay optimization for several node case studies using Pareto front curve

Number of nodes	Delay upper Bound (msec)	Energy (J)	Run-time (sec)	Energy Upper Bound (J)	Delay (msec)	Run-Time (sec)	Energy (J)	Delay (msec)	Run-Time (sec)
Five	D_{max}= 20	1456	79.97	E_{Δ}= 1	112	79.97	2.2	103.5	105.22
	D_{max}= 32	300	82.46	E_{Δ}= 10	108	128.46	2.3	103.0	105.22
	D_{max}= 100	77	85.19	E_{Δ}= 20	108	85.19	2.4	102.5	105.22
	D_{max}= 200	39	86.00	E_{Δ}= 50	108	85.00	2.8	102.0	105.22
	D_{max}= 400	5.6	88.48	E_{Δ}= 100	101	88.48	3.6	101.5	105.22
Seven	D_{max}= 20	1734	551.32	E_{Δ}= 1	114.7	537.71	1.6	111	668.15
	D_{max}= 32	380	537.71	E_{Δ}= 10	112.6	551.32	2.0	104.0	668.15
	D_{max}= 100	120	469.37	E_{Δ}= 20	110.6	469.37	2.2	102.0	668.15
	D_{max}= 200	50	437.27	E_{Δ}= 50	109.6	437.27	2.4	101.0	668.15
	D_{max}= 400	10.7	368.15	E_{Δ}= 100	105.6	668.15	3.2	100.0	668.15
Sixteen	D_{max}= 20	1872	1399.61	E_{Δ}= 1	100.6	1399.61	1.7	112.5	1399.61
	D_{max}= 32	430	1399.61	E_{Δ}= 10	100.4	1399.61	1.9	106.0	1399.61
	D_{max}= 100	150	1399.61	E_{Δ}= 20	100.2	1399.61	2.2	102.5	1399.61
	D_{max}= 200	65	1399.61	E_{Δ}= 50	100.1	1399.61	2.4	101.3	1399.61
	D_{max}= 400	15.4	1399.61	E_{Δ}= 100	98.4	1399.61	2.8	100.5	1399.61
Twenty	D_{max}= 20	1980	1737.32	E_{Δ}= 1	135	1737.32	1.9	135	1737.32
	D_{max}= 32	500	1737.32	E_{Δ}= 10	134	1737.32	2.9	134	1737.32
	D_{max}= 100	175	1737.32	E_{Δ}= 20	133	1737.32	3.4	133	1737.32
	D_{max}= 200	80	1737.32	E_{Δ}= 50	132	1737.32	5.7	132	1737.32
	D_{max}= 400	21	1737.32	E_{Δ}= 100	130	1737.32	6.9	130	1737.32
Thirty	D_{max}= 20	2194	2955.62	E_{Δ}= 1	154.3	2955.62	3.1	154.3	3139.34
	D_{max}= 32	616	2955.62	E_{Δ}= 10	154	2955.62	3.5	154.0	3139.34
	D_{max}= 100	189	2955.62	E_{Δ}= 20	153	2955.62	5.2	152.3	3139.34
	D_{max}= 200	90	2955.62	E_{Δ}= 50	152	2955.62	6.7	152.0	3139.34
	D_{max}= 400	24	2955.62	E_{Δ}= 100	150.8	2955.62	8.4	150.8	3139.34
Fifty	D_{max}= 20	2353	82078.62	E_{Δ}= 1	228.6	82078.62	99.9000	228.6	82078.62
	D_{max}= 32	782	82078.62	E_{Δ}= 10	228	82078.62	99.9001	228.6	82078.62
	D_{max}= 100	230	82078.62	E_{Δ}= 20	227.8	82078.62	99.9010	228.6	82078.62
	D_{max}= 200	135	82078.62	E_{Δ}= 50	225.7	82078.62	99.9016	228.6	82078.62
	D_{max}= 400	71	82078.62	E_{Δ}= 100	220.7	82078.62	99.9020	228.6	82078.62

different network parameters on delay. Simulation results provide more understanding of this effect for large-scale simulations. Table 3.1 results show the delay for different case studies under the energy bound of 1, 10, 20, 50, and 100 joules. As the energy upper bound increases the run-time increases. This means that more solutions will be available in the search space, which makes the delay minimized to lower values.

MOPT Results

Network energy consumption is minimized under a delay constraint as shown in Section 3.5.1. The delay is reduced under an energy constraint outlined in Section 3.5.1. We combine both energy and delay into a single objective function. Both objectives to be minimized simultaneously using the weighted sum method.

The PF is useful in WSNs design to focus attention on a set of efficient solutions. Network designers can make trade-offs with these solutions in the knee rather than consider the full set of all possible solutions. The MOPT simulation results presented in the next section show how the knee is selected for different network sizes.

To evaluate the relationship between energy consumption and delay, a network with a different number of nodes is simulated. The PF curve is found to be an exponential curve, which represents the relationship between the two objectives. Using the PF curve, the knee is selected based on a small change in energy, which reflects a substantial reduction in delay and vice versa. The Pareto-optimal is calculated to find the minimum possible energy for a given delay while the optimal trade-off curve defines the knee. The knee for the network design is the region where energy-delay pairs are between the starting pair (E_{sp}, D_{sp}) and the ending pair (E_{nd}, D_{nd}).

For a given network topology, the network energy-delay region consists of all the achievable pairs under the assumptions of that network model. The energy-delay region is a convex set. The energy-delay points (E_{sp}, D_{sp}) and (E_{nd}, D_{nd}) are contained within this knee region. The gain of energy efficiency is more significant in the knee than other parts of the PF curve.

Both energy and delay for different network sizes are determined using MATLAB with the MOGA optimization toolbox (*gamultiobj*). The possible solution is represented by circles and the fitted curve for the PF is represented by a solid line. The knee is represented by arrows pointing to the knee start and knee end with the associated weighting factor.

In this section, the PF is determined for different network sizes, and then, a fitted curve is found for each case. The fitted curve follows the exponential equation in the following: $\zeta = \alpha e^{\beta \chi} + \gamma$, where ζ is the objective shown on the vertical axis as a function of χ. The objective is shown on the horizontal axis in addition to α, β, γ is the coefficients of the exponential equation.

Knee Determination Results

For the five-node case study, one source, four possible paths, and seven links are considered as in [44]. The energy and delay are calculated for the case study, and the PF is shown in Fig. 3.1. The increases in energy consumption have no more reduction in delay outside the knee as shown in Fig. 3.1. The simulation results match the analytical results found in Section 3.4.1. Coefficients shown with the minimum and maximum limits for the exponential fitted curve for the five-node case study are as follows (with 95% confidence bounds): α = 3.896e+004 (-2.675e+004, 1.047e+005), β = -0.006176 (-0.006857, -0.005495), and γ = 0.1048 (0.1037, 0.106).

The knee is the points between the (2.2 J,111 ms) and (3.6 J,101.5 ms) pairs. The fitted equation is used to regenerate the PF curve. To verify the work, the five-node network case study is solved by hand. Both analysis and simulation results match. Similarly, the fitted equations are calculated for the different network case studies.

The end-to-end delay, on link congestion for different values of energy consumption, is shown in Fig. 3.2. A seven-node case study network with two source nodes, six possible paths, and thirteen links is considered. The energy consumption reduction is more significant in the knee because a slight change in delay produces a large change in the energy consumption. The gain in energy efficiency is more significant in the region of the (1.6 J, 111 ms) and (3.2 J, 100 ms) pair as shown in Fig. 3.2.

In Fig. 3.3, a sixteen-node case study network with two source nodes, six possible paths, and twenty-three links is studied. The gain in energy reduction is more significant in the knee, which happens in the region of the (1.7 J, 112.5 ms) and (2.8 J, 100.5 ms) pair as demonstrated in Fig. 3.3.

Results of MOPT are presented within the PF where the PF is shown according to the operating conditions. Also, the results of MOPT formulations are listed in columns 8 to 10 in Table 3.1. For the twenty-node network case study, only one source node, seven possible paths, and twenty-three variables are considered. Nodes are located on a grid line where each line has two nodes. Lines are equally separated where the length of the field is set to 100. For the thirty-node network case study, four source nodes, nine possible paths, and thirty-five variables are considered. Nodes are located on five grid lines with five nodes on each line. Similarly, lines are equally separated in the field. All pairs are generated from one run for the optimization function. The number of variables considered increase as the run-time increases exponentially. The results show a set of solutions in the knee where both delay and energy are minimized.

The run-time result is approximately two days for a network size of fifty-node. Due to its long run-time, only one MOPT model run is held. Also for twenty-node and thirty-node case studies, run-time makes plotting the fitted PF curve difficult.

As shown, the MOPT generates solutions in the knee where more reduction is accomplished with little increases in the other parameters. This range corresponds to the area of interest for network designers. This finding is important because instead of selecting from the 137 possible solutions on the curve, only 20 solutions exist in the selected region. The knee achieves a speed-up of 85% less than the full PF. Speed-up helps the network designers produce better solutions in reasonable time. The behaviour of the PF is different outside the knee where an increase in the delay limit will not significantly reduce the energy consumption.

The knee of the achievable energy-delay pair is found using a PF curve generated from the MOPT solver. The weighting factor for each objective is determined by the weighted sum method. A calculated weighting factor shows a tendency for energy to affect the path selection more than the delay. The objective function values are compared with the energy and delay values.

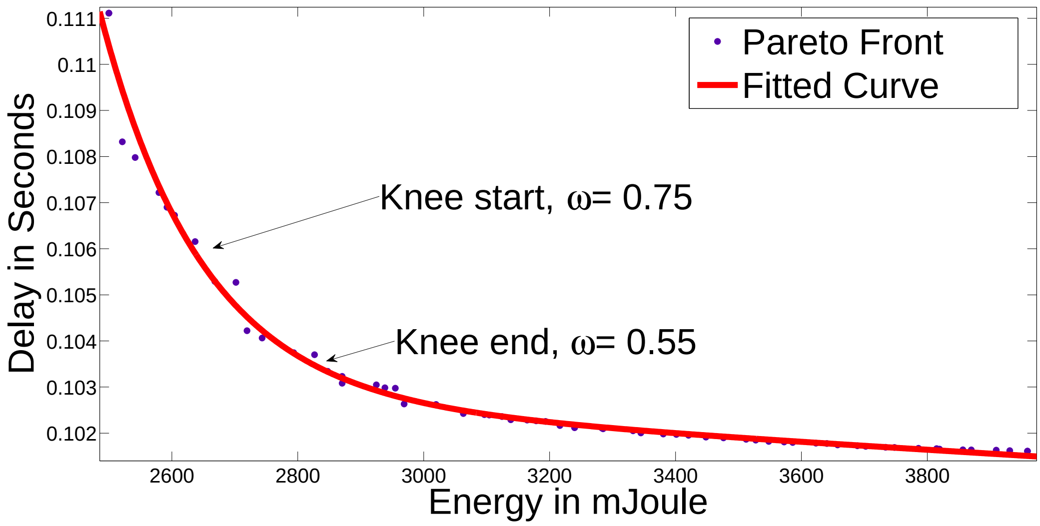

Fig. 3.1: Pareto front for the five-node case.

3.5.2 MOGA Results

Mathematical solutions are obtained for WSNs with a number of nodes between 5 and 50 in the network. The initial energy E_{Δ} is set to 1 J while the maximum delay is set to 1.8 seconds as in [2]. For our MOGA implementation, GA operators are selected such that

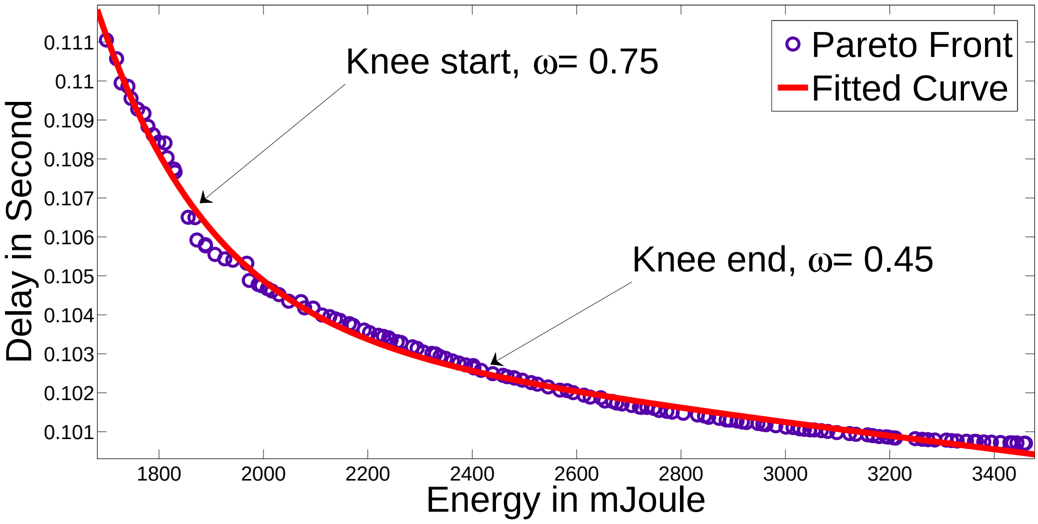

Fig. 3.2: Pareto front for the seven-node case.

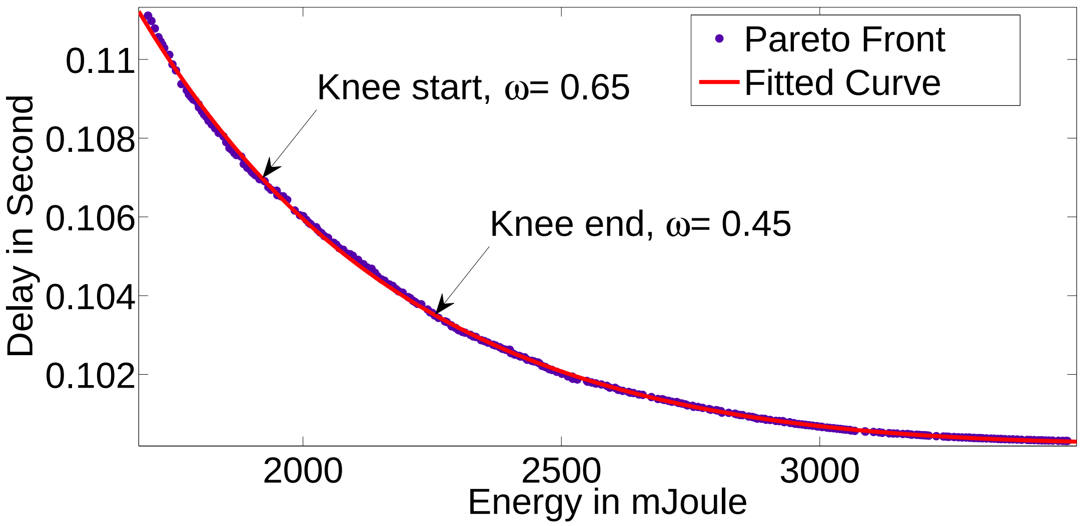

Fig. 3.3: Pareto front for the sixteen-node case.

the crossover probability is equal to 0.8, and the mutation probability is 0.2. Meanwhile, the population size is 300, and the upper limit number of generations is chosen to be 300. We also simulate the HGR algorithm [2] for comparison purposes. The sub-optimal energy results for different network sizes are determined by the MOGA solver. The results related to the delay for different network sizes for the studied methods are decided to utilize the network simulator fed by the optimal flow rates calculated in each instance. The network simulator is used for calculating the metrics under these flows.

The energy, and the delay are shown for different weighting factors ω in Fig. 3.4 and Fig. 3.5, respectively. The optimal solution given in these figures is generated from Eq. (3.11). The energy is obtained using the Newton-Raphson method applying the optimal weighting factor ω^*. The optimization results from [8] and MOPT with $\omega = 0.5$ is presented.

Fig. 3.4 shows the energy consumption versus ω. The results related to the energy show how the energy consumption, under each ω, affects the performance. It is evident that MOGA achieves 40% saving in the energy consumption compared to that of the HGR algorithm at ω close to one. MOGA is getting two times savings compared to HGR at ω equals to half. Results are significantly lower for various ω not only for the optimal solution, but also for a sub-optimal solution obtained by MOGA than HGR [2].

Fig. 3.5 shows the average end-to-end delay versus the different weighting factors. MOGA results are 25% lower than HGR results at ω equals to zero. The results show that MOGA has slightly higher energy consumption than that of the optimal solution and MOGA, particularly at the small N.

A trade-off between the energy and the delay is obtained when both, the energy and the delay, are combined in a single objective function. The combined objective function allows both objectives to be minimized simultaneously. Fig. 3.6 shows the energy consumption versus the number of nodes. For the optimal solution, the energy consumption is 15% of that of the HGR algorithm while the energy consumption of MOGA is 50% of that of the

HGR algorithm at $N = 50$.

Fig. 3.7 depicts the delay versus the number of nodes. The results show that delay of MOGA is longer than that of the optimal one because the GA get trapped at local optimum solutions. Furthermore, the gap between MOGA and the HGR increases as the number of nodes increases because of the parallelism of GA in finding the solution.

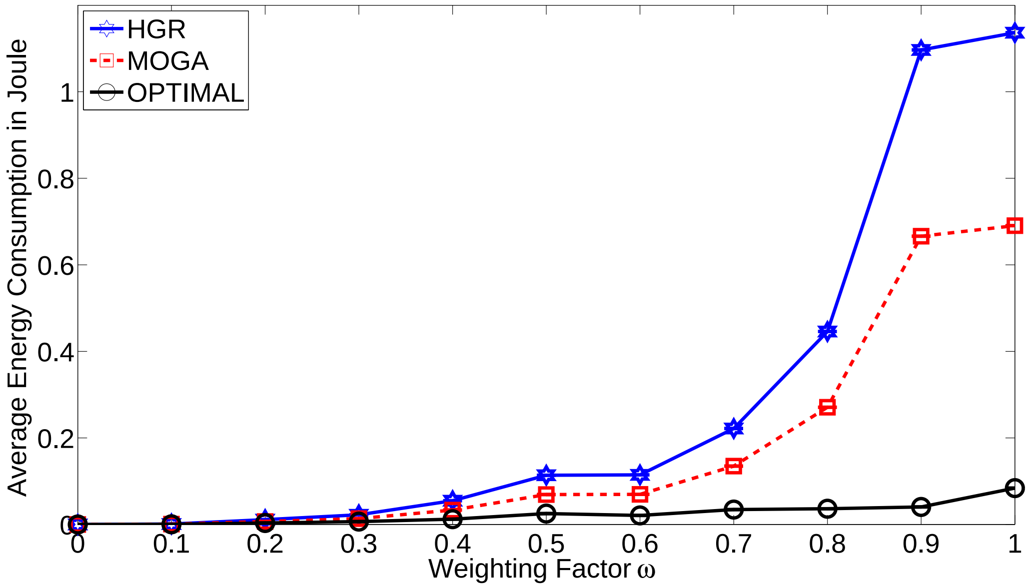

Fig. 3.4: Energy consumption versus the weighting factor.

3.5.3 Simulation Results

The network traffic simulator (OMNeT++) [45] is used for the algorithms simulation which is developed by C language. The parameters used in the simulation is presented in Table 3.2 and are listed as follows: a number of nodes, N, are placed at random in a network area. Nodes are assumed to be stationary, and since the only sink exists in the network area, nodes start with an energy of 2.5 J. We have evaluated and analyzed the performance of JFA-HGR with the OMNeT++ network simulator [45]. The node density is maintained constant to evaluate the scalability of the algorithms in a better way.

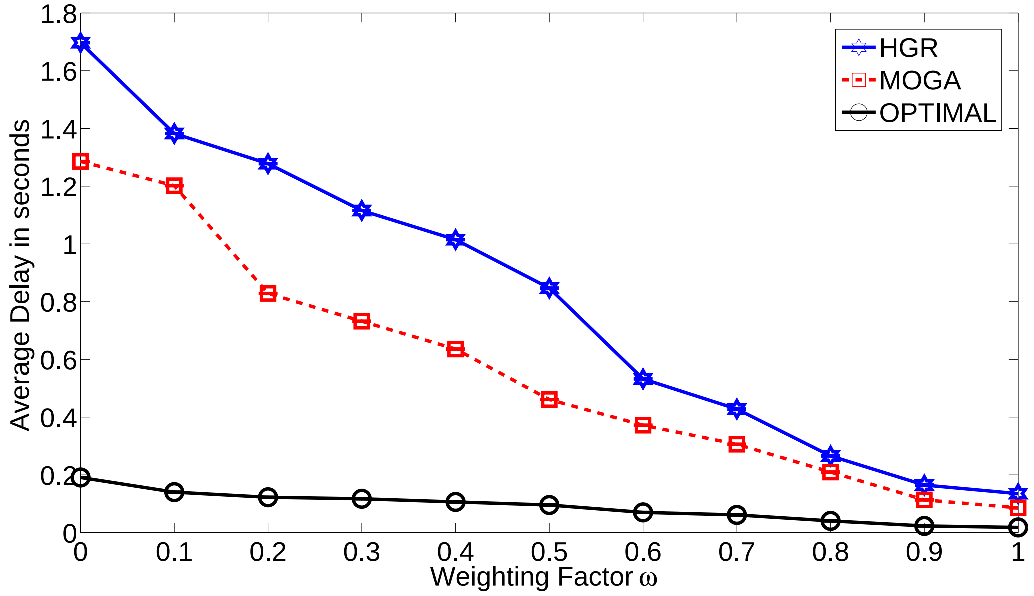

Fig. 3.5: Average delay versus the weighting factor.

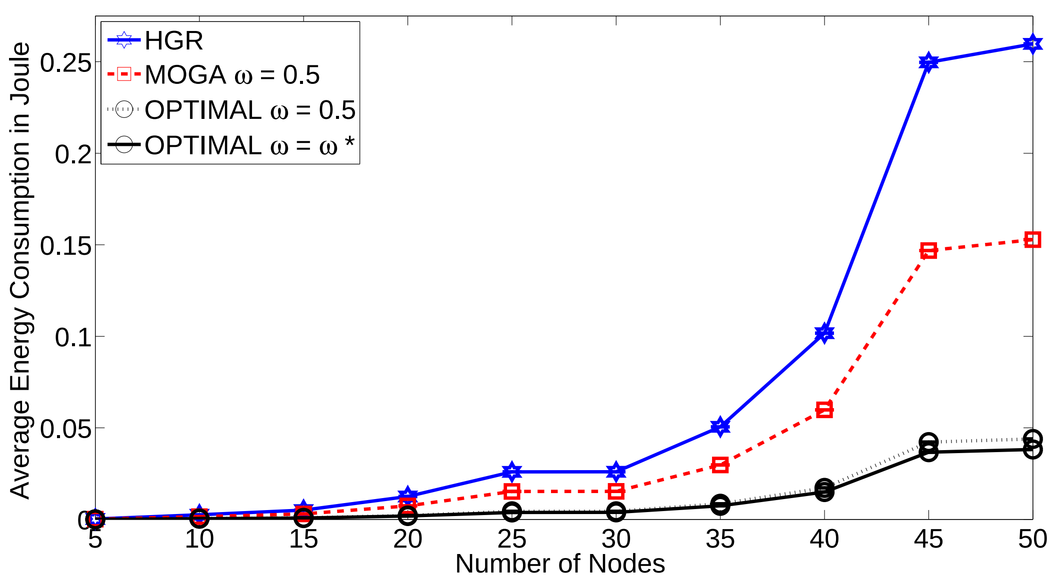

Fig. 3.6: Energy consumption versus the number of nodes.

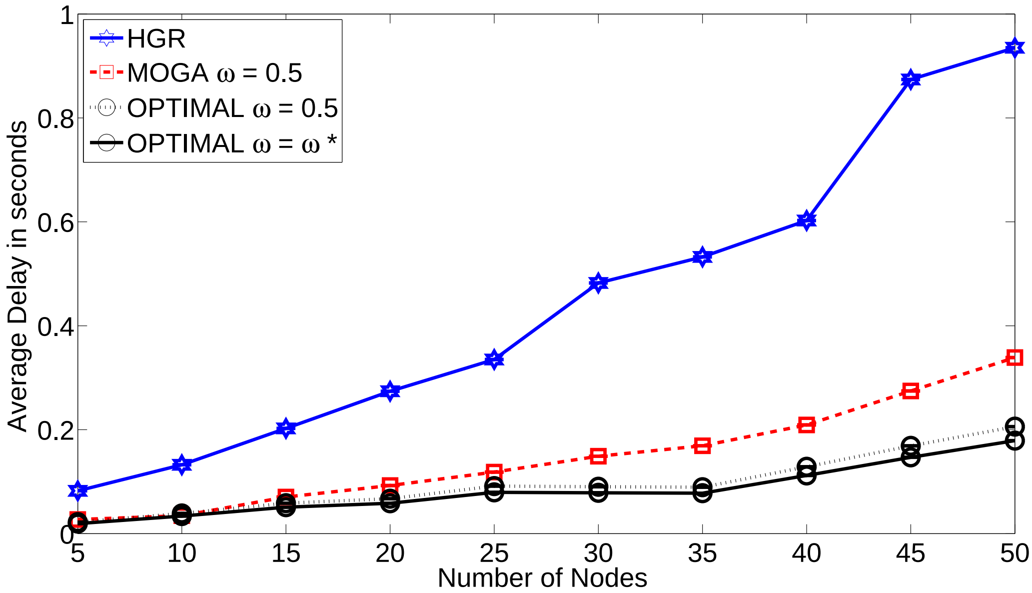

Fig. 3.7: Average delay versus the number of nodes.

Table 3.2: The simulation parameters

Parameter	Value used
Simulation Time	1 hour
Network Dimension	100 m × 100 m
Number of Nodes	10, 20, 30, 40, 50
Propagation model	Two-ray
Radio Frequency	2.4 GHz
Radio Bandwidth	1 $Mbps$
Routing Algorithms	AODV, FA, JFA-HGR, HGR, MLR
MAC Algorithm	CSMA/CD (802.11)

Simulation Metrics

The evaluation of performance of routing algorithms can be considered under the following metrics: end-to-end delay, jitter, throughput, hop count and network lifetime. The delay is the sum of the time taken to reach the destination averaged over all number of nodes in the network. Jitter, the variation in delay, is often used as a metric of the variability over time of the packet delay across a network. A network with a constant delay has no variation or jitter. Packet jitter is expressed as an average of the deviation from the average network delay. Throughput is measured in bits per second, which determines how many bits are successfully received by the sink node. The number of visited nodes in the path from the source node to the sink is defined as the hop count. The lower number of hops, the better the algorithm.

An alternative performance metric is the network lifetime. The definition of the term network lifetime for WSNs varies. Chang [3] defines the network lifetime as the time until the first node depletes its battery that makes the rest of the network inaccessible. However, lifetime is defined as the time until a number of data sources cannot reach the sink [29]. We adopt Chang's definition that is the time until the first node depletes its battery. As the results show, battery depletion is often not directly proportional to the total energy consumption, however, the definition is still a good metric for the evaluation of WSNs and used for the characterization of the system performance. The two definitions of the node lifetime and the network lifetime are listed below, respectively:

Definition 1: the lifetime of node i for a given flow [3] is defined by T_i as follows:

$$T_i = \frac{E_\Delta}{\sum\limits_{i,j \in N} \epsilon_r c_{ji} x_{ji} + (\epsilon_t + \epsilon_{amp} d_{ij}^2) c_{ij} x_{ij}}. \tag{3.20}$$

Definition 2: the network lifetime for a given flow is defined as the time until the first battery drains out [3]. The lifetime of the network T is the minimum lifetime over all nodes and is given as follows:

$$T = \min_{i \in N} \quad T_i \quad \forall i \in N. \tag{3.21}$$

In the following sections, the performance of the five routing algorithms studied is shown. Starting from the ad-hoc on-demand distance vector (AODV) [35] algorithm that tends to approach the destination in a minimum number of hops, then FA the algorithm that get the residuals energy level from neighbours and choose paths that extend the lifetime to near optimal values. Finally, the proposed algorithm, JFA-HGR, is shown that compromise between previously mentioned algorithms.

Network Lifetime

In Fig. 3.8, the network lifetime is simulated versus N. Results show that network lifetime decreases as the number of nodes is increased for different case studies and AODV has the lowest lifetime. At $N = 10$, FA has the highest lifetime at five times the network lifetime achieved using AODV. At $N = 50$, FA lasts four times the AODV lifetime.

The increase in network lifetime is because of the division of flow over all paths. It has a longer lifetime as the load is balanced among all nodes. For JFA-HGR, the lifetime is 20% less than the FA. However, it has a diminishing loss when other metrics are considered. The results in Fig. 3.8 show a trend where that the network lifetime decreases by a noticeable margin when increasing the number of nodes. The margin, then starts to level for $N \geq 30$. The network lifetime is shown in Fig. 3.8 for the proposed algorithm is acceptable to most of the applications in sensor networks.

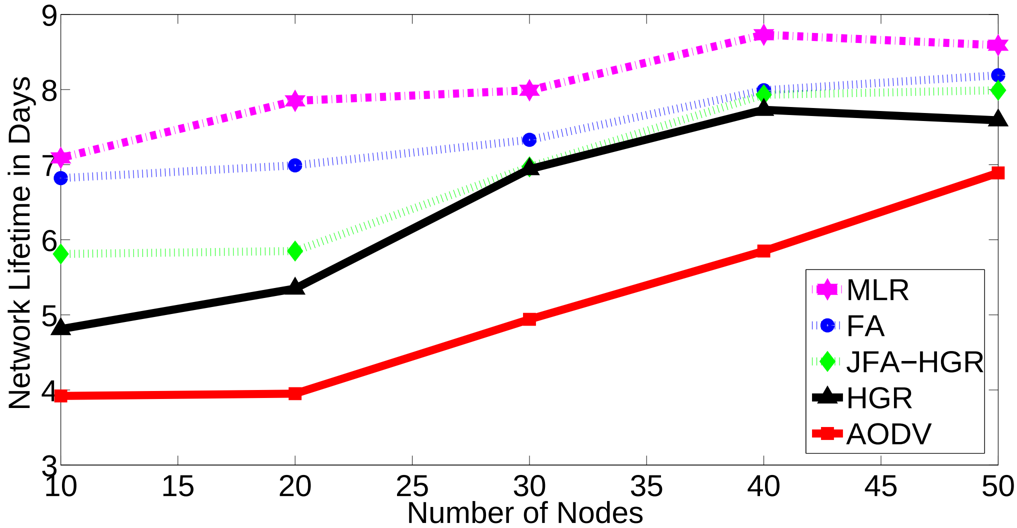

Fig. 3.8: Network lifetime versus the number of nodes.

Energy Consumption

The initial energy in the sensor node forces a limitation to the communication of the node. Unless the node uses its limited resource efficiently, all its functionality will be stopped. The data also needs to satisfy delay requirements. JFA-HGR outperforms AODV and FA in overall metrics. Therefore, the JFA-HGR is a preferred solution for routing under limited energy constraints and delay requirements. In Fig. 3.9, the energy consumption is shown for the algorithms in study.

Delay

In Fig. 3.10, the average end-to-end delay is simulated versus a number of nodes. The five chosen routing algorithms - AODV, FA, HGR, MLR, and JFA-HGR - are used in this simulation. AODV has the lowest average delay of 7 milliseconds, and it increases as a number of nodes increases. FA has the highest delay at more than five times the delay of AODV for this case. It also goes to three times the AODV delay on average. The delay for FA is around half of the maximum value of the cases evaluated. This happened

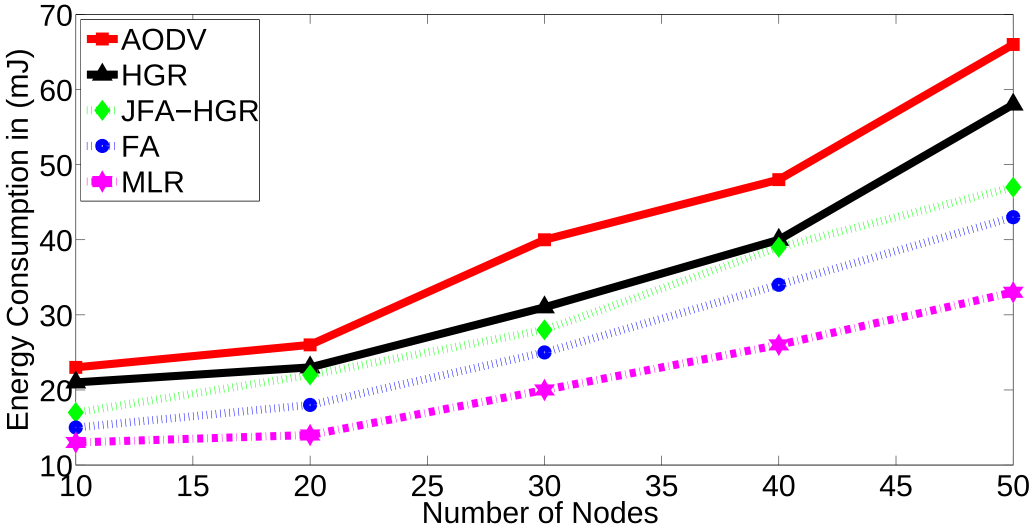

Fig. 3.9: Energy consumption versus the number of nodes.

because of the FA tendency to divide the traffic among paths to conserve the balance. The increase in delay is because of the flow division over all paths. The increase in delay offers a longer lifetime as the load is balanced among all nodes. However, it also leads to higher delays as it will not choose the shortest path. For JFA-HGR, the delay is 60% less than the FA, which is a good improvement for such an important metric that is often required in many applications.

In Fig. 3.10, AODV has the lowest delay, and it increases with the number of nodes. FA has the highest delay with more than four times the delay of AODV with the ten-node case. It also doubles the AODV delay on average. The delay for FA varies up to three times the AODV value of the thirty-node case. For JFA-HGR, the delay is 50% less than the FA for $N = 10$. Also, for fifty-node, it is 30% of the average delay. JFA-HGR produces short delay closer to AODV with a higher lifetime closer to FA values.

The results in Fig. 3.10 show the delay encountered by the HGR and JFA-HGR algorithms with a certain trend. The trend suggests that for the several network sizes, the delay is monotonically increasing as the network size increases. The grounds behind the trend of the graph are that large network size makes the number of sensor nodes in WSNs and, therefore, the effects of interference are reduced. It can as well be determined from Fig. 3.10 that the delay is higher when the routing is done very often.

For JFA-HGR, the delay also increases when the number of nodes increases. This is because the large network size means more available routes. Nevertheless, due to reasons that the HGR does not look at the flow assignment and allows any selection of nodes, the delay of JFA-HGR be less than those of HGR when network sizes are coming near the maximum number of nodes.

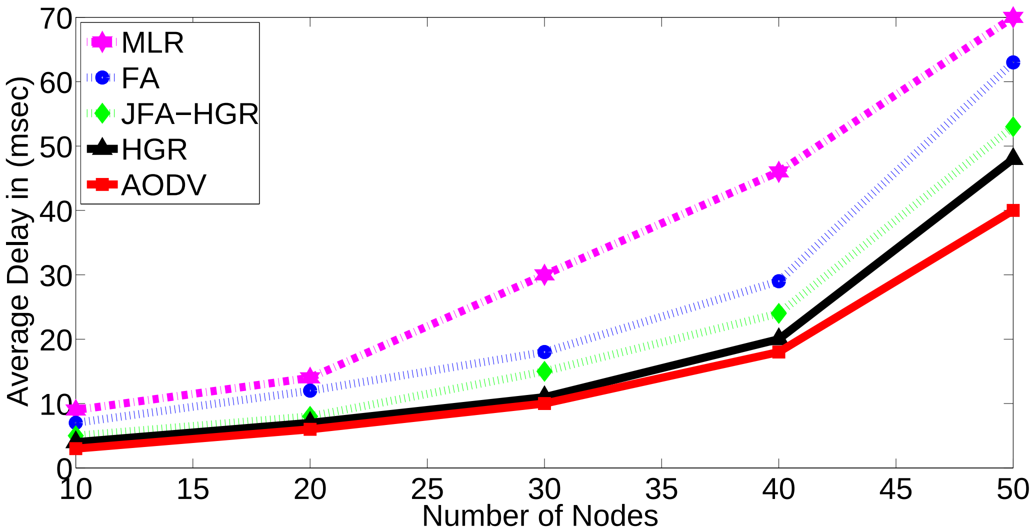

Fig. 3.10: End-to-end delay versus the number of nodes.

Jitter

In Fig. 3.11, the average jitter is simulated versus N. Results show that FA has the highest jitter, having more than six times the AODV jitter (the lowest jitter) on average. The jitter for FA varies reaching half the maximum value at $N = 50$. While the jitter is still eight times the lowest value of AODV.

The increase in jitter is because of the division of the flow over all paths. It gives longer lifetime as the load is balanced among all nodes, but also leads to higher delays facing the traffic as it will not choose the shortest path. It results in higher jitter at $N = 10$. For JFA-HGR, the jitter is 76% less than the FA, which is a good improvement for an important metric affecting many applications.

FA has the highest jitter at more than three times the jitter of AODV with ten-node. It also goes to one and a half times the AODV jitter on the fifty-node. The jitter for FA varies to two times the AODV value with thirty-node. For JFA-HGR, the delay is 60% less than the FA with ten-node. For fifty-node, the delay is 20% on the fifty-node. Results show that there is a real improvement for an important metric for JFA-HGR over FA. JFA-HGR offers a low jitter that is closer to one offered by AODV even though it has a large lifetime that is closer to the one provided by FA.

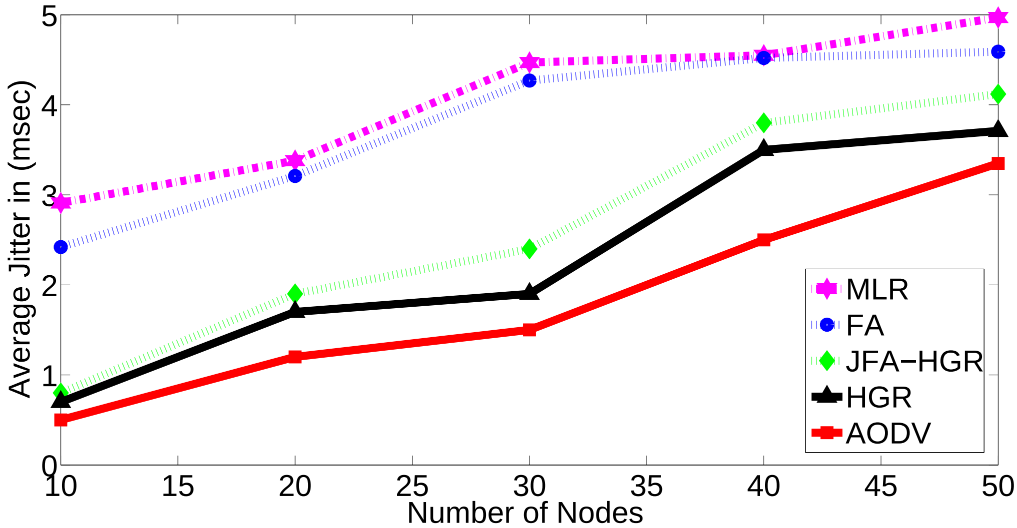

Fig. 3.11: Jitter versus the number of nodes.

Throughput

In Fig. 3.12, the average throughput is simulated versus N. AODV has the lowest throughput, and FA has the highest throughput with more than 5 bits per second more than the throughput of AODV at $N = 20$. It also reaches 2.5 bits per second on average. The throughput for FA is 5 bits per second lower than the maximum value at $N = 50$. Its average is still higher than the largest value offered by AODV.

While AODV has the lowest throughput increasing the number of nodes. However, FA has the highest throughput, even more, throughput than AODV with ten-node. It offers 2 bits per second more than the AODV throughput with fifty-node. The throughput for FA is similar to the throughput for AODV with the thirty-node values. For JFA-HGR, the throughput is less than that for FA with ten-node. Also, with fifty-node, it is similar to AODV.

Fig. 3.12 illustrates the cumulative number of packets, delivered within a certain time after sending. We observe that our JFA-HGR algorithm can deliver nearly 6 bits per second within WSNs. We have evaluated our proposed algorithm and it's shown to be better than HGR by 53%. These results indicate that JFA-HGR can deliver data. We measure the throughput by using traffic traces generated by a routing algorithm of the packets to the final destination. MLR and FA algorithm shows poor performance because the location-based routing has to update the lookup tables every interval to make the routing decision.

Hop Count

In Fig. 3.13, the hop count is simulated versus a different number of nodes. AODV has the lowest hop count increasing the number of nodes. While FA has the highest hop count, even more, hop count than AODV with the ten-node case, JFA-HGR offers 1 to 2 hops less than the FA. Hop count is shown in Fig. 3.13 for the algorithms in the study. The principle of hop count in WSNs is important, as the number of nodes can be large and leads to higher delays suffered.

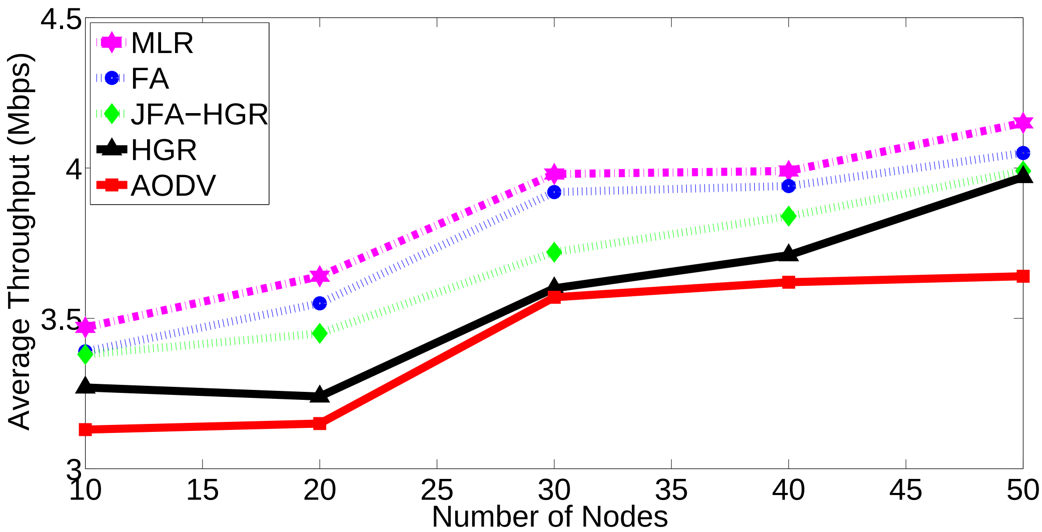

Fig. 3.12: Throughput versus the number of nodes.

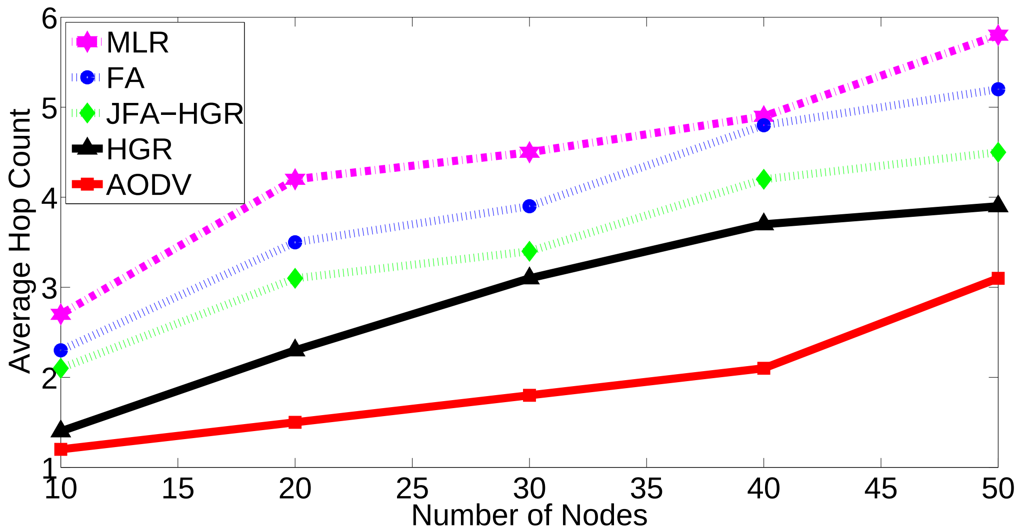

Fig. 3.13: Hop count versus the number of nodes

Complexity

In Fig. 3.14, the run-time is calculated versus N. The simulation uses five routing algorithms MLR, AODV, FA, HGR as well as JFA-HGR. JFA-HGR has the lowest run-time that increases with the number of nodes. While FA and optimal have the highest run-time, JFA-HGR offers 20% run-time savings less than the FA. This makes JFA-HGR a preferred solution regarding the longevity of the sensor nodes.

The novelty of the proposed algorithm stems from their complexity in the order of $O(N)$, whereas the complexity of the latest routing algorithm found in [7] is $O(N^2 log(2N))$. The reduced complexity makes the proposed algorithm appropriate for large-scale networks.

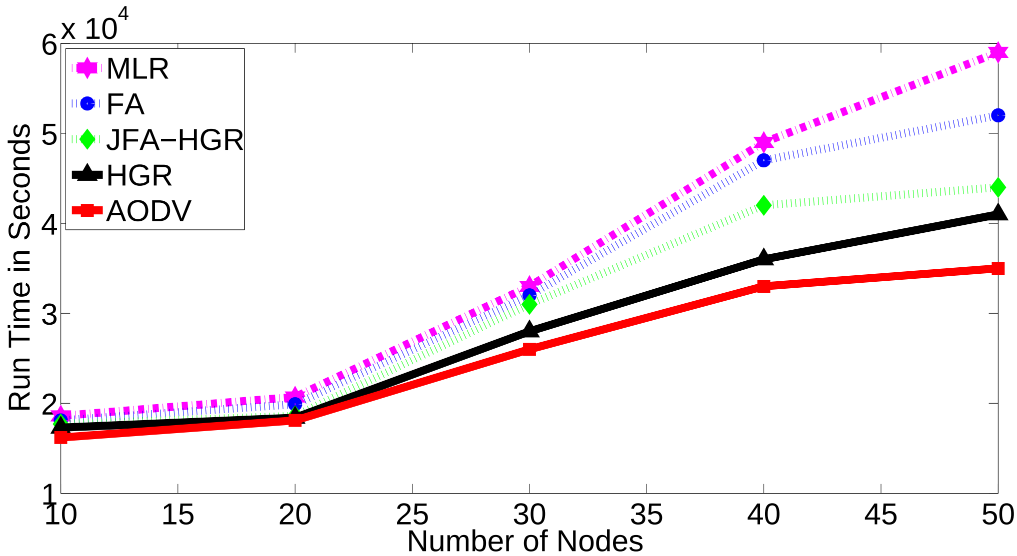

Fig. 3.14: Run-time versus the number of nodes

Discussion

Results are conducted using OMNeT++ network simulator [45]. Simulation studies are also delivered to complement and extend the results, allowing metrics such as average end-to-end delay and throughput to be judged. The strength of the proposed routing algorithm is examined using these metrics. In conclusion, JFA-HGR is a novel algorithm that achieves a balance between cost of the delivery and revenue from this delivery. Results show that there is a significant improvement for that important metric for JFA-HGR over FA. JFA-HGR offers a similar throughput closer to that offered by FA with a lower delay and a jitter close to that of AODV. The simulation results are summarized as follows: FA has the longest network lifetime while AODV has the lowest delay and jitter. JFA-HGR presents a trade-off between the two with an acceptable near-optimal lifetime and a low delay. Also, JFA-HGR offers a lower jitter value with a high throughput to evaluate accurately.

The increase in throughput is because of the division of the flow over all paths. It produces a longer lifetime as the load is balanced among all nodes, but it also leads to a higher throughput facing the traffic as it will not choose the shortest path. It results in a higher throughput for a different network size. For JFA-HGR, the throughput is 5 bits per second less than the FA, which is a good improvement for an important metric affecting many applications.

The implementation of the five routing algorithms studied is shown to be starting from the AODV. The data tend to approach the sink node in the minimal number of hops. With FA, the routing algorithm receives information about residual energy from its neighbours and chooses routes that generate network lifetime to near-optimal values. Finally, the proposed algorithm, JFA-HGR, is proven to compromise between previously mentioned algorithms.

The loss in the network lifetime of JFA-HGR and its throughput are diminished with the gain in delay and jitter over FA. FA requires a large amount of information to be passed to the nodes to make routing decisions. This required information for FA complicates the routing operation. Even it can be prohibitive for the sensor node capabilities regarding computational power and retention demands. This makes the demand for a more simplified routing algorithm that meets the practical parameters of sensor nodes. JFA-HGR is the routing algorithm that matched the sensor node capability and gave near-optimal network lifetime. In fact, it made a low delay and jitter values close to AODV.

A novel distributed routing algorithm, JFA-HGR, is proposed that forwards data based on location information with the objective of minimizing the complexity and maximizing the network lifetime. The proposed algorithm uses the angular directionality to choose the best path. The proposed algorithm achieves optimal flow in different cases with an average percentage of 80%. The run-time for the proposed algorithm is found to be five times lower than introduced by FA as shown in various studies. Hence, the reduced complexity makes the proposed algorithm implementation amenable to current sensor capabilities, which are planned to fit in large-scale networks.

Simulation results show that the JFA-HGR algorithm produces a near-optimal network lifetime. The computations needed for the proposed algorithm are simple and can be held in sensor nodes with its restricted computational power. Simulation results show that when compared with JFA-HGR has a higher throughput, lower jitter, and low end-to-end delay. Particularly for large-scale networks, JFA-HGR achieves 25% higher throughput than HGR, with 20% lower jitter. This denotes that JFA-HGR has better scalability than HGR.

3.6 Conclusion

The contributions of this chapter are as follows:

(a) The MOPT problem of energy and delay is formulated for WSNs using convex formulations. A proper solver for the given formulation is chosen. Solutions from the solver are found and the results from the designated solver are compared with the existing results. The performance of the obtained results is analyzed to show the efficiency of the formulation for WSNs.

(b) A routing algorithm for WSNs inspired by the MOPT formulation is proposed. The proposed heuristic algorithm should have these features: first, it should maximize the minimum network lifetime; second, it should match the application constraint imposed by the battery capacity; lastly, it should achieve short period of delay. The evaluation of the proposed routing algorithm for WSNs is completed using network metrics. Results will show the performance of the proposed algorithm under different scenarios in terms of network metrics. Energy and delay optimization is formulated for WSNs as a MOPT problem. A reduced complexity for the given problem formulation is presented in order to cope with the node limited resources.

(c) A comparison of the proposed routing algorithms for each one of the three systems is performed using the chosen metrics. The comparison is done versus existing routing algorithms such as AODV, FAR and HGR. Not only the different heuristics approaches are compared, but also the optimal and sub-optimal mathematical results are compared.

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Chapter 4

Joint Optimal Placement, Routing, and Flow Assignment in Wireless Sensor Networks for Structural Health Monitoring

4.1 Abstract

In this chapter, joint optimization of sensor placement, routing, and flow assignment is introduced and solved using mixed-integer programming modelling. Sensor node placement optimization has a significant role in wireless sensor networks, especially in structural health monitoring. Since sensor node placement affects the routing, optimization should be done for the node placement and routing jointly. Existing work optimizes the node placement and routing separately (by performing routing after carrying out the node placement). However, this approach does not guarantee the optimality of the overall solution. Finding an optimal solution for this joint

problem is too complex. Hence, a near-optimal solution is obtained using genetic algorithms with reduced complexity. Moreover, a heuristic algorithm for joint routing and flow assignment with placement is proposed using the effective independence model, which optimizes the information quality and energy consumption for efficient communication. Last but not least, the results are presented in a nine-floor building to compare the three proposed algorithms with the heuristic algorithm introduced. The numerical results show the efficiency of the proposed algorithms and the trade-off between the effectiveness and complexity. After we have addressed this problem using a single objective to minimize the energy consumption, we consider another approach to solving the designated problem.

4.2 Introduction

Several applications, such as surveillance, tracking, and monitoring, use WSNs. SHM is one of the applications of WSNs, which are used in critical infrastructure and different buildings [2]. The importance of SHM is not only in preventing economic losses but also for avoiding catastrophic failures and loss of human lives. SHM using WSNs has the potential to become the most efficient solution compared to traditional wired sensor networks motivated by their simplicity of installation, ability to be applied to an existing construction and low maintenance costs [3].

Numerous challenges for resource constrained WSNs arise when used in SHM. These challenges facing WSNs for SHM are listed as: the high amount of the generated data, synchronization among nodes, and efficient routing especially for large-scale networks. The recent advances in sensing and telecommunication technology helped the WSNs for SHM to be more effective. Based on this feature, the availability and the reliability of the data are guaranteed. To ensure that the data is accurate, WSNs should be able to transfer huge amounts of data in order to increase the safety. Hence, WSNs for SHM can provide an early warning for forthcoming structural risks [4]. WSNs are considered the best candidate of stable structures for future SHM systems because of the attributes mentioned above [5].

In WSNs for SHM, sensor nodes are placed in strategic locations that can capture the structure response (in terms of vibrations) due to external effects such as the wind or dynamic loads. The sensor node placement process is defined as the selection of the best location to collect information about the structure's state, while routing is described as finding the sequence of the links to be used from the source node to the destination node. As routing is affected heavily by the node locations; therefore, the optimization of sensor node placement and its corresponding routing will be essential for energy-efficient communication and long-lasting structures.

This work aims to maximize the information quality and minimize the energy consumption with the joint placement and routing optimization. The contributions of this chapter are summarized in the following points:

(a) We propose a novel formulation that jointly optimizes the placement and the routing. The optimal result is found using integer programming that satisfies both civil engineering and networking constraints.

(b) We find a heuristic solution using evolutionary GAs. We propose a sensor deployment and routing algorithm based on GAs that efficiently deals with the sensor placement optimization problem and achieves near-optimal energy consumption and information quality for communication between sensor nodes.

(c) We propose a joint routing and placement algorithm using the effective independence model (JR-SPEM) as a heuristic algorithm. The novel heuristic SPEM-based placement and routing algorithm achieves a low-complexity near-optimal solution. JR-SPEM selects the near-optimal path route based on Dijkstra's algorithm, a well-known algorithm used for computing the shortest path in a network, fed with the cost objective function.

(d) We evaluate the efficiency of the proposed algorithms. Results show that these algorithms significantly reduce the total energy consumption of the deployed sensors and improve the information quality. The complexity of all algorithms in the study is found and compared to the traditional placement algorithm. The proposed algorithms achieve a consolidated placement and routing in an efficient way.

The reminder of the chapter develops as follows: Section 4.3 presents the system model and the new formulation of the sensor placement and routing optimization problem. Section 4.4 demonstrates a GA-based approach for finding a heuristic solution. Section 4.5 describes the proposed heuristic algorithm based on SPEM for the sensor placement and routing optimization in SHM. Section 4.6 provides the numerical results of the proposed algorithms. Finally, Section 4.7 concludes the chapter work.

4.3 System Model

The sensor node placement problem is the process of selecting N locations out of the total M potential locations given by the civil engineering model. The sensor placement problem in SHM is formulated as finding a location indicator set $\mathbf{S} = \{s_1, s_2, \ldots, s_M\}$, where s_i is a binary indicator that is equal to one if location i is selected and zero otherwise. Each element in matrix $\mathbf{x}$ represents the number of flows that use a particular link. For instance, if $x_{12} = 3$ this means that there are 3 flows that use the link from node 1 to node 2. It should be noted that matrix $\mathbf{x}$ reflects the selected route of each flow from all sensor nodes to the sink. The decision variables for the mathematical model are the following: s_i is a binary indicator where the location is selected $s_i \in \{0, 1\}, \forall i$, x_{ij} is a non-negative integer variable that shows how many times link $i - j$ is utilized by all flows, $x_{ij} \in \{0, 1, \ldots, N\}, \forall i, j$, i and j are sensor node indices such that $i, j \in \{0, 1, \ldots, M\}$ and $i \neq j$, and s_0 is the sink node indicator where all traffic needs to be delivered.

The maximization of the ratio between the information quality and total energy consumption is the objective of the sensor node placement optimization in this work. The information quality is a function of the measured vibrations represented by the mode shape, where a mode shape is a distinct pattern of vibration executed by a structure at a particular frequency; basically different mode shapes are associated with different frequencies. The mode shape matrix $\mathbf{\Phi}$ is given by:

$$\mathbf{\Phi} = \begin{bmatrix} \delta_{11} & \delta_{12} & \ldots & \delta_{1k} & \ldots & \delta_{1K} \\ \ldots & \ldots & \ldots & \ldots & \ldots & \ldots \\ \delta_{M1} & \delta_{M2} & \ldots & \delta_{Mk} & \ldots & \delta_{MK} \end{bmatrix}, \tag{4.1}$$

where $\mathbf{\Phi}$ conveys the individual contribution of all sensors. δ_{Mk} is the measured vibrations collected by the Mth sensor for the kth mode shape, where k is the order of the mode shape for all sensors and K is the total number of mode shapes. However, each column of the matrix in Eq. (5.1), ϕ^k, is the kth order mode shape for all sensors and is represented as follows:

$$\phi^k = [\delta_{1k}, \delta_{2k}, \ldots, \delta_{jk}, \ldots, \delta_{Mk}]^T, \tag{4.2}$$

while each row of the matrix in Eq. (5.1), ϕ_j, represents all mode shapes measured by the jth sensor and is given as follows:

$$\phi_j = [\delta_{j1}, \delta_{j2}, \ldots, \delta_{jk}, \ldots, \delta_{jK}]. \tag{4.3}$$

The FIM determinant $|\mathbf{Q}(\mathbf{S})|$ [1] is given as follows:

$$|\mathbf{Q}(\mathbf{S})| = \det[(\mathbf{\Phi})^{\mathbf{T}}\mathbf{R}^{-\mathbf{1}}\mathbf{\Phi}], \tag{4.4}$$

where $\mathbf{R}$ is the covariance matrix representing the noise in the mode shape measurements. Let $\mathbf{\Psi}$ correspond to the normalized sensor information quality and is defined as follows:

$$\mathbf{\Psi} = |\mathbf{Q}(\mathbf{S})|/|\mathbf{Q}_{max}(\mathbf{S})|, \tag{4.5}$$

where $|\mathbf{Q}(\mathbf{S})|$ is the FIM determinant for a set of selected sensor nodes and $|\mathbf{Q}_{max}(\mathbf{S})|$ is the FIM determinant when all sensor nodes are selected. $\mathbf{Q}(\mathbf{S})$=$\mathbf{Q}_{max}(\mathbf{S})$ when $\mathbf{S}$ equals all one vector

The minimization of the total energy consumption is an important part in the sensor node optimization process. The calculation of the total energy consumption, the denominator of the objective function, begins by finding the Euclidean distance between two nodes. d_{ij} is the Euclidean distance between sensor node i and sensor node j is given as follows:

$$d_{ij} = \sqrt{(c_u(i) - c_u(j))^2 + (c_v(i) - c_v(j))^2}, \quad \forall i, j, \tag{4.6}$$

where $c(i) = (c_u(i), c_v(i))$ is the Cartesian coordinate of a sensor node i in a two-dimensional plane. $\mathfrak{C} = \{c(1), c(2), \ldots, c(M)\}$ is the coordinates matrix of the M candidate nodes.

In this chapter, we maximize ratio of the information quality per unit energy. The total energy consumption includes the transmission and reception energy. Let $e_t(ij)$ be the transmission energy consumption on link $i-j$ that is defined as follows:

$$e_t(ij) = (\epsilon_t + \epsilon_{amp} d_{ij}^{\alpha}) n^b x_{ij} s_i s_j, \quad \forall i, j, \tag{4.7}$$

where n^b is the number of bits per packet and α is the path loss exponent. The radio parameter ϵ_{amp}, and ϵ_t are the transmitter amplifier cost and the energy cost for transmission, respectively as in [15]. x_{ij}, which is an element in matrix $\mathbf{x}$, is defined as the number of routes where the link $i-j$ is used. Let $E_t(i)$ be the energy consumed during the transmission by each sensor node i. The transmission energy is calculated as follows:

$$E_t(i) = \sum_{j=0}^{M} e_t(ij). \tag{4.8}$$

The reception energy $e_r(ji)$ at sensor node i when it receives from node j is given as follows

$$e_r(ji) = \epsilon_r n^b x_{ji} s_i s_j, \quad \forall i, j, \tag{4.9}$$

where ϵ_r is the energy coefficient for the reception. $E_r(i)$ is the total reception energy consumption of node i and is calculated as follows:

$$E_r(i) = \sum_{j=1}^{M} e_r(ji). \tag{4.10}$$

The total energy consumed during the transmission and the reception in sensor node i is given by:

$$E(i) = E_t(i) + E_r(i). \tag{4.11}$$

Let $E_{total}(\mathbf{S}, \mathbf{x})$ be the total energy consumption by all nodes which is given as follows:

$$E_{total}(\mathbf{S}, \mathbf{x}) = \sum_{i=1}^{M} E(i). \tag{4.12}$$

The ratio between the information quality and the total energy consumption is represented by $\mho$ and can be defined as follows:

$$\mho = |\mathbf{Q}(\mathbf{S})| / E_{total}(\mathbf{S}, \mathbf{x}), \tag{4.13}$$

where the ratio $\mho$ physically determines how much information can be collected per energy unit from one sensor or a combination of many sensors. When the objective function is presented with the ratio $\mho$, the decision variables in this formulation are the location indicator $\mathbf{S}$ and the link utilization matrix $\mathbf{x}$.

4.3.1 Case I: Basic Case without Flow Assignment

The joint routing and placement optimization problem is formulated as follows:

$$
\begin{aligned}
\underset{\mathbf{S},\mathbf{x}}{\text{Maximize}} \quad & |\mathbf{Q}(\mathbf{S})|/E_{total}(\mathbf{S},\mathbf{x}) \\
\text{Subject to}: \quad & \\
\text{(c1)} \quad & d_{ij} I(x_{ij} > 0) \leq r_c, \\
& \forall i, j, i \neq j, \\
\text{(c2)} \quad & E(i) \leq E_{\text{init}}, \quad \forall i, \\
\text{(c3)} \quad & \sum_{i=1}^{M} s_i = N, \\
\text{(c4)} \quad & s_j + \sum_{i=1}^{M} x_{ij} = \sum_{i=0}^{M} x_{ji}, \\
& \forall j, j \neq 0, j \neq i, \\
\text{(c5)} \quad & \sum_{i=1}^{M} x_{ij} \leq s_j(N-1), \\
& \forall j, j \neq 0, j \neq i, \\
\text{(c6)} \quad & \sum_{i=1}^{M} x_{i0} = N, \\
\text{(c7)} \quad & \sum_{j=0}^{M} x_{ij} \leq s_i N, \\
& \forall i, i \neq 0, i \neq j, \\
\text{(c8)} \quad & x_{0i} = 0, \quad \forall i.
\end{aligned}
\tag{4.14}
$$

The formulation has the following constraints: (c1) guarantees the node connectivity by ensuring that the distance, d_{ij}, between any two nodes does not exceed the maximum transmission range r_c, $I(x_{ij} > 0)$ is a binary indicator whether link $i - j$

is used at least once, i.e., x_{ij}, is greater than zero, (c2) ensures that the consumed energy does not exceed the initial energy, E_{init}, stored in each node, (c3) imposes that the number of selected nodes must be equal to N, (c4) enforces that the number of input links to a sensor node plus the sensor node generated traffic is equal to the number of output links (excluding the sink), (c5) ensures that a sensor node (e.g. node j) does not receive more than $(N-1)$ flows (the upper limit $(N-1)$ will happen if node j receives from all other nodes in the network), (c6) imposes that the N flows are sent to the sink node because all N flows must terminate at node 0 (sink node), (c7) ensures that every node does not send more than N flows. For instance, the maximum number of flows that node j has to send will happen if node j receives $(N-1)$ flows (if node j receives the flows of all other nodes), then node j has to send its own flow plus $(N-1)$ received flows (which is equal to N flows) to the sink. Finally, (c8) guarantees that the sink node is not generating any traffic.

4.3.2 Case II: Basic Case with Flow Assignment

Case II considers the flow assignment where x_{ij} takes a rational value between zero and N. This means that the traffic generated at node i can be split among different links.

Flow assignment is needed to avoid overloading the links in the network. The fundamental goal of flow assignment is to decide the flow rate that balances the load among all links. In the previous sections, the data from a source node to the destination node are sent to a single, minimum cost path between them. This model is impractical as only one path between every source and destination pair is utilized even if many paths exist with the same or nearly same cost.

Case II may be reasonable in types of networks where few alternative routes exist and have a large difference in the link cost. This case may also be used to identify the path the data travels to avoid overloading certain links.

Fig. 4.1 and 4.2 show the idea of the flow assignment and how it affects the number of links used and how traffic is divided between the available links. In Fig. 4.1, node 1 sends all of its traffic to the next node, node 6. Meanwhile, the traffic from node 1, when the flow assignment constraint imposed, is divided among the three various paths as shown in Fig. 4.2. The mathematical formulation remains the same with the exception that x_{ij} can take rational values as mentioned above.

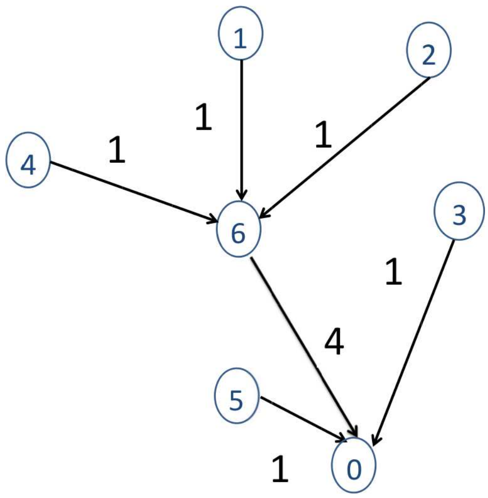

Fig. 4.1: Case I: Basic case without flow assignment.

4.4 Sensor Placement and Routing Using Genetic Algorithms

Mixed-integer programming (MIP) is used to determine the optimal solution of the aforementioned formulation. MIP is employed to solve the optimization problem formulated in Section 4.3. The MIP method may include a large number of variables that can take a large amount of processing time and computing power. Moreover,

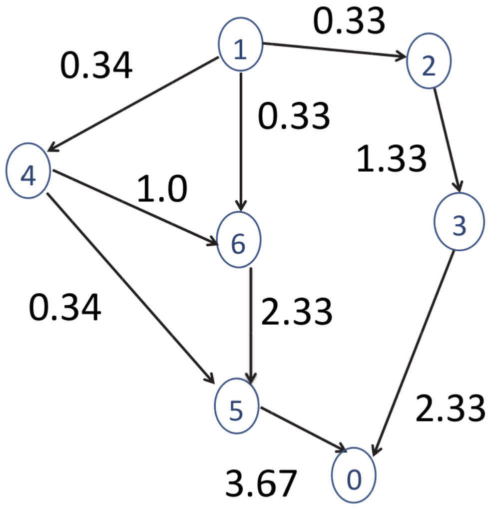

Fig. 4.2: Case II: Basic case with flow assignment.

the optimal solution can be found in a reasonable time for the relatively small sizes of the WSNs. The optimal solution has a high complexity that is bounded by $O(N^M + M^2)$ which is further explained in Subsection 4.6.4. To reduce the associated complexity, a simpler heuristic approach is needed. The formulation of the optimization problem is found to be an NP-hard problem as demonstrated in [1]. Placement is represented by a binary variable which makes it easily represented in GAs. Therefore, this problem is a good candidate to be solved using evolutionary algorithms such as GAs.

GAs are well-known approaches for solving optimization problems because of their capability to check partially ordered search space for various trade-offs as demonstrated in [17]. Furthermore, GAs evaluate several solutions simultaneously and find the near-optimal solution by combining efficient solutions. After the optimization problem is formulated as shown in Eq. (4.14), GAs are employed using the previous formulation as an objective function to find a near-optimal solution with a reduced complexity. Since the sensor placement and routing is a critical problem in SHM, GAs are used to place nodes and find routes to maximize the information quality and minimize the total energy consumption.

A solution of the optimization problem is called a chromosome. The chromosome is represented by a list of variables called genes [17]. If the gene value is 1, then the corresponding sensor node is placed. If no sensor node is placed, the gene value is 0. A chromosome's size should be equal to the number of possible locations plus the number of possible links as shown in Fig. 4.3. The genes representing link utilization x_{ij} are not binary (but rather integer variables in the rang [0, N]).

GAs create a number of solutions randomly to form an initial population, and then the fittest survived solutions move on to the next generation. The generated solutions share some features taken from each possible solution. A new population of generated solutions is produced by the selection of the best solutions for the current generation and then performing crossover between them to produce the next generation. Mutation is also used to introduce some randomness to the new generation creation. The process of generation and selection is repeated until the stopping criteria are reached. The population will converge to a near-optimal solution when the GAs parameters, such as the crossover rate, are properly tuned as shown in [17].

In our GAs implementation, the chromosome represents a solution that has a max-

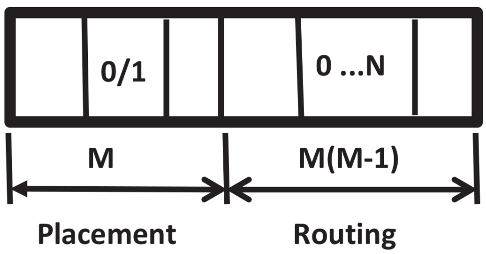

Fig. 4.3: Solution representation in GAs with the placement and routing included.

imum of M sensors. Meanwhile, the possible links can be $M(M-1)$ links, so the number of variables will be M^2. Roulette-wheel selection is used in which the chromosome that has a large fitness function value has a higher probability to survive to the next generation over others. During the crossover operation, the chromosomes are recombined resulting in two new child chromosomes to be appended to the next generation population. The probability of crossover is equal to p_c. Increasing this value may improve performance, which leads to increasing the crossover occurrence. In this chapter, the single point crossover operator is used. After selecting the chromosomes, GAs generate random numbers to select where to split the chromosome into two parts to then be recombined. Lastly, the mutation operator flips some of the genes of the chromosome. Similar to the crossover operator, increasing this probability will increase the mutation occurrence. A mutation probability of p_m is taken in order to make our GAs search visit the corners of the search space to check for isolated solutions.

The calculation of the $\mho$ ratio used in Eq. (4.14) measures the chromosome fitness or performance. As a part of its task, the GAs try to find the largest fitness function value in order to get near-optimal placement and routing. GAs then check for the best chromosome found in the population. A larger fitness function value means a higher upper-limit information quality and minimum energy consumption. Nevertheless, after the number of runs is larger than or equal to M^2 multiplied by the number of variables, the variations in GAs results will be low. Consequently, GAs are terminated immediately after a specified number of generations is reached or the stopping criterion occurs.

4.5 Sensor Placement and Routing Using Enhanced SPEM-based Heuristic Approaches

In this Section, the details of the SPEM, p-SPEM, and JR-SPEM methodologies are explored. SPEM is a traditional sensor placement algorithm introduced in [6], later, modified to be power-aware with a reduced complexity in p-SPEM [1]. We propose JR-SPEM, a practical, heuristic algorithm, to improve the SPEM placement algorithm [1] by jointly performing placement and routing. The description of SPEM and JR-SPEM algorithm is given in subsections 4.5.1 and 4.5.2, respectively.

4.5.1 SPEM Algorithm Description

SPEM algorithm is a sensor placement that calculates the determinant of the FIM, based on the structure mode shape measurements [5]. The p-SPEM algorithm solves the sensor placement optimization problem based on a local search between all possible locations among all candidate locations selected by SPEM.

The pseudo-code of the SPEM algorithm [1] is given in Algorithm 2. The input to SPEM is M potential locations selected by civil engineers. SPEM then selects a set of N locations for the sensor placement (line 2). The algorithm computes the normalized sensor information quality, Ψ, in the pseudo-code (line 3). Then, SPEM sorts the set of the sensor node location indicators (line 4) and removes the element with the least contributions (line 5). The algorithm iterates to find the best location indicators (lines 2 - 6). The output of SPEM algorithm is the location indicator set $\mathbf{S}$ (line 7). The above steps of pseudo-code of SPEM are summarized as shown in Algorithm 2.

For brevity, only SPEM pseudo-code is presented without the details of the energy

Algorithm 2 SPEM Algorithm [6]

1: **Inputs** M is the number of candidate locations, and N is the number of sensor nodes used for the effective placement.
2: **for** $i = 1 : 1 : M - N$ **do**
3: Compute, Ψ, the normalized sensor information quality.
4: Sort $\mathbf{S}$ according to Ψ.
5: Removes the element with the least contribution in Ψ.
6: **end for**
7: **Outputs** The set of location indicator $\mathbf{S}$ of the selected sensor N locations out from M total candidate location.

estimation algorithm (e-Estimator) and local search (l-Search) algorithm. These two modules are both explained in the p-SPEM version found in [1]. Finding the location indicator $\mathbf{S}$ and choosing data routes is also an NP-hard problem [1]. The data routing is solved in a separate module based on values found by e-Estimator algorithm, an algorithm that estimates the energy consumption for each sensor node, using the chosen routing model. The shortest path routing model is used to decide how to route the data. Euclidean distance is chosen in this routing model as a metric for making the routing decisions.

The p-SPEM algorithm calls the SPEM algorithm in order to achieve the placement optimization of the sensor nodes. After calling SPEM, the p-SPEM algorithm attempts to maximize the objective function given by the determinant of the FIM, with M possible sensor locations and N required number of nodes. The output $\mathbf{S}$ is the best location indicator for the sensor placement that gives the highest fitness value. The objective is improved iteratively by replacing the sensors with the least contribution to the $|\mathbf{Q}(\mathbf{S})|$. The iteration proceeds until no further improvement is observed in the objective function. The l-Search algorithm is used to find the best nodes to be inserted into the $\mathbf{S}$ to optimize the objective function. In each iteration, all sensors try the neighbour within a specific distance to determine if any of them can improve the placement metrics. If no improvement is found, then the iteration stops.

4.5.2 Joint Routing SPEM (JR-SPEM) Algorithm Description

Considering the problem formulation above, a novel, heuristic SPEM-based placement and routing algorithm is proposed to achieve a feasible solution. JR-SPEM selects the near-optimal path route based on Dijkstra's algorithm, a well-known algorithm used for computing the shortest path in a network, fed with the cost objective function (line 6).

The JR-SPEM placement and routing algorithm is applied to find the best sensor node location and to find a route from each selected sensor node to the sink with its designated flow. As shown in Algorithm 2, JR-SPEM algorithm calls SPEM with all candidate locations (line 2) and SPEM chooses the best N sensor locations according to the objective function in the formulation (by calculating $\mho_{initial}$ in line 3). The best route for improving the performance is found in an iterative way. To improve the objective, the sensor with the least contribution to the determinant of the FIM is replaced in $\mathbf{S}$ (line 8). Then, the algorithm searches the other previously removed sensors in $\mathbf{S}_{temp}$ (line 9), and the temporary sensor location indicators, to improve the ratio $\mho$ by comparing it to $\mho_{max}$ (lines 11 - 14). The iterations (lines 5 - 15) proceed until no further improvement can be observed. The output is the best N locations according to the routing model (line 16).

Algorithm 3 Joint Routing Sensor Placement (JR-SPEM)

Inputs M is the number of candidate locations, and N is the number of chosen sensor nodes for the placement.
Compute the sensor location indicators set $\mathbf{S}$ by SPEM().
Calculate $\mho_{initial}$ for the N nodes selected by SPEM().
Set $\mho_{max} = \mho_{initial}$
while true **do**
    Find $\mathbf{x}$ through Dijkstra Algorithm.
    Sort locations in $\mathbf{S}$ with the ratio $\mho$.
    Remove the sensor node with the lowest ratio in $\mathbf{S}$.
    Add another randomly chosen sensor node to create $\mathbf{S}_{temp}$ set.
    Calculate the ratio $\mho_{temp}$ for the $\mathbf{S}_{temp}$ set.
    if $\mho_{temp} \geq \mho_{max}$ **then**
        Update the sensor location indicators set $\mathbf{S}$.
    else Skip the sensor node **Break**
    end if
end while
Outputs The selected N sensor location indicators $\mathbf{S}$ with the highest metric $\mho_{max}$, and the link indicator matrix $\mathbf{x}$.

4.6 Numerical Results

In this section, we evaluate the performance of the optimal algorithm, GA-based algorithm, and the JR-SPEM algorithm of different N for a nine-floor building. Performance metrics include the total energy consumption $E_{total}(\mathbf{S}, \mathbf{x})$, the information quality $|\mathbf{Q}(\mathbf{S})|$ and the normalized information quality to the total energy consumption ratio $\mho_{norm}$. For comparison, p-SPEM and JR-SPEM placement algorithms are evaluated.

The general algebraic modeling system (GAMS) [**?**] is used for modeling the problem and the BARON solver [**?**] is employed for finding the MIP solution.

4.6.1 Performance Parameters

Table 4.1 lists the parameters used in the numerical results with their associated values. The initial energy E_{init} is chosen to be 1500 mAhr as in [15], and the number of bits per packet n^b is equal to 2 Kb [1]. The transmission range r_c is set to be 30 m [20]. The path loss exponent α is chosen to be 2 as in [15], the radio parameters are selected as in [15] where the transmission energy cost is ϵ_t, the reception energy cost ϵ_r, and the power amplifier energy cost ϵ_{amp} are chosen to be equal to 50 nJ/bit, 50 nJ/bit, 1 $nJ/bit/m^2$, respectively [15]. The building's height is considered to be a 30 m $\times$ 20 m as shown in Fig. 4.4. A two-dimensional plane is assumed with its sink node located at (20, 0) with a floor height of 3.33 m. GAs parameters are chosen as follows: the crossover probability is 0.8 and the mutation probability is 0.1.

Assume all sensor nodes have the same transmission range and that sensor node candidate locations are one location in each floor on the nine-floor building. Moreover, the results are shown for 3-8 sensors chosen from the nine candidate locations in the nine-floor building. A sensor node has the node coordinates of its neighbours.

4.6.2 Performance Metrics

The three metrics used for measuring the proposed algorithms' performance are the total energy consumption $E_{total}(\mathbf{S}, \mathbf{x})$, the information quality $|\mathbf{Q}(\mathbf{S})|$ and the ratio $\mho_{norm}$. The normalized information quality (NIQ) is the metric for the amount of information collected by the sensor node. NIQ is calculated by Eq. (5.3) for the selected sensor node location indicators and then normalized by dividing the result by the maximum information quality. The last metric used is the NIQ to the total

Table 4.1: Parameter values used in the numerical results

Symbol	Description	Value
E_{init}	The initial energy	1500 $mAhr$ [20]
n^b	The number of bits per packet	2 Kb [1]
r_c	The maximum transmission range	30 m [20]
α	The path loss exponent	2 [15]
ϵ_{amp}	The power amplifier energy cost	1 $nJ/bit/m^2$ [15]
ϵ_r	The reception energy cost	50 nJ/bit [15]
ϵ_t	The transmission energy cost	50 nJ/bit [15]
p_c	The crossover probability	0.8 [17]
p_m	The mutation probability	0.1 [17]

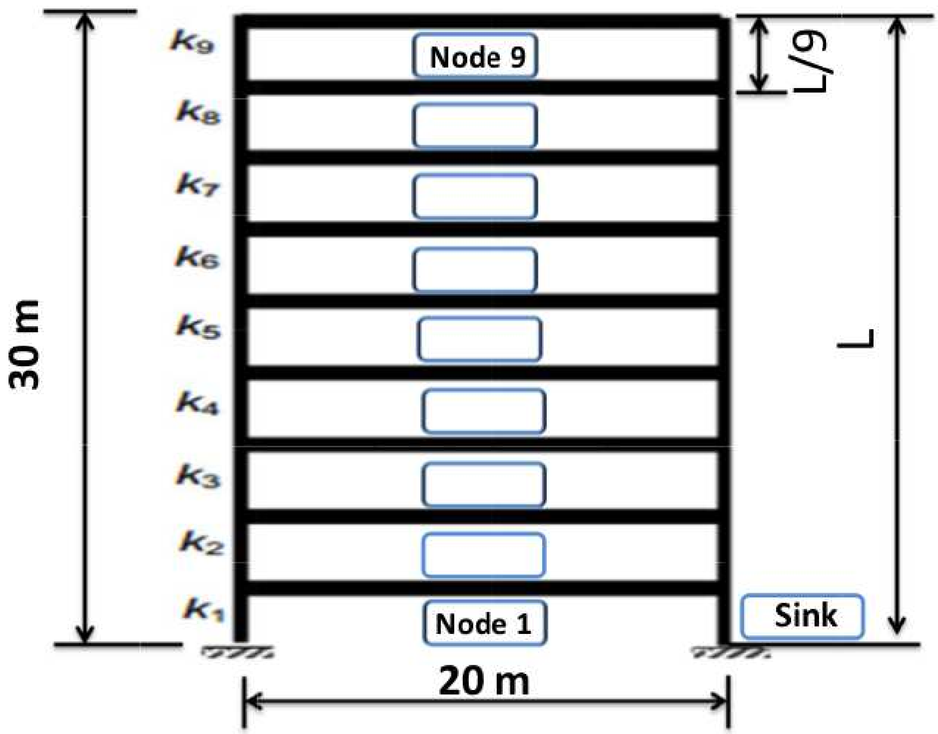

Fig. 4.4: The nine-floor building of length L = 30 m and the sink node is located at (20,0).

energy consumption ratio, $\mho_{norm}$. The normalized $\mho_{norm}$ ratio is calculated as the ratio between the NIQ and the normalized energy (found by dividing the energy value by the maximum energy consumption).

4.6.3 Performance Evaluation

Case I: Numerical results for basic case without flow assignment

Results are generated for three different algorithms: the optimal algorithm using MIP optimization, GAs, and JR-SPEM. All proposed algorithms are then compared with the p-SPEM presented in [1]. The performance of the proposed algorithm is presented based on the above formulation in order to evaluate the performance of the algorithms for different values of N. The results for the basic case which is based on the formulation in Eq. (4.14) are shown in Fig. 4.5 to Fig. 4.7.

Fig. 4.5 summarizes NIQ results for the four considered algorithms under different values of N. As expected, NIQ increases as more sensors are added to collect information from various points in the structure. Using MIP, NIQ values for $N = 5$ and $N = 7$ are about 22% and 48%, respectively. The NIQ achieved using GAs for the same N are about 22% and 45%, respectively, whereas the values for JR-SPEM are about 19% and 38%, respectively, and the NIQ achieved using p-SPEM for the same N are about 15% and 25%, respectively. The NIQ improvement occurred with JR-SPEM against the p-SPEM is due to the increased focus on NIQ and efficient routing when performing the local search. The JR-SPEM has more than 10%, 40%, and 80% improvement in the NIQ for $N = 6, 7$ and 8, respectively. Results demonstrate that the JR-SPEM can increase the NIQ significantly over p-SPEM for $N = 5$ to $N = 9$.

Fig. 4.6 depicts that the energy consumption increases with an increase in the number of nodes. In fact, when N increases there are two conflicting factors that affect the energy consumption. In the first one, as N increases we add more nodes, flows and packet transmission. Hence, the energy consumption increases. However, in the second factor, as N increases more nodes become available so we can make the links shorter and also nodes find more and better routes (with less energy consumption) to send their packets to the destination. For instance, in Fig. 4.4 when $N = 8$ all nodes are selected except node 1. Thus, node 2 sends its traffic (and traffic from some other nodes) to the sink (node 0) using link 2-0. When N increases to 9, one more flow is added (due to adding a node at location 1), which increases the energy consumption (first factor). However, node 2 can send its own traffic (and traffic from some other nodes) to node 1 which, in turn, forwards it to the sink. The use of shorter links (2-1 and 1-0), rather than link 2-0, causes significant reduction in the energy consumption (second factor) since the transmission power is adjusted based on the links distance according to Eq. (7). Due to these two conflicting factors, sometimes increasing N leads to energy consumption increase and other times it leads to energy consumption decrease depending on the dominating factor.

In Fig. 4.6, we summarize the results of all the algorithms in study for different N. We observe that the energy consumption increases as the number of sensor nodes increases. This rise in the energy consumption is a consequence of the node energy budget increasing with the traffic. Fig. 4.6 results indicate that the solutions obtained by the optimal and GA-based algorithms perform efficiently. About 25% energy consumption savings exist for the optimal and GAs solutions over JR-SPEM and p-SPEM for $N = 6$. JR-SPEM performs well with more than 27% of the energy saving over p-SPEM for $N = 5$. It is also evident that p-SPEM consumes higher energy over all algorithms.

Fig. 4.7 presents the $\mho_{norm}$ ratio for the four algorithms. With the increase of N, the ratio $\mho_{norm}$ increases for all algorithms. The optimal algorithm always achieves the best ratio, and GAs achieve a higher performance about 70% better than the p-SPEM algorithm. Results show that the JR-SPEM can achieve about 50% improvement in the normalized ratio compared to that of the p-SPEM when the network size is increased above $N = 8$. However, compared to p-SPEM, the ratio for the optimal, GAs and JR-SPEM are still higher. The JR-SPEM ratio is higher due to the failure of p-SPEM to balance the load among the sensor nodes, which leads to a smaller ratio.

From Fig. 4.5 to Fig. 4.7, we can make the following observations: First, the optimal algorithm is outperforming the other algorithms, followed by the GAs, then JR-SPEM and finally p-SPEM. The second observation is that as the number of selected nodes increases, the JR-SPEM solution achieves higher ratio than the p-SPEM due to the efficient joint of the routing with the placement rather than local search and energy estimation in p-SPEM.

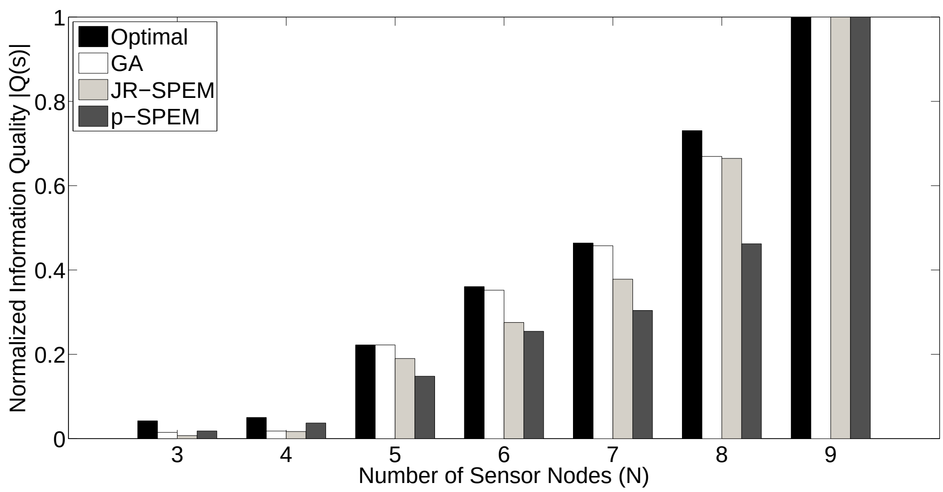

Fig. 4.5: Normalized information quality for optimal, GA-based and SPEM-based heuristic algorithms in a nine-floor building using the system model for Case I.

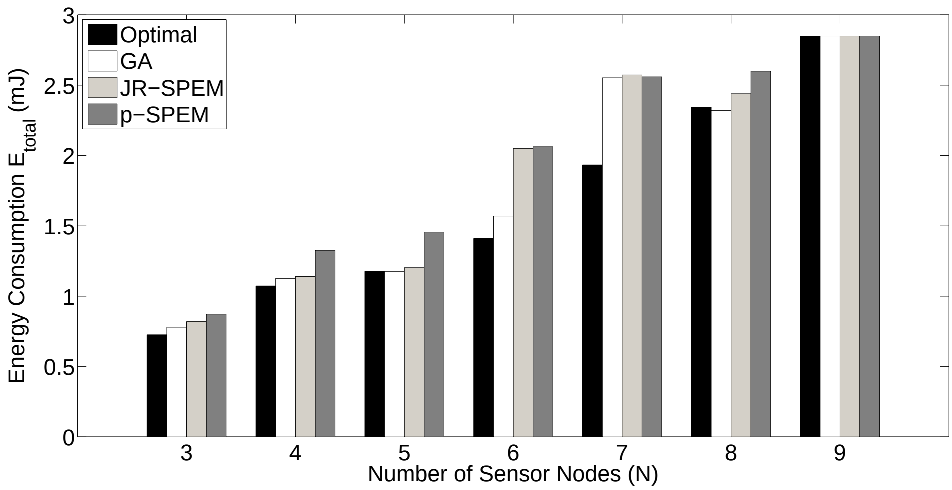

Fig. 4.6: Total energy consumption for optimal, GA-based and SPEM-based heuristic algorithms in a nine-floor building using the system model for Case I.

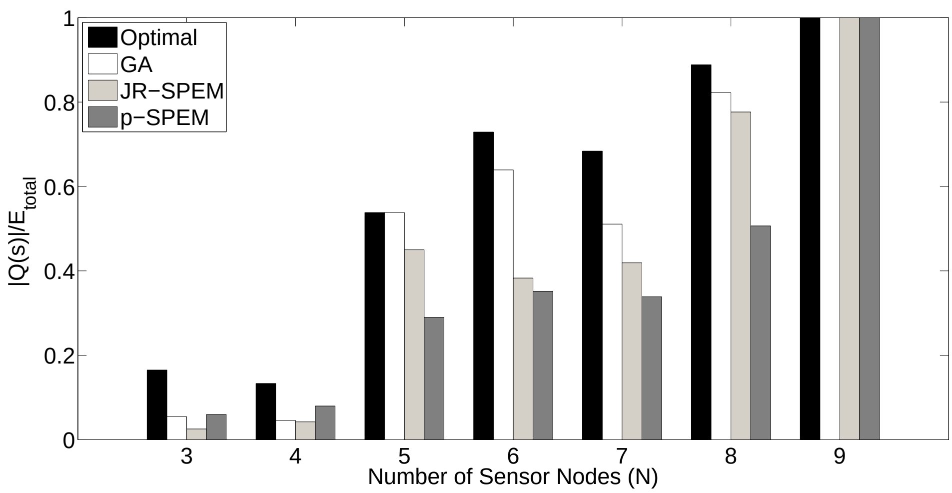

Fig. 4.7: The $\mho_{norm}$ ratio for optimal, GA-based and SPEM-based heuristic algorithms in a nine-floor building using the system model for Case I.

Case II: Numerical results for basic case with flow assignment

NIQ increases as the number of the nodes in the network increases for several algorithms as shown in Fig. 4.8. The increase occurs because of the higher number of nodes placed in positions that results in a higher quality of information collected by the sensors. For most of the network sizes, the JR-SPEM is proven to have a greater rate of improvement in the NIQ for different N. However, for $N = 5$ to 9, JR-SPEM results are always higher than p-SPEM, which demonstrates the dominance of JR-SPEM algorithm in collecting information. The optimal algorithm outperforms all other algorithms under high N values while GAs performance is also better than p-SPEM for different N as demonstrated in Fig. 4.8. The optimal solution obtained using MIP exceeds the p-SPEM solution.

Fig. 4.9 exhibits a comparison of the energy consumption for the four placement algorithms with flow assignment. The optimal algorithm achieves the lowest energy consumption for all N values, Moreover, GAs and JR-SPEM are the same for $N = 8$. In Case II, the JR-SPEM energy consumption results save around 2% to 11% compared to p-SPEM. Meanwhile, p-SPEM energy consumption is higher than the optimal and GAs but close to JR-SPEM for $N = 4$. Results also indicate that JR-SPEM does not perform well compared to the optimal, as an additional 25% of the energy is consumed for $N = 8$. In Case II, JR-SPEM performs well with more than 6% of energy saving over p-SPEM for $N = 5$. However, p-SPEM achieves poor results compared to the other algorithms.

Analyzing this difference in energy consumption helps discover the nature of p-SPEM and JR-SPEM, which affects the amount of data transmission in the network. The energy consumption increases when increasing the number of nodes due to a higher amount of traffic flowing through the network. For Case II compared to Case I results, low energy consumption is achieved for all the proposed algorithms with higher N values.

For the demonstration of the effect of the flow assignment on the normalized ratio, Fig. 4.10 plots the ratio $\mho_{norm}$ versus N for the four algorithms. The optimal solution achieves the highest ratio while JR-SPEM achieves almost the same GAs result when compared to p-SPEM. The trend in results occurs because p-SPEM is unable to balance the energy consumption among nodes to avoid the rapid depletion of the node's battery.

Case II has more energy consumption for all N. Under the same set of inputs, Case II results show that the energy consumption of the selected nodes is higher in Case II over Case I due to the use of more routes. In Case II, the normalized ratio still rises with the number of nodes. The optimal algorithm achieves an increase in the normalized ratio due to the efficient distribution of the flows over all possible routes. The reason the energy consumption for JR-SPEM is higher than the corresponding p-SPEM is because the data stream is split among different paths in an efficient way.

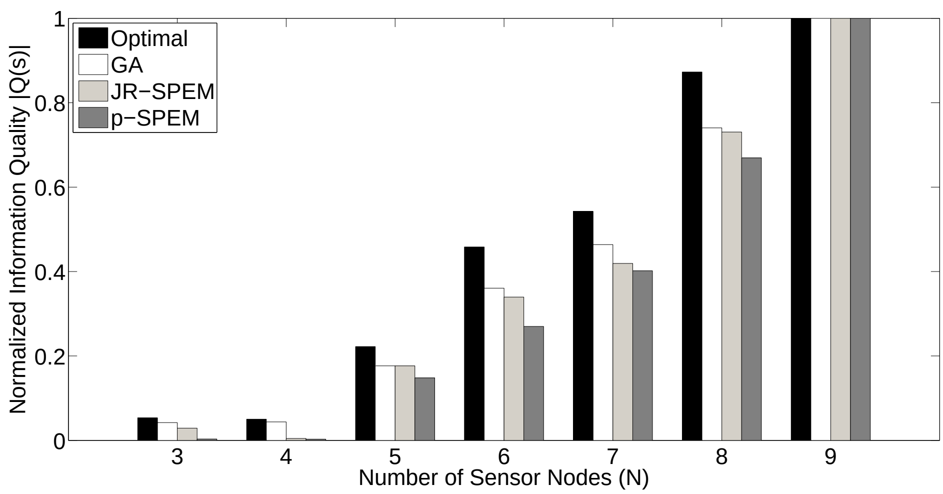

Fig. 4.8: Normalized information quality for optimal, GA-based and SPEM-based heuristic algorithms in a nine-floor building using the system model for Case II.

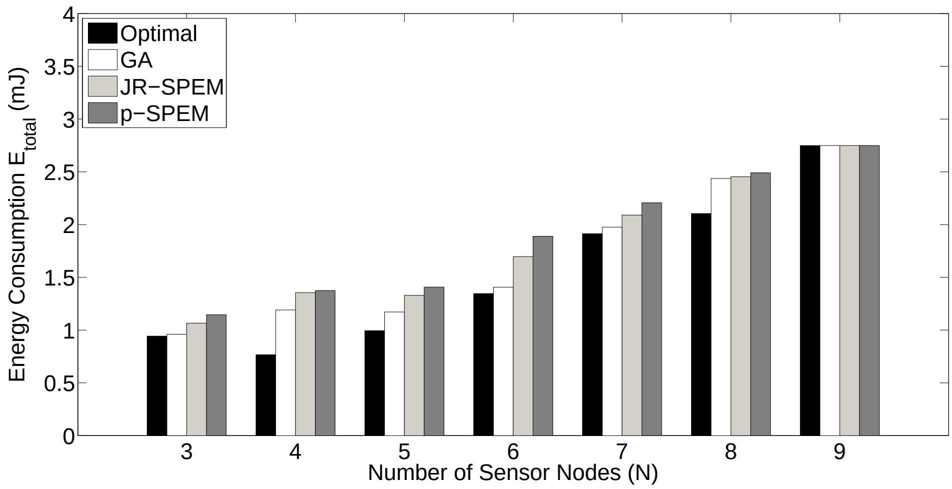

Fig. 4.9: Total energy consumption for optimal, GA-based and SPEM-based heuristic algorithms in a nine-floor building using the system model for Case II.

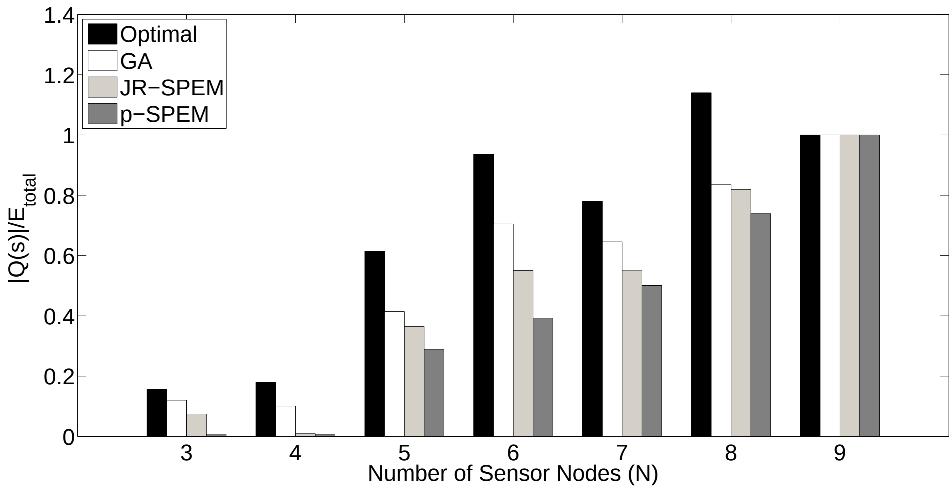

Fig. 4.10: The $\mho_{norm}$ ratio for optimal, GA-based and SPEM-based heuristic algorithms in a nine-floor building using the system model for Case II.

4.6.4 Complexity of the Algorithms in Study

In this section, we characterize the complexity of the placement and the routing and their combined algorithm. It has been shown in [1] that the complexity of the SPEM algorithm is given by $O(N^4M)$. The following analysis shows the complexity for these five algorithms in the study, but it is approximated for the nearest order for the sake of simplicity.

Routing, as demonstrated in [1], is determined inside the p-SPEM after a candidate set **S** is selected. Next, the corresponding energy consumption is estimated for the chosen set of nodes. An energy estimation algorithm is called iteratively three times inside the local search algorithm in the p-SPEM as shown in [1], which gives a higher complexity bound by $O(N^4M)$. The embedded complexity in [1] shows the shortcomings in their routing approach. Due to the limitations of p-SPEM, the JR-SPEM is considered to be better than other sensor placement approaches because the placement and routing are merged together into one module to improve the $\mho_{norm}$.

Moreover, the p-SPEM algorithm finds a suitable placement, then it employs the e-Estimator algorithm to calculate the energy consumption. Estimating the energy consumption is not efficient when a greater number of nodes are used due to its complexity. Although, p-SPEM finds balanced solutions in a polynomial time. The p-SPEM computational complexity is even quite high where the complexity bound is $O(N^4M)$ [1]. To address these concerns, a JR-SPEM heuristic algorithm has a complexity of $O(NM^2)$, calculated based on the complexity of its sub-modules, is used to find an energy-efficient and high information quality placement solution.

Table 4.2 reflects the complexity of the algorithms studied in this work. The complexity of the placement algorithm and routing algorithms are shown in the table both separately and with their summation together. An approximated complexity of both the placement and routing is also shown for the five algorithms in study. The total complexity of the proposed algorithms consists of the inherent complexity of the placement and routing. This is shown in [1], where the high complexity is bound by $O(N^4M)$. Unlike p-SPEM, the placement and routing in JR-SPEM are merged together into one module to improve the ratio $\mho_{norm}$. The complexity of the SPEM placement used in [1] is $O(NM)$. The complexity of the modified local search and routing presented in [1] is bound by $O(N^4M + M^2)$. The complexity of the routing using the optimal algorithm is $O(N^M)$ for M possible locations as shown in [22] and [23]. However, as there are M^2 possible links from the solution representation. The complexity of the routing using this work's GAs implementation is $O(M^6)$ because the complexity of GAs is the cubic order of the building block [**?**] of either the placement or the routing. The complexity of the routing using Dijkstra's algorithm, which is used in works involving JR-SPEM, is $O(NM^2)$. A modified version of the Dijkstra's algorithm is introduced in [24] and used in this work. Embedding the routing inside the algorithm leads to reduced complexity in JR-SPEM compared to all approaches used for finding the best solution in previous work [1].

In Fig. 4.11, the histogram of the running time for the algorithms in study is shown versus N. The optimal algorithm has the highest running time for N greater than 5, while the GAs-based solution has the same complexity for all N due to its fixed number of variables for chromosome representation. Considering the SPEM-based heuristic algorithms, the JR-SPEM has a shorter running time compared to the p-SPEM. This histogram shows the efficiency of the JR-SPEM as a placement and routing algorithm with shorter running time than its competitors.

Table 4.2: Complexity of the algorithms in study

Algorithm	Optimal	GA-Based	JR-SPEM	p-SPEM	SPEM
Placement	O(N^M)	O(M^3)	O(NM^2)	O($NM + N^4M$)	O($N(M - N)$)
Routing	O(M^2)	O($(M^2)^3$)	O(M^2)	O(M^2)	O(N^2)
Placement Routing	O(N^M $+M^2$)	O(M^3) $+(M^2)^3$	O(NM^2 $+M^2$)	O($NM + N^4M$ $+M^2$)	O($N(M - N)$ $+N^2$)
Approximation	O(N^M)	O(M^6)	O(NM^2)	O(N^4M)	O(NM)

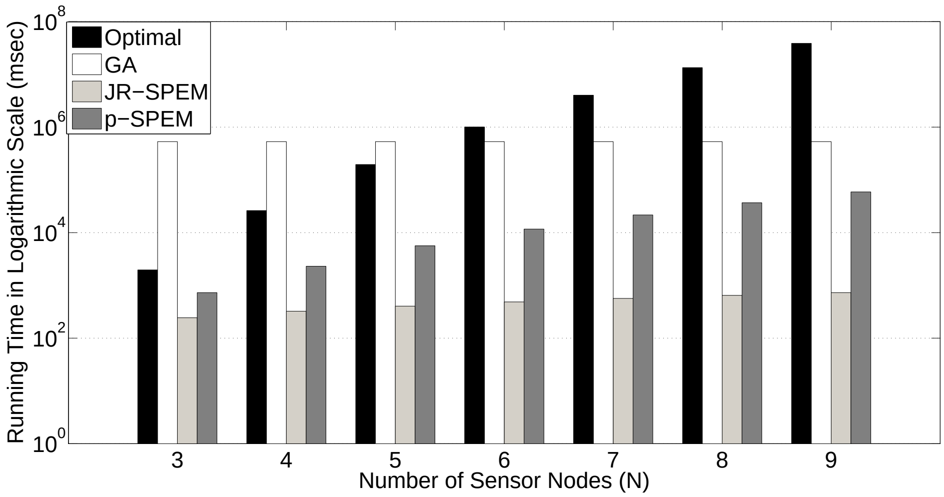

Fig. 4.11: The histogram of the running time for the algorithms in study versus number of nodes.

4.7 Conclusion

This chapter presents a novel joint formulation that optimizes placement, routing and flow assignment. In addition to the optimal solution obtained from the aforementioned formulation, a low-complexity, near-optimal, GA-based solution, that achieves promising results, is presented. Furthermore, a heuristic solution, JR-SPEM, is developed and found to give close results to the optimal algorithm. The JR-SPEM algorithm is introduced to improve SPEM and p-SPEM by jointly optimizing the placement and routing. Metrics such as the information quality, the total energy consumption, and their normalized ratio are determined for each algorithm. The numerical results are evaluated for a nine-floor building to analyze the performance of the proposed algorithms. The numerical results show the efficiency of the proposed algorithms and demonstrate trade-off between the efficiency and complexity.

In the next chapter, we will focus on the proposal of a multi-objective algorithm for placement and routing of WSNs for SHM. Moreover, we will consider different cases, including the limited capacity of links and the node-disjoint routing.

Acknowledgment

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Chapter 5

Node Placement in WSNs for SHM with Multi-Objective Optimization

5.1 Abstract

Node placement is one of the most significant factors that affect the performance of wireless sensor networks (WSNs), especially for structural health monitoring (SHM). Optimal node placement tries to find the best sensor node locations that optimize an objective function (e.g., energy consumption or information quality) taking the networking requirements and other constraints into account. In [1], we have addressed this problem using a single objective to minimize the energy consumption. In this chapter, we revisit the placement problem in WSNs for SHM by using multi-objective optimization for minimizing the energy consumption and maximizing the information quality simultaneously. Furthermore, in this chapter, we take into consideration some constraints that were not taken into account in [1]. This includes

the maximum capacity per link and the node-disjoint routing. While maximum capacity constraint is essential to guarantee the packet delivery over WSN links, node-disjoint routing is important to achieve load balancing and longer WSN lifetime. We propose algorithms for joint placement, routing and flow assignments using multi-objective optimization with/without link capacity constraints and node-disjoint routing. Results show the superiority of the proposed algorithms compared with existing algorithms in the literature.

5.2 Introduction

Structural health monitoring (SHM) is an emerging application where many objectives need to be met in the lively fields of critical infrastructure and construction monitoring. SHM can facilitate the monitoring of the state of the building through the deployment of many sensor nodes. The task of SHM is essential not only for prevention of financial losses, but also for catastrophic failures avoidance and notably human lives loss.

Wireless sensor networks (WSNs) have become the most efficient solution for SHM (compared to traditional wired sensor networks) due to their simplicity of installation, ability to be applied to an existing structure and low maintenance costs [2]. However, WSNs for SHM face various challenges such as the energy consumption, network scalability for large structures, and data accuracy.

In SHM, the structural ambient vibrations is measured using accelerometer sensors. Then, the vibration signals are used to calculate the mode shapes which are used to detect the structure damage and determine its location. Node placement deals with determining the best locations for sensor deployment across the structure. The inputs to the placement algorithm are the mode shape that is a vibration pattern of the structure, the number of M candidate locations given by the civil engineering experts, the number of sensor nodes placed (N) besides the assumptions related to the routing. The placement algorithm outputs the set of the selected locations that ensures the highest information quality which is measured by the Fisher information matrix (FIM). Basically, Fisher information describes the amount of information data provide about an unknown parameter.

In [1], we have addressed this problem using a single objective to minimize the energy consumption. This work aims to execute the sensor node optimization with the joint placement, routing and flow assignment optimization using multi-objective optimization and with new constraints. The flow assignment defines an efficient splitting of data traffic on multiple disjoint paths. Node-disjoint routing implies that no two different paths pass through the same sensor node in the network at a time. Routing with node-disjoint paths disjoint routing is used mainly for load balancing and it has important feature in WSNs where collision between the packets passing the same node should be avoided. The upper bound on the maximum per-link capacity of a WSN is limiting the amount of traffic to be transferred through a certain link under given constraints. The main contributions of this chapter are the following:

(a) We formulate the joint placement, routing and flow assignment problem as a multi-objective optimization. This formulation is used to show the trade-off between the different objectives, namely the energy consumption and the information quality.

(b) We introduce maximum capacity constraint for each link. This is more realistic case and helps to guarantee the packet delivery in all links.

(c) We consider node-disjoint routing to achieve load balancing and longer WSN lifetime.

The rest of the chapter is organized as follows: Section 5.3 outlines some related work on WSNs for SHM. Section 5.4 formulates the system model and the sensor placement and routing optimization problem under various constraints. Section 5.5 demonstrates the proposed approach for finding a heuristic solution using an evolutionary algorithm. Section 5.6 evaluates the proposed algorithms via numerical results. Finally, Section 5.7 concludes the work in this chapter.

5.3 Related Work

Sensor placement is an integral function for all SHM applications, where sensor nodes are positioned at locations with the architectural importance from a civil engineering point of view. Hence, optimization of sensor placement is crucial to lead to energy-efficient communication. Previous works [3–11] study the sensor placement optimization for WSNs for SHM.

In [3], the authors offer a benchmark developed in MATLAB for sensor placement algorithm using the effective independence method (SPEM) that implements the sensor placement algorithm for SHM. In this case, SPEM uses both synthetic and real data examples for evaluation.

The authors in [4] propose a method to find optimal locations for the sensor nodes taking into consideration both civil engineering requirements such as coverage of critical locations in the structure as well as communication requirements such as network connectivity. Sensor placement optimization in SHM introduced in [5] ensures the optimization of an objective function, which depends on the FIM, the location placement indicator, and the energy consumption. Moreover, the authors in [5] introduce a power-aware sensor placement algorithm using the effective independence method (p-SPEM) algorithm to solve the sensor placement optimization problem. This algorithm is designed to reduce the overall energy consumption to prolong the battery life for sensor nodes. Locations selected by p-SPEM are based on a local search between all possible locations among all candidates.

The authors in [6] present a sensor placement for WSNs that uses huge amounts of prior information about the sensor nodes. The objectives of the proposed placement algorithm are the minimum energy consumption and maximum sensing coverage while capturing most of the available information. This placement algorithm also improves energy-efficiency, sensing coverage and operational lifetime of WSNs. This algorithm, however, requires many calculations, which makes it impractical for real structures due to its complicated computational complexity.

The authors in [7] introduce an energy-efficient placement algorithm with acceptable coverage based on genetic algorithms (GA). The two objectives taken into consideration are the sensing coverage and the network lifetime. The numerical results show an improvement in the performance. However, a vast increase in the number of generations in GA is needed, which increases the search time.

Fault tolerance is additionally used as an objective for the sensor placement optimization problem for WSNs for SHM as shown in [8]. The authors select a heterogeneous network consisting of three groups of sensor nodes, resource-rich nodes, resource-constrained nodes, and redundant nodes. The three node groups are then placed to allow the fault tolerance in the network. The authors also present an approach named three-phase sensor placement (TPSP) to help in placing these three groups efficiently to obtain the node positions. The three phases of TPSP are employed as follows: First, a near-optimal location is found for resource-rich nodes. Second, the optimal location is chosen for resource-constrained nodes, whereas connectivity is guaranteed. Finally, redundant nodes are placed to alleviate the sensor failure. The placement optimization targets to satisfy the networking demands and lower the chance of failures in WSNs and consequently maintain reliability and low-complexity placement.

The authors in [9] study sensor placement optimization for SHM of bridge constructions. They present a method for maximizing the system lifetime and employ network coding in sensor placement optimization for linear network topologies to match the structure type. Bridges, for example, can have sensors placed along its length. Optimization aims to downplay the link connectivity problems and maximize the lifetime of the network. Both packet relay and network coding are considered for routing collected data packets towards two sink nodes positioned at both ends of the bridge. The mathematical analysis in [9] shows that their method saves energy, prolongs the system lifetime and eliminates bottlenecks in the networks. The work in [9], however, lacks comprehensive numerical results and experimental work to support authors' claims.

In [10], the authors formulate the sensor placement optimization problem with the following objectives to be optimized: coverage, energy consumption, and connectivity. A decomposition approach used for converting the multi-objective into a single objective. The performance of their algorithm is compared with other evolutionary algorithms.

Energy-efficient routing is introduced in [11] for emergency sensor networks by using an iterative algorithm. The objective is the optimization of the network lifetime where the flow bounded by the node's data rate. Also, the derivation of bounds on the network lifetime is introduced. The development of optimal algorithms, which can be implemented in a distributed manner, is presented. This work shows the need for a low-complexity algorithm to deal with the special characteristics of WSNs.

5.4 System Model

The node placement problem is defined as the process of selecting N locations out of M, the total number of candidate locations decided by the civil engineering experts. The sensor node placement problem for SHM is formulated as finding the optimal binary location indicator set $\mathbf{S} = \{s_1, s_2, \ldots, s_M\}$. Each node generates a certain flow every cycle which we call it a flow rate. By the flow rate, we mean the packet stream of each node at fixed time in one cycle. x_{ij} is a non-negative integer indicator that shows how many times link $i-j$ is used by flows generated by all placed nodes, $x_{ij} \in \{0, 1, \ldots, N\}, \forall i, j$, i and j are node indices such that $i, j \in \{0, 1, \ldots, M\}$ and $i \neq j$. The notations in this work are listed in Table 5.2.

First objective: Maximizing the information quality.

The mode shape is represented by a function of the measured vibrations. The mode shape $\mathbf{\Phi}$ is given by:

$$\mathbf{\Phi} = \begin{bmatrix} \delta_{11} & \delta_{12} & \ldots & \delta_{1k} & \ldots & \delta_{1K} \\ \ldots & \ldots & \ldots & \ldots & \ldots & \ldots \\ \delta_{M1} & \delta_{M2} & \ldots & \delta_{Mk} & \ldots & \delta_{MK} \end{bmatrix}, \tag{5.1}$$

where $\mathbf{\Phi}$ imparts the sensor node contribution to the measurement data matrix, k is the order mode shape for all sensors, and K is the total number of mode shapes. Each row of the matrix in Eq. (5.1) represents the mode shape measured by a specific sensor node. Each column of the matrix in Eq. (5.1) represents a particular

Table 5.1: Notations used in this work.

Symbol	Description
M	The number of all candidate locations.
N	The number of sensor locations selected.
$\mathbf{S}$	The set of location indicator.
$\mathbf{\Phi}$	The mode shape matrix.
ϕ_j	The mode shape measured by the jth sensor.
ϕ^k	The kth order mode shape for all sensors.
$\mathbf{Q}$	The Fisher information matrix.
$\mathbf{x}$	The matrix that shows the number of flows per link.
x_{ij}	The link indicator from node i to node j.
Γ	The normalized sensor information quality (NIQ).
$\mathbf{R}$	The covariance matrix.
$E(i)$	The total energy consumed during the transmission and the reception in node i.
E_{init}	The initial energy in the sensor node.
n^b	The number of bits per packet.
r_c	The maximum transmission distance.
$\mathbf{C}$	The coordinates matrix.
$e_t(ij)$	The transmission energy on link $i-j$.
$e_r(ji)$	The reception energy on link $j-i$.
$E_t(i)$	The total transmission energy consumed by node i.
$E_r(i)$	The total reception energy consumed by node i.
$E_{total}(\mathbf{S}, \mathbf{x})$	The total energy consumption by all nodes.
d_{ij}	The distance between node i and node j.
s_i	The link indicator for node i.
s_j	The link indicator for node j.
C_l	The capacity of the link.
$\mathbf{S}_{temp}$	The temporary sensor location indicators set.
δ_{Mk}	The measured vibrations collected by the Mth sensor representing the kth the mode shape.

Table 5.2: Notations used in this work [Continued].

Symbol	Description
α	The path loss exponent.
ϵ_r	The reception energy cost per data unit.
ϵ_t	The transmission energy cost per data unit.
ϵ_{amp}	The power amplifier energy cost per data unit per m^2.
ω	The weighting factor of the objective function.
$\mho$	The information quality to the total energy consumption ratio.
$\mho_{norm}$	The normalized information quality to the total energy consumption ratio.

mode shape for all sensors. The FIM determinant $|\mathbf{Q(S)}|$ [5] is given as follows:

$$|\mathbf{Q(S)}| = \det[(\mathbf{\Phi})^{\mathbf{T}}\mathbf{R^{-1}\Phi}], \tag{5.2}$$

where $\mathbf{R}$ is the covariance matrix of the noise in the mode shape measurements. Let Γ correspond to the normalized sensor information quality (NIQ) which is defined as follows:

$$\Gamma = |\mathbf{Q}(\mathbf{S})|/|\mathbf{Q}_{max}(\mathbf{S})|, \tag{5.3}$$

where $|\mathbf{Q}(\mathbf{S})|$ is the FIM determinant for a set of selected sensor nodes and $|\mathbf{Q}_{max}(\mathbf{S})|$ is the FIM determinant when all sensor nodes are selected.

Second objective: Minimizing the total energy consumption.

We minimize the total energy consumption of all nodes under predefined constraints. This is done by minimizing the energy consumption in both transmission and reception. Let $E_{total}(\mathbf{S}, \mathbf{x})$ be the total energy consumption by all nodes which is given as follows:

$$
\begin{aligned}
E_{total}(\mathbf{S}, \mathbf{x}) &= \textstyle\sum_{j=0}^{M} (\epsilon_t + \epsilon_{amp} d_{ij}^{\alpha}) n^b x_{ij} s_i s_j \\
&\quad + \textstyle\sum_{j=1}^{M} \epsilon_r n^b x_{ji} s_i s_j, \forall i, j,
\end{aligned} \tag{5.4}
$$

where n^b be the number of bits per packet, α is the path-loss exponent and d_{ij} is the Euclidean distance between node i and node j. The radio parameter ϵ_{amp} and ϵ_t are the transmitter amplifier cost and the energy cost for transmission, respectively as demonstrated in [12], while ϵ_r is the energy cost for the reception.

5.4.1 Single objective function formulation

The ratio of the information quality to the total energy consumption, $\mho$, is given as follows:

$$
\mho = |\mathbf{Q}(\mathbf{S})| / E_{total}(\mathbf{S}, \mathbf{x}), \tag{5.5}
$$

where this ratio physically determines how much information can be collected per energy unit from one sensor or a combination of many sensors. The ratio is used as the objective function in [1, 5]; however, this objective does not show the possible trade-offs between the two objectives. We use this case here as a reference case.

Case I: Basic Case Formulation without Node-disjoint Routing and Flow Assignment

We formulate the optimization problem as an integer linear programming (ILP) where all variables are either integers or binary variables. This formulation is introduced with full details in [1] and it is mentioned here for the sake of comparison. The decision variables in our formulation are the following: s_i is a binary indicator showing if this location is selected where $s_i \in \{0,1\}, \forall i$, the link indicator matrix is $\mathbf{x}$. The joint placement and routing optimization problem is formulated as follows:

$$
\begin{aligned}
\underset{\mathbf{S},\mathbf{x}}{\text{Maximize}} \quad & |\mathbf{Q}(\mathbf{S})|/E_{total}(\mathbf{S},\mathbf{x}) \\
\text{Subject} \quad \text{to}: \quad & \\
\text{(c1)} \quad & d_{ij} I(x_{ij} > 0) \leq r_c, \\
& \forall i, j, i \neq j, \\
\text{(c2)} \quad & E(i) \leq E_{\text{init}}, \quad \forall i, \\
\text{(c3)} \quad & \sum_{i=1}^{M} s_i = N, \\
\text{(c4)} \quad & s_j + \sum_{i=1}^{M} x_{ij} = \sum_{i=0}^{M} x_{ji}, \\
& \forall j, j \neq 0, j \neq i, \\
\text{(c5)} \quad & \sum_{i=1}^{M} x_{ij} \leq s_j(N-1), \\
& \forall j, j \neq 0, j \neq i, \\
\text{(c6)} \quad & \sum_{i=1}^{M} x_{i0} = N, \\
\text{(c7)} \quad & \sum_{j=0}^{M} x_{ij} \leq s_i N, \\
& \forall i, i \neq 0, i \neq j, \\
\text{(c8)} \quad & x_{0i} = 0, \quad \forall i.
\end{aligned} \tag{5.6}
$$

The above formulation has the following constraints: (c1) guarantees the node connectivity by ensuring that the distance, d_{ij}, between any two nodes does not exceed the allowable transmission range r_c, where $I(x_{ij} > 0)$ is a binary indicator whether link $i - j$ is used or not, i.e., x_{ij}, is greater than zero. (c2) ensures that the total energy consumption does not exceed the initial energy stored in each node E_{init}. (c3) imposes that the total number of nodes selected by the placement algorithm is equal to N. (c4) enforces that the number of input links to a sensor node plus the sensor node generated traffic is equal to the number of output links (excluding the sink). (c5) ensures a sensor node does not receive from a number of nodes more than $N-1$. (c6) imposes that the sink node, s_0 is the sink node indicator where all traffic needs to be delivered, does not receive more than N times. (c7) ensures that a link is not used more than N times. Finally, (c8) guarantees that the sink node does not generate any traffic.

Case II: Basic Case with Maximum Link Capacity Constraint

In this section, Case II imposes the maximum link capacity constraint. The formulation for Case II will be as follows:

$$\begin{aligned}
\underset{\mathbf{S},\mathbf{x}}{\text{Maximize}} \quad & |\mathbf{Q}(\mathbf{S})|/E_{total}(\mathbf{S},\mathbf{x}). \\
\text{Subject} \quad \text{to}: \quad & (\text{c1}) \quad to \quad (\text{c8}), \\
(\text{c9}) \quad & x_{ij} \le C_l, \\
& \forall i, i \neq 0, i \neq j,
\end{aligned} \tag{5.7}$$

where C_l is a unit-less quantity which represents an upper limit for the link indicator. C_l is the capacity of the link divided by the information generation rate of the sensor node.

We introduce this new constraint to ensure the message integrity and the information delivery. The sum of the flows through any link must not exceed its capacity and this is ensured by the constraints in (c9). When the maximum link capacity is enforced, then the packet error rate will be higher as there will be more packets dropped. The set of constraints in Eq. (5.7) ensure that the flow of packets on a link does not exceed its capacity.

Case III: Basic Case with Node-disjoint Routing Constraint

Disjoint routing aims to achieve load balancing for all nodes in the network. When considering the multi-path routing problem in WSNs for SHM, there are two primary types of multi-paths: node-disjoint paths and link-disjoint paths. Node-disjoint paths are defined as a set of paths, from a source node to a destination node where no two paths share a common node, except for the source and destination. On the other hand, a set of link-disjoint paths consists of a set of partially node-disjoint paths intersecting at one or more common nodes.

In Fig. 5.1 and Fig. 5.4, a demonstrative example is shown to explain the effect of both the node-disjoint routing and the flow assignment. On each link a number indicates the flow rate on this link. It is an arbitrary number to clarify and explain behind several cases starting from Case I to Case III. As shown in Fig. 5.1, an intermediate node, such as sensor node 6, is also a source node that has its own traffic. In the basic case without the node-disjoint routing nor flow assignment constraints, sensor node 6 receives flows from three other nodes. On the other hand, the basic case with the node-disjoint routing case allows, at most, one received flow as shown in Fig. 5.2.

Traffic routing plays an important role when intermediate nodes are also used as source nodes in SHM. Several algorithms have been used for finding both optimal and heuristic paths applying node-disjoint routing in [13, 14]. Here, a modified node-disjoint model is shown in Fig. 5.2 and Fig. 5.4 where all nodes are sources that do not receive from more than one sensor node. Each sensor node generates a unity traffic load routed through other nodes to the sink (node 0). In the basic

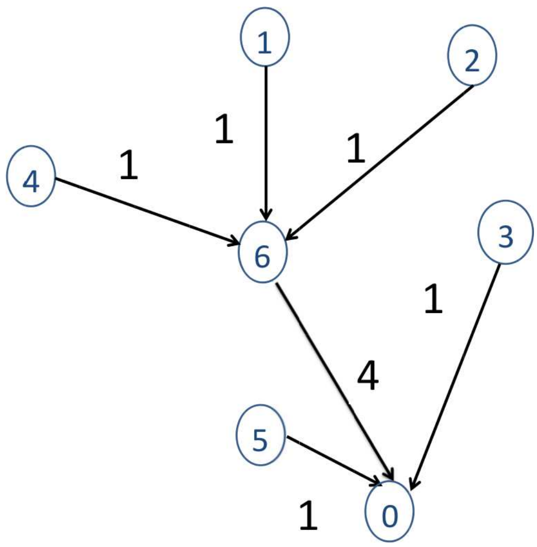

Fig. 5.1: Basic case without node-disjoint routing and flow assignment.

case without node-disjoint routing case, shown in Fig. 5.3, sensor node 5 and 6 accept traffic from more than one sensor node, while the traffic from only one node is allowed in the basic case with the node-disjoint routing as shown in Fig. 5.4. To include the node-disjoint routing in the basic formulation, the problem is modified as follows:

$$\begin{aligned} \underset{\mathbf{S},\mathbf{x}}{\text{Maximize}} \quad & |\mathbf{Q}(\mathbf{S})|/E_{total}(\mathbf{S},\mathbf{x}). \\ \text{Subject} \quad \text{to}: \quad & \text{(c1)} \quad to \quad \text{(c4)}, \\ \text{(c5)} \quad & \sum_{i=1}^{M} x_{ij} = \underset{i}{\text{Maximum}} \quad (x_{ij}) \\ & i \neq j, i \neq 0, j \neq 0, \\ & \text{(c6)} \quad to \quad \text{(c9)}, \end{aligned} \tag{5.8}$$

where constraint (c5) is modified compared to that in Eq. (5.6) to reflect the node-disjoint routing case. For every link going to a specific node, except for the sink node, the constraint allows only one link.

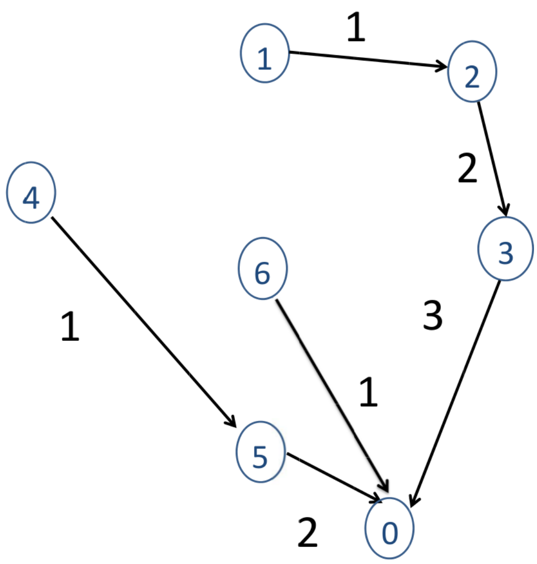

Fig. 5.2: Basic case with node-disjoint routing.

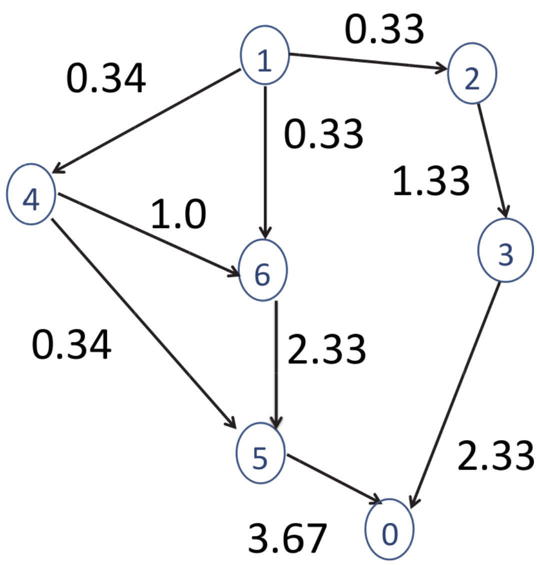

Fig. 5.3: Basic case with flow assignment.

Case IV: Basic Case with Flow Assignment and Node-disjoint Routing Constraints

The flow assignment has a substantial benefit of balancing the load among all links by deciding the current flow on each connection. When just one path is found between every source and destination pair, this theoretical assumption is not prac-

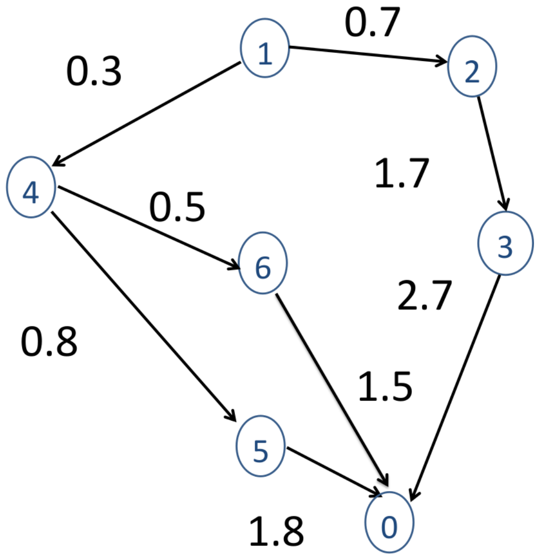

Fig. 5.4: Basic case with both node-disjoint and flow assignment.

tically utilized. The data are always sent on a distinct, least cost path from a source node to the destination node as in the previous case. Nevertheless, in the event of multi-path existence, flow assignment is required to avoid overloading the links in this type of network.

Case IV may be more realistic in the kinds of networks where few alternative paths exist and cause a large difference in the link cost. This example may also be employed to identify the path the data travels to avoid overloading individual links. In Case IV, the flow assignment is applied in conjunction with the node-disjoint. This case considers the variable x_{ij} takes a rational value between zero and N. Therefore, the traffic from node i can be separated between different connections.

5.4.2 Multi-objective Function Formulation

The design of WSNs has multiple objectives and these objectives are usually conflicting [15]. The primary design objective in WSNs is often to reduce energy consumption, while in SHM, nodes placement is used to achieve an acceptable information quality. The proposed multi-objective approach considers both minimizing the energy consumption and maximizing the information quality as its objective function. We formulate the placement and routing problem as a multi-objective problem with two objectives, namely the information quality maximization and the total energy consumption minimization. The two objectives are shown to be conflicting. Therefore, the overall objective is to obtain a possible trade-off between these two objectives.

Case V: Basic case with multi-objective optimization

We jointly optimize the two objective functions through joint placement and routing. The formulation for joint placement and routing where the total energy consumption and FIM determinant are optimized as follows:

$$\begin{aligned} \underset{\mathbf{S}}{\text{Maximize}} \quad & |\mathbf{Q}(\mathbf{S})|, \\ \underset{\mathbf{S},\mathbf{x}}{\text{Minimize}} \quad & E_{total}(\mathbf{S},\mathbf{x}) \\ \text{Subject} \quad \text{to}: \quad & (\text{c1}) \quad to \quad (\text{c8}). \end{aligned} \tag{5.9}$$

The first objective of this work is to maximize the information quality measured by the the determinant of the FIM which serves as an indicator of the quality of the sensed data. It is also serving as the civil engineering requirements in the SHM. Maximization of this metric is required to identify the information quality of the sensor, followed by the second objective, the total energy consumption minimization, which represents a network requirement from the computer engineering perspective and a design constraint requirement in the SHM.

We use the weighted sum method to turn the objective function into a single-objective optimization problem where the weighting factors are assigned to each objective based on its relative importance [16]. The multi-objective model is used for combining the two objective functions into a single one. The weighted sum objective function can be rewritten as follows:

$$\begin{aligned} \underset{\mathbf{S},\mathbf{x}}{\text{Minimize}} \quad & \omega E_{total}(\mathbf{S},\mathbf{x}) - (1-\omega)|\mathbf{Q}(\mathbf{S})| \\ \text{Subject} \quad \text{to}: \quad & \text{(c1)} \quad to \quad \text{(c8)}. \end{aligned} \tag{5.10}$$

As listed in Table 5.3, we have covered six cases in this work. There are many other cases that can be considered in the future work. Some possible combination for these sub cases are mentioned below. Multi-objective function can be considered with link capacity as one of the constraints in the problem and can be added as another sub-case. The link capacity constraint can be imposed which limits the possible routes and may affect the routing metrics. Another sub-case can consider the modified node-disjoint routing and its associated constraint should be added. With the weighted sum objective function presented in Eq. (5.10), the node-disjoint routing and flow assignment can be imposed. The flow assignment constraint is added to present the possibility of dividing the flow among the possible links. Multi-objective function can be considered with link capacity as one of the constraints in the problem. The link capacity constraint can be imposed which limits the possible routes and may affect the routing metrics. Another sub-case can consider the modified node-disjoint routing and its associated constraint should be added. With the weighted sum objective function presented in Eq. (5.10), the node-disjoint routing and flow assignment can be imposed. The flow assignment constraint is added to present the possibility of dividing the flow among the possible links.

Table 5.3: List of the cases used in the testing environment

Case No.	Section No.	Description
Case I	Section 5.6.2	Case without node-disjoint routing nor flow assignment
Case II	Section 5.6.2	Case with the link capacity constraint imposed
Case III	Section 5.6.2	Case with the node-disjoint routing constraint imposed
Case IV	Section 5.6.2	Case with the node-disjoint routing and flow assignment constraint imposed
Case V	Section 5.6.3	Case with multi-objective optimization
Case VI	Section 5.6.3	Case with different weighting factors

5.5 Sensor Placement and Routing Using Multi-Objective Genetic Algorithms

The optimization problem formulated in the previous section is solved using the ILP techniques such as branch-and-bound. Unfortunately, finding a solution using this approach has a high complexity and can take an enormous amount of processing time. The formulation of the optimization problem is shown in the previous section and is found to be an NP-hard problem [5]. The NP-hard problem with multi-objective is a good candidate to be solved using an evolutionary algorithm such as multi-objective genetic algorithms (MOGA). Therefore, a heuristic algorithm is presented based on the MOGA approach to work out such models in a relatively acceptable run time for larger problem instances. After the formulation is introduced, a practical, low complexity algorithm has to be used to match the resources-limited sensor nodes as explained below. MOGA is an evolutionary algorithm that searches a population of random solutions for the designated problem to find a heuristic solution [17]. A fitness function is calculated for all the solutions to determine their suitability. The solutions with the highest fitness are more likely to be chosen to generate a newer solution through the crossover.

MOGA is a well-known approach to solve optimization problems because of their capability to check partially ordered search space for various trade-offs [17]. Furthermore, MOGA evaluates several solutions simultaneously and find the near-optimal solution by combining efficient solutions. After the optimization problem is formulated as shown in Eq. (5.6), MOGA is employed as a heuristic approach to optimize the objective function with reduced complexity.

MOGA is an efficient search approach due to its parallel features in finding a near-optimal solution [18]. The generated solutions share features taken from each previous solution since a novel population of generating solutions is produced by the selection of the best from the current generation. The procedure of the selection and new population generation are repeated until the stopping criteria is achieved. With the proper tuning of the parameters of MOGA such as the crossover rate, the algorithm will converge to a near-optimal solution [17].

Any single solution to a problem is called chromosome. A list of parameters represents the chromosome are called genes [17]. If the gene value is 1, then the corresponding node is a node chosen to be placed. The size of a chromosome should be equal to the number of possible locations M plus the possible links $M(M-1)$. However, the number of chromosomes studied at each iteration are determined by the population size parameter in which increasing the population size leads to increasing the number of evaluated solutions.

A roulette wheel method is used to perform the selection operation in which the chromosome that has a large fitness function value has a higher probability to survive to the next generation over others. In crossover operation, the chromosomes are recombined resulting in two new child chromosomes to be appended to the next generation population.

A single point crossover operator is used. MOGA generates a random number to select where to split the chromosome into two parts to then be recombined. The MOGA implementation used in this work has a probability of crossover equal to p_c. Lastly, the mutation operator flips some of the bits of the chromosome. Similar to crossover operator, increasing this probability will increase the mutation occurrence. A mutation probability of p_m is used in order to make the MOGA searches visit the corners of the search space to check for unique and different solutions. The chromosome can be inherited representing a solution has M sensors. Meanwhile, the possible links can be $M(M-1)$ links, so the total number of variables will be M^2.

Measuring the fitness or performance of chromosomes is done by the calculation of the weighted sum objective function used in Eq. (5.7). MOGA is terminated right after a specified number of generations is reached. Nevertheless, after the number of runs is greater than or equal to M^2 times the number of variables, the variations in MOGA results will be small.

5.6 Performance Evaluation

In this section, we evaluate the performance of the proposed algorithms through the numerical results of different number of placed sensors N for a nine-floor structure. These proposed algorithms include: optimal, GA and JR-SPEM. This is in addition to their multi-objective versions. The total energy consumption $E_{total}(\mathbf{S}, \mathbf{x})$, the information quality $|\mathbf{Q}(\mathbf{S})|$ and the normalized information quality to the total energy consumption ratio $\mho_{norm}$ are the measured metrics. For comparison, we implement p-SPEM and mop-SPEM placement algorithms, evaluate their performance and compare the system metrics for both of them.

5.6.1 Numerical Results Environment

The numerical results of different number of placed sensors N for a nine-floor structure evaluate the performance of the proposed algorithm. The general algebraic modeling system (GAMS) [19] is used for modeling the problem. The branch-and-reduce optimization navigator (BARON) solver [20] is employed for finding the solution for ILP formulation.

The parameters used in the performance analysis are presented in Table 5.4. The considered structure is a 30 m × 20 m with a floor height of 3.33 m. A two-dimensional plane is assumed with a sink node located at (20, 0).

For the study, we assume all sensor nodes have identical transmission range and

Table 5.4: Parameter values used in the numerical results

Symbol	Description	Value
E_{init}	The initial energy	1500 $mAhr$ [21]
n^b	The number of bits per packet	2 Kb [5]
p_c	The crossover probability	0.8 [17]
p_m	The mutation probability	0.1 [17]
r_c	The maximum transmission range	30 m [21]
α	The path loss exponent	2 [12]
ϵ_{amp}	The power amplifier energy cost	1 $nJ/bit/m^2$ [12]
ϵ_r	The reception energy cost	50 nJ/bit [12]
ϵ_t	The transmission energy cost	50 nJ/bit [12]

the candidate node locations are one on each floor in the nine-floor structure. The numerical results choose 3 - 9 sensors out of the nine candidate locations in the nine-floor structure and we assume that a sensor node is aware of the node coordinates of its neighbours.

5.6.2 Single Objective Case Results

Case I: Numerical results for basic case without node-disjoint routing nor flow assignment

Results are generated for three different algorithms: the optimal algorithm using MIP optimization, GAs, and JR-SPEM. All proposed algorithms are then compared with the p-SPEM presented in [5]. The performance of the proposed algorithm is presented based on the above formulation in order to evaluate the performance of the algorithms for different values of N. The results for the basic case which is based on the formulation in Eq. (5.6) are shown in Fig. 5.5 to Fig. 5.7.

Fig. 5.5 depicts that the energy consumption increases with an increase in the number of nodes. In fact, when N increases there are two conflicting factors that affect the energy consumption. In the first one, as N increases we add more nodes, flows and packet transmission. Hence, the energy consumption increases. However, in the second factor, as N increases more nodes become available so we can make the links shorter and also nodes find more and better routes (with less energy consumption) to send their packets to the destination. Due to these two conflicting factors, sometimes increasing N leads to energy consumption increase and other times it leads to energy consumption decrease depending on the dominating factor.

In Fig. 5.5, we summarize the results of all the algorithms in study for different N. We observe that the energy consumption increases as the number of sensor nodes increases. This rise in the energy consumption is a consequence of the node energy budget increasing with the traffic. Fig. 5.6 summarizes NIQ results for the four considered algorithms under different values of N. As expected, NIQ increases as more sensors are added to collect information from various points in the structure. Fig. 5.7 presents the $\mho_{norm}$ ratio for the four algorithms. With the increase of N, the ratio $\mho_{norm}$ increases for all algorithms. The optimal algorithm always achieves the best ratio, and GAs achieve a higher performance about 70% better than the p-SPEM algorithm. However, compared to p-SPEM, the information quality to energy consumption ratio for the optimal, GAs and JR-SPEM are still higher. The JR-SPEM ratio is higher due to the failure of p-SPEM to balance the load among the sensor nodes, which leads to a smaller ratio. For the full details of the results of Case I, refer to the full discussion in [1].

From Fig. 5.5 to Fig. 5.7, we can make the following observations: First, the optimal algorithm is outperforming the other algorithms, followed by the GAs, then JR-SPEM and finally p-SPEM. The second observation is that as the number of selected locations increases, the JR-SPEM solution achieves higher ratio than the p-SPEM due to the efficient joint of the routing with the placement rather than local search and energy estimation in p-SPEM.

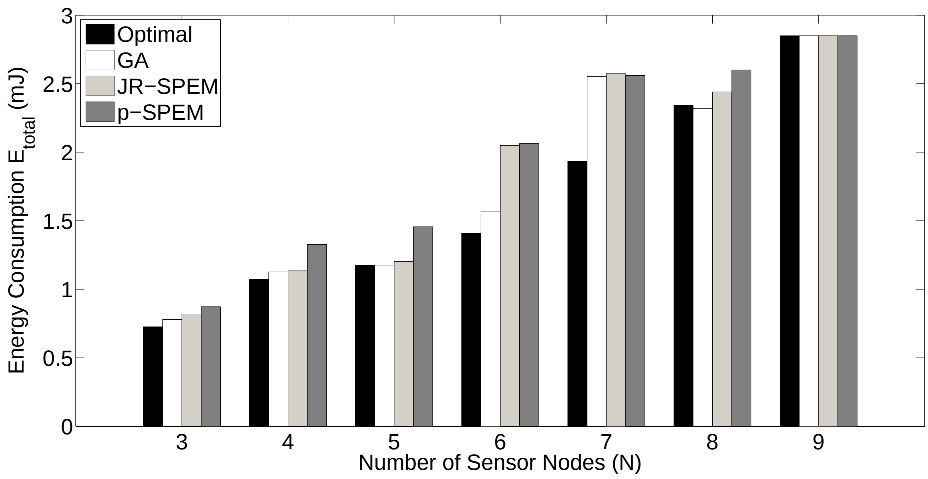

Fig. 5.5: Total energy consumption for optimal, GA-based and heuristic algorithms imposing the maximum link capacity constraint in a nine-floor structure for Case I formulation.

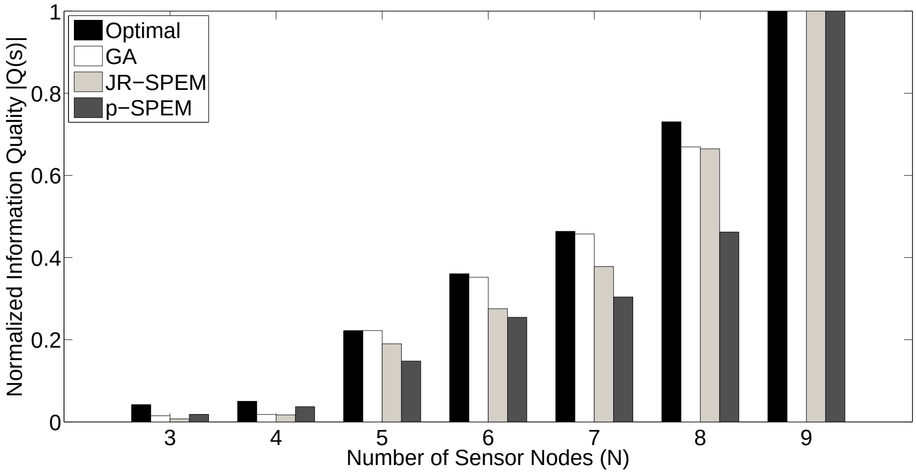

Fig. 5.6: Normalized information quality for optimal, GA-based and heuristic algorithms imposing the maximum link capacity constraint in a nine-floor structure for Case I formulation.

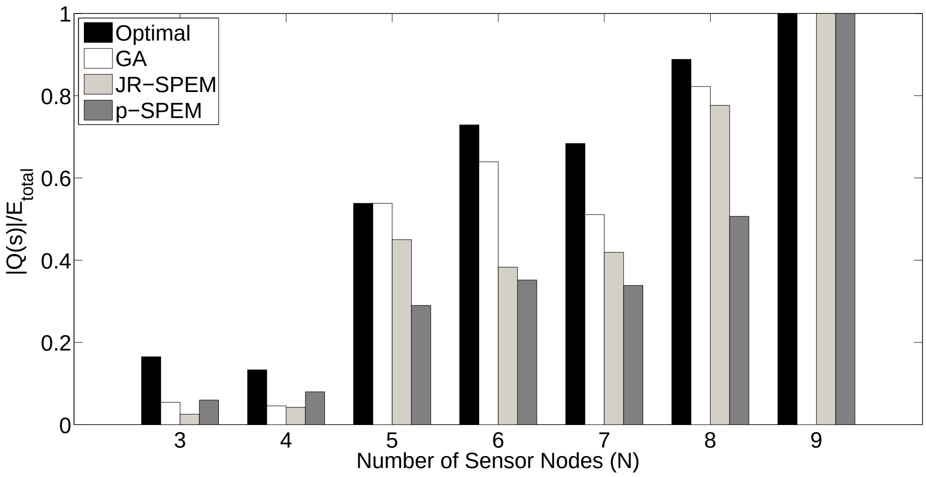

Fig. 5.7: The $\mho_{norm}$ ratio for optimal, GA-based and heuristic algorithms imposing the maximum link capacity constraint in a nine-floor structure for Case I formulation.

Case II: Numerical results for the basic case with the link capacity constraint imposed

Fig. 5.8 to Fig. 5.10 demonstrate the performance of the algorithms used in Case II under the maximum link capacity constraint. Performance is evaluated for the metrics mentioned in Section 5.2 using different values of placed sensors N. This work uses a maximum normalized link capacity of 5. At $N = 8$, the energy consumption is higher than at $N = 9$ because at $N = 8$, sensor node 2 sends the data of three nodes (nodes 2 - 4) directly to the sink. Data is sent to the sink in this case because no sensor node is placed at location 1. At $N = 9$ sensor node 2 sends the data of the same three nodes to sensor node 1, which in turn forwards the signals of four nodes (1 - 4) to the sink.

The energy consumption is proportional to the square of the floor height multiplied by the floor number and the number of flows from a sensor node to the next hop. Detailed calculations of the energy consumption of these two scenarios (with $N = 8$ and 9) are given as follows. For a nine-floor structure of a height L, the floor height is $L/9$. It is shown that for $N = 8$ p-SPEM achieves higher energy consumption than that for $N = 9$. This is because an added $4 * (L/9)^2$ flows resulting in an increase in the energy consumption. However, due to the link capacity limit, there is an extra amount of energy consumption of equal $3^2 * (L/9)^2$ that is caused by the increased travelling distance to the sink. The difference between these two components achieves $5 * (L/9)^2$ energy saving that leads to lower total energy consumption for $N = 9$.

Fig. 5.8 illustrates an increase in energy consumption when N increases from 5 to 8. When we compare results in Case II to results in Case I, it is found that the energy consumption is higher due to a link capacity limitation imposed by the maximum link constraint. The optimal and GA solutions consume 21% less energy compared to p-SPEM. However, JR-SPEM performs well with more than 17% of energy saving over p-SPEM for $N = 5$.

Fig. 5.9 plots the NIQ for the four considered algorithms versus the number of placed sensors N. As expected, as N increases NIQ improves. Additional sensors help collect more information from various points in the structure and aids in achieving higher NIQ. As shown, JR-SPEM has an improved result compared to p-SPEM as it is a joint placement algorithm where the focus is on energy consumption and NIQ. The JR-SPEM has more improvement over p-SPEM in the NIQ for all N values. However, JR-SPEM measurement has a higher NIQ than p-SPEM for N between 5 to 9. A higher result demonstrates the ability of the JR-SPEM to select the node locations efficiently.

Fig. 5.10 depicts the normalized information quality per unit energy $\mho_{norm}$ for the four algorithms used. As N increases, $\mho_{norm}$ of all algorithms also increases. The normalized ratio for JR-SPEM is higher compared to p-SPEM because p-SPEM poorly balances energy consumption among nodes. The imbalance in energy consumption results in early depletion of the node's battery. The optimal algorithm is obtained using ILP and surpasses the other heuristic algorithms while GA achieves a result close to the heuristic solution based on JR-SPEM. The results of Case II show similar trends to those found in the basic case, introduced in [1], with a slight increase in the energy consumption as shown in Fig. 5.8. However, the optimization process is not a pure energy minimization function.

Case II results in higher energy consumption for all values of N compared to the basic case. JR-SPEM also has a higher normalized ratio for Case II due to the restrained link capacity, which limits the possible routes. As mentioned at the beginning of this section, p-SPEM shows the worst performance (for $N = 8$) because of the missing node and limitations on the link capacity. The rise in the ratio is

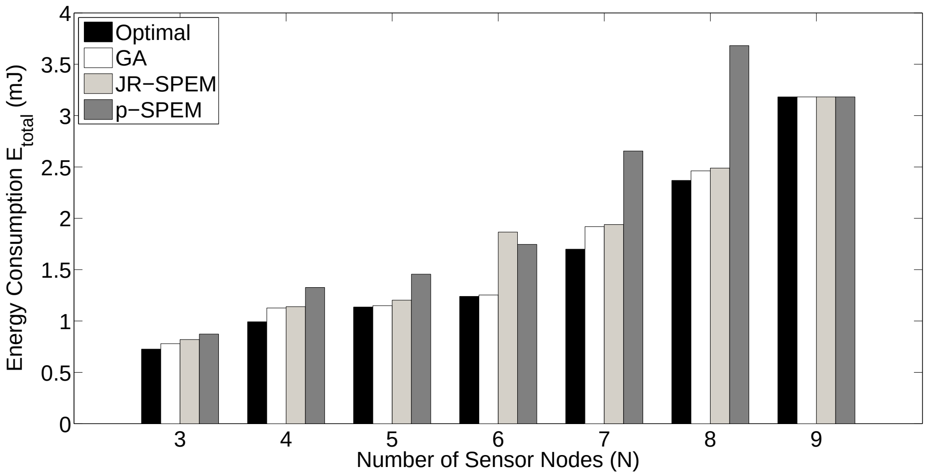

Fig. 5.8: Total energy consumption for optimal, GA-based and heuristic algorithms imposing the maximum link capacity constraint in a nine-floor structure for Case II formulation.

not surprising as the number of nodes in Case II also increases. If the basic case and Case II are compared, JR-SPEM achieves better results in Case II for a large N due to the difference in the ratio. Another reason is that the routing energy consumption for p-SPEM is higher than those for the optimal algorithm. The optimal algorithm achieves a lower normalized ratio because of the limitation on the number of possible routes.

The introduction of the link capacity limit results in higher energy consumption; while the four studied algorithms achieve better information quality. Both trends in energy consumption and information quality in Case II results in wider difference in ratio values compared to results in Case I especially for a large number of nodes.

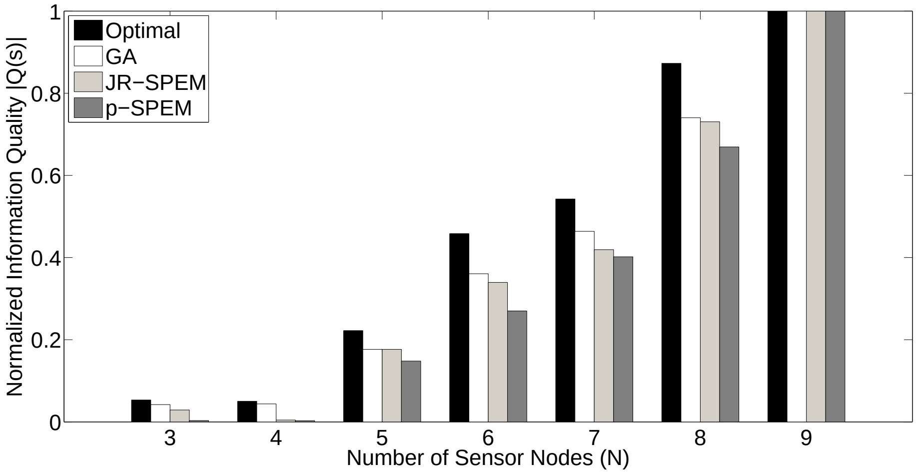

Fig. 5.9: Normalized information quality for optimal, GA-based and heuristic algorithms imposing the maximum link capacity constraint in a nine-floor structure for Case II formulation.

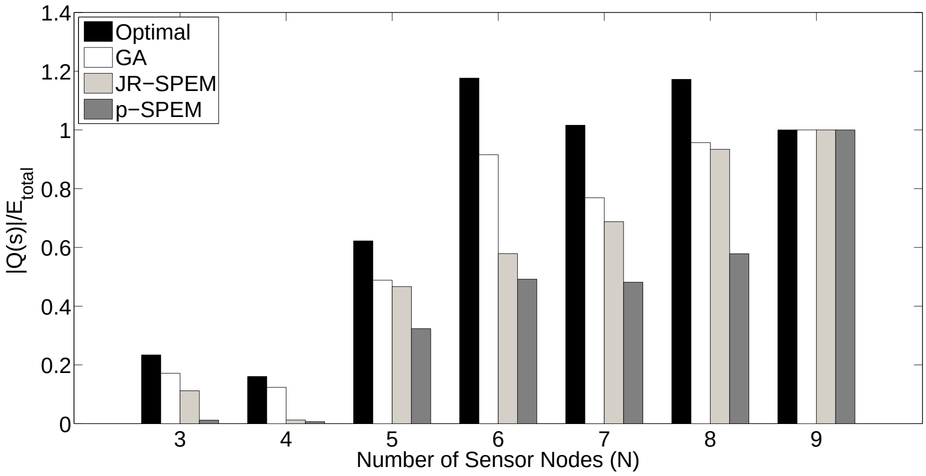

Fig. 5.10: The $\mho_{norm}$ ratio for optimal, GA-based and heuristic algorithms imposing the maximum link capacity constraint in a nine-floor structure for Case II formulation.

Case III: Numerical results for the basic case with the node-disjoint routing constraint imposed

As shown earlier in the chapter, when networking and civil requirements are taken into consideration, the optimal placement algorithm can achieve the highest information quality to the total energy consumption ratio compared to the other algorithms. The optimal algorithm achieves this by efficiently routing the number of packets the sensor node generates or receives at each round. However, the effect of the node-disjoint routing has not yet been studied.

Fig. 5.11 to Fig. 5.13 show the results of the four algorithms when node-disjoint routing is employed. As more sensor nodes are added to the network, placement becomes more significant. Fig. 5.11 illustrates the increase in energy consumption when the number of nodes increases from $N = 3$ to $N = 9$. The increase occurs as a consequence of energy consumption increasing with the traffic for the four placement algorithms. Case III results also show that the optimal algorithm and GA outperform p-SPEM. More than 40% of energy consumption is saved for both algorithms at $N = 6$. The results for Case III show that the JR-SPEM can achieve about one-third saving in energy consumption compared to that of the p-SPEM when the network size is increased above $N = 6$. In Case III, JR-SPEM performs well with more than 33% of energy saving over p-SPEM for $N = 5$. JR-SPEM has higher energy saving compared to p-SPEM. This trend demonstrates the effect of node-disjoint and load balancing for p-SPEM and JR-SPEM. In addition, the newly added constraint in Eq. (5.8) affects the data traffic in the network and energy consumption distribution in both algorithms.

Fig. 5.12 demonstrates the gain of the NIQ as the number of nodes increases. Fig. 5.12 also outlines the NIQ for the four considered algorithms under different network sizes. The NIQ increases as N increases for all algorithms. The increase in the NIQ is due to a larger amount of information collected by the system as a result of the increase in the number of nodes placed. Most of the network sizes show improvement in energy consumption for the JR-SPEM as well as the NIQ. However, for $N = 5$ to $N = 9$, the NIQ does not have any measurements higher than JR-SPEM, which demonstrates that the JR-SPEM can increase the NIQ significantly.

The ratio $\mho_{norm}$ is plotted versus N in Fig. 5.13 for the four designated algorithms in the study. Node-disjoint routing is assumed for each algorithm and affects the solution metrics. The optimal solution achieves the highest $\mho_{norm}$ ratio, however, JR-SPEM achieves a result close to the GA solution. The ratio of all algorithms increases with the increase in N, hence, the optimal algorithm achieves the best ratio. GA has better performance for different N values compared to p-SPEM, nevertheless, JR-SPEM algorithm performs better than p-SPEM algorithms under high N values. Since p-SPEM is unable to balance the energy consumption among sensor nodes to avoid early energy depletion of the network.

A lower normalized ratio occurs at $N = 7$ for all algorithms due to a small increase in the NIQ and large increase in the energy consumption. The increase is a result of extra traffic and longer distances travelled. When node-disjoint routing is used, $N = 8$ has higher energy consumption because of the extra distance the traffic needs to travel due to the missing node.

Case III shows that the energy consumption is increased for all N compared with the basic case. Despite the introduction of the node-disjoint routing the NIQ remains unchanged. The results for p-SPEM in Case III results are worse than its results for the basic case as the routing decision inside the node selection is not enabled as in JR-SPEM when the node-disjoint is employed.

Node-disjoint routing results in a lower number of links in the network and better load balancing among nodes. The downside of node-disjoint routing is that the links are loaded with higher flow, which requires more capacity to be allocated.

Energy consumption in Case III is lower than the corresponding values in Case I for a small number of nodes. Meanwhile, for a large number of nodes, the energy consumption is much higher those in Case I. When we evaluate case III versus Case I then we notice the information quality is almost the same values for the studied algorithms. Consequently, the ratio in Case III is much better for small N. As the change in the energy consumption is the dominate component in this case.

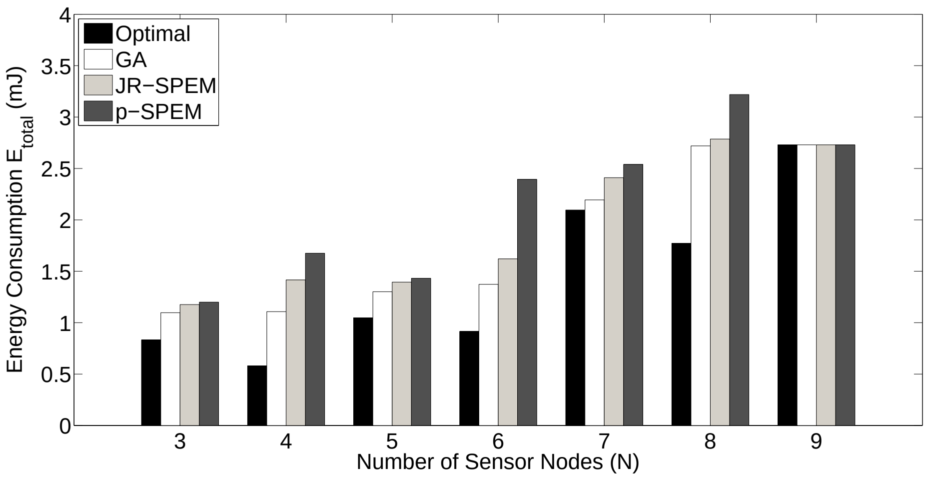

Fig. 5.11: Total energy consumption for optimal, GA-based and heuristic algorithms with node-disjoint routing constraint imposed in a nine-floor structure for Case III formulation.

Case IV: Numerical results for the basic case with the node-disjoint routing and flow assignment constraint imposed

Fig. 5.14 illustrates that the energy consumption increases when the number of nodes increases from $N = 3$ to $N = 9$. The increase occurs as a consequence of energy consumption increasing with the traffic for the four placement algorithms. However, further study is needed concerning the effect of the node-disjoint routing when the flow assignment is applied as the flow can be split among links between

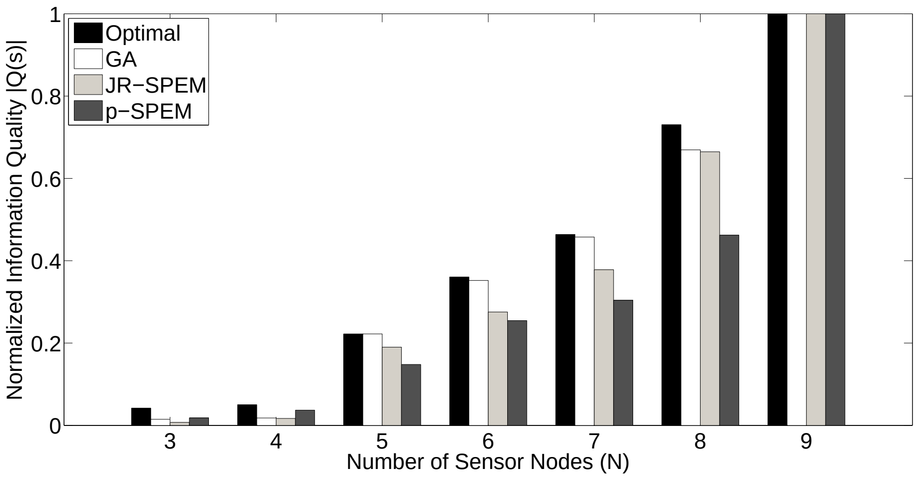

Fig. 5.12: Normalized information quality for optimal, GA-based and heuristic algorithms with node-disjoint routing constraint imposed in a nine-floor structure for Case III formulation.

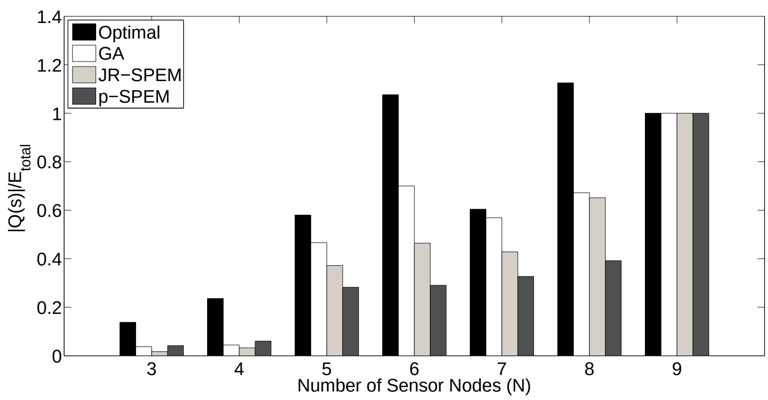

Fig. 5.13: The $\mho_{norm}$ ratio for optimal, GA-based and heuristic algorithms with node-disjoint routing constraint imposed in a nine-floor structure for Case III formulation.

source and destination sensors.

The JR-SPEM in this case performs well with more than 40% energy saving over p-SPEM for $N = 6$. Case IV results show that the optimal algorithm and GA outperform p-SPEM, while JR-SPEM has higher energy consumption but it achieves energy consumption reduction compared to p-SPEM. This trend demonstrates the effect of node-disjoint and load balancing for p-SPEM and JR-SPEM. Both algorithms are affected by the new constraint added in terms of the amount of data traffic in the network as well as energy consumption distribution.

The NIQ in Case IV remains unchanged despite the introduction of node-disjoint routing. The lack of change appears to have no effect on the ratio as it is generally low for JR-SPEM. Similar to Case III, Case IV also shows that sensor node energy consumption is increased for all N compared with the results of the basic case explained in [1]. Regarding p-SPEM, Case IV also does not have the routing decision in the node selection enabled as opposed to JR-SPEM when the node-disjoint and flow assignment are employed. The results, therefore, are worse than those in the reference case. A small increase in the NIQ and a large increase in the energy consumption causes a lower normalized ratio at $N = 7$ for all algorithms in study. When node-disjoint routing and flow assignment are used, $N = 8$ has higher energy consumption as the missing node requires traffic to travel a longer distance. The normalized ratio goes over unity for $N = 6$ and $N = 8$ because the results are normalized to the energy consumption at $N = 9$.

The gain of the NIQ with the increase in the number of nodes is illustrated in Fig. 5.15. Respecting the JR-SPEM algorithm, the NIQ increases as N increases due to a larger collection of information by the system caused by an increase in the number of placed nodes. Energy consumption for the JR-SPEM as well as the NIQ is improved for all N, however, the NIQ has no measurements higher than JR-SPEM for $N = 5$ to $N = 9$. Node-disjoint routing affects the solution metrics when used for all algorithms in study. Although the optimal solution is better than JR-SPEM, JR-SPEM is still a good option because of the low complexity. JR-SPEM and the GA solution achieve similar results, however, the optimal solution achieves the highest $\mho_{norm}$ ratio.

Fig. 5.16 illustrates the $\mho_{norm}$ ratio for the four designated algorithms in the study. On the grounds that p-SPEM is unable to balance the energy consumption among sensor nodes to avoid early energy depletion of the network, no significant performance difference is noticed between JR-SPEM and p-SPEM when N is low.

In conclusion, the results for Case IV show that the JR-SPEM algorithm can provide close results for the normalized ratio as the optimal and GA results. Nevertheless, for higher N, JR-SPEM outperforms the results of p-SPEM concerning NIQ and energy consumption. Case IV employs the flow assignment constraint and demonstrates that the optimal algorithm achieves the highest information quality compared to the other algorithms.

Evaluating the results of Case IV compared to results in Case I, it is found that the energy consumption is lower due to the split of the flows among possible paths. Also, the results show a better information quality retrieved in this case compared to the basic case in Case I. therefore, the ratio between the information quality and energy consumption is better than their peers in Case I. This trend is most seen for the optimal algorithm. Flow assignment improved the ratio and give superior results versus similar ones in Case I.

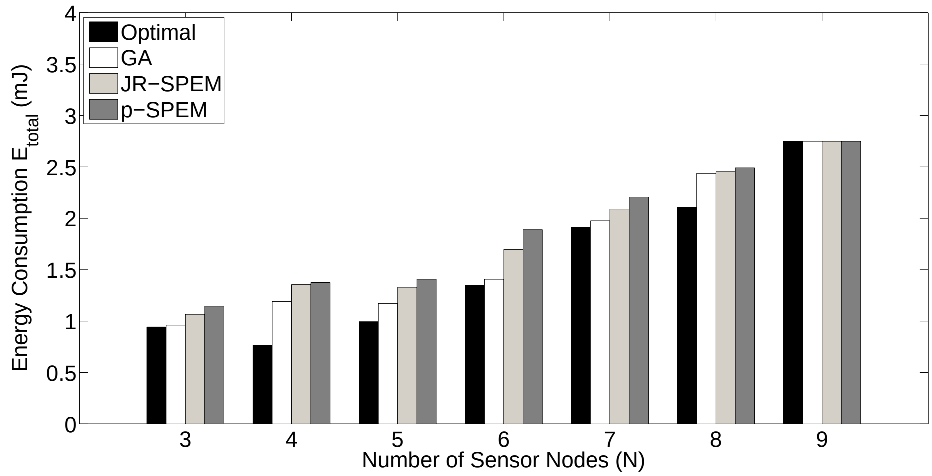

Fig. 5.14: Total energy consumption for optimal, GA-based and heuristic algorithms using flow assignment in a nine-floor structure for Case IV formulation.

5.6.3 Multi-objective Case Results

The multi-objective approach is employed using the formulation in Eq. (5.10). The results of the four algorithms are compared in different cases. Fig. 5.17 to Fig. 5.19 show the metrics for the MOJR-SPEM algorithm for the same structure used in the previous section. Moreover, the multi-objective function can be used in the optimal approach such as MOPT and MOGA. The results of the multi-objective algorithms with the node-disjoint routing and link capacity constraints imposed are omitted for brevity as they are following the same trend as their single-objective ones.

Case V: Numerical results for the basic case with multi-objective optimization

Fig. 5.17 to Fig. 5.19 demonstrate the algorithms used in Case V employing the multi-objective approach using different N. The results of Case V show similar tendencies to those found in the previous cases, introduced in [1], with a better saving in the energy consumption as recorded in Fig. 5.17. Results illustrate an increase

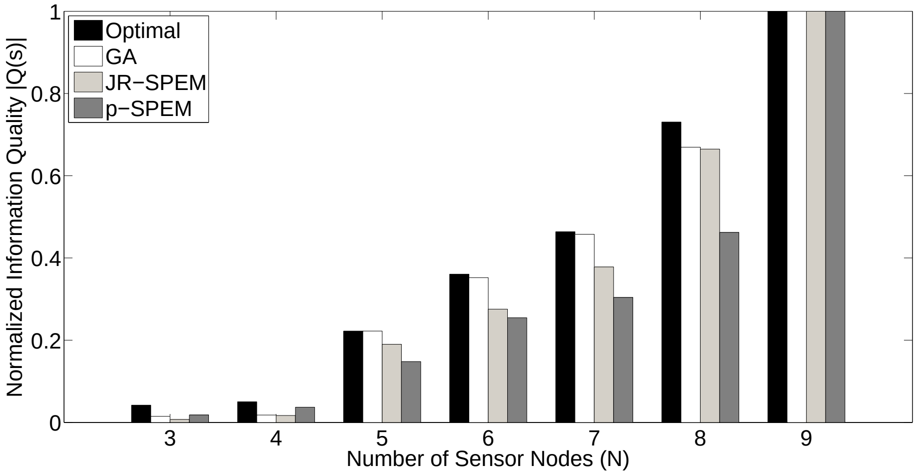

Fig. 5.15: Normalized information quality for optimal, GA-based and heuristic algorithms using flow assignment in a nine-floor structure for Case IV formulation.

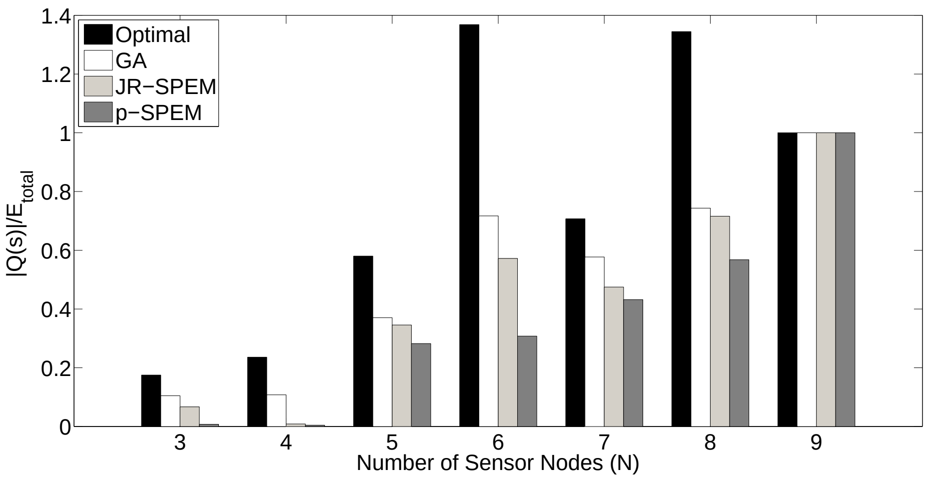

Fig. 5.16: The $\mho_{norm}$ ratio for optimal, GA-based and heuristic algorithms using flow assignment in a nine-floor structure for Case IV formulation.

in energy consumption when N increases from 5 to 8. The energy consumption is higher due to more focus on energy consumption in the weighted sum objective function. The MOPT consume 22% less energy compared to mop-SPEM. However, MOGA performs well with more than 16% of energy saving over mop-SPEM for $N = 6$. However, MOJR-SPEM achieves the same results as mop-SPEM at the same case. It is evident that energy savings happen when the multi-objective approach is applied to algorithms in study.

The NIQ of the four algorithms are plotted in Fig. 5.18. MOJR-SPEM has an improved result as it is a common placement algorithm where the focus is on energy consumption and NIQ. The MOJR-SPEM has more than 40%, 13%, and 3% improvement over mop-SPEM in the NIQ for N = 4, 6 and 8, respectively. Meanwhile, MOJR-SPEM measurement has a higher or equal NIQ than mop-SPEM for all N. A higher result demonstrates the ability of the MOJR-SPEM to select the node locations efficiently.

Fig. 5.18 indicates the increase in NIQ as the number of sensor nodes used for taking measurements at each location increases. This is because the MOJR-SPEM is a joint placement algorithm where both the energy consumption and the NIQ are optimized simultaneously. For most of the network sizes, MOPT, MOGA, and MOJR-SPEM, has more improvement in the NIQ over the mop-SPEM for $\omega = 0.5$. Yet, for mop-SPEM placement from $N = 5$ to $N = 9$, it does not take in any measurements higher than MOJR-SPEM for $\omega = 0.5$. This shows that the proposed algorithm improves the NIQ significantly.

Fig. 5.19 depicts the ratio $\mho_{norm}$ for the four studied algorithms. As N increases, the ratio $\mho_{norm}$ of all algorithms also increases, which implies that the optimal algorithm should achieve the best proportion. Nevertheless, the normalized ratio for MOJR-SPEM is still higher compared to mop-SPEM because the mop-SPEM has

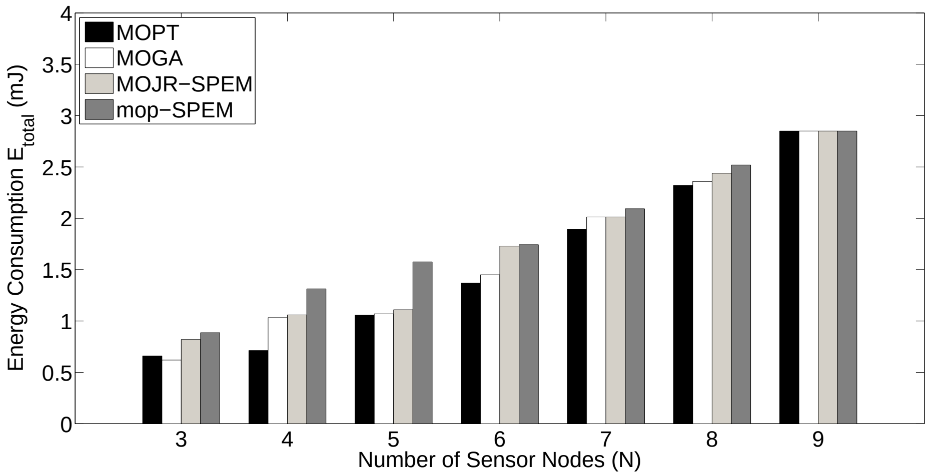

Fig. 5.17: Total energy consumption for MOPT, MOGA, MOJR-SPEM, and mop-SPEM algorithms in a nine-floor structure for Case V formulation.

a low balanced energy consumption among nodes. The energy imbalance results in the early depletion of the node's battery. The MOPT solution surpasses the other heuristic algorithms while MOGA achieves a result close to the analytical solution based on MOJR-SPEM. The ratio $\mho_{norm}$ acts as a metric of how much information is calculated per energy unit. The best solution achieves the highest ratio, and MOJR-SPEM produces a higher result compared to their corresponding algorithms with a single-objective solution.

Effect of Weighting Factor Results

The performance of a sensor placement solution is evaluated. Furthermore, results obtained for the specified multi-objective method using different weighting factors are compared and analyzed. All sensor nodes are assumed to have the same transmission range and that sensor node potential locations are one location on each floor on the nine-floor building. In the numerical results, the optimization chooses 3 - 9 sensors out of the nine candidate locations.

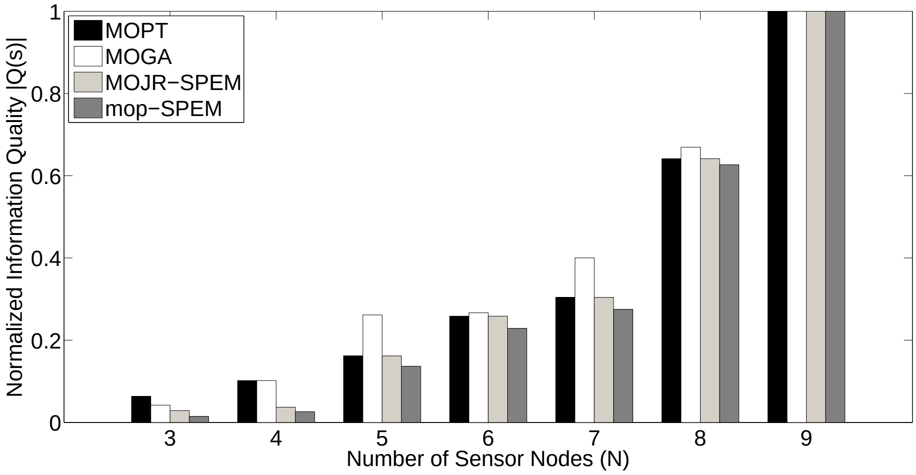

Fig. 5.18: Normalized information quality for MOPT, MOGA, MOJR-SPEM, and mop-SPEM algorithms in a nine-floor structure for Case V formulation.

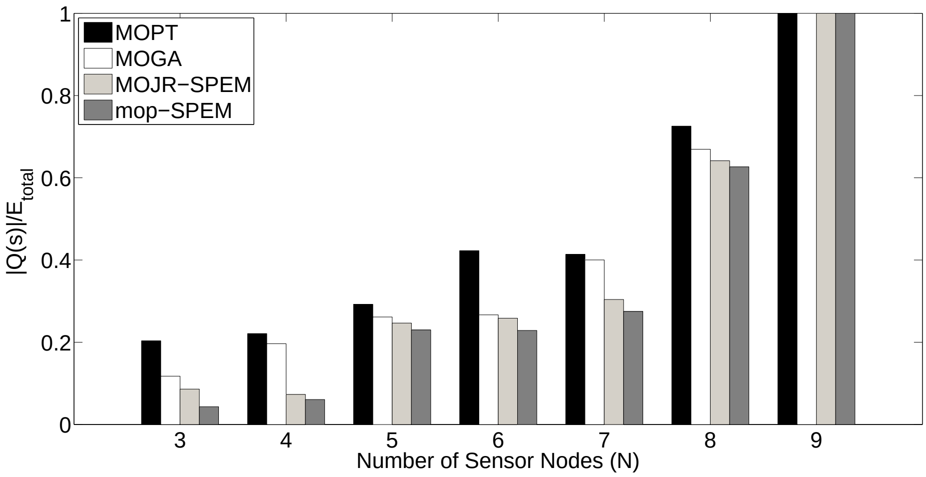

Fig. 5.19: The $\mho_{norm}$ ratio for MOPT, MOGA, MOJR-SPEM, and mop-SPEM algorithms in a nine-floor structure for Case V formulation.

Observing the above results, the multi-objective approaches indicate a better performance compared to p-SPEM placement. The mop-SPEM is introduced with $\omega = 0.5$ to reflect the balanced interest in both objectives. Furthermore, MOPT with $\omega = 0.9$ is presented to reflect a focus on the energy consumption minimization. On the other hand, MOPT with $\omega = 0.1$ is shown to reflect the emphasis on the information quality maximization in the network design phase. Fig. 5.20 shows the comparison of the energy consumption for the available placement algorithms for $N = 3$ to 9. A mop-SPEM algorithm is introduced where the objective function is a combination of the weighted sum of the two objectives in consideration. mop-SPEM with $\omega = 0.5$ achieves moderate results compared to p-SPEM. This behaviour leads to determining the routing scheme of p-SPEM and mop-SPEM, as well as the amount of transmitted data that consumes energy in the network.
Fig. 5.21 shows the increase in NIQ as the number of sensor nodes, placed and used for collecting more information, increase in the network. The improvement of the NIQ of mop-SPEM over the p-SPEM is due to the intensive focus on the NIQ for $\omega = 0.1$. The information quality to the total energy consumption ratio acts as a metric of how much information can be collected by the sensor nodes per energy unit. Fig. 5.22 shows this ratio for the mop-SPEM algorithms at different ω compared with the single objective alternative. As more sensor nodes are added in the network, our mop-SPEM placement solution achieves a significant improvement in information quality. This leads to a better performance in all considered cases compared to previous work in [5] on p-SPEM.
For the information quality to the total energy consumption ratio, mop-SPEM placement generally shows an advantage over single objective p-SPEM. The performance gain in terms of NIQ to total energy consumption ratio over the single path p-SPEM varies under different network sizes. It is shown that the performance of p-SPEM

easily degrades compared to that of mop-SPEM when N is small. Moreover, mop-SPEM placement disparately behaves in NIQ with different N. As expected, the mop-SPEM with $\omega = 0.1$ attains the highest NIQ, whereas the p-SPEM achieves the lowest one. This trend is also reflected in the ratio for different network size. Observing the above results, the multi-objective approach indicates a better performance than the p-SPEM algorithm.

Generally, multi-objective achieves better ratio for heuristic algorithms and results in good balance for all algorithms. The effect of the weighting factor on the results of the p-SPEM algorithm is studied. Small variations happened for these algorithms as shown in the results.

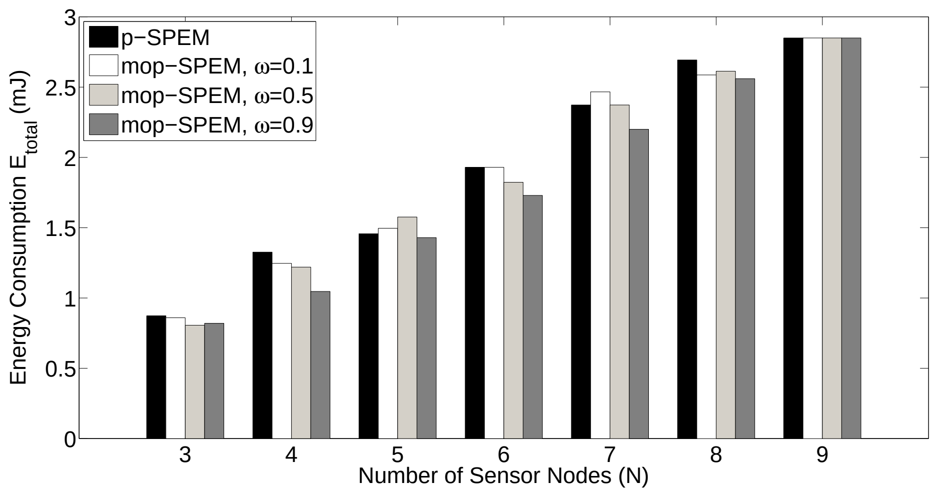

Fig. 5.20: Total energy consumption for p-SPEM and mop-SPEM algorithms with different weighting factors in a nine-floor structure.

5.7 Conclusion

Unlike existing WSNs for SHM deployments that primarily focus on reducing data communication among sensor nodes or on increasing the amount of retrieved infor-

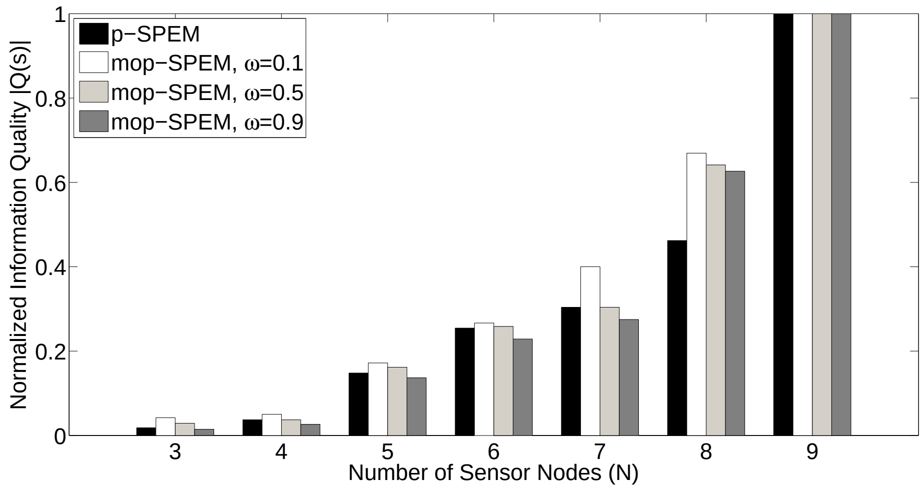

Fig. 5.21: Normalized information quality for p-SPEM and mop-SPEM algorithms with different weighting factors in a nine-floor structure.

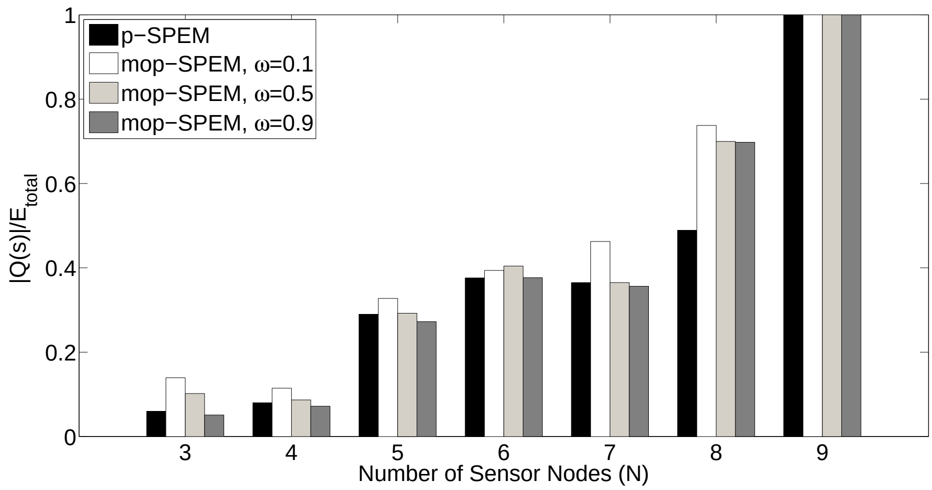

Fig. 5.22: The $\mho_{norm}$ ratio for p-SPEM and mop-SPEM algorithms with different weighting factors in a nine-floor structure.

mation. Our proposed algorithms focus on the integration of both types of aspects for WSNs for SHM with the link capacity and node-disjoint routing constraints imposed. Multi-objective optimization is used for sensor node placement and routing due to the presence of trade-offs between the conflicting objectives of information quality and energy consumption. Multi-objective algorithms, for optimal and heuristic approaches, are employed to jointly optimize the placement, routing and flow assignment for the SHM in a simplified way. The numerical results show that as a whole, MOPT, MOGA, and MOJR-SPEM outperform mop-SPEM in terms of the information quality to total energy consumption ratio. The numerical results held on a nine-floor structure demonstrate the competence of the proposed multi-objective algorithms.

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Chapter 6

Conclusion and Future Work

6.1 Introduction

A joint optimization is an approach that used to find solutions that match two objectives. In this dissertation, we aim to minimize energy consumption and optimizes another objective subject to several constraints, employing node-disjoint routing, maximum link capacity and multi-objective optimization. In this chapter, we summarize the contributions presented in this dissertation, draw main conclusions, and discuss several potential extensions to our work. This chapter is organized as follows: summary of the thesis' conclusions is explained in Section 6.2, the future work is shown in Section 6.3.

6.2 Conclusions

The optimization problem of energy and delay in WSNs is tackled for SHM using WSNs systems. The problem varies from one system to another, and the optimal

solution is distinct in each system. To solve the optimization problem, three approaches are used: optimal solution found through KKT analysis, a sub-optimal solution using MOGA, and finally a practical solution using the heuristic approach. Optimization can be very cumbersome which shed the light on sub-optimal solutions. The sub-optimal solutions reflect the system nature of each case. Heuristic ones make the solution more practical to be implemented although the measured network metrics are reduced; additionally, it enables increased flexibility in the design process. The designing process tends to be more complicated and costly with the emergence of the scalability in recent SHM applications. Without the loss of generality, a heuristic approach is proposed to achieve sound results. The network metrics shrink is negligible compared to the reduced complexity.
The contributions of this dissertation are as follows:

(a) The problem of multi-objective energy and delay optimization is formulated using convex formulations. An efficient solver of the formulation is chosen. Solutions from the solver are found and the results from the chosen solver are compared with the results from the preferred simulator. The results are discussed to explain how the formulation works better for each application.

(b) A routing algorithm for WSNs, based on the proposed model formulation, is proposed for WSNs. The proposed algorithm has three properties: first, it does not go lower than an acceptable network lifetime; second, it has low overhead; lastly, it has a low end-to-end delay, which can be set by a user or by an application.

(c) The evaluation of the proposed routing algorithm for WSNs is completed using chosen metrics. Results show that the proposed algorithm performs well under different scenarios in terms of lifetime, delay, throughput, and hop count.

(d) The comparison of the proposed routing algorithm and existing routing algorithms is performed. The proposed algorithm is compared with two popular algorithms: AODV and FA, which were chosen to represent a delay-efficient and an energy-efficient algorithm, respectively. The detailed comparison for the all considered metrics is presented. The evaluation of the proposed algorithms shows its efficiency as a compromise between existing algorithms.

(e) A joint MOPT formulation for both energy and delay is introduced. KKT analysis is done to make the optimal solution for each formulation. Second, found by the simulation done for the MOPT formulation, computations are completed for the PF curve. Third, the trade-off curve between energy and delay is quantified. In this case, the knee is shown using an exponential fitted PF curve. Lastly, we compute the optimal weighting factor for both objectives. The evaluation and testing of knee determination on the PF curve is outlined, which adapts to the network designer demand, yet limits WSN design solutions.

(f) The Newton - Raphson method is applied to solve the Lagrangian associated system of equalities. The influence of the given expression using the energy and delay is assessed. The sub-optimal solution is applied to bring down the high computational complexity needed by the optimal algorithm. Moreover, a sub-optimal solution obtained using MOGA that requires lower complexity. The rise in energy expenditure and delay is minor compared with the immense savings regarding the complexity.

(g) A novel, distributed routing algorithm, JFA-HGR, is proposed where data is forwarded with the objective of maximizing the network lifetime while minimizing the encountered complexity. JFA-HGR uses the deviation angle to find the best path. The run-time for JFA-HGR is found to be five times more depressed than the run-time faced by FA as shown in the simulation studies.

The proposed algorithm achieves near-optimal flow for different network sizes.

(h) A novel formulation that jointly optimizes the placement and the routing is proposed. The optimal result is found using integer programming that satisfies both civil engineering and networking constraints.

(i) A heuristic solution is found using evolutionary GAs. We propose a sensor deployment and routing algorithm, which is based on GAs that efficiently deals with the sensor placement optimization problem and that achieves near-optimal energy consumption and information quality for communication between sensor nodes.

(j) A joint routing and placement algorithm called JR-SPEM is proposed using a heuristic algorithm. The proposed algorithm is novel heuristic SPEM-based placement and routing algorithm that achieves a low-complexity near-optimal solution. JR-SPEM selects the near-optimal path route based on Dijkstra's algorithm, a well-known algorithm used for computing the shortest path in a network, fed with the cost objective function.

(k) The efficiency of the proposed algorithms is evaluated. Results show that these algorithms significantly reduce the total energy consumption of the deployed sensors and improve the information quality. The complexity of all algorithms in the study is found and compared to the traditional placement algorithm. The proposed algorithms achieve a consolidated placement and routing in an efficient way.

(l) The joint placement, routing and flow assignment problem is formulated as a multi-objective optimization. This formulation is used to show the trade-off between the different objectives, namely the energy consumption and the information quality. The maximum capacity constraint of each link is introduced.

Node-disjoint routing is considered to achieve load balancing and longer WSN lifetime.

6.3 Future Work

In this dissertation, we have presented a comprehensive review of existing routing algorithms for WSNs. The main challenges, associated with optimal routing and the design requirements of algorithms for WSNs, are discussed to provide an insight into the optimization of placement and routing algorithms. An accurate classification of the algorithms is given and the merits and disadvantages of the algorithms are determined. Despite a large number of research activities and the rapid and significant progress that is made in WSNs resources joint optimization in recent years, several avenues for further research remain. The following research issues are outlined for future investigation:

(a) The possibility of the heterogeneous sensor nodes used in WSNs needs to be investigated. The nodes can be assumed similar in the power source and transmission capabilities. Cases where high-end nodes with extra capabilities need to be investigated. Additional battery can be placed on some sensor nodes which will lead to a modified formulation and changes the optimization results.

(b) Future work will deal with the idea of the heterogeneity in WSN as well as introducing the cases of identifying, which nodes should have transmit-only capabilities and which nodes should have both transmit and receive capabilities. Managing this capability can reduce the financial cost of the building nodes in WSN and will keep the energy consumption within acceptable limits.

(c) Different types of structures are to be considered such as high-rise building, bridges or even large-scale machinery. The effect of the building structure needs to be studied and results for this effect needs to be outlined. The analysis of the energy-delay trade-offs can be extended to the case of mobile nodes. The formulation from the previous chapters shows how the increase in the network size can affect the optimization algorithm. The associated complexity with a large number of nodes would be an effective extension of the research work.

(d) This thesis introduces MOPT formulation, but only energy and delay are considered. However, more objectives will be considered such as throughput and reliability of the communication. Several scenarios need to be considered where, at least, two paths need to exist between the source and sink nodes.

(e) The thesis studies the formulation of the energy and delay optimization problem and the solution found using MATLAB; however, several other solvers can be used, such as NEOS server to advise new trade-offs that address this problem. More killer applications of the proposed routing algorithms need to be investigated. This would be beneficial in data collection and would help in different smart environment aspects.

(f) Other possibilities exist when the placement algorithm allows for different types of nodes. The power source of the sensor node is chosen to be a limited battery. However, the energy model needs to be changed if the renewable energy is presented. The optimization of the sensor node needs to be reconsidered. In the renewable energy case, a process of charging and discharging is occurring over short time intervals in the sensor node. The charging rate and the discharging cycle affect the optimization and more investigation is needed.

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Chapter 1

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Chapter 5

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