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For many envisioned applications of wireless sensor networks (WSNs), the information processing involves dealing with distributed data in the context of accurate signal detection and energy-efficient routing, which have been active research topics for many years, respectively. In this paper, we relate these two aspects via joint optimization. Considering the scenario of using distributed radar-like sensors to detect the presence of an object through active sensing, we formulate the problem of energy-efficient routing for signal detection under the Neyman-Pearson criterion, apparently for the first time. The joint optimization of detection and routing is carried out in a fusion center which precomputes the routes as a function of the geographic location to be monitored. Accordingly, we propose three different routing metrics that aim at an appropriate tradeoff between the detection performance and the energy expenditure. In particular, each metric relates the detection performance explicitly in terms of probabilities of detection and false alarm, with the energy consumed in sensing and routing. The routing problems are formulated as combinatorial optimization programs, and we provide solutions drawing on operations research. We present extensive simulation results that demonstrate the energy and detection performance tradeoffs for each proposed routing metric.

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Energy-Efficient Routing for Signal Detection in Wireless Sensor Networks

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***Abstract*—For many envisioned applications of wireless sensor networks (WSNs), the information processing involves dealing with distributed data in the context of accurate signal detection and energy-efficient routing, which have been active research topics for many years, respectively. In this paper, we relate these two aspects via joint optimization. Considering the scenario of using distributed radar-like sensors to detect the presence of an object through active sensing, we formulate the problem of energy-efficient routing for signal detection under the Neyman–Pearson criterion, apparently for the first time. The joint optimization of detection and routing is carried out in a fusion center which precomputes the routes as a function of the geographic location to be monitored. Accordingly, we propose three different routing metrics that aim at an appropriate tradeoff between the detection performance and the energy expenditure. In particular, each metric relates the detection performance explicitly in terms of probabilities of detection and false alarm, with the energy consumed in sensing and routing. The routing problems are formulated as combinatorial optimization programs, and we provide solutions drawing on operations research. We present extensive simulation results that demonstrate the energy and detection performance tradeoffs for each proposed routing metric.**

***Index Terms*—Combinatorial optimization, constrained shortest path, energy efficiency, Lagrangian relaxation, Neyman–Pearson criterion, parametric shortest path, routing, signal detection, wireless sensor networks.**

I. Introduction

WIRELESS sensor networks (WSNs) have numerous applications in both the military and civil domains (see [1] and [2] for tutorial treatments), and signal detection (e.g., object or event detection) often serves as the initial objective. In fact, signal detection in WSNs has been extensively studied for many years (see [3]–[8] and references therein). The traditional techniques of signal detection in WSNs or multisensor systems usually feature a fusion-centric approach by assuming that there is a designated fusion center where a final decision will be made, and largely focus on various detection-based performance measures such as error probabilities. The limited energy supply is a critical issue that poses many challenges to network design and management. Thus, recent research efforts have tried to optimize the signal detection performance jointly with the energy dissipation in the system. For example, [9] proposes a sensor censoring scheme for distributed detection to reduce the cost of transmission, where each sensor transmits only highly informative observations. Along this line, [10] and [11] further propose different but effective measurement or transmission approaches to optimize the cost and detection performance. A hybrid energy-driven detection scheme is proposed in [12] where the transmission from each sensor may vary from 1-bit decision to all its observations. Three options for multihop fusion are proposed in [13]. It is noticed that [9]–[11] all assume a simple parallel sensor network topology, which however could result in significant energy expenditure, especially when some sensor nodes are far from the fusion center. In contrast, both [12] and [13] consider multihop information transmission, although multihop routing is not addressed.

The constrained energy supply in typical WSNs further renders the task of finding and maintaining energy-efficient routes nontrivial. Consequently, it is highly desirable to find methods for energy-efficient route discovery and relaying of data from the sensor nodes to the fusion center so that the lifetime of the network is maximized. Over the past few years, many new algorithms have been proposed for the routing problem in WSNs (see [14] and references therein). For example, consider the approaches in [15] and [16]. The authors of [15] propose a minimum cost path routing algorithm which aims at maximizing the network lifetime. Alternatively, the authors of [16] introduce information-directed routing with the objective to minimize communication cost while maximizing information gain.

Obviously, the literature on energy-efficient routing or signal detection in WSNs is abundant, respectively; however, there is much less research on routing for signal detection, let alone the consideration of their joint optimization. Some recent related work includes [17] and [18]. In particular, [17] studies a serial fusion method for collaborative signal detection in WSNs, and also develops a space-filling curve-based routing technique, where an imaginary curve is drawn in the geographical region of interest that fills that region, and the sensor network is passed across along this curve to implement serial fusion. In [18], the authors consider the problem of routing for detection of a correlated random signal field, and further propose a Chernoff routing metric using the Chernoff information. This routing metric necessitates further consideration of practical issues, nevertheless

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it is very interesting and attractive, since it allows one to characterize the overall detection performance based on the sensors along a route. In contrast to both [17] and [18], we consider here a much different signal detection and routing problem where an emitter or reflector produces a signal of interest from a point in space, and we wish to find optimal routing which strives for a balance between the energy consumption and detection performance. More specifically, we focus on energy-efficient routing while optimizing the Neyman–Pearson detection criterion.

The Neyman–Pearson criterion [19], as an alternative to the common Bayesian framework, is fundamental to the development of the theory of hypothesis testing, and it is commonly employed for surveillance systems [20], [21]. Recognizing a basic asymmetry in the importance of the hypotheses (i.e., the target present hypothesis H_1 and the null hypothesis H_0), the Neyman–Pearson criterion maximizes the probability of detection subject to a predetermined bound on the probability of false alarm. Thus, it will be advantageous to employ this criterion in WSNs tasked with solving signal detection problems. However, to the best of our knowledge, there has not been any work on energy-efficient routing for detection that specifically considers the Neyman–Pearson criterion. This basically motivates our work.

In this paper, we address the problem of energy-efficient routing for signal detection under the Neyman–Pearson criterion. We consider a set of sensors which are distributed over an area to detect the possible presence of an illuminated target at a specific location through active sensing. The fusion center is assumed to have the knowledge of geographical location of each sensor, and will determine the location to be probed as well as the communications routing (i.e., centralized routing is employed). The observations at each sensor are assumed to be independent conditioned on the hypothesis. Each sensor node makes a measurement to test for a target at the predetermined location, and then transforms the measurement into a likelihood ratio. This can be regarded as one particular type of in-network processing in WSNs; that is, instead of sending the raw data, each sensor node uses its processing ability to transform its measurement into a sensor likelihood ratio, a sufficient statistic for the problems we consider (conditionally independent sensor data) that provides significant compression. After collecting all the likelihood ratios from the sensor nodes along a route, the fusion center will make a final decision.

Our work exploits a synergistic approach by incorporating aspects of signal processing, computer science, and operations research, and can be regarded as one special type of the cross-layer network design. To summarize, the novelty and contributions of this paper are threefold.

1) We formulate the problem of energy efficient routing for detection under the Neyman–Pearson criterion, widely adopted for target detection and surveillance related applications. This formulation, as far as we are aware, is the first one which accounts for both the energy consumption in sensing and routing, and detection performance (in terms of detection probability and false alarm probability) at the same time.
2) We propose three routing metrics, and for each of them, the detection performance and the energy expenditure are considered jointly in a different but interesting way by which an appropriate tradeoff between them is attained. We also formulate the routing problems under these metrics into different combinatorial optimization programs, where the objectives are to maximize or minimize a quantity of interest.
3) We provide algorithms for solving those formulated integer programming problems, based on state-of-the-art operations research results. In cases where the optimum solution is computationally intensive, we provide methods where we can specify the acceptable complexity and a solution that can be made arbitrarily close to the optimum solution when its complexity is increased appropriately. We also present extensive simulation results which help quantify the difference between these proposed routing metrics.

The remainder of this paper is organized as follows. In Section II, we formulate the problem of routing for signal detection, which includes the description of the system and signal model, the analysis of both Neyman–Pearson detection and energy consumption in WSNs, and the introduction of a graph model. In Section III, we propose the maximum path detection efficiency routing metric, which aims for a route with the maximum mean detection-probability-to-energy ratio. An algorithm based on combinatorial optimization is also provided to identify the optimal route. After that, we consider the energy or detection performance constrained routing problems, which include the minimum energy routing with guaranteed detection performance problem in Section IV, and the maximum detection-probability routing under constrained energy consumption problem in Section V. Linear integer programming formulations of these problems are provided, together with the methods and algorithms to solve them. We provide a brief discussion in Section VI, and present the simulation results in Section VII. This paper is concluded in Section VIII.

II. System Description and Problem Statement

A. System and Signal Model

Let us consider a scenario as depicted in Fig. 1, where some sensors are scattered over an area to detect the presence of an object. This scenario may correspond to monitoring the presence of people, vehicles, or military targets using radar-like sensors[1] that emanate specific electromagnetic signals into the region of interest. For this active sensing application, the monitored space is typically divided into many range resolution cells.[2] Each range cell could be probed sequentially in turn to determine the presence of a target by using radar pulses that are possibly launched by directional antennas.

We assume the position of each sensor node is fixed.[3] Each sensor node is assumed to be aware of its own position (e.g., by

[1]An example of such a radar sensor is the micropower impulse radar [22], which can be used in unstructured sensor network environment where only limited energy supplies are available. A platform of radar-enabled sensor networks is described in [23].

[2]A range cell is the smallest range increment that the radar is capable of probing.

[3]The placement of sensors will certainly affect the detection performance and energy consumption. However, this is beyond the scope of this paper, and we simply assume the sensors are already placed in our ensuing analysis and simulations. Interested readers can refer to [24].

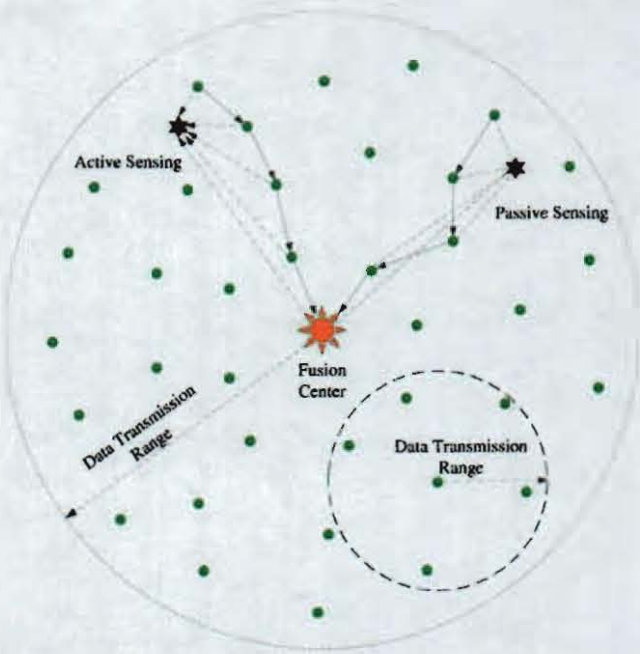

Fig. 1. Routing in WSNs for signal detection.

using methods based on triangulation [25]), and has knowledge about the location of the sensors in its local neighborhood. We assume the fusion center has information about the geographical location of each sensor, and will determine the location to be probed (for target presence) as well as the sensors that will be involved in signal detection and information transmission. This basically is a destination initiated routing, and the routing algorithm can be implemented offline, ahead of time, at the fusion center. The system will sequentially probe each location of interest, and collect the information from sensor nodes lying on a precomputed path in a predetermined order.

It is worth noting that there exist several ways for active sensors to illuminate the target. For example, in one methodology, each sensor transmits exactly the energy it needs to obtain some received signal-to-noise ratio (SNR) if a target is present at a certain location. This means that the sensing unit should be able to dynamically adjust its transmitted power. Alternatively, each radar sensor could transmit the same energy to the region of interest, so that those sensors which are closer to the target will have a better observation. This might be the situation when the sensing unit is extremely simple and does not allow power variation. For brevity, in this paper we only consider the second case, but its extension to the first case is straightforward. Therefore, let us denote e_{tr} as the amount of energy with which each sensor involved in the signal detection uses to illuminate the target. Then the energy received by an antenna at a distance of r meters away will be $\xi \cdot e_{\mathrm{tr}}/r^{\gamma}$, where ξ is a known constant. Here a simple geometric path loss model [26] is assumed, and the path loss is proportional to $1/r^{\gamma}$, where γ is the path loss exponent, an environment-dependent constant typically between 2 and 4.

Suppose the fusion center designates N sensors to perform signal detection and routing. Thus, after matched filtering to the known signal shape (which loses no optimality in a Gaussian noise and interference environment [27]) at sensor i, the observations under the two different hypotheses are given by[4]

$$y_i = \begin{cases} \sqrt{\frac{\xi \cdot e_{\mathrm{tr}}}{r^{\gamma}}} + n_i & H_1 \\ n_i & H_0 \end{cases} \tag{1}$$

where y_i is the received signal, and n_i denotes the noise and interference. Moreover, under hypothesis H_1, the distance that the active sensing signal traverses, r, is equal to $2R_{ti}$, where R_{ti} denote the distance between the target $(x[t], y[t])$ and the sensor $(x[i], y[i])$, i.e.,

$$R_{ti} \triangleq \sqrt{(x[t]-x[i])^2 + (y[t]-y[i])^2}.$$

Since we only focus on the simple active sensing case in this paper, for notational convenience, we define a scalar $\beta \triangleq \sqrt{\xi \cdot e_{\mathrm{tr}}/2^{\gamma}}$. Then, under H_1, the received signal can be rewritten as

$$y_i = \frac{\beta}{R_{ti}^{\gamma/2}} + n_i.$$

B. Neyman–Pearson Detection

For the observation from sensor i, let us define the likelihood, or probability density function (pdf) under H_1 as $f_1(y_i)$, and the likelihood under H_0 as $f_0(y_i)$. Thus, the likelihood ratio at sensor i is simply given by

$$L(y_i) \triangleq \frac{f_1(y_i)}{f_0(y_i)} = \frac{f_{N_i}\left(y_i - \beta/R_{ti}^{\gamma/2}\right)}{f_{N_i}(y_i)}$$

where $f_{N_i}(y_i)$ denotes the pdf of the noise at sensor i. For this detection problem, we explicitly make the following assumption with regard to the noise.

Assumption 1: The noise at each sensor is assumed to be statistically independent, and its probability distribution does not depend on which hypothesis is true. □

Based on this assumption, the joint probability of the observations is simply the product of the individual probability densities. We define $\mathbf{y} \triangleq [y_1, \ldots, y_N]$, thus the conditional pdf of the observation $\mathbf{y}$ under H_j can be expressed as

$$p(\mathbf{y} \mid H_j) = \prod_{i=1}^{N} f_j(y_i), \quad j = \{0, 1\}$$

and the log-likelihood ratio is given by

$$\ln L(\mathbf{y}) \triangleq \ln \frac{p(\mathbf{y} \mid H_1)}{p(\mathbf{y} \mid H_0)} = \sum_{i=1}^{N} \ln L(y_i). \tag{2}$$

Then under the Neyman–Pearson criterion, the optimal decision rule ϑ is the solution to the following constrained optimization problem [27]:

$$\begin{array}{ll} \max_{\vartheta} & P_D(\vartheta) \\ \text{s.t.} & P_F(\vartheta) \le \alpha. \end{array}$$

where $P_D(\vartheta) \triangleq \Pr(\text{Choose } H_1 \mid H_1 \text{ true})$ and $P_F(\vartheta) \triangleq \Pr(\text{Choose } H_1 \mid H_0 \text{ true})$ are the detection and false alarm

[4]A narrowband signal model with random phase is considered in [28].

probabilities when the rule ϑ is used, and α is the level of the test. According to the Neyman–Pearson lemma [27] and assuming no point masses in the pdf of $L(\mathbf{y})$, the optimal decision rule for our hypothesis testing problem can be written as

$$\vartheta(\mathbf{y}) = \begin{cases} \text{Decide for } H_1, & \text{if } \ln L(\mathbf{y}) \geq \eta \\ \text{Decide for } H_0, & \text{if } \ln L(\mathbf{y}) < \eta \end{cases} \tag{3}$$

where η is uniquely determined by solving $P_F = \alpha$.

It is well known [27] that the Neyman–Pearson optimum test (3) is a likelihood ratio test. Since the overall log-likelihood ratio given in (2) is simply the sum of the log-likelihood ratios collected at each sensor, it follows that eaeh sensor will make a partial contribution to the overall detection eapability, which depends on R_{ti} and the noise properties. As the Gaussian environment is the most important case and is justified by the central limit theorem, we focus here on the white Gaussian noise case by further assuming that $n_i \sim \mathcal{N}(0, \sigma_i^2)$. Thus, the log-likelihood ratio in (2) can be formulated into

$$\ln L(\mathbf{y}) = \sum_{i=1}^{N} \frac{1}{2\sigma_i^2} \left(\frac{2\beta y_i}{R_{ti}^{\gamma/2}} - \frac{\beta^2}{R_{ti}^{\gamma}} \right).$$

As a consequence, the likelihood ratio test can be written as

$$\underbrace{\sum_{i=1}^{N} \frac{\beta y_i}{\sigma_i^2 R_{ti}^{\gamma/2}}}_{g} \underset{H_0}{\overset{H_1}{\gtrless}} \underbrace{\eta + \sum_{i=1}^{N} \frac{\beta^2}{2\sigma_i^2 R_{ti}^{\gamma}}}_{\tau}$$

where we have defined the test statistics g and the new threshold τ. For a fixed set of sensors, the second part of τ will be fixed and known. The variable g is actually a *sufficient statistic* [20], and when making a decision, knowing the value of g will be just as good as knowing $\mathbf{y}$. For notational convenience, let us define

$$\psi \triangleq \sum_{i=1}^{N} \frac{\beta^2}{\sigma_i^2 R_{ti}^{\gamma}} \tag{4}$$

where it is noted that $\beta^2/\sigma_i^2 R_{ti}^{\gamma}$ actually denotes the SNR level at sensor i. Then, invoking the model for n_i, the hypothesis pair can be written as

$$\text{versus} \quad \begin{matrix} H_0 : g \sim \mathcal{N}(0, \psi) \\ H_1 : g \sim \mathcal{N}(\psi, \psi). \end{matrix} \tag{5}$$

Thus, the false alarm probability is

$$P_F = \Pr(g > \tau \mid H_0) = 1 - \Phi\left(\frac{\tau}{\sqrt{\psi}} \right) \tag{6}$$

where $\Phi(\cdot)$ is the standard Gaussian cumulative distribution function, i.e.,

$$\Phi(z) = \int_{-\infty}^{z} \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{z^2}{2} \right) \mathrm{d}z.$$

Suppose we define the allowed level of false alarm as $P_F = \alpha$, then from (6), the threshold can be computed by

$$\tau = \sqrt{\psi} \cdot \Phi^{-1}(1 - \alpha).$$

Therefore, the detection probability P_D is given by

$$P_D = 1 - \Phi(\Phi^{-1}(1 - \alpha) - \sqrt{\psi}). \tag{7}$$

Since $\Phi(\cdot)$ is a monotonically increasing function, we have the following:

Proposition 1: Given a specific value of α, maximizing P_D is equivalent to maximizing ψ, the sum of SNR ratios at each sensor, or alternatively: $\max P_D \equiv \max \psi$. □

Hence, it is clear that the term ψ essentially quantifies the detection performance gain earned across all these N sensors. Also, for a fixed value of ψ, we immediately obtain the following:

Proposition 2: Given a specific value of ψ, P_D is monotonically increasing with respect to α. In other words, in order to achieve a larger value of P_D, we must also increase α. □

C. Energy Consumption

In WSNs, the energy consumption consists of two parts [15]: one is concerned with the communication between sensor nodes, and the other with the noncommunication related energy (this includes sensing, signal processing, etc.). We consider these two types of energy consumption as follows.

1) We assume that each sensor node is able to dynamically adjust its data transmission energy depending on the distance over which it transmits the signal, and that there exists a distanee limit for such information transmission (cf. Fig. 1). Therefore, the transmitting energy at sensor node i is $\delta R_{i,i+1}^{\gamma_c}$, where $R_{i,i+1}$ is the distance between node i and node $(i+1)$, which is below the distance limit; δ is a constant; and γ_c is the communication propagation coefficient. To maintain generality, we have assumed the propagation coefficients for data transmission and active sensing (e.g., γ_c and γ) can be different.
2) In Section II-A, we assumed a simple sensing unit which does not allow power variation, and the sensing energy is e_{tr}. However, it might happen in large networks that a node participating in routing is not able to provide an essential contribution to the overall detection performance when it is far away from the target. This indicates that the operations of routing and sensing should be decoupled in principle. Thus, we introduce a binary parameter ρ_i to indicate whether node i is involved in the detection test. There are several ways to evaluate this parameter. A simple method, which we choose, is to assume a sensing range, and let only sensor nodes that are within range of the target location perform both sensing and routing, and the rest of the sensors merely relay the information. In this case, ρ_i is simply an indicator of whether node i is within the sensing range.[5] Therefore, the sensing energy at sensor i is $\rho_i e_{\mathrm{tr}}$. In addition, to avoid specific hardware assumptions, we simply use e_{sp}^i to denote all other energy consumed at node

[5]It is also possible to further optimize ρ_i such that it is not tied to the sensing range. This can bring forth another optimization problem which however is not the focus of this paper.

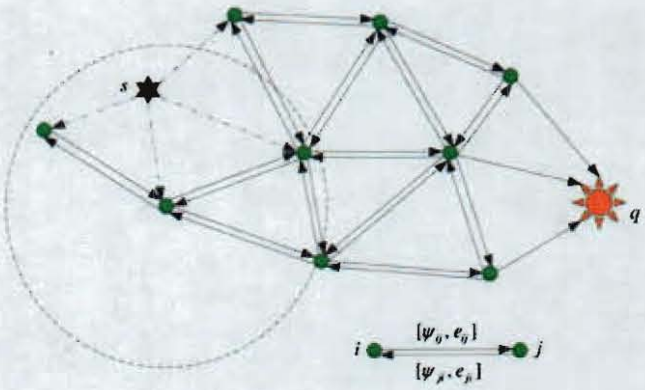

Fig. 2. Transformed graph $\mathcal{G}$.

i. This includes the computing and signal processing energy together with the energy consumed in the transceiver circuitry.

Therefore, the overall energy consumed at the ith sensor can be expressed as

$$e_i = \rho_i\, e_{\text{tr}} + \delta R_{i,i+1}^{\gamma_c} + e_{\text{sp}}^i.$$

We further assume that there is one sensor q placed at the fusion center, which of course need not perform data transmission, but can operate at the sensing mode. Therefore, the total energy consumption for signal detection and relaying over a route consisting of N sensors is

$$E = (e_{\text{tr}} + e_{\text{sp}}^q) + \sum_{i=1}^{N-1} e_i.$$

As a special case, when the probing location is nearby the fusion center and it suffices to detect the target using only the sensor q at the fusion center, there will be no actual routing involved and the total consumed energy is simply $e_{\text{tr}} + e_{\text{sp}}^q$.

Note that what we consider here is a general model for energy consumption. While it may be desirable to consider a more detailed energy consumption model in some cases, this will inevitably involve the consideration of hardware specifications that vary with implementation. To avoid such problems, we keep our model general, but we note that our approach can easily be modified in an obvious way to incorporate alternative energy modeling.

D. Graph Model

Now we introduce a graph model as illustrated in Fig. 2 that will reflect the WSN topology (e.g., Fig. 1). Moreover, this graph model also incorporates the information on signal detection performance and energy consumption, and will serve as the basis for our ensuing analysis on routing metrics and algorithms.

Let $\mathcal{G} = (\mathcal{N}, \mathcal{A})$ denote a finite and strongly connected network defined by a set $\mathcal{N}$ of nodes and a set $\mathcal{A}$ of directed arcs. The cardinalities of $\mathcal{N}$ and $\mathcal{A}$ are $|\mathcal{N}|$ and $|\mathcal{A}|$, respectively. By strongly connected network,[6] we mean that for any $i, j \in \mathcal{N}$, there exists at least one path which connects the nodes i and j. Sinee targets are also nodes in the graph, it is guaranteed that each potential target location can be reached by sensing signals, and the information can be transmitted back to the fusion center, which is also a node.

We denote the target location (to be probed) as node s, and the fusion center as node q. A path Ω from s to q is a sequence of N nonrepeated nodes and connecting arcs. Associated with each arc $(i, j) \in \mathcal{A}$, there are two positive numbers:

1) ψ_{ij}, which specifies the detection performance gain earned from the connection from node i to node j; or specifically, we have

$$\psi_{ij} \triangleq \frac{\rho_j\, \beta^2}{\sigma_j^2 R_{ij}^{\gamma}};$$

2) e_{ij}, which denotes the energy consumption used by the connection from node i to node j; or specifically, we have

$$e_{ij} \triangleq \begin{cases} \rho_i\, e_{\text{tr}} + \delta R_{i,j}^{\gamma_c} + e_{\text{sp}}^i, & i \neq s \\ e_{\text{tr}} + e_{\text{sp}}^i & i = s. \end{cases}$$

In other words, the first arc of each path connects the target to a sensor node, which is a virtual path and obviously has no communication-related energy consumption.

Associated with any path Ω of the network $\mathcal{G}$ that connects s to q, we define two quantities:

$$D(\Omega) \triangleq \sum_{(i,j)\in\Omega} \psi_{ij}, \quad \text{and} \quad E(\Omega) \triangleq \sum_{(i,j)\in\Omega} e_{ij}$$

which denote the detection gain and consumed energy, respectively. For notational convenience, throughout this paper, we denote S as the (minimum energy) shortest path[7] which connects s to q in a graph, i.e.,

$$S = \arg\min_{\Omega} E(\Omega).$$

III. Maximum Path Detection Efficiency Routing

To relate the detection performance to the energy consumption, we propose a measure called the mean detection-probability-to-energy ratio, which is defined as

$$\lambda(\Omega) \triangleq \frac{D(\Omega)}{E(\Omega)}.$$

According to this measure, our objective is to identify a path which achieves the largest possible value of $\lambda(\Omega)$, or the maximum path detection efficiency. In particular we are only concerned with loopless paths or elementary paths. Obviously this metric aims at a tradeoff between the detection performance and the energy consumption. To facilitate solving this problem, we

[6]This desired connectivity can be achieved by employing a topology control technique in network design (e.g., [29]), which, however, is beyond the scope of this paper.

[7]In the areas of combinatorial optimization and graph theory, shortest path usually refers to the shortest weighted path between two nodes in an edge-weighted graph [30]. Thus, in the sequel, we will use minimum-energy path and shortest path interchangeably.

choose to re-express our criterion as minimizing $E(\Omega)/D(\Omega)$. Thus, the problem can be stated as follows:

A: Given $s, q \in \mathcal{N}$, find an optimal path Ω^* which satisfies

$$\Omega^* = \arg\min_{\Omega} \frac{E(\Omega)}{D(\Omega)}.$$

This is a combinatorial optimization problem. Note that when $s = q$, problem A turns out to be the *minimum cost-to-time ratio cycle problem*, which arises in an application known as the *tramp steamer problem* [30, Ch. 3, Sec. 13]. This enables us to follow a similar parametric approach to that used in [30] for solving the minimum cost-to-time ratio cycle problem. Such an approach will transform problem A into a parametric shortest path problem [32], as described in the following.

Let us denote μ^* as the optimal value to problem A, i.e.,

$$\mu^* \triangleq \frac{E(\Omega^*)}{D(\Omega^*)}$$

and define μ as another nonnegative scalar. We assign each arc a modified length

$$l_{ij} \triangleq e_{ij} - \mu \psi_{ij}$$

for an arbitrarily chosen value of μ, and denote

$$\bar{q}(\mu, \Omega) \triangleq \sum_{(i,j)\in\Omega} l_{ij} = E(\Omega) - \mu D(\Omega)$$

as the length of a specific path Ω. Also, let $\mathcal{G}_\mu$ denote the original graph with new length l_{ij} on each arc under the parameter μ. Adopting a similar geometric approach as in [31], we depict $\bar{q}(\mu, \Omega)$ with regard to μ for a given path Ω in Fig. 3, where without loss of generality, we assume $S \neq \Omega^*$. Since for each path Ω, $E(\Omega)$ and $D(\Omega)$ are strictly positive, each straight line in Fig. 3 has a negative slope, and intersects the μ axis at

$$\mu_\Omega = \frac{E(\Omega)}{D(\Omega)} > 0.$$

Consequently, the lower envelope of the straight lines, i.e., the bold segmented line in Fig. 3 forms the shape of a convex polygon. This bold boundary is the collection of the shortest paths of $\mathcal{G}_\mu$ corresponding to various μ values. Since the bold boundary has a convex-polygon shape, its intersection with the μ axis uniquely determines the optimal solution μ^*.

Therefore, algorithms for finding a solution to problem A can be designed to simply search for the intersection of the bold boundary and the μ-axis. Such searching procedures basically employ the testing of successive trial values of μ to find the path Ω^* and the optimal value μ^*. Obviously, there are three situations that may exist with respect to the path lengths $\bar{q}(\mu, \Omega)$ for the guessed value μ in the search process:

1) *$\mathcal{G}_\mu$ contains a negative length path.*
This case corresponds to $\bar{q}(\mu, \Omega) < 0$, or alternatively,

$$\mu^* \leq \frac{E(\Omega)}{D(\Omega)} < \mu.$$

Thus μ is a strict upper bound on μ^*.

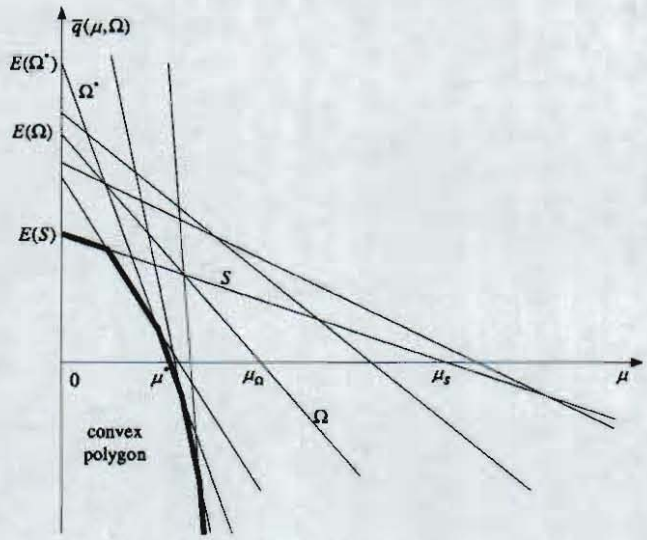

Fig. 3. Illustration of $\bar{q}(\mu, \Omega)$ versus μ.

2) *$\mathcal{G}_\mu$ contains no negative length path, but the length of the shortest path Ω^* is exactly zero.*
In this case, the fact that there is no negative length path in $\mathcal{G}_\mu$ implies $\bar{q}(\mu, \Omega) \geq 0$ or alternatively,

$$\mu \leq \frac{E(\Omega)}{D(\Omega)}$$

for every path Ω. The faet that the length of the shortest path Ω^* is exactly zero implies that $\bar{q}(\mu, \Omega^*) = 0$ or

$$\mu = \frac{E(\Omega^*)}{D(\Omega^*)}$$

for path Ω^*. Thus, the guessed value μ is exactly equal to μ^*, and Ω^* is the path which gives the maximum detection efficiency.

3) *$\mathcal{G}_\mu$ contains no negative length path, and length of the shortest path is strictly positive.*
This case corresponds to $\bar{q}(\mu, \Omega) > 0$, or

$$\mu < \frac{E(\Omega)}{D(\Omega)} \leq \mu^*$$

for every path Ω. Thus, the guessed value μ is a strict lower bound on μ^*.

Based on the preceding development, and adapting the binary search procedures in [30] and [31], we summarize our algorithm for solving problem A in Algorithm 1, where the parameter ε denotes the amount of error that we want to tolerate when comparing two numbers. Algorithm 1 involves a subroutine for either detecting negative length paths, or finding a nonnegative length shortest path with no repeated nodes. An exact implementation of such a subroutine has been described, for example in [31], but is very complicated. To lower the complexity of this subroutine, we propose an approximate approach for detecting negative length cycles instead of negative length paths, whose effectiveness is well demonstrated by our numerical results in Section VII. To apply this approximate approach, we can use the Bellman–Ford algorithm [33, Ch. 5] or some other improved negative-cycle detection algorithms (e.g., [34]), for

which the best time complexity is $O(|\mathcal{A}| \cdot |\mathcal{N}|)$. Therefore, the time complexity of Algorithm 1 is approximately $O(|\mathcal{A}| \cdot |\mathcal{N}| \cdot \log(\max(\psi_{ij})/\varepsilon))$.

Algorithm 1: Maximum Path Detection Efficiency Routing

Input: A strongly connected network $\mathcal{G} = (\mathcal{N}, \mathcal{A})$, and e_{ij}, ψ_{ij} for each arc $(i,j) \in \mathcal{A}$

Output: A path Ω^* of $\mathcal{G}$ from s to q

1: Use Dijkstra's algorithm [33, Ch. 4] to obtain a shortest path S from s to q of $\mathcal{G}_\mu$ for $\mu = 0$;
2: $\bar{\mu} \leftarrow E(S)/D(S)$;
3: $\underline{\mu} \leftarrow 0$;
4: $mark \leftarrow true$;
5: **While** $mark$ && $\bar{\mu} - \underline{\mu} > \varepsilon$ **do**
6: $\mu = (\underline{\mu} + \bar{\mu})/2$;
7: $l_{i,j} = e_{i,j} - \mu d_{i,j}$;
8: find a negative length path Ω' (i.e., $\bar{q}(\mu, \Omega') < 0$) or a nonnegative length shortest path $\hat{\Omega}$ (i.e., $\bar{q}(\mu, \hat{\Omega}) \geq 0$), from s to q of $\mathcal{G}_\mu$ with the current μ;
9: **if** any negative length path Ω' is found **then**
10: $\bar{\mu} \leftarrow E(\Omega')/D(\Omega')$;
11: **else if** $\bar{q}(\mu, \hat{\Omega}) = 0$ for the shortest path $\hat{\Omega}$ **then**
12: $\mu^* \leftarrow \mu$;
13: $\Omega^* \leftarrow \hat{\Omega}$;
14: $mark \leftarrow false$;
15: **else**
16: $\underline{\mu} \leftarrow \mu$;
17: $\bar{\mu} \leftarrow \min\{\bar{\mu}, E(\hat{\Omega})/D(\hat{\Omega})\}$;
18: **end if**
19: **end while**

IV. Minimum Energy Routing With Guaranteed Detection Performance

The maximum path detection efficiency is meaningful as a routing metric, since it reflects a certain relationship between the detection performance and consumed energy. However, as one drawback, this metric does not explicitly tell us what kind of detection performance we could achieve or how much energy we need to use. In this section, instead of considering a ratio, we are interested in finding a route which exactly quantifies the detection performance. In other words, our objective is to identify a path which minimizes the consumed energy, while maintaining an acceptable level of detection probability.

To define a desired level of detection probability, based on *Proposition 1*, it is natural to employ a lower bound constraint, i.e.,

$$D(\Omega) \geq \underline{\psi}.$$

Here $\underline{\psi}$ can be calculated from (7) for given values of α and P_D (e.g., $\bar{\alpha} = 5\%$, $P_D = 95\%$) as

$$\underline{\psi} = [\Phi^{-1}(1-\alpha) - \Phi^{-1}(1-P_D)]^2$$

which is clearly nonnegative. We also impose an upper bound[8] on ψ, given by $\bar{\psi}$. Thus, this routing metric can be described as follows[9]:

B: Given $s, q \in \mathcal{N}$, find an optimal path Ω^* which satisfies

$$\Omega^* = \arg \min_{\Omega \in \Pi} E(\Omega)$$

where Π is the set of paths from s to q for which the detection gain is bounded by

$$\underline{\psi} \leq D(\Omega) \leq \bar{\psi}.$$

To mathematically formulate problem B, we adopt the idea of network flow [33], and view this problem as sending 1 unit of flow as cheaply as possible from node s to q subject to a constraint on the achieved performance. This interpretation gives rise to the following integer programming formulation, which we refer to as problem B_1 :

$$\min \quad \sum_{(i,j)\in\mathcal{A}} e_{ij} \cdot x_{ij} \tag{8}$$

$$\text{s.t.} \quad \sum_{\{j:(i,j)\in\mathcal{A}\}} x_{ij} - \sum_{\{j:(j,i)\in\mathcal{A}\}} x_{ji} = \begin{cases} 1 & i = s \\ -1 & i = q \\ 0 & \text{otherwise} \end{cases} \tag{9}$$

$$\underline{\psi} \leq \sum_{(i,j)\in\mathcal{A}} \psi_{ij} x_{ij} \leq \bar{\psi} \tag{10}$$

$$x_{ij} = \{0, 1\}, \quad \forall (i,j) \in \mathcal{A}. \tag{11}$$

The first set of constraints given in (9) are called *flow balance constraints* which guarantee that, for all nodes on the path, except the source and destination nodes, the inflow is equal to its outflow. In the case of the source node ($i = s$), the outflow is exactly one more than its inflow, while in the case of the destination node ($i = q$), its inflow is exactly one more than its outflow. Equation (10) denotes the two-sided weight constraint, and (11) is the flow capacity constraint of each arc. Each arc is either included in the path ($x_{ij} = 1$) or not included ($x_{ij} = 0$). For convenience, we denote f^* as the optimal cost of problem B_1, and define vectors $\mathbf{x} \triangleq \{x_{ij} \,|\, (i,j) \in \mathcal{A}\}$, $\mathbf{e} \triangleq \{e_{ij} \,|\, (i,j) \in \mathcal{A}\}$, and $\boldsymbol{\psi} \triangleq \{\psi_{ij} \,|\, (i,j) \in \mathcal{A}\}$.

Problem B_1 is a *constrained shortest path* problem, which is a special case of a broader set of optimization models known as network flow problems with side constraints. Unfortunately, this problem, in the parlance of computational complexity theory, is $\mathcal{NP}$-hard [35, pp. 214], and no polynomial-time algorithm is available. In the literature, various methods have been proposed to solve this constrained shortest path problem (see a detailed review in [37] or [38]), including Lagrangian relaxation, e.g., [39]–[43]. This approach is attractive because it can be easily extended to constrained shortest path problems with multiple

[8]The upper bound $\bar{\psi}$ appears redundant in this problem, but for applications where available resources are constrained (e.g., time or bandwidth), this upper bound would become the parameter of interest. For the purpose of completeness, we include this upper bound here.

[9]It is worth noting that our formulation appears similar to constraint-based path selection in the problems of quality-of-service (QoS) routing under diverse network conditions or resource constraints (see [36] for an overview).

side constraints, which may arise when several factors of interest are considered simultaneously, e.g., delay, bandwidth and so on. Therefore, in this paper, we adopt this method to solve the doubly constrained shortest path problem B_1.

The Lagrangian relaxation approach basically relaxes the linear constraints by bringing them into the objective function with associated Lagrange multipliers [33]. Let $\mu_1 \geq 0$ represent the Lagrange multiplier for the left inequality in (10), and $\mu_2 \geq 0$ be the Lagrange multiplier for the right-hand inequality in (10). Then by relaxation, we obtain the resulting problem B_2:

$$\min \quad \sum_{(i,j)\in\mathcal{A}} [e_{ij} + (\mu_2 - \mu_1)\psi_{ij}] \cdot x_{ij} + (\mu_1 \underline{\psi} - \mu_2 \bar{\psi}) \tag{12}$$

$$\text{s.t.} \quad \sum_{\{j:(i,j)\in\mathcal{A}\}} x_{ij} - \sum_{\{j:(j,i)\in\mathcal{A}\}} x_{ji} = \begin{cases} 1 & i = s \\ -1 & i = q \\ 0 & \text{otherwise} \end{cases} \tag{13}$$

$$x_{ij} = \{0, 1\}, \quad \forall (i,j) \in \mathcal{A} \tag{14}$$

which is referred to as the *Lagrangian subproblem* of problem B_1. This program is a minimum cost network flow problem of sending 1 unit of flow from s to q subject to the flow conservation constraints (13) with a capacity limit of 1 on each arc (14). This subproblem can be easily solved, although its solution is not necessarily feasible for the original problem B_1. However, a key idea of Lagrangian relaxation is that regardless of the choice of μ_1 and μ_2, this subproblem yields a lower bound to the optimal cost of problem B_1 (i.e., f^*), as shown by the following bounding principle.

Lemma 1: Let $\mathbf{X}$ be the set of vectors $\mathbf{x}$ satisfying constraints (13) and (14). For any $\mathbf{x} \in \mathbf{X}$, define the *Lagrangian function*

$$L(\mu_1, \mu_2, \mathbf{x}) \triangleq \sum_{(i,j)\in\mathcal{A}} [e_{ij} + (\mu_2 - \mu_1)\psi_{ij}] \cdot x_{ij} + (\mu_1 \underline{\psi} - \mu_2 \bar{\psi})$$

and let

$$L(\mu_1, \mu_2) \triangleq \min_{\mathbf{x}\in\mathbf{X}} L(\mu_1, \mu_2, \mathbf{x}). \tag{15}$$

Then, it holds that

$$L(\mu_1, \mu_2) \leq f^*, \quad \forall \mu_1, \mu_2 \geq 0. \tag{16}$$

Proof: See Appendix I. □

It is noted that the function $L(\mu_1, \mu_2)$ defined in *Lemma 1* is concave and piecewise linear, since it is the minimum of a finite collection of linear functions of the Lagrange multipliers. Also as indicated by *Lemma 1*, to solve problem B_1, it is important to find the tightest possible lower bound. This involves finding multipliers μ_1 and μ_2 which correspond to

$$\begin{aligned} \max \quad & L(\mu_1, \mu_2) \\ \text{s.t.} \quad & \mu_1, \mu_2 \geq 0. \end{aligned}$$

This program is referred to as the *Lagrangian dual problem*. Solution to this problem yields the sharpest lower bound to the optimal cost of problem B_1. Also, implicated by *Lemma 1*, we immediately have the following theorem which describes the *weak duality*.

Theorem 1: The optimal solution of the Lagrangian dual problem, $L^* \triangleq \max L(\mu_1, \mu_2)$, is always a lower bound to the optimal value of the original problem B_1, i.e., $L^* \leq f^*$. □

In other words, the optimal values of μ_1 and μ_2 will maximize the Lagrangian dual function, and give us an optimistic estimate of the optimal value to the original problem. Such an estimate will be quite useful when the main objective is not to find the optimum, but to get a good solution. This is another attractive aspect of this Lagrangian relaxation approach, especially considering the fact that the quality of such an estimate is guaranteed, as shown by the following theorem:

Theorem 2: The optimal value of the Lagrangian dual problem, L^*, is equal to the optimal cost of the following linear programming problem:

$$\begin{aligned} \min \quad & \mathbf{e}^T \mathbf{x} \\ \text{s.t.} \quad & \underline{\psi} \leq \boldsymbol{\psi}^T \mathbf{x} \leq \bar{\psi} \\ & \mathbf{x} \in \text{conv}(\mathbf{X}) \end{aligned}$$

where $\text{conv}(\mathbf{X})$ denotes the convex hull of the set $\mathbf{X}$, i.e., the set of all convex combinations of the elements in $\mathbf{X}$.

Proof: See Appendix II. □

Algorithm 2: Minimum Energy Routing With Guaranteed Detection Performance

Input: A strongly connected network $\mathcal{G} = (\mathcal{N}, \mathcal{A})$, and e_{ij}, ψ_{ij} for each arc $(i,j) \in \mathcal{A}$

Output A path Ω^* of $\mathcal{G}$ from s to q

1: Initialize the maximum lower bound found $\zeta_{\max} \leftarrow -\infty$;
2: Initialize the multipliers: $\mu_1 \leftarrow 0$; $\mu_2 \leftarrow 0$;
3: Initialize the iteration number: $\kappa \leftarrow 0$;
4: $mark \leftarrow true$;
5: **while** $mark$ && $\kappa < \kappa_{\max}$ **do**
6: given the current values of multipliers μ_1 and μ_2, use shortest path algorithms to solve problem B_2, and let the solution be $\tilde{\mathbf{x}}$;
7: compute the corresponding lower bound: $LB \leftarrow L(\mu_1, \mu_2, \tilde{\mathbf{x}})$;
8: let $UB \leftarrow 50LB$ if $\kappa = 0$;
9: **if** $LB > \zeta_{\max}$ **then**
10: $\zeta_{\max} \leftarrow LB$;
11: **end if**
12: **if** $\tilde{\mathbf{x}}$ is a feasible solution to problem B_1 **then**
13: $UB \leftarrow \mathbf{e}^T \tilde{\mathbf{x}}$;
14: **end if**
15: **if** $\zeta_{\max} = UB$ **then**
16: $mark \leftarrow false$;
17: **else**
18: calculate the subgradients: $g \leftarrow \underline{\psi} - \boldsymbol{\psi}^T \tilde{\mathbf{x}}$, $h \leftarrow -\bar{\psi} + \boldsymbol{\psi}^T \tilde{\mathbf{x}}$;
19: compute the step size: $\epsilon = \varpi(UB - LB)/(g^2 + h^2)$;
20: update the multipliers by: $\mu_1 = \max(0, \mu_1 + \epsilon g)$, $\mu_2 = \max(0, \mu_2 + \epsilon h)$;
21: **end if**
22: $\kappa \leftarrow \kappa + 1$;
23: **end while**
24: Resolve problem B_2 using μ_1, μ_2 that are associated with the resulting best lower bound $\zeta_{\max}$;

To this end, we summarize the algorithm for solving problem B_1 based on Lagrangian relaxation as shown in Algorithm 2, which was adapted from the subgradient method in [40], [41]. Here ϵ is a step size, ϖ is a parameter satisfying $0 < \varpi \leq 2$, and $\kappa_{\max}$ is the maximum number of iterations allowed. This algorithm terminates when the optimal solution to problem B_1 is found, or the iteration count κ exceeds $\kappa_{\max}$. For both cases when the Bellman–Ford algorithm is used, the worst-case time complexity of Algorithm 2 will be roughly $O(\kappa_{\max} \cdot |\mathcal{A}| \cdot |\mathcal{N}|)$. However, in the latter case, the best lower bound $\zeta_{\max}$ is strictly less than the optimal value of problem B_1, thus a *duality gap* is said to exist, which is also implied in *Theorem 1*. Methods for closing such a duality gap include the path ranking approach [39], the tree search procedure [41], the labeling methods [42], and so on. For brevity, we omit any further discussion on this issue.

V. Maximum Detection-Probability Routing Under Constrained Energy Consumption

In some applications, there might exist a predefined (or estimated) limited energy budget for one single instance of the target detection and information transmission. Given such an energy constraint, we may be interested in finding a route whieh will achieve the maximum possible detection performance, or in other words, make the decisions as confidently as possible. Thus, we now consider the maximum detection-probability routing subject to a constraint on the energy consumption. This is dual to problem B, and can be stated as follows.

C: Given $s, q \in \mathcal{N}$, find an optimal path Ω^* which satisfies

$$\Omega^* = \arg \max_{(i,j)\in\Pi} D(\Omega)$$

where Π is the set of paths from s to q for which the energy consumption is bounded by

$$E(\Omega) \leq \bar{E}.$$

It follows that the integer programming formulation can be expressed as below (labeled C_1):

$$\max \quad \sum_{(i,j)\in\mathcal{A}} \psi_{ij} \cdot x_{ij} \tag{17}$$

$$\text{s.t.} \quad \sum_{\{j:(i,j)\in\mathcal{A}\}} x_{ij} - \sum_{\{j:(j,i)\in\mathcal{A}\}} x_{ji} = \begin{cases} 1 & i = s \\ -1 & i = q \\ 0 & \text{otherwise} \end{cases} \tag{18}$$

$$\sum_{(i,j)\in\mathcal{A}} e_{ij} x_{ij} \leq \bar{E} \tag{19}$$

$$x_{ij} = \{0, 1\}, \quad \forall (i,j) \in \mathcal{A}. \tag{20}$$

Problem C_1 turns out to be a longest-path problem with constraints. However, the longest path problem between two nodes in a weighted graph is already $\mathcal{NP}$-hard, since it includes the *Hamiltonian path problem* as a special case, which is one of the most well known $\mathcal{NP}$-hard problems [35]. There exists some work in combinatorial optimization which seeks polynomial-time approximation algorithms for longest paths (e.g., [45] and [46]), but these approaches are only applicable to some specific cases. And, the side constraint in (19) brings additional complexity to solving this longest path problem.

As it is our inclination to formulate shortest path (rather than longest path) problems, for this given problem C_1 we propose an algorithm based on a *k-shortest-path* paradigm [47]. This approach basically enumerates, in order of increasing length (i.e., energy consumption $E(\Omega)$), all paths between s and q with length smaller than the given value $\bar{E}$. Suppose the total number of these paths is M. We simply compare the detection gain of all these M valid paths, and select the path with the largest value of detection gain. We summarize the idea in Algorithm 3, but it should be noted that implementation of this algorithm necessitates a subroutine which can list the shortest paths between s and q in order. An example of such a subroutine is the recursive enumeration algorithm given in [48]. If this subroutine is used, the total time complexity of Algorithm 3 is about $O(|\mathcal{A}| + M \cdot |\mathcal{N}| \cdot \log(|\mathcal{A}|/|\mathcal{N}|))$.

This approach is attractive and efficient when the network size is moderate or the difference between $\bar{E}$ and $E(S)$ is small, where $E(S)$ is the consumed energy of the shortest path S. But in general, it is hard to predict M, the number of paths of nondecreasing length that we need to produce to satisfy the energy constraint in (19). Also, unlike the Lagrangian relaxation method, this method does not directly apply to the case of multiple side constraints, and does not provide a lower bound.

Algorithm 3: Max-detection-Probability Routing With Constrained Energy

Input A strongly connected network $\mathcal{G} = (\mathcal{N}, \mathcal{A})$, and e_{ij}, ψ_{ij} for each arc $(i,j) \in \mathcal{A}$

Output A path Ω^* of $\mathcal{G}$ from s to q

```
φ ← 0;
i ← 1;
mark ← true;
while mark do
   find the ith shortest path Ω_i from s to q in G;
   if E(Ω_i) < Ē then
    if D(Ω_i) > φ then
     Ω* ← Ω_i;
     φ ← D(Ω_i);
    end if
    i ← i + 1;
   else
    mark ← false;
   end if
end while
```

VI. Discussion

Thus far, we have focused on signal detection in the Gaussian environment. Unfortunately, its extension to the general non-Gaussian case is not easy, because it requires the choice of a specific non-Gaussian pdf, the computation of the required probabilities (e.g., P_F and P_D) is often analytically difficult, and it seldom yields tractable closed-form expressions. As a result, a generalization of our problem formulation to the non-Gaussian

environment is nontrivial, although there exist some very special cases (e.g., correlation detection in additive Cauchy noise [27, p. 84]), where it is possible to obtain similar closed-form expressions as (7) in Section II. Despite this, it should be noted that in practice, when the pdf of the non-Gaussian noise is unknown, the output SNR maximization seems natural, and can be a convenient and practical method for detection (e.g., [49]). In this respect, the approach (routing algorithms) described in this paper could apply to non-Gaussian environments as well, since our approach essentially amounts to maximizing the sum of the SNR ratios at each sensor, assuming only the second-order statistics of the noise is known. Furthermore, our approach is also applicable to certain passive sensing scenarios (cf. Fig. 1), for example if the system operates in a similar way as in the active sensing case, by systematically detecting targets in geographic cells.

We can also incorporate node energy lifetime, to enforce route diversity and avoid unfairly burdening some nodes (e.g., avoiding hotspot nodes [50]). For example, we can use residual battery energy [51], as follows. Let b_i denote the residual battery capacity at node i, and $c_i(b_i)$ be a battery cost function which denotes the reluctance of node i to perform sensing and routing. Then, mapping $c_i(b_i)$ to the arc weight in graph $\mathcal{G}$, and substituting the new weight for e_{ij} in problems A, B and C yields modified objective functions that result in balancing sensor lifetime and the probability of detection. Consequently, all the algorithms provided in Sections III, IV, and V would still apply.

VII. Simulation Results

Now we present simulation results for the proposed routing metrics for detection in WSNs. While, it is highly desirable to test these algorithms with real data sets, due to limited facilities, all of the simulation results given in the following are obtained purely by specialized computer programs written in C++ and LEDA [52]. Some results based on modifying existing routing protocols implemented by the network simulator *ns-2* are provided in [53].

In our simulations, we consider WSN scenarios where the field has a square shape of size $10^3 m \times 10^3 m$, 50 sensors are randomly distributed over this field, and the fusion center is placed at position (500, 500), as shown by a specific example in Fig. 4. We assume that the fusion center wants to determine the presence of targets at different locations (e.g., stars in Fig. 4), and needs to find routes based on our proposed metrics and algorithms. We adopt $\gamma = \gamma_c = 2$, $\xi = 1$, and set $\delta = 10^{-2}$, $\xi \cdot e_{\mathrm{tr}} = \beta^2 2^\gamma = 640$ nJ (nano joules), and $e^i_{\mathrm{sp}} = 500$ nJ for all $i \in \mathcal{N}$. We assume the data transmission range for each sensor node is 250 m, and the sensing range is 550 m. For simplicity, we assume β^2/σ_i^2 in (4) is the same for every sensor node, and further set it to 4×10^4, which amounts to a 6-dB SNR ratio at the distance of $R_{ti} = 100$ m. We use $D(\Omega)$ (equal to ψ of (4)) to quantify the detection performance over a path Ω. However, for a given false alarm probability $P_F = \alpha$, the actual value of P_D can be easily computed from (7). In addition, we use our proposed approximate approach for step 8 in Algorithm 1 to lower the complexity, and we adopt the path ranking approach to close the duality gap after Algorithm 2. For the above setup, our computer programs can output the results almost instantly on an ordinary Pentium computer.

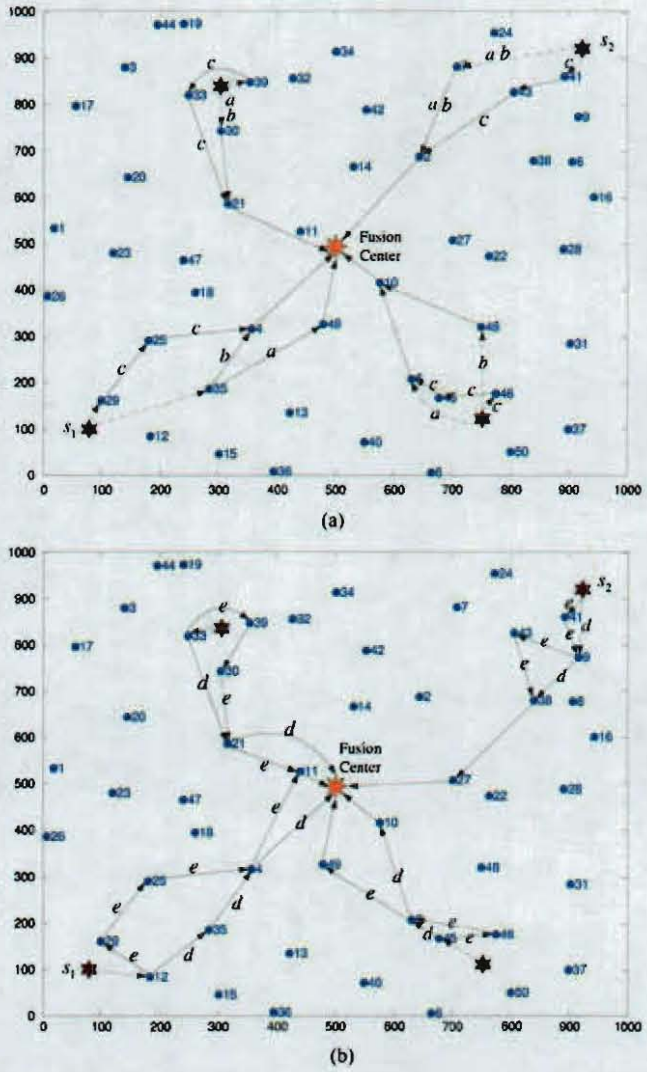

Fig. 4. Example of routing in WSNs for signal detection: (a) Example part A and (b) Example part B.

We plot in Fig. 4 an example of routing for detection in a specific WSN. This example illustrates the different ways in which the routes from different target locations to the fusion center are generated under our proposed routing metrics and some traditional routing metrics. In Fig. 4(a), we use a to denote the routes found under the traditional minimum-hop routing (min-hop); b for the routes under the minimum-energy routing (min-energy); and c for the paths under the maximum path detection efficiency routing (max-efficiency). In Fig. 4(b), we denote d for the routes identified by the minimum energy routing with guaranteed detection performance, where we make $\bar{\psi}$ redundant by assigning it a large value, and set $\bar{\psi} = 2D(S)$ (S is the corresponding shortest path from a specific target location to the fusion center). Similarly, we use e in Fig. 4(b) for the routes determined by the maximum detection-probability routing under constrained energy consumption, and set $\bar{E} = 2E(S)$.

In Fig. 4(a), it is observed that for some targets, the min-hop paths are not the same as the min-energy paths, even though both of them have the same number of hops. This is because min-hop

TABLE I
PATHS IDENTIFIED UNDER DIFFERENT ROUTING METRICS FOR TARGET LOCATION (80, 100); $\alpha = 5\%$

Type	Description	Ω	$E(\Omega)$	$D(\Omega)$	$\lambda(\Omega)$	P_D
a	min-hop	$s_1 \to 35 \to 40 \to q$	$4.30\,\mu J$	1.12	0.26	27.85%
b	min-energy	$s_1 \to 35 \to 4 \to q$	$4.19\,\mu J$	1.25	0.30	29.97%
c	max-efficiency	$s_1 \to 29 \to 25 \to 4 \to q$	$5.66\,\mu J$	11.31	2.00	95.71%
d	detection-constrained	$s_1 \to 12 \to 35 \to 4 \to q$	$5.53\,\mu J$	4.86	0.88	71.18%
e	energy-constrained	$s_1 \to 12 \to 29 \to 25 \to 4 \to 11 \to q$	$8.08\,\mu J$	15.04	1.86	98.72%

paths may not be unique and we simply pick up the earliest identified one. Interestingly in this example, it is seen that for the maximum detection efficiency metric, the nearest sensor to the target location is nearly always selected and usually serves as the actual source node in the route. It is intuitively pleasing that this route should start with the sensor closest to the target location under test. However, our joint optimization would not necessarily always pick all the sensors that are close to the target location [cf. Fig. 4(a)], but instead will trade off closeness to the target location (i.e., those with best SNR) against the energy consumption of the route.

Meanwhile, to clearly illustrate the difference between those routes, we consider the target location (80, 100) (labeled as s_1) in Fig. 4 for example, and list in Table I all the obtained paths as well as the associated parameters of interest.[10] Also, by setting $\alpha = 5\%$ for instance, we compute the detection probability P_D from (7) with respect to each different path. It is not surprising to see that both min-hop and min-energy paths lead to inferior P_D performance to their counterparts under our proposed metrics, because detection performance is not taken into account by either of them. In addition, these results in Table I also reveal that our proposed three routing metrics are suitable to different situations. To be more specific, if one has a stringent energy budget, he might want to consider using the maximum detection-probability routing under constrained energy consumption, implemented by Algorithm 3. If one cares more about the detection performance (e.g., he wants to make sure the decision is at least 95% correct), the minimum energy routing with guaranteed detection performance implemented with Algorithm 2, would be more suitable to his need. These two routing metrics are basically designed to cater for different requirements, but in essence, they are not much different, and are actually dual to each other. For example, we can set the constraints so that the two metrics provide the same solution. As for the max-efficiency routing, one might consider employing it when there is no strict requirement on either energy or detection performance, but it is desirable to squeeze the most performance return from every unit of energy put in both sensing and routing.

Further, to illustrate the affect of the lower bound $\underline{\psi}$ over the route selection when solving problem B_1, we conduct a simple experiment for the target location (920, 920) (referred to as s_2) at the upper right corner of Fig. 4. In this instance, we assign $\underline{\psi}$ different values, i.e., $\underline{\psi} = D(S), 1.5D(S), 2D(S), 2.5D(S)$, and $9.5D(S)$. For each value of $\underline{\psi}$, we resolve problem B_1, and record the selected path. The results are shown in Table II, in which we also provide the values of P_D for $\alpha = 5\%$. Intuitively, different lower bounds $\underline{\psi}$ may lead to different paths. For example, when $\underline{\psi} = D(S)$, the constrained shortest path is simply the min-energy path; when $\underline{\psi} = 2.5D(S)$, the resulting path, for this example, happens to be the max-efficiency path. However, it should be noted that due to the discrete characteristics of

[10]The unit for the detection efficiency $\lambda(\Omega)$ is $1/\mu J$.

TABLE II
PATHS FOUND BY VARYING $\underline{\psi}$ IN PROBLEM B_1 FOR TARGET LOCATION (920, 920); $\alpha = 5\%$

$\underline{\psi}/D(S)$	Ω	$E(\Omega)$	$D(\Omega)$	P_D
1.0	$s_2 \to 7 \to 2 \to q$	$4.39\,\mu J$	1.28	30.38%
1.5	$s_2 \to 43 \to 2 \to q$	$4.44\,\mu J$	2.27	44.50%
2.0	$s_2 \to 9 \to 38 \to 27 \to q$	$5.60\,\mu J$	2.80	51.14%
2.5	$s_2 \to 41 \to 43 \to 2 \to q$	$5.67\,\mu J$	11.62	96.12%
9.5	$s_2 \to 41 \to 9 \to 28 \to 2 \to q$	$6.87\,\mu J$	12.28	96.85%

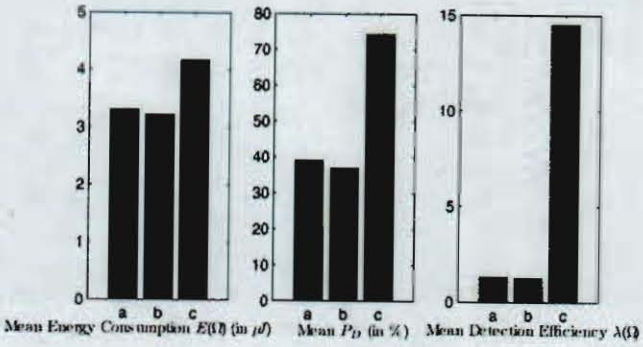

Fig. 5. Average parameters of interest.

problem B_1, a change to $\underline{\psi}$ does not necessarily lead to a change in the resulting path. For instance, when we set $\underline{\psi} = 9D(S)$, the output of the algorithm remains to be the max-efficiency path for the case in Table II. A similar phenomenon also occurs when we solve C_1 under different energy constraints (i.e., $\bar{E}$). We omit further results and discussion for brevity.

We also investigate the statistical performance of the three routing metrics: min-hop, min-energy, and max-efficiency, which are basically parameter free and do not depend on any side constraints. In our experiments, we generate 25 000 random sensor placements, and one random target location for each sensor placement is tested. We identify the corresponding routes and calculate the performance metrics of interest. In particular, we compute P_D given $\alpha = 5\%$, and use it instead of $D(\Omega)$ to represent the detection performance. We average these results, and plot them in Fig. 5. For a fair comparison, we also plot the empirical cumulative distribution function (CDF) of the energy consumption $E(\Omega)$, detection probability P_D, and detection efficiency $\lambda(\Omega)$ in Fig. 6. From both figures, it is shown that our max-efficiency routing uses about 1 μJ more energy than the other two. This is not surprising because min-energy routing consumes the least energy and min-hop routing closely resembles it in our experiment set-up. However, the superiority of the proposed max-efficiency metric can be easily verified from Figs. 5 and 6 by examining the detection probability and efficiency. For example, as shown in Fig. 6(b), almost 50% of the resulting paths under our metric give a detection probability P_D which is larger or equal to 90%, while only around 3% of the paths under either min-hop or min-energy metric have such performance. Therefore, using a path which consumes a bit more energy than a path under the traditional methods, we actually have utilized every unit of consumed energy much more efficiently. This demonstrates achieving the desired tradeoff between energy consumption and detection performance.

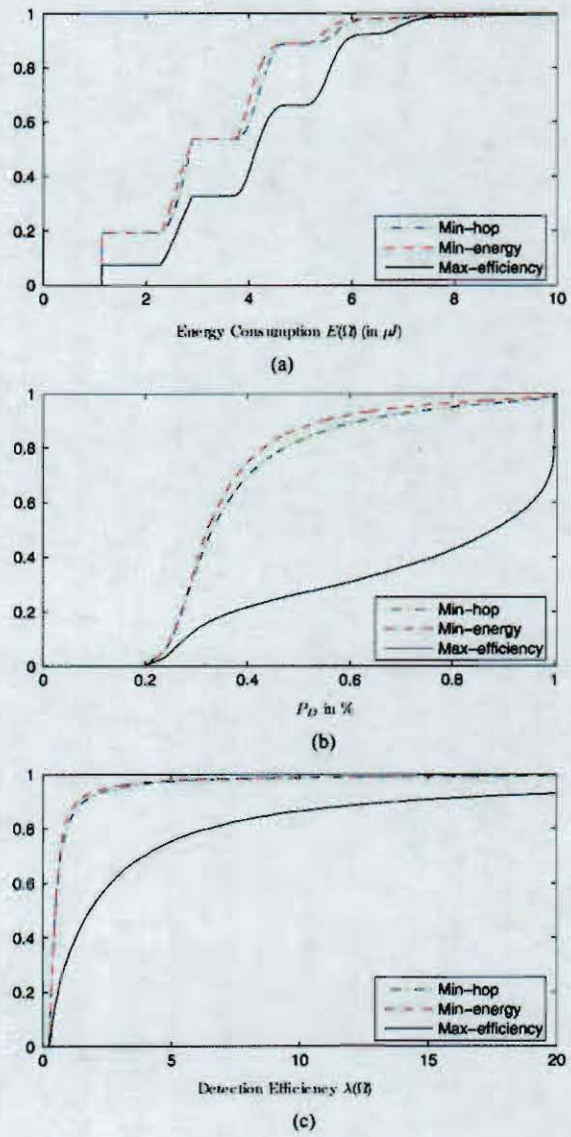

Fig. 6. Empirical CDF for parameters of interest. (a) Empirical CDF of energy consumption $E(\Omega)$ (in μJ), (b) Empirical CDF of P_D in %, (c) Empirical CDF of detection efficiency $\lambda(\Omega)$.

VIII. Conclusion and Future Work

For a target location problem of great interest, we formulated the problem of energy-efficient routing for detection in a wireless sensor network under the Neyman–Pearson detection criterion, which relates both the energy consumption and detection performance (in terms of the probabilities of detection and false alarm) in routing. We also proposed three routing metrics which strive for a balance between the consumed energy and detection performance. With respect to each different routing metric, we formulated the corresponding routing problem into a combinatorial optimization program, and further provided an efficient algorithm for finding the optimum solution based on techniques from operations research. A specific simulation example was presented, which illustrates the manner in which the paths are selected under these proposed different routing metrics. We also provided an example which indicates the impact of the side constraint on route selection, and further demonstrates the flexibility of our algorithms in balancing various factors. Moreover, Monte Carlo simulation results based on generating a large number of random topologies were also given, demonstrating how the maximum path detection efficiency metrie achieves superior detection performance and energy consumption tradeoffs over the traditional min-hop and min-energy routing metrics.

Our work, however, can be further improved and extended. For example, one could easily imagine using several parallel routes for robustness. Further, the detection/routing idea could be generalized to include target tracking. It might also be interesting to consider an extensive study of the network lifetime jointly with the detection performance in the routing problem. This in turn will require more statistical data with regard to the flow status of each node, which we did not assume in this paper. Further, it would be desirable to develop distributed routing algorithms for multitarget detection and tracking.

Appendix I
Proof of Lemma 1

Proof: Using vectors $\mathbf{x}$, $\mathbf{e}$, and $\boldsymbol{\psi}$, the Lagrangian function can be reformulated into

$$L(\mu_1, \mu_2, \mathbf{x}) = \mathbf{e}^T\mathbf{x} + (\mu_2 - \mu_1)\boldsymbol{\psi}^T\mathbf{x} + (\mu_1\underline{\psi} - \mu_2\bar{\psi})$$

and the two-side weight constraint in (10) can be written as $\underline{\psi} \le \boldsymbol{\psi}^T\mathbf{x} \le \bar{\psi}$. Thus, we have the following:

$$\begin{aligned} &L(\mu_1, \mu_2) \\ &\quad = \min_{\mathbf{x}\in\mathbf{X}}\{\mathbf{e}^T\mathbf{x} + (\mu_2 - \mu_1)\boldsymbol{\psi}^T\mathbf{x} + (\mu_1\underline{\psi} - \mu_2\bar{\psi})\} \\ &\quad \le \min_{\mathbf{x}\in\mathbf{X}, \underline{\psi}\le\boldsymbol{\psi}^T\mathbf{x}\le\bar{\psi}} \{\mathbf{e}^T\mathbf{x} \\ &\qquad + \mu_1(\underline{\psi} - \boldsymbol{\psi}^T\mathbf{x}) + \mu_2(\boldsymbol{\psi}^T\mathbf{x} - \bar{\psi})\} \\ &\quad \le \min_{\mathbf{x}\in\mathbf{X}, \underline{\psi}\le\boldsymbol{\psi}^T\mathbf{x}\le\bar{\psi}} \mathbf{e}^T\mathbf{x} \end{aligned}$$

where the equality follows from the definition (15); the first inequality follows because the minimum of the right-hand side of this inequality is taken over a subset of $\mathbf{X}$ ($\mathbf{x}$ has to satisfy the doubly constraint as well); and the second inequality follows because of the nonnegativity of μ_1 and μ_2. Since the right-hand side of the second inequality denotes the optimal value of the problem B_1, i.e.,

$$f^* = \min_{\mathbf{x}\in,\mathbf{X}, \underline{\psi}\le\boldsymbol{\psi}^T\mathbf{x}\le\bar{\psi}} \mathbf{e}^T\mathbf{x},$$

we immediately obtain (16). □

Appendix II
Proof of Theorem 2

Proof: By the definition in (15), $L(\mu_1, \mu_2)$ is linear in $\mathbf{x}$, thus the optimal cost remains the same if we allow convex combinations of the elements of $\mathbf{X}$. As a result, we have

$$L(\mu_1, \mu_2) = \min_{\mathbf{x}\in\text{conv}(\mathbf{X})} L(\mu_1, \mu_2, \mathbf{x})$$

and further

$$L^* = \max_{\mu_1,\mu_2 \geq 0} \min_{\mathbf{x} \in \text{conv}(\mathbf{X})} L(\mu_1, \mu_2, \mathbf{x}).$$

Since the set $\mathbf{X}$ has finite elements, $\text{conv}(\mathbf{X})$ is a bounded polyhedron. Let $\mathbf{x}^k, k \in \mathcal{K}$, be the extreme points of $\text{conv}(\mathbf{X})$, where $\mathcal{K} = \{1, \ldots, K\}$ is a finite set of integers. Then, for any fixed values of μ_1 and μ_2, we have

$$L(\mu_1, \mu_2) = \min_{k \in \mathcal{K}} L(\mu_1, \mu_2, \mathbf{x}^k)$$

which follows from the faet that for a linear programming problem of minimization, there exists an extreme point which is optimal if the optimal cost is not unbounded [44, Theorem 2.8].

Therefore, the Lagrangian dual problem is equivalent to and has the same optimal value L^* as the problem

$$\begin{aligned} \max \quad & \min_{k \in \mathcal{K}} L(\mu_1, \mu_2, \mathbf{x}^k) \\ \text{s.t.} \quad & \mu_1, \mu_2 \geq 0. \end{aligned}$$

By introducing an auxiliary variable z, the above problem can be equivalently reformulated into the following:

$$\begin{aligned} \max \quad & z \\ \text{s.t.} \quad & z + \mu_1(\boldsymbol{\psi}^T \mathbf{x}^k - \underline{\psi}) + \mu_2(\bar{\psi} - \boldsymbol{\psi}^T \mathbf{x}^k) \\ & \leq \mathbf{e}^T \mathbf{x}^k, k \in \mathcal{K} \\ & \mu_1, \mu_2 \geq 0. \end{aligned}$$

Taking the linear programming dual of the above problem, and applying strong duality [44, Theorem 4.4], we can see that L^* is equal to the optimal cost of the following problem:

$$\begin{aligned} \min \quad & \mathbf{e}^T \left(\sum_{k \in \mathcal{K}} \alpha_k \mathbf{x}^k \right) \\ \text{s.t.} \quad & \sum_{k \in \mathcal{K}} \alpha_k = 1 \\ & \underline{\psi} \leq \boldsymbol{\psi}^T \left(\sum_{k \in \mathcal{K}} \alpha_k \mathbf{x}^k \right) \leq \bar{\psi} \\ & \alpha_k \geq 0, \quad k \in \mathcal{K}. \end{aligned}$$

Since $\text{conv}(\mathbf{X})$ denotes the set of all convex combinations of the elements in $\mathbf{X}$, we have

$$\text{conv}(\mathbf{X}) = \left\{ \sum_{k \in \mathcal{K}} \alpha_k \mathbf{x}^k \middle| \sum_{k \in \mathcal{K}} \alpha_k = 1, \alpha_k \geq 0, k \in \mathcal{K} \right\}.$$

Therefore, the foregoing linear programming dual can be reformulated into

$$\begin{aligned} \min \quad & \mathbf{e}^T \mathbf{x} \\ \text{s.t.} \quad & \underline{\psi} \leq \boldsymbol{\psi}^T \mathbf{x} \leq \bar{\psi} \\ & \mathbf{x} \in \text{conv}(\mathbf{X}) \end{aligned}$$

whose optimal cost is equal to L^*. □

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