Energy-Efficient Unified Routing Algorithm for Multi-hop Wireless Networks

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***Abstract*—In this paper, we develop an energy-efficient routing scheme that takes into account four key wireless system elements: *transmission power*; *interference*; *residual energy*; and *energy replenishment*. Since energy is a scarce resource, many energy-aware routing algorithms have been proposed to improve network performance. However, previous algorithms have been designed for a subset of these four main elements, which could limit their applicability. Thus, our contribution is here to develop a unified routing algorithm called the Energy-efficient Unified Routing (EURo) algorithm that accommodates any combination of these above key elements and adapts to varying wireless environments. We study the impact of key wireless elements on routing, and show via simulations that EURo outperforms the state-of-the-art.**

***Index Terms*—wireless communication, routing protocols, energy conservation, cross-layer, simulations.**

I. Introduction

Energy is a precious resource in wireless networks. For many multi-hop networking scenarios, nodes are battery-operated, thus requiring efficient energy management to ensure connectivity across the network. Even when wireless networks are connected to power outlets, due to interference between active links the network may demand excessive energy per unit time (Power) so that the overall performance is reduced. Since energy efficiency is directly connected to the network life-time or network capacity, there have been many efforts to study energy-efficient networks in the wireless network community [2]. In the case of multi-hop wireless networks [3], [4], efficient routing algorithms are critical for network performance. The energy efficiency of multi-hop wireless networks is also receiving increasing attention due to its increasing importance of sensor networks in smart grids [5].

In previous works, four main metrics have been used for energy-efficient routing: transmission power, interference, residual battery energy, and energy replenishment.

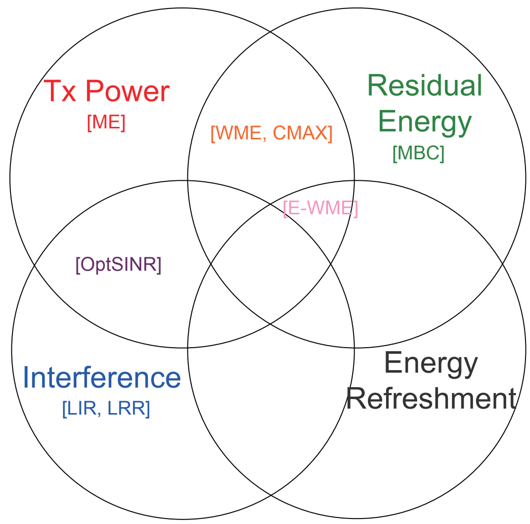

Fig. 1. Previous works for energy-efficient routing: ME, LIR, LRR, WME, E-WME, CMAX, OptSINR, and MBC.

However, previous works typically deal with either one or two of these metrics, as illustrated in Fig. 1. For example, in [6], [7], energy-efficient routing mechanisms have been developed to find Minimum Energy (ME) routes in multi-hop wireless networks, but these algorithms do not account for the interference with other links nor battery energy. The authors in [8] study end-to-end QoS constraints, but ignore the impact of routing a new flow on the interference and power requirements of the network, i.e., they do not consider how routing a new flow interferes with ongoing flows in the network. In [9], [10], [11], [12], the authors choose routes that use only interference between links as a metric for routing. In [9], [10] Least-Interference Routing (LIR) algorithms are developed to minimize the amount of interference caused by a transmission, while in [11], [12], Least-Resistance Routing (LRR) algorithms are developed to minimize the amount of interference encountered by a transmission. These algorithms in [9], [10], [11], [12] may result in choosing energy-inefficient routes because they do not explicitly consider energy efficiency and residual energy, but only interference.

In [13], [14], [15], the authors show that residual energy plays an important role in improving network

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performance, and thus propose power-aware algorithms based on this insight. The Maximum Battery Capacity (MBC) algorithm in [13] considers only residual battery energy as routing metrics, while CMAX [15] and the Weighted Minimum Energy (WME) routing algorithm [14] consider additional energy metrics, they do not take into account interference among active links. The authors in [14] also propose the Energy-opportunistic Weighted Minimum Energy (E-WME) routing algorithm for the renewable energy case. However, E-WME still does ignore the impact of interference on the network.

In [16], the authors show that the interference between links significantly affects network performance and proposed the energy-efficient interference-based routing algorithm, called Optimal SINR Routing (OptSINR). However, the residual energy is not taken into account.

In practice, the four key elements *transmission power, interference, residual battery energy*, and *energy replenishment* affect the choice of finding energy-efficient routes. For a given wireless network, the roles of the key elements can change. For example, the interference of light traffic is negligible while heavy traffic induces a plenty of interference in the network. However, because previous studies have ignored one or more of these metrics, the resultant algorithms may not be energy efficient in a real wireless environment, where all of these elements play an important role. Thus, it is necessary to develop a simple and energy-efficient algorithm that takes into account all of these critical metrics and adapts to the varying environments.

In this paper, we make the following contributions. We develop a unified energy-efficient routing algorithm that parameterizes all the four key metrics: transmission power, interference between links (or routes), residual battery energy, and energy replenishment. We also show how the proposed algorithm works in different environments and how the proposed algorithm is related to other algorithms proposed in previous works. Throughout this paper, unless stated otherwise, we use boldface notation to denote either a matrix or a vector.

The rest of the paper is organized as follows. In Section II, we describe the system model and state our basic assumptions. In Section III, we develop an energy-efficient unified routing algorithm. In Section IV, we study the properties of the proposed routing algorithm in various environments. In Section V, we provide numerical results to study the efficacy of the scheme. We conclude in Section VI.

II. System Model and Power Control

A. System model

We consider a power-controlled wireless network that supports multi-hop routing, i.e., each node can control its transmission power. We further assume that flow dynamics are over a much larger time-scale than power control dynamics, so that the time required for power control to converge is negligible. The multi-hop wireless network is modeled as a directed graph $G = (\mathcal{N}, \mathcal{L})$, where $\mathcal{N}$ represents the set of nodes and $\mathcal{L}$ the set of edges that represent communication links between nodes in the network. Each node n in $\mathcal{N}$ has initial energy ε_n^{init} and an energy replenishment rate ξ_n. Each link l in $\mathcal{L}$ is identified by an ordered pair of nodes, i.e., the transmitter $T(l)$ and receiver $R(l)$. Links sharing the same frequency interfere with other links when simultaneously activated. A new service with data ζ to be transmitted requires a fixed data rate Δq, so that the service flow has a fixed duration μ, i.e., $\mu = \frac{\zeta}{\Delta q}$. For this paper, we assume that a flow will be routed over only a single route for the entire duration of the flow. We define, $E(l)$, the energy consumption of link l to be $E(l) = P(l)\mu^l$, where $P(l)$ is the transmission power of link l and μ^l is the amount of time it takes the flow to be served at link l.

B. Wireless link model

As mentioned earlier, due to the shared nature of the wireless medium, wireless links interfere with each other. The impact of interference affects the available capacity of these links.

We define an increasing function $g(\cdot)$ that maps the achievable bandwidth (channel capacity) $r(l)$ to the corresponding signal-to-interference-and-noise-ratio (SINR) $\theta(l)$ as $\theta(l) = g(r(l))$. We assume that the function g is differentiable with respect to $r(l)$, almost everywhere.

In the case of band-limited additive white Gaussian noise (AWGN) channel, the channel capacity (also called the Shannon's capacity) at link l, $r(l)$, is given by $r(l) = B(l)\log(1+\theta(l))$, where $B(l)$ represents the channel bandwidth at link l. Hence, the required SINR becomes $\theta(l) = \exp\left(\frac{r(l)}{B(l)}\right) - 1$. In the low SINR region, the available capacity is often assumed to be a linear function of SINR [17], that is expressed as

$$\theta(l) \quad = \quad Kr(l), \qquad (1)$$

where K is a constant.

Since there exists an one-to-one mapping from a minimum bandwidth to the corresponding minimum SINR, we replace a rate constraint by an SINR constraint as a measure of the minimum quality required on the link. We let Δc denote an additional SINR constraint at a link when a new flow with an additional bandwidth Δq comes into the link. In the case of the linear SINR regime, the additional SINR constraint Δc is equal to $K\Delta q$ from (1).

The SINR $\theta(l)$ at each link l is defined as

$$\begin{aligned}\theta(l) &= \frac{G(T(l),R(l))P(l)}{\sum_{m:m\neq l} P(m)G(T(m),R(l)) + \sigma_{R(l)}} \\ &= \frac{G(T(l),R(l))P(l)}{\eta_{R(l)}},\end{aligned} \tag{2}$$

where $\sigma_{R(l)}$ is the ambient noise at node $R(l)$, $P(l)$ is the transmission power at node $T(l)$, $G(T(m),R(l))$ is the path gain between transmitter $T(m)$ and receiver $R(l)$, and $\eta_{R(l)}$ is the sum of interference and noise at node $R(l)$. The path gain $G(T(m),R(l))$ is modeled as

$$G(T(m),R(l)) = K_{T(m)R(l)} d_{T(m)R(l)}^{-\delta}, \tag{3}$$

where $K_{T(m)R(l)}$ is the attenuation factor that models power loss due to shadowing, $d_{T(m)R(l)}$ is the distance between nodes $T(m)$ and $R(l)$, and δ is the path loss exponent that typically ranges between 2 and 6 [18].

C. Power control

Recall that $\mathcal{L}$ is the set of links. We let $\mathbf{P}$ denote the power vector defined by

$$\mathbf{P} = (P(1), \cdots, P(L_{\mathcal{L}}))^T,$$

where $L_{\mathcal{L}}$ is the number of links in set $\mathcal{L}$. Each link has a minimum requirement $c(l)$ in terms of SINR, i.e. $\theta(l) \geq c(l)$. Using (2), we can rewrite the minimum SINR requirements in matrix form as

$$\mathbf{P} \geq \mathbf{F}\mathbf{P} + \mathbf{b}, \tag{4}$$

where $\mathbf{b} = (b(1), \cdots, b(L_{\mathcal{L}}))^T$ such that $b(l) = \frac{c(l)\sigma_{R(l)}}{G(T(l),R(l))}$, and $\mathbf{F}$ is the $L_{\mathcal{L}} \times L_{\mathcal{L}}$ matrix with (l,m) entry

$$F(l,m) = \begin{cases} \frac{G(T(m),R(l))c(l)}{G(T(l),R(l))} & , \ l \neq m \\ 0 & , \ l = m. \end{cases} \tag{5}$$

Matrix $\mathbf{F}$ defined by (5) has non-negative elements, and since the links interact with each other, it is also irreducible. Hence, we have the following theorem [19] from the Perron-Frobenius theorem and standard matrix theory.

Theorem 1: The following statements are equivalent:

1) $\rho_{\mathbf{F}} \leq 1$ where $\rho_{\mathbf{F}}$ is the Perron-Frobenius eigenvalue of $\mathbf{F}$.
2) There exists a vector $\mathbf{P} > 0$ such that $(\mathbf{I}-\mathbf{F})\mathbf{P} \geq \mathbf{b}$.
3) $(\mathbf{I}-\mathbf{F})^{-\mathbf{1}}$ exists and is positive componentwise.

If there exists a positive feasible vector $\mathbf{P}$, it follows from Theorem 1 that $(\mathbf{I}-\mathbf{F})^{-\mathbf{1}}$ exists. From (4) we obtain $\mathbf{P} \geq (\mathbf{I}-\mathbf{F})^{-\mathbf{1}}\mathbf{b}$. Hence, we have the Pareto optimal[1] solution $(\mathbf{I}-\mathbf{F})^{-\mathbf{1}}\mathbf{b}$ that supports the network topology defined by links in $\mathcal{L}$, and their associated minimum requirements. One can use a distributed power control algorithm [19] to achieve this minimum power vector. As is well known, link scheduling can improve network performance. However, in general, when a link scheduling algorithm is used, some links will not be activated. This means that those entries in $\mathbf{F}$, for which the links are not activated, will be zero so that $(\mathbf{I}-\mathbf{F})$ will not have a full rank. In this case, the optimal solution $(\mathbf{I}-\mathbf{F})^{-\mathbf{1}}\mathbf{b}$ can be found using a Moore-Penrose inverse matrix [20]. The entry of the solution has non-negative values when the link is activated, and zero otherwise.

We let $(\mathbf{I}-\mathbf{F})^{-1}_{(l)}$ denote the lth column vector of matrix $(\mathbf{I}-\mathbf{F})^{-\mathbf{1}}$ and $(\mathbf{I}-\mathbf{F})^{-1}_{\sum^l}$ the element-wise sum of vector $(\mathbf{I}-\mathbf{F})^{-1}_{(l)}$. Then, the minimum energy increment $\Delta\mathbf{E}^*_l$ of each link in the network, when a new flow with additional constraint Δc and duration μ arrives at link l, can be expressed as

$$\begin{aligned}\Delta\mathbf{E}^*_l &= \Delta\mathbf{P}^*_l \ \mu \\ &= (\mathbf{I}-\mathbf{F}')^{-1}_{(l)} \left(\frac{\eta_{R(l)}}{G(T(l),R(l))}\right) \Delta c \ \mu,\end{aligned} \tag{6}$$

where $\Delta\mathbf{P}^*_l$ is the minimum power addition required in the network to serve the new flow at link l, $\mathbf{F}'$ is the matrix corresponding to $\mathbf{F}$ in the new environment. Similarly, when a flow is served by a set Λ of links at a given time slot, the increased energy consumption $\Delta\mathbf{E}_\Lambda$ can be expressed as

$$\Delta\mathbf{E}^*_\Lambda = \sum_{l\in\Lambda} (\mathbf{I}-\mathbf{F}')^{-1}_{(l)} \left(\frac{\eta_{R(l)}}{G(T(l),R(l))}\right) \Delta c \ \mu.$$

D. Problem formulation

The objective is to maximize the throughput over some finite time period $[0,t]$, i.e.,

$$(A) \qquad \max \sum_{j:j\leq k(t)} \zeta_j I(j),$$

where j is the index of a flow arrived at the network, $I(j)$ is the indicator function that takes on a value of one only when flow j is successfully delivered from the source to destination, ζ_j is the amount of data of j, and $k(t)$ is the index of the last arrival during time t, under following constraints:

$$\begin{aligned} &(AC-1) \quad \theta(l) \geq c(l) \quad \forall l \in \mathcal{L}, \\ &(AC-2) \quad P^{\max}(l) \geq P(l) \geq 0 \quad \forall l \in \mathcal{L}, \\ &(AC-3) \quad \varepsilon_n \geq 0 \quad \forall n \in \mathcal{N}. \end{aligned}$$

To that end, our problem is to find a route that is energy-efficient and satisfies the constraints when a flow comes into the network.

[1] $\mathbf{P}^*$ is said to be Pareto optimal if $\mathbf{P}^*$ is feasible and any feasible $\mathbf{P}$ satisfies $\mathbf{P} \geq \mathbf{P}^*$ componentwise.

III. Unified Energy-Efficient Routing (EURo) Algorithm

To solve problem (A) under the three constraints, we use a two-step approach. We first review the case without interference constraints. We then add interference constraints to develop a unified routing algorithm. We begin without considering scheduling, and then extend the developed algorithm to the case when the links are randomly scheduled.

A. Energy-efficient routing for battery-operated networks in the absence of interference

In [14], it is shown that WME routing is *an asymptotically optimal solution* to problem (A) with constraints $(AC-2)$ and $(AC-3)$ by balancing the energy consumption across the network. In the absence of interference, WME can be expressed as follows.

$$\begin{aligned} (B) \quad \mathrm{argmin}_R \quad & \sum_{l \in R} \mathbf{W} \Delta \mathbf{E}_l \\ \text{subject to} \quad & P^{\max}(l) \geq P(l) \geq 0 \quad \forall l \in \mathcal{L}, \\ & \varepsilon_n \geq 0 \quad \forall n \in \mathcal{N}, \end{aligned}$$

where $\mathbf{W}$ is a weight vector that is a function of the residual energy of nodes when a new flow arrives to the network, and $\Delta \mathbf{E}_l$ is the energy increment over the network when the new flow is served at link l. In the interference-free environment, the lth entry of $\Delta \mathbf{E}_l$ is equal to the transmission energy increment of link l, which is used in [14], [15] when a new flow traverses over link l. The weight vector $\mathbf{W}$ is a row vector $\mathbf{W} = (W(1), W(2), \cdots, W(L_{\mathcal{L}}))$. To maximize the lifetime over all nodes and the throughput served by the network, routes need to avoid nodes with small residual energy and balance the energy consumption across all the nodes. To that end, the weight for each link is proposed to be an exponential function of the nodal residual energy in [14], [15], i.e.,

$$W(l) = \varepsilon_{T(l)}^{init} (\gamma^{\lambda(l)} - 1), \qquad (7)$$

where γ is a constant, and $\lambda(l)$ is the ratio of the depleted energy to the initial energy at transmitter $T(l)$ of link l. In the case of renewable energy [14], [21], the weight adds a multiplicative factor of an inversely linear function the replenishment rate in [14], which is defined as

$$W(l) = \frac{\varepsilon_{T(l)}^{init}}{\xi_{T(l)}} (\gamma^{\lambda(l)} - 1). \qquad (8)$$

Hence, the weight vector $\mathbf{W}$ can express the impact of the battery (including residual energy and replenishment) on routing.

B. Unified energy-efficient routing

As a preliminary step, we need to discuss if the optimality of (6) is also applicable to the weighted sum case with (7). Let $\mathbf{E}^*$ be a Pareto optimal solution required to meet the SINR requirement. The weights defined in (7) are always nonnegative. Hence, for a given route R, we have the following inequality:

$$\begin{aligned} & \sum_{l \in R} \mathbf{W} \Delta \mathbf{E}_l - \sum_{l \in R} \mathbf{W} \Delta \mathbf{E}_l^* \\ = & \sum_{l \in R} \mathbf{W} \left((\mathbf{E}_l - \mathbf{E}) - (\mathbf{E}_l^* - \mathbf{E}) \right) \\ = & \sum_{l \in R} \mathbf{W} \left(\mathbf{E}_l - \mathbf{E}_l^* \right) \geq 0, \end{aligned}$$

where $\mathbf{E}$, $\mathbf{E}_l$, and $\mathbf{E}_l^*$ represent the current transmission power of links, the transmission power of links when a new flow comes into link l, and the Pareto optimal transmission power of links when a new flow comes into link l, respectively. Hence, the Pareto optimal $\mathbf{E}^*$ makes the weighted energy also Pareto optimal.

We now are in a position to solve problem (A) with the three constraints, which is really the problem (B), but with interference constraints. Since the Pareto optimal energy makes the weighted energy Pareto optimal, our energy-efficient solution to (A) is expressed as

$$\begin{aligned} (C) \quad \mathrm{argmin}_R \quad & \sum_{l \in R} \mathbf{W} \Delta \mathbf{E}_l^* \\ \text{subject to} \quad & P^{\max}(l) \geq P(l) \geq 0 \quad \forall l \in \mathcal{L}, \\ & \theta(l) \geq c(l) \quad \forall l \in \mathcal{L}, \\ & \varepsilon_n \geq 0 \quad \forall n \in \mathcal{N}. \end{aligned}$$

As Δc goes to zero, $\mathbf{F}'$ in (6) converges to $\mathbf{F}$ element-wise so that the minimum energy $\Delta \mathbf{E}_l^*$ that meets all the SINR constraints becomes

$$\Delta \mathbf{E}_l^* = (\mathbf{I} - \mathbf{F})_{(l)}^{-1} \left(\frac{\eta_{R(l)}}{G(T(l), R(l))} \right) \Delta c \; \mu. \qquad (9)$$

When the minimum SINR for the incoming flow is infinitesimally small, our energy-efficient routing algorithm can be formally expressed as

$$\underset{R \in R(i,j)}{\mathrm{argmin}} \quad \sum_{l \in R} \left(\mathbf{W} (\mathbf{I} - \mathbf{F})_{(l)}^{-1} \left(\frac{\eta_{R(l)}}{G(T(l), R(l))} \right) \right) \qquad (10)$$

where $R(i,j)$ is the set of possible routes from source node i to destination node j of the incoming flow. Instead of $\Delta \mathbf{E}_l$, the exact value of the network energy increment over a route, we can choose a minimum energy route from the interference measured at $R(l)$, $\frac{\eta_{R(l)}}{G(T(l),R(l))}$, and $(\mathbf{I} - \mathbf{F})_{(l)}^{-1}$.

In the EURo algorithm outlined in Algorithm 1, each node checks the availability of two resources for an incoming flow: battery energy including energy replenishment and transmission power. If the better is depleted or the transmission power is saturated at a node, the node denies the incoming flow. For implementation, a predefined threshold can be used to check energy depletion for admitting the new incoming flows. If the battery level of a given node is below the threshold, then the battery is assumed to be depleted and the new flow is rejected. Otherwise, the new flow is admitted when transmission power of the node is not saturated.

Algorithm 1: Energy-efficient Unified Routing (EURo) algorithm

Construct a directed graph $G = (\mathcal{N}, \mathcal{L})$;
For an incoming flow, check if resources are available;
if *yes* **then**
  Measure the interference strength at all nodes in $\mathcal{N}$;
  Calculate $(\mathbf{I}-\mathbf{F})^{-\mathbf{1}}$ based on path loss and constraints;
  Calculate the present weight vector $\mathbf{W}$ taking into account energy replenshiment;
  Calculate link cost $\mathbf{W}(\mathbf{I}-\mathbf{F})^{-1}_{(l)}\left(\frac{\eta_{R(l)}}{G(T(l),R(l))}\right)$ $\forall l \in \mathcal{L}$;
  Apply a shortest path algorithm to find the minimum cost route;
else
  Reject the incoming flow;
  Notify the rejection to the source;
end

C. Link scheduling

To capture the dynamics of scheduling, we define $\mathbf{P}_\tau = \mathbf{S}_\tau \mathbf{P}$ such that scheduling matrix $\mathbf{S}_\tau$ is an $L_\mathcal{L} \times L_\mathcal{L}$ diagonal matrix at time slot τ with (l,l) entry defined as one, if link l is active, zero otherwise. Then, (4) can be modified as $\mathbf{S}_\tau\mathbf{P} \geq \mathbf{F}_\tau\mathbf{P} + \mathbf{S}_\tau\mathbf{b},\ \forall \tau \in T$, where T is a set of time slots and $\mathbf{F}_\tau$ is an $L_\mathcal{L} \times L_\mathcal{L}$ matrix with (l,m) entry defined as

$$F(l,m) = \begin{cases} \frac{1_{\tau,(l,m)} G(T(m),R(l))c(l)}{G(T(l),R(l))} & ,\ l \neq m \\ 0 & ,\ l = m, \end{cases}$$

where $1_{\tau,(l,m)}$ is one, if links l and m are simultaneously active at time τ, otherwise zero. Since in practice nodes cannot have perfect information of link scheduling of all the nodes in the network and since flows randomly arrive at and depart from the network, we consider the impact of random scheduling on the routing algorithm.

We now assume that links are randomly scheduled and that the statistics of the links are available at each node. Let $\mathbf{\Pi}$ be an $L_\mathcal{L} \times L_\mathcal{L}$ diagonal matrix such that the (l,l) entry of $\mathbf{\Pi}$ is defined as the probability that link l is activated. We let $\pi_{m|l}$ denote the conditional probability that link m is active given that link l is active. From [16], the additional expected network energy $\Delta\bar{\mathbf{E}}_l$ is given by

$$\Delta\bar{\mathbf{E}}_l^* = \left(\mathbf{\Pi}(\mathbf{I}-\bar{\mathbf{F}})^{-\mathbf{1}}\right)_{(l)} \left(\frac{\bar{\eta}_{R(l)}}{G(T(l),R(l))}\right) \Delta c\ \mu,$$

where $\bar{\eta}_{R(n)}$ is the average of the interference and noise measured at the receiving node of link n when link n is active, and $\bar{\mathbf{F}}$ is an $L_\mathcal{L} \times L_\mathcal{L}$ matrix with entry (l,m) $F_\tau(l,m)$ defined as $\frac{1_{\tau,(l,m)} G(T(m),R(l))c(l)}{G(T(l),R(l))}$ if $m \neq l$, zero otherwise. Hence, our energy-efficient routing algorithm for random link scheduling schemes can be expressed as, with the same constraints of (C),

$$\underset{R \in R(i,j)}{\text{argmin}} \sum_{l \in R} \left(\mathbf{W}\left(\mathbf{\Pi}(\mathbf{I}-\bar{\mathbf{F}})^{-1}\right)_{(l)} \frac{\bar{\eta}_{R(l)}}{G(T(l),R(l))}\right).$$

The algorithm procedure is also similar to the procedure that we have discussed above.

D. Distributed algorithm

Our routing algorithm (10) described in the previous subsection requires global information such as $\mathbf{W}$ and $(\mathbf{I}-\mathbf{F})^{-1}_{(l)}$. The global information for link costs does not lead itself immediately to distributed implementation. The computational complexity for link costs exponentially increase as the number of nodes goes by. However, since wireless signal strength exponentially decays in terms of distance, as in (3), distant wireless links barely affect each other. In large networks, update information could be also stale. Hence, gathering global information is not effective.

To reduce the computational complexity, we define the *information range* as the range for a node to locally disseminate its information (e.g. residual energy and minimum SINR to transmit) to neighboring nodes in the range. The computational complexity of the local information is independent of the network size but depends on only the number of neighboring nodes to share information.

For a distributed version of EURo, we can employ a distributed shortest path routing algorithm such as the Bellman-Ford algorithm [22]. For link costs in (10), we use $\tilde{\mathbf{W}}$ and $(\mathbf{I}-\tilde{\mathbf{F}})^{-1}$, instead of $\mathbf{W}$ and $(\mathbf{I}-\mathbf{F})^{-1}$ that need global information, where $\tilde{\mathbf{W}}$ and $(\mathbf{I}-\tilde{\mathbf{F}})^{-1}$ are correspondingly reduced matrices using local information from nodes in the preset information range of a node. The interference and noise strength $\eta_{R(l)}$ and the path gain $G(T(l),R(l))$ in (10) are locally measurable [18]. Hence, each node can locally compute link costs for the distributed algorithm.

Nodes in the network can update the information for routing in several ways [23]. A simple method is that nodes periodically broadcast their status to other nodes, and their neighboring nodes update their stored information. Another way is to use piggy-backing. When the status information is relatively small compared to the data being transmitted, each node attaches its information to transmitting data in order to disseminate the information. A control channel can be used for information distribution. The combination of these methods is also an alternative option to implement.

When the information range is set such that nodes distribute their status information to only adjacent nodes and a distributed version of EURo uses only this limited information from adjacent nodes, the information to be shared will be sufficiently small. Since piggy-backing status information does not require additional transactions, the overhead for the distributed version of EURo with only adjacent node information will be quite negligible.

IV. Properties of the Unified Routing Algorithm

We study the properties of the unified routing algorithm proposed in the previous section.The metric used in our routing algorithm (10) is composed of the product of three components that represent energy, transmission power, and the impact of the transmission power. As explained in the previous section, residual energy and energy replenishment can be represented as $\mathbf{W}$, together. Hence, we categorize measurement elements regarding battery energy as a single class, as shown in Table I, and study the impact of battery energy in subsection IV-B.

In various wireless environments as summarized in Table I, we study how each component plays a role and show how our routing algorithm relates to other previous routing algorithms.

A. No interference and infinite energy

We assume here that interference is negligible and that each node's energy is unlimited. For example, a system is connected to an outlet and the arrival rate into the system is very low.

Since there is no interference, matrix $\mathbf{F}$ becomes a zero matrix from (5). The unlimited energy constraint means that the weight $W(l)$ is constant for all links. In the case of homogeneous networks, the ambient noise is identical. Hence the algorithm becomes

$$\begin{aligned} & \operatorname*{argmin}_{R\in R(i,j)} \sum_{l\in R} \left(\mathbf{W}(\mathbf{I}-\mathbf{F})^{-1}_{(l)} \left(\frac{\eta_{R(l)}}{G(T(l),R(l))} \right) \right) \\ = \; & \operatorname*{argmin}_{R\in R(i,j)} \sum_{l\in R} \left(\frac{1}{G(T(l),R(l))} \right). \end{aligned}$$

This is then the same as the Minimum Energy routing algorithm so that under this assumption our routing algorithm performs at least as well as the Minimum Energy routing algorithm.

B. No interference with energy limitation

We assume that interference is negligible and that each node is operated using a battery. Since there is no interference, matrix $\mathbf{F}$ becomes zero as in the previous case. Hence, in this environment our routing algorithm can be simplified as

$$\begin{aligned} & \operatorname*{argmin}_{R\in R(i,j)} \sum_{l\in R} \left(\mathbf{W}(\mathbf{I}-\mathbf{F})^{-1}_{(l)} \left(\frac{\eta_{R(l)}}{G(T(l),R(l))} \right) \right) \\ = \; & \operatorname*{argmin}_{R\in R(i,j)} \sum_{l\in R} \left(W(l) \frac{\sigma_{R(l)}}{G(T(l),R(l))} \right). \end{aligned}$$

The weight $W(l)$ depends on the presence or absence of replenishment functionality in the network. When all the nodes in the network have no replenishment resource, the weight becomes (7). In the case when all the nodes have rechargeable resource, the weight is expressed by (8), which includes the impact of energy replenishment. Hence, this algorithm is now identical to the Weighted Minimum Energy routing algorithm, given in [14], [15] (or E-WME in [14]). In the general wireless environment our routing algorithm considering interference can distribute the relay load over the network in terms of battery energy (including residual energy and energy replenishment) so that the performance of our routing algorithm is at least as high as that of the WME (or E-WME) routing algorithm.

C. Interference and infinite energy

We assume that interference is significant and that each node is connected to a power outlet such as a wireless mesh network with a significant incoming flow rate. Since there is no constraint on the available energy (power outlet is available), the weight of each node in (10) is identical. Hence our routing algorithm can now be expressed as

$$\begin{aligned} & \operatorname*{argmin}_{R\in R(i,j)} \sum_{l\in R} \left(\mathbf{W}(\mathbf{I}-\mathbf{F})^{-1}_{(l)} \left(\frac{\eta_{R(l)}}{G(T(l),R(l))} \right) \right) \\ = \; & \operatorname*{argmin}_{R\in R(i,j)} \sum_{l\in R} \left((\mathbf{I}-\mathbf{F})^{-1}_{\sum^{l}} \left(\frac{\eta_{R(l)}}{G(T(l),R(l))} \right) \right), \end{aligned}$$

which is identical to the OptSINR routing algorithm [16]. In this wireless environment, our routing algorithm performs as well as OptSINR.

D. Interference only

We consider the case when only interference is used as the metric for choosing a route. The case can be categorized into two cases: minimize the interference experienced by a route, and minimize the interference induced by a route.

TABLE I

COMPARISON OF ALGORITHMS: WE CONSIDER FIVE DIFFERENT ENVIRONMENTS DEPENDING ON CONSIDERED METRIC. WE MARK WITH AN O WHEN AN ALGORITHM CONSIDERS THAT METRIC, OTHERWISE, WE MARK AN X.

Case (Section)	Measure elements				Algorithms
	Interference	Transmission power	Battery energy		
			Residual energy	Energy replenishment	
1 (IV-A)	X	O	X	X	ME
2 (IV-B)	X	O	O	X	WME, CMAX
	X	O	O	O	E-WME
3 (IV-C)	O	O	X	X	OptSINR
4 (IV-D)	O	X	X	X	LIR, LRR
5	O	O	O	O	EURo

To study routing algorithms that consider only interference, we need to investigate the physical meaning of (9). Since the inverse matrix of $(\mathbf{I}-\mathbf{F})$ is expressed by $\mathbf{I}+\mathbf{F}+\mathbf{F^2}+\mathbf{F^3}+\cdots$, the additional energy over the network can be rewritten as follows.

$$\begin{aligned}
&\Delta\mathbf{E}_l^* \\
=\;& (\mathbf{I}_{\sum^l}+\mathbf{F}_{\sum^l}+\mathbf{F}^2_{\sum^l}+\cdots)\left(\frac{\eta_{R(l)}}{G(T(l),R(l))}\right)\Delta c\;\mu \\
=\;& (\underbrace{0,\cdots,0}_{l-1},\left(\frac{\eta_{R(l)}}{G(T(l),R(l))}\right)\Delta c\;\mu,\underbrace{0,\cdots,0}_{L_{\mathcal{L}}-l})^T \\
+\;& \mathbf{F}_{\sum^l}\left(\frac{\eta_{R(l)}}{G(T(l),R(l))}\right)\Delta c\;\mu+\cdots. \qquad (11)
\end{aligned}$$

The first term in (11) represents the amount of additional energy at each link when link l serves a new flow with additional constraint Δc. The second term is the amount of additional energy over the network when link l increases its transmission energy by the first term to serve the new incoming flow. In the same way, each term in (11) represents the iterated energy over the network induced by interference.

The routing algorithm to minimize the interference experienced by a route, called LRR [11], can be expressed as

$$\underset{R\in R(i,j)}{\operatorname{argmin}}\sum_{l\in R}\eta_{R(l)},$$

where $\eta_{R(l)}$ is the interference measured at the receiver node $R(l)$ of link l.

From Equation (11), the routing algorithm minimizing the experienced interference is the same as the minimization of the element-wise summation of only the first terms when the path gain of link l is ignored. Since the impact of the interference on the network (the second and higher order terms in (11)) and the path gain are ignored, the routing algorithm could choose less energy-efficient routes than OptSINR and our unified energy-efficient routing algorithm.

In [9], [10], the following routing algorithm is used to minimize the interference induced by a route, called LIR[2] in [9],

$$\underset{R\in R(i,j)}{\operatorname{argmin}}\sum_{l\in R}\left(\sum_{m\in\mathcal{L}-\{l\}}G(T(l),R(m))\right), \qquad (12)$$

where $G(T(l),R(m))$ is the path gain from the transmitter of link l to the receiver of link m. This algorithm (12) corresponds to (11), when we fix $G(T(l),R(l))$ $\forall l\in\mathcal{L}$ to be a constant value and ignore the transmission power of link l (the first term in (11)) and the impact of interference on the network (the third and higher order terms in (11)). Thus, the routing algorithm (12) results in choosing less energy-efficient routes than OptSINR as well as our routing algorithm.

From IV-A, IV-B, IV-C, and IV-D, we show that our routing algorithm includes all the factors separately considered in the previous works and adapts to different network environments. Furthermore, our routing algorithm performs better than or at least as well as the other algorithms that are designed under marginal environments.

V. SIMULATIONS

In this section we use simulations to verify the performance of our algorithm *EURo*. We compare the performance of EURo to WME, LIR, and ME. Other algorithms have been extensively studied in comparison with WME and OptSINR in [14], [16], and WME and OptSINR have been found to perform better than these other algorithms. Therefore, in this section we compare the performance only between these four algorithms. In the first three scenarios, we consider the four algorithms with global information to obtain the achievable performance in each marginal environment. In the last two scenarios, we compare distributed EURo (dEURo) with other four algorithms (EURo, WME, LIR, and ME). In

[2]The original routing algorithm proposed in [9] defines the potential interference as the number of links of which interference levels are above a certain threshold. To generalize the problem, we use here the total amount of interference level.

the renewable energy environment, we also compare its performance with E-WME.

For all the algorithms compared, we assume that the nodes employ power control. In each case, when sending flows through the routes chosen by the algorithm, each node adjusts its transmission power to satisfy the new minimum constraint at the links. For the simulations, we use a seven by seven grid network, and the separation between adjacent nodes in the $x-$ and $y-$ coordinates is one unit of distance. We fix the path loss exponent at three, the attenuation factor at one, and the ambient noise at one. We assume that all ambient noise is identical and that each link is directional. We assume that wireless links are linear, as defined in (1), and that the required SINR of a new service flow is fixed at 0.1 (-10 dB) under the same constraints of (C). In an IS-95 direct sequence code division multiple access (DS-CDMA) system with bandwidth 1.23 MHz, the minimum SINR for a 9.6 kbps channel is -14 dB (0.0398) [18]. We set a minimum SINR for each incoming service flow at -10 dB in this simulation.

For link scheduling, we use the fixed and periodic link scheduling scheme used in [16], [24]. We fix γ in (7) at 200 and a packet length at 200 slots. For each simulation, we use 10 different random seeds and average the performance.

For dEURo, we set the information range of each node to include only adjacent nodes to share the information to compute link costs for distributed shortest path routing. To update local information, each node periodically announces its status information to its adjacent neighbors.

We define *the number of partitions* as the number of transmission failures due to depleted relay nodes and use this measure to compare the performance of the various schemes, as in [14].

A. No interference

We first consider the case when there is no interference between routes. The service times of flows here do not overlap in the networks so that routes do not interfere with each other. Each node initially has 10 units of energy, and the battery energy is non-renewable. In this case, the metrics of WME and EURo are identical so that EURo works the same as WME, as shown in Figs. 2 and 3. Because they take into account residual energy in their cost functions, WME and EURo outperform LIR and ME. Since LIR can distribute load over the network better than ME, for a given number of node partitions, LIR successfully delivers more packets to their destinations than ME.

B. Impact of interference

In this subsection, we consider the impact of interference on the algorithms. We assume that the initial battery energy of each node is 10 units of energy and that the battery energy is non-renewable. For simplicity, we fix the ongoing link between two adjacent nodes. The ongoing link continuously transmits a flow with 2 dB SINR. Flows with -10 dB SINR between the other nodes randomly arrive in the network, and the arrival rate is assumed to be small enough for the flows to not overlap. In this environment, EURo outperforms the other algorithms.

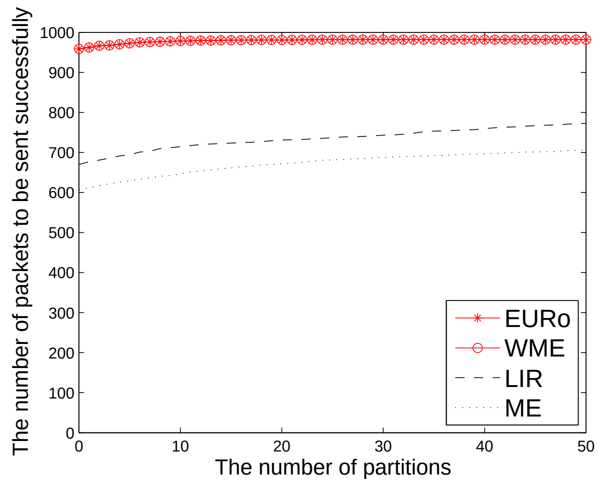

Fig. 2. Accumulated throughput versus the number of partitions when there exists no interference between links

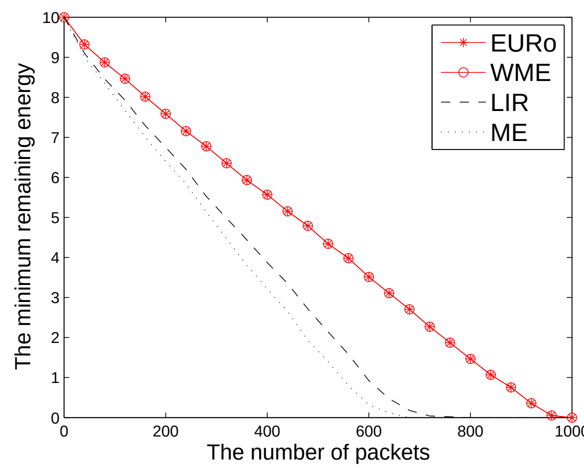

Fig. 3. The minimum remaining energy versus the number of arrived packets when there exists no interference between links

Fig. 4 shows the number of successfully delivered flows versus the number of partitions. EURo is almost constant over the number of partitions. However, due to interference, routes chosen by WME expend more energy than those of EURo, so that WME results in a smaller throughput. Compared to the previous case in

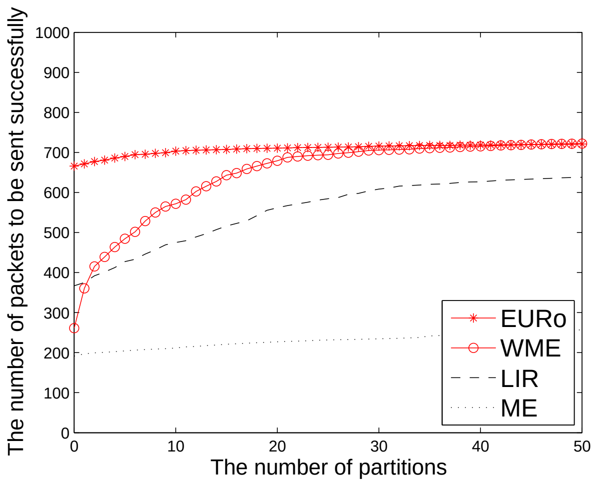

Fig. 4. Accumulated throughput versus the number of partitions when links interfere with each other

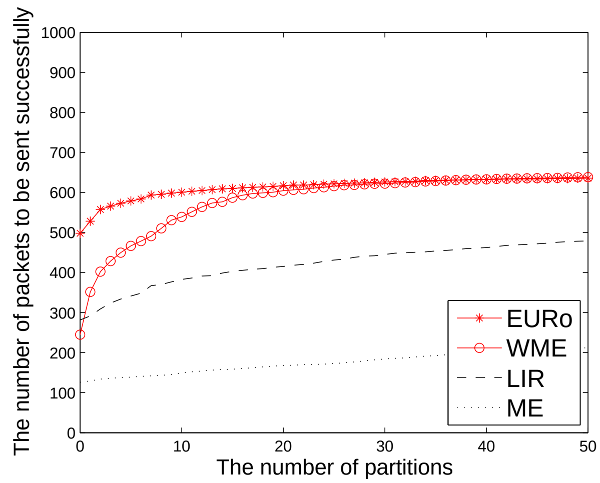

Fig. 6. Accumulated throughput versus the number of partitions when battery energy is unevenly distributed over the network

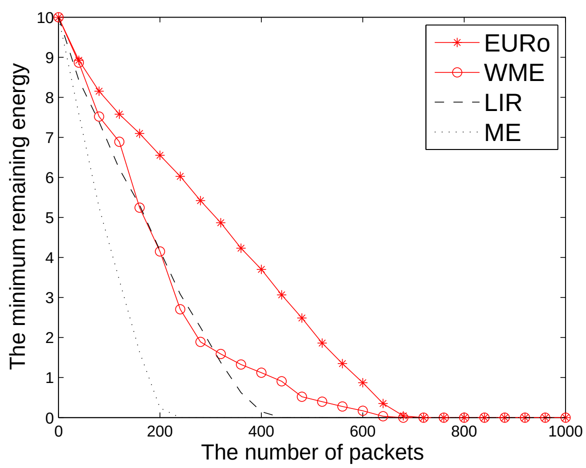

Fig. 5. The minimum remaining energy versus the number of arrived packets when links interfere with each other

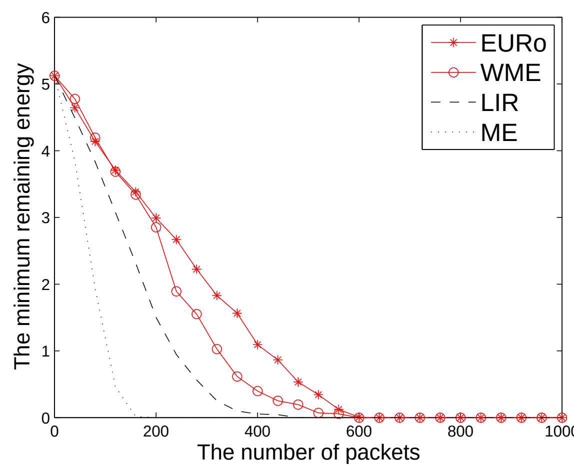

Fig. 7. The minimum remaining energy versus the number of arrived packets when battery energy is unevenly distributed over the network

subsection V-A, WME still performs better than LIR, but the performance differential is reduced.

Fig. 5 shows the minimum energy among the nodes in the network after every transmission. Since the impact of interference between the ongoing link and new routes, the energy consumption rate of WME is steeper than EURo, which considers the residual energy and the interference.

C. Impact of unevenly distributed initial energy

This scenario includes heterogeneous sensor networks. Even in homogenous network environments, multiple deployments of nodes can make the initial battery levels uneven. Under the same environment as in the previous subsection, we consider the impact of unevenly distributed initial battery energy. We assume that the initial battery energy of the network follows a uniform distribution between 5 and 15 units of energy so that the mean of the distribution is 10 units of energy. Due to the variation of battery energy, the weights $W(l)$ in the algorithm play a more important role for choosing a route than those in the homogeneous battery case. Hence the performance of WME shown in Figs. 6 and 7 is closer to the performance of EURo compared to the previous case in subsection V-B.

D. Impact of random arrival flows and local information

To study the impact of random flow arrivals on the routing algorithms, we fix the initial energy of each node at 10 units in the absence of energy replenishment and compare the performance with two different arrival rates of 0.025 and 0.625 packet per slot, as shown Figs. 8 and 9. When the arrival rate is low, the average of the flows in the network is low so that the performance is close to, but slightly poorer than the performance in the case when there is no interference, as in Fig. 8.

In the case when the arrival rate is high, due to interference between the links, the algorithms that do not consider the impact of interference are more affected than EURo, as shown in Fig. 9. As can be seen from the figures, even if EURo uses local information from only adjacent neighborhoods, it outperforms other routing algorithms. Hence, EURo can be totally implemented in a distributed manner collaborating with a distributed shortest path routing algorithm. As we would expect, the performance of dEURo the distributed version which uses only truncated information, is slightly poorer than EURo.

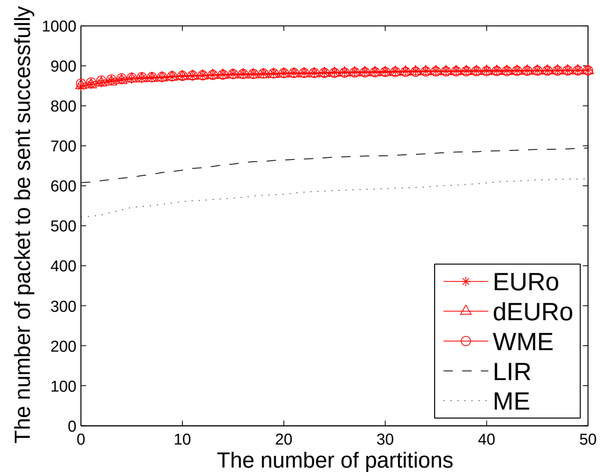

Fig. 8. Accumulated throughput versus the number of partitions when links interfere with each other and arrival rate is 0.025 packet per slot

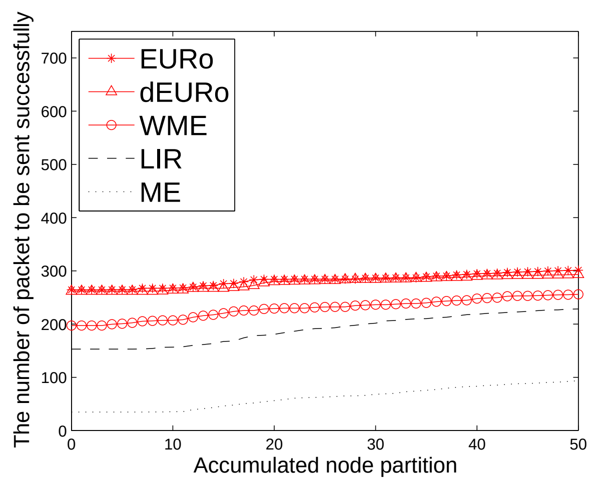

Fig. 9. Accumulated throughput versus the number of partitions when links interfere with each other and arrival rate is 0.625 packet per slot

E. Impact of renewable energy source

To study the impact of energy replenishment on the routing algorithms, we fix the initial energy of each node at 10 units of energy and a packet arrival rate at 0.625 packet per slot as in the previous subsection. All the nodes are assumed to be equipped with renewable batteries. At each time slot, the amount of energy that a node recharges is assumed to be uniformly distributed between ξ and 2ξ, where $\xi = 1 \times 10^{-3}$ so that the average renewal rate is $1.5 \times \xi$.

Fig. 10 shows the performance comparison between our proposed algorithms and previous algorithms. As would be expected, when comparing to the simulation results in the previous subsection, it can be seen that the network with renewable source performs better than the network without energy renewal for all the routing algorithms. Our proposed algorithms outperform the others because they consider all the four key elements, and hence manage efficiency better than the other algorithms in the literature. Furthermore, even if dEURo takes into account only limited neighbor information in this environment, the performance of dEURo is almost identical to that of EURo that uses global information.

VI. Conclusion

In this paper, we have developed EURo, an energy-efficient unified routing scheme. Unlike previous works, the proposed algorithm simultaneously takes into account four critical system parameters: transmission power, interference, residual energy, and energy replenishment. We show that our algorithm maps to the state of the art, when certain quantities are kept fixed. Via simulations we show that our algorithm outperforms other energy-efficient routing algorithm in various environments. We also provide a distributed versions of EURo that use local information, and show via simulations that it outperforms state-of-the-art routing algorithms.

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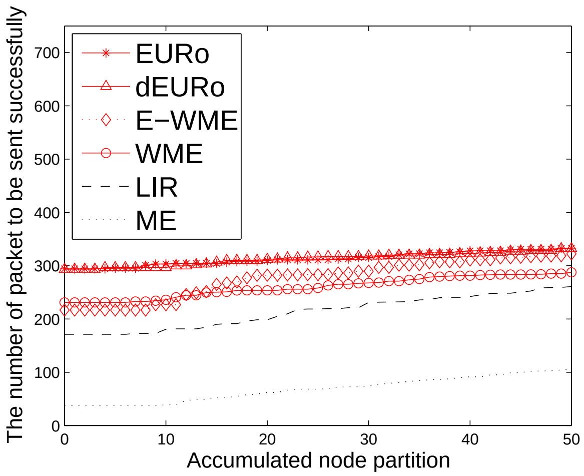

Fig. 10. Accumulated throughput versus the number of partitions when nodes have renewable batteries.

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