Multi-Hop MIMO Relaying Based on Simultaneous Wireless Information and Power Transfer

KWADWO BOATENG OFORI-AMANFO†, (Member, IEEE),
DEREK KWAKU POBI ASIEDU‡, (Member, IEEE),
ROGER KWAO AHIADORMEY§, (Member, IEEE),
AND KYOUNG-JAE LEE∥, (Senior Member, IEEE)

†Department of Electronic Engineering, Hanbat National University, Daejeon 34158, South Korea
‡Department of Electrical and Information Engineering, Seoul National University of Science and Technology, Seoul 01835, South Korea
§Department of Information and Communication Engineering, Yeungnam University, Gyeongsan-si 38541, South Korea

Corresponding author: Kyoung-Jae Lee (kyoungjae@hanbat.ac.kr)

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ABSTRACT This paper studies a multiple-input and multiple-output (MIMO) multi-hop decode-and-forward (DF) relaying wireless network. Communication between a source node and a destination node is aided via multi-hop relays with simultaneous wireless information and power transfer (SWIPT). We investigate the separate application of both power splitting (PS) and time splitting (TS) based SWIPT relaying protocols in our system model. The performances of the two are then compared and analyzed. The SWIPT protocol enables the current relay to harvest energy from the immediately preceding relay node, to reliably forward the information signals between the source and the destination. We aim to minimize the transmit power at the source under the end-to-end system throughput constraint by optimizing either PS or TS ratios at each relay node. For that, the global solutions for the ratios of either PS or TS are attained via convex optimization techniques. A closed-form solution was reached for the SWIPT PS approach. However, the SWIPT TS approach is achieved via an iterative algorithm. Also, we propose a simple routing algorithm based on Dijkstra’s algorithm for our proposed DF-SWIPT multi-hop system. Finally, we compare the proposed PS and TS ratio schemes to their corresponding fixed PS and TS ratio schemes, in terms of source power resource consumption, computational complexity, and overhead analysis. It is found that the PS outperforms the TS, owing to the higher computationally demands of the TS.

INDEX TERMS Multiple-input multiple-output (MIMO), multi-hop decode-and-forward (DF) relay, simultaneous wireless information and power transfer (SWIPT), source transmit power minimization, power splitting, time splitting.

I. INTRODUCTION

A wireless network consists of several wireless nodes, gateways, and a central system, communicating with each other by routing schemes [1]–[3]. These routing schemes may involve either/both a direct or relayed communication between a gateway and a particular wireless node [2], [3].

The main purpose of relays is to facilitate information forwarding and an increase in communication system throughput [4], [5]. In carrying out these tasks they depend on their limited resources to aid communication between two nodes [4], [5]. To reduce the strain on the relay node’s resources, energy harvesting (EH) from a portion of received radio frequency (RF) signal at the relay node can be a source of power for information signal relaying [4], [5]. The technique used for EH from RF signals is wireless power
transmission (WPT) [4]–[6]. WPT implementation in a cellular communication system is accomplished through two main approaches, i.e., wireless powered communication networks (WPCN) and simultaneous wireless information and power transfer (SWIPT) [4], [5], [7]. SWIPT involves both wireless information transfer (WIT) and WPT being used concurrently [4], [5]. To implement SWIPT, the two main techniques of time splitting (TS) and power splitting (PS) are utilized in wireless systems [4], [5], [8].

For TS schemes, a fraction of the time is used for EH and information decoding (ID). PS on the other hand splits the received signal power at the same time and uses a portion of the signal for EH and the other portion for ID and re-transmission. In this case, the two operations happen at the same time [4]. For the alternative of WPCN, the steps of successive transmission of wireless energy transfer (WET) and wireless information transfer (WIT) constitute the method used in its implementation [4], [5]. In performing the inter-node information transfer, two of the most commonly used forwarding protocols are the amplify-and-forward (AF) protocol and the decode-and-forward (DF) protocol [9]–[11]. Comparatively, a DF system has greater complexity than an AF system; in that, it involves decoding, remodulating and re-transmitting the received signal. AF on the other hand, simply amplifies and relays the signal received. The choice between the two depends on the available resources, system architecture and the problem being solved.

Some studies have sought to combine relaying with SWIPT and multi-antenna techniques [12]–[14]. The work in [13] considered a system model, where a multi-antenna SWIPT relay node supports a non-direct link source-to-destination communication. The source and destination nodes possessed single antennas, while at the multi-antenna relay nodes, two types of antenna architecture were considered: separate and cluster antenna configurations [13]. As was the authors’ goal, the maximization of the end-to-end (E2E) achievable rate based on the joint optimization of the transmit power and PS ratio on each relay antenna [13] was attained by utilizing two proposed clustering algorithms. Namely, the optimal antenna clustering (AC) algorithm and the greedy AC algorithm, which they compared in their simulation results [13]. Of key note from the results, is the realization that the former offers exponential complexity whereas the latter provides linear complexity.

When considering MIMO systems and the related works done there, in extension of the discussed ideas, there has been some limited additions in that domain. For instance, a MIMO relay system is studied in [14], where each multi-antenna relay supports its operations through energy harvesting. Here, the authors investigated the PS and TS schemes with the purpose of maximizing the achievable rate by optimizing the source-relay beamforming vectors, the power and the TS/PS ratios.

From the recent literature, it is seen that although wireless networks are not new, a lot of current research still could be done to improve such systems. The two recent fields of WPCN and SWIPT spawned out of WPT have aimed at tackling the EH problems encountered [4], [5]. The cited studies upon which our work is based, looked at systems with predominantly single-input single-output (SISO) configurations. This is a limitation our work seeks to address by using MIMO configuration for our purposes. This is motivated by the desire to offer a generalized solution to the inherent problems to the MIMO case.

Some of these EH systems have also evolved overtime to mitigate the limitations imposed by channel fading conditions via the introduction of relays. However, these relays usually have single antennas [4] or in the cases where multiple antennas are used, provide only a single [13] relay. Thus, the joint benefits of spatial multiplexing realized by the use of multiple antennas as well as signal sustenance via multiple relays are not achieved concurrently. This paper adapts to this scenario by relying on multi-antenna relays. In looking at the body of work available to us therefore, we identified that there still existed a gap in system configuration which handles SWIPT demands in MIMO systems, particularly in a multiple relay scenario. This served as a key motivation for our work. Additionally, the realization of the absence of such a known system - which in addition to solving the underlying information theory problem also provides routing considerations as a layered add-on - to offer a more practical and algorithmic solution gave further impetus to this study.

This paper investigates the application of MIMO DF-SWIPT multi-hop relaying system. A source node communicates with its destination node through this relaying system. Here, all nodes are equipped with multiple antennas. At each fixed DF-SWIPT relay node, energy is harvested using a fraction of the RF signal it receives via either the PS or TS protocols, implemented in the system architecture. In the next hop, the harvested energy is used to forward the decoded information signal. Unlike previous works in [15], and [16], we consider a multi-antenna configuration at each relay node, imperfect channel state information (CSI), the use of either the SWIPT PS or TS architectures, and introduce a novel routing algorithm for our energy-constrained wireless network model. Thus as SWIPT-(PS/TS) based routing is the focus of this study, our work does not consider detailed energy modeling. To distinguish our work in its novelty and contribution, we benchmark our results against an exiting PS enabled SISO model [15]. Hence, the main contributions of this paper are as follows:

- First, we seek to identify the minimum amount of source power to support source-to-destination communication via the multi-hop DF-SWIPT wireless nodes. By tackling this problem, we reduce the strain (i.e., the depletion of the source and routing nodes’ power resources) on the source and relaying wireless nodes during routing of information in the network. For the PS technique, we derived closed-form solutions for the minimum source power needed to support E2E communication.
• Secondly, we consider the TS technique as an alternative to PS in the minimization of source power for source-to-destination communication. To obtain the splitting ratios for the PS scheme, a closed-form non-iterative algorithm is presented. On the other hand, the solution for the TS technique is achieved using an iterative algorithm.
• Based on the energy minimization solutions, we propose centralized and distributed methods by which each relay node’s PS/TS ratio can be determined in real-world wireless networks.
• Additionally, we propose a routing algorithm, based on Dijkstra’s algorithm (DA), for our MIMO DF-SWIPT multi-hop wireless network. The weighting factor for our implementation of DA is the inverse of the inter-node channel gains.
• Finally, we compare the performance of the proposed optimal PS and TS schemes to the fixed PS and TS schemes in terms of source power consumption, computational complexity, and overhead analysis.

The rest of this paper is organized as follows: Section II presents the detailed system model and the problem formulation setups for our optimization. The closed-form solution for the PS as well as the iteration driven solution of the TS optimization problems, are found in Section III. Next, we present our routing algorithm, the implementation and analysis in sections IV and V respectively. Afterwards, the results of our simulations and the related discussions are given in Section VI. Finally, concluding remarks and possible extensions to the work are provided in Section VII.

Notations: \( \mathbf{A} \in \mathbb{C}^{N \times M} \) is a matrix with dimensions \( N \) by \( M \). \( \text{tr} \{ \mathbf{A} \} \) and \( \mathbf{A}^\dagger \) represent the trace and conjugate transpose of matrix \( \mathbf{A} \). \( | \mathbf{A} | \) and \( \parallel \mathbf{A} \parallel \) are the determinant operation and the norm of a matrix \( \mathbf{A} \), respectively. \( \mathbf{I}_N \) denotes an \( N \times N \) identity matrix. \( n \sim \mathcal{CN}(0, \delta^2) \) denotes a circularly symmetric complex Gaussian random variable \( n \), with zero-mean and a variance of \( \delta^2 \). \( \mathbb{E}_X \{ f(X) \} \) is the expectation operation over random variable \( X \). \( f(X) \) and \( R(X) \) represent a general function and a rate function respectively which are dependent on the variable \( X \). Throughout this work, variables with subscripts 0 and \( K + 1 \) represent the variables for the source and destination nodes, respectively.

II. SYSTEM MODEL AND PROBLEM FORMULATION

We consider a scenario where a source node, \( S \), (i.e., the gateway, internet, and external system) communicates with a destination node, \( D \), through routing over \( K \) SWIPT multi-hop wireless node relays within an \( M \) wireless network as shown in Fig. 1. Each node in the network is equipped with multiple antennas, \( L_i \) (i.e., \( i = 0, 1, \ldots, K, K + 1 \)). The source and destination nodes operate using their battery (i.e., installed power resource) for the transmission and decoding of information. To preserve the battery power of the relaying nodes, each relay uses the SWIPT EH technique (i.e., either the PS or the TS architectures)\(^2\) for the DF routing. For simplicity, we do not consider the energy processing demands at each relay node. We further assume that the coherence time is large enough for stable transmission needed for the stable reception of data. Additionally, we assume that the received data is forwarded without any data aggregation or fusion. Each relay utilizes a supercapacitor to store the harvested power for relaying purposes from a portion of the RF signal it receives [13]. The rest of the RF signal received at the relay node is then decoded and forwarded to the next node by means of the energy stored by the supercapacitor. Since the source consists of the gateway and the external systems, we assume that the source has knowledge of the CSI for

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1 Please note that \( M \) is the total number of nodes within the wireless network, \( L \) is the total number of antennas per node, while \( K \) is the total number of nodes used in routing.

2 In this work, the clustered antenna design is used [13]. This is because the clustered antenna approach uses fewer resources and components than the separate antenna design [13].
all communicating nodes within the wireless network. We further assume each wireless node knows only the CSI of the channels it communicates on. Concerning the communication links, we assume there is no direct link between the source node and the destination node [15]. Also, there is no direct link between relay nodes [15]. The link assumptions are based on the routing implementation, and an assumed large inter-node distance [14], [20], [21]. The detailed operation and stepwise derivation of our research problems will now be presented for both the SWIPT PS and TS EH techniques.

A. SWIPT PS Technique

Under the assumption of imperfect CSI, the received RF signal vector at node $k$ from the previous node is given as

$$
y_k = H_k F_k^{-1} x_{k-1} + n_k, \quad k = 1, \ldots, K + 1,
$$

(1)

where $F_k^{-1} \in \mathbb{C}^{G_{k-1} \times G_k}$ is the beamforming matrix of the previous node of $\mathbb{Z}_{k-1}$ antennas, with a power constraint of $\|F_k^{-1}\| \leq E_k^{-1}$. The vectors $x_{k-1}$ and $n_k \sim \mathcal{CN}(0, \sigma_k^2 I_{G_k})$ are the information signal vector from the preceding node and the antenna noise vector at the current node, respectively. Also, $H_k \in \mathbb{C}^{G_k \times G_{k-1}}$ represents the channel coefficient matrix between the current and previous nodes. Since CSI is imperfect, $H_k = \tilde{H}_k + E_k$, where $\tilde{H}_k$ and $E_k$ are the estimated channel matrix and estimated channel error matrix, respectively. Each element of $H_k$ is modeled as $h_{ij,k} = \sqrt{\mu} \tilde{h}_{ij,k}$, where $\tilde{h}_{ij,k} \sim \mathcal{CN}(0, 1 - \sigma_i^2)$, and $\mu_{ij,k}$ denotes the large scale fading coefficient, with the subscripts $i$ and $j$ delineating the antennas on successive nodes. The large scale fading coefficient is defined as $\mu_{ij,k} = C_0 d^{-\alpha_p}$, where $C_0$, $d$, and $\alpha_p$ are the signal attenuation coefficient, distance, and the pathloss exponent between a transmitter and receiver nodes, respectively. Likewise, each $(i,j)$-th element of $E_k$ is modeled as $e_{ij,k} = \sqrt{\mu} \tilde{e}_{ij,k}$, where $\tilde{e}_{ij,k} \sim \mathcal{CN}(0, \sigma_i^2)$. Please note that we assume that the estimation error variance for each antenna component, $\sigma_i^2$ is also determined a priori.

Based on the PS ratios, the received RF signal at node $k$ is split into two, for EH and ID. The portion of the RF signal used for EH and ID are, respectively, written as

$$
y_k^{EH} = \sqrt{\rho_k} \tilde{H}_k F_k^{-1} \tilde{x}_{k-1} + \sqrt{\rho_k} n_k, \quad k = 1, \ldots, K + 1,
$$

(2)

$$
y_k^{ID} = (1 - \rho_k)^{1/2} W_k \tilde{H}_k F_k^{-1} \tilde{x}_{k-1}
+ (1 - \rho_k)^{1/2} n_k + z_k,
$$

(3)

where $\rho_k$ is the PS ratio for node $k$, $z_k \sim \mathcal{CN}(0, \sigma_k^2)$ is the additional noise introduced by the ID circuitry and $W_k \in \mathbb{C}^{G_{k-1} \times G_k}$ is the receive combining matrix [24]–[26].

3 The CSI can be estimated during the training phase for the channel gain estimation in a wireless network, and all the CSI is also available at the data gatherer (i.e., the gateway node and the central system) [17]–[19].

4 For simplicity, we use the general pathloss model that could be applied to ad-hoc and wireless sensor networks (WSNs). For WSNs one may have to consider other models but that is not the focus of this work.

5 We focus on the effects of estimation error on the system performance. However, based on channel dynamics and estimation schemes, the value used for $\sigma_i^2$ is found by using [22], [23].

From (2), the harvested energy stored in the supercapacitor is deduced as

$$
E_k = \beta_k \mathbb{E}_{x_{k-1}, n_k} \left[ |y_k^{EH}|^2 \right] \geq \beta_k \| \rho_k^{1/2} \tilde{H}_k F_k^{-1/2} \|^2,
$$

(4)

where $\beta_k$ is the energy conversion efficiency of the EH device for the $k$th node. The achievable rate at node $k$ is determined from (3) as

$$
R_k = \log_2 \left[ 1 + \frac{(1 - \rho_k) W_k^H \tilde{H}_k F_k^{-1} \tilde{H}_k^H \tilde{x}_{k-1}}{q_1} \right],
$$

\[= \log_2 \left[ 1 + \frac{(1 - \rho_k) W_k^H \tilde{H}_k F_k^{-1} \tilde{H}_k^H \tilde{x}_{k-1}}{q_2} \right],
$$

(5)

where $q_1 = ((1 - \rho_k) \sigma_k^2 + \sigma_q^2)$ and $q_2 = \sigma_q^2$. Equation (5) is deduced under the assumption, $\delta_k^2 \ll \sigma_k^2$. This implies that the antenna noise is negligible as compared to the ID circuit noise power [27]–[29].

Applying the singular value decomposition (SVD) of $\tilde{H}_k = \hat{U}_k \Sigma_k \hat{V}_k^H$, the optimal beamforming matrix at the previous node and the receive combining matrix at the current node are expressed as $F_k^{-1} = \hat{V}_k \Phi_k^{-1} \hat{V}_k^H$ and $W_k = \hat{U}_k$, respectively [14], [24], [26], [30]. $\hat{U}_k$ and $\hat{V}_k$ are unitary matrices. $\Sigma_k = \text{diag}(\xi_{k,1}, \ldots, \xi_{k,K})$ represents a non-negative diagonal matrix, while $\Phi_k^{-1} = \text{diag}(P_{k-1,1}, \ldots, P_{k-1,K})$ denotes the diagonal matrix consisting of the precoding power allocation for node $k - 1$ [14], [24], [26], [30]. Here, $\Sigma_k = \text{min}(\Sigma_{k-1}, \Sigma_k)$ represents the number of active channels corresponding to the non-zero singular values of $\tilde{H}_k$ [14], [24], [26], [30]. Hence, the energy harvested at each relay node becomes

$$
E_{k}^{PS} = \beta_k \rho_k \sum_{i=0}^{L_k} \xi_{k,i}^2 \xi_{k,i}^2
$$

(6)

Also, the achievable rate at each node is defined as

$$
R_k^{PS} = \log_2 \left( 1 + \frac{(1 - \rho_k) \sum_{i=0}^{L_k} \xi_{k,i}^2 \xi_{k,i}^2}{\sigma_k^2} \right).
$$

(7)

The minimization problem for the source transmit power, $E_0^{PS}$, is then given as

$$
\minimize \quad E_0^{PS} \quad \text{subject to} \quad \frac{\Psi_k^{PS}}{\beta_k \sigma_k^2} \geq \tilde{y}_{th}, \quad E_0^{PS} \geq 0,
$$

$$
0 \leq \rho_k \leq 1, \quad k = 1, \ldots, K + 1,
$$

(8)

where $\tilde{y}_{th}$ is the required rate threshold, and $\Psi_k^{PS} = E_0^{PS} \prod_{j=1}^{k} \rho_j (1 - \rho_j) \sum_{i=0}^{L_j} \Gamma_{k-1,i} \xi_{k-1,i}^2$ as given by [15]. $\Psi_k^{PS}$ was obtained by following equivalent derivations for the SISO case given in [15] and by utilizing equations (2) and (3) to obtain the MIMO SNR. The derivation is presented in Appendix C.

6 The rate, energy, and optimization problem were derived by following steps in [15], [16], [31]–[33] by use of simple arithmetic.
Algorithm 1: Transmit Power Minimization Algorithm

repeat

\[ w_k \leftarrow \text{initialized} \]
Calculate \( Q^* \)
Calculate \( \alpha_k \) and \( \sigma_k^* \)
Update \( w_k^* \)

until \( Q^* \) converges

\[ E_{TS}^* \leftarrow \frac{1}{Q^*} \]
\[ T_{k}^* \leftarrow \left( \frac{w_k^*}{\sigma_k^*} \right) \]
\[ \alpha_k^* = 1 - \left( \prod_{j=1}^{K-1} \alpha_j \right)^{-1} \left[ Q^* \beta_k \sigma_k^2 \left( \frac{\theta_{TH,k}}{w_k^*} - 1 \right) \right] \]

B. SWIPT TS Technique

For our work, as captured in Fig. 2, we assume that the splitting ratios for either technique, is the same for each antenna. This is done to reduce computational complexity and follows directly from our decision to use the clustered antenna configuration. In Fig. 2, the difference between the TS and the PS technique lies in how the EH occurs. While the PS splits the signal power for EH and ID, the TS splits the time between EH and ID. Hence, by following a similar procedure to that presented for the SWIPT PS technique, the energy harvested at the \( k \)th node is given by

\[ E_{TS} = \alpha_k \beta_k \sum_{i=0}^{L_k} P_{k-1,i} \xi_{k,i}^2 \]

and the achievable rate is deduced as

\[ R_{TS} = (1 - \alpha_k) \log_2 \left( 1 + \frac{(1 - \alpha_k) \sum_{i=0}^{L_k} P_{k-1,i} \xi_{k,i}^2}{\sigma_k^2} \right) \]

The optimal source transmit power and PS ratio are found using Theorem 1 as follows.

**Theorem 1:** For the joint optimization problem given in (8), the optimal source transmit power, \( E_{PS}^* \), is deduced as

\[ E_{PS}^* = \sum_{k=1}^{K+1} \beta_k \gamma_{th} \sigma_k^2 \]

with the optimal PS ratio, \( \rho_k^* \), at node \( k \) defined as

\[ \rho_k^* = \left\{ \begin{array}{ll} 1 - \frac{1}{\prod_{j=1}^{K} \rho_j \sum_{k=1}^{K+1} \beta_k \gamma_{th} \sigma_k^2 \sum_{i=1}^{L} \Gamma_{k,i}} & \text{for all } k \leq K, \\ 0, & \text{for } k = K+1. \end{array} \right. \]

**Proof:** See Appendix A.

A closed-form solution was not achieved for the SWIPT TS technique - as would be seen from (50) - due to the continual presence of the variable, under optimization, \( \alpha_k \), in the final optimization solution. This is as a result of legacy values from the previous nodes (i.e., \( E_{TS} \) and \( \alpha_k^* \) are dependent on each other) in successive computations. Therefore, we propose an iterative algorithm for the TS method. For the TS technique, the theorem for determining the optimal transmit power and optimal TS ratio is provided as follows.

**Theorem 2:** For the joint optimization problem given in (11), the optimal source transmit power, \( E_{TS}^* \), and the optimal TS ratio, \( \alpha^* \), for a given total time of \( T_T \) with a rate threshold \( \gamma_{th} = R_{TH} \) can be deduced using an iterative algorithm. This iterative algorithm is presented in Algorithm 1 with \( Q^* \) defined as

\[ Q^* = \left\lfloor \sum_{k=1}^{K+1} \beta_k \sigma_k^2 \left( 2 \frac{R_{TH,k}}{w_k^*} - 1 \right) \right\rfloor^{-1} \]

**Proof:** See Appendix B.

IV. MULTI-HOP ROUTING SCHEME

In this section, we discuss the routing algorithm developed for the MIMO DF-SWIPT energy constrained wireless network. We propose Algorithm 2 by adopting a DA framework [34], [35]. Here, the weight matrix used for the DA is the inverse average inter-node channel gains (IAICG). This choice is due to the fact that the channel gain model consists of the channel effects (i.e., inter-node distance, signal fading and Rayleigh fading). Also, the larger the channel gain the smaller its inverse (i.e., the smaller the weights). Hence, by using the IAICG, the DA selects the shortest path based on the best channel gains and smallest number of nodes. In addition, the paths are selected based on the energy and rate constraint of each node. These constraints mean that each routing node must meet the rate requirement of that node (i.e., \( R_{KS} \leq R_{TH,k} \) or \( R_{KS} \geq R_{TH,k} \)). Additionally, \( E_{0}^{\Omega} \leq E_{0,\text{max}} \).

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Algorithm 2: Routing Algorithm Based on the DA

Set the source node, the destination node, and the graph matrix, $G$ with inter-node inverse average channel gains (i.e., $g_{ij} = 1/\hat{h}_{ij}^2$ with $\hat{h}_{ij} = E[H_{ij}]$)

for each vertex $v \in G$ do
  $g_{ji}[v] = \infty$, and set previous $g_{ji}[v - 1] = \text{undefined}$
  Set $g_{ji}[\text{source}] = 0$, and let $\hat{Q} = G$
  while $\hat{Q} \neq \emptyset$ do
    Set $u = v$ in $\hat{Q}$ with smallest $g_{ji}[ ]$
    Remove $u$ from $\hat{Q}$
    for all $v \in \text{neighbor}(u)$ do
      if $g_{ji}[v] < g_{ji}[u] + \text{inter-dist}(u, v)$ then
        $\tilde{g}_{ji}[v] = \text{dist}(g_{ji}[u] + \text{inter-dist}(u, v))$
        Let previous $g_{ji}[v] = u$
      end if
    end for
  end while
  Calculate $E_{0}^{\hat{Q}}$ with returned indexes from the for loop
  if $E_{0}^{\hat{Q}} \leq E_{0,\max}$ then
    Use selected nodes for transmission
  end if

sets up another constraint where the amount of source power needed for the routing, should be at most, or equal to the power available at the source node (i.e., $E_{0}^{\hat{Q}} = E_{0}^{PS,\ast} \leq E_{0,\max}$ or $E_{0}^{\hat{Q}} = E_{0}^{TS,\ast} \leq E_{0,\max}$). If this condition does not hold, a new path is chosen.

A discussion on the routing algorithm is summarized as follows. The routing algorithm adopts a centralized method, with its implementation at the central node, that is, the source node. To begin, the source node identifies and develops a graph matrix, $G$, consisting of all the edges and vertices within the wireless network denoted by $\hat{E}$ and $\hat{V}$ respectively. The current or most recent node serving as the source node, $g_{ji}[\text{source}] = 0$, having as its new matrix $\hat{Q}$, is instantiated with values of $G$. Within $\hat{Q}$, node $g_{ji}[v] = \infty$ and the previous is made undefined (i.e., $g_{ji}[v - 1] = \text{undefined}$). This prevents the reselection of all previously selected nodes. The source node then identifies the first node connection with the lowest weighing factor $g_{ji}[v]$ which satisfies the rate and source node power constraint. At the current node, the same process is repeated until the destination node is reached. All the selected nodes after running the algorithm are used for routing.

V. IMPLEMENTATION AND ANALYSIS

This section discusses how the proposed centralized and distributed SWIPT ratio protocols could be implemented [15], [16].

We first discuss the SWIPT PS ratio technique in a centralized implementation. For the centralized method, the source node knows all the channel gains for the selected relay nodes in the network. It can therefore calculate the PS ratio for each relay node. The source node calculates the PS ratio for each node using either $\rho_{k}^{\ast}$ and the source power minimization depending on the antenna structure. After these calculations, the source node transmits the PS ratio, the selected relay nodes’ indexes, and the information signal to the first relay node. With the centralized system, the relay node $k$ must transmit its decoded information along with succeeding relay nodes’ indexes and PS ratio (i.e., $(K - k) \times i_{0}$ and $(\rho_{k}^{\ast})_{k}$, respectively) to the next relay node. In realizing a centralized approach via the SWIPT TS ratio based technique, Algorithm 1 needs to be run by the source node to find all the TS ratios and the source transmit power. Within the implementation of Algorithm 1, there are four different arithmetic equations used. Hence, its computation involves iterating over these arithmetic calculation. Therefore, the TS technique uses more computational power compared to the PS technique. However, the data transmissions at each node is the same for both the TS and PS ratio. This is because both techniques transmit actual information signal, SWIPT ratio and indices.

In the SWIPT PS distributed approach, the source node calculates the PS ratio(s) of the first relay node as

$$\rho_{1} = 1 - \bar{\psi}_{1}, \quad (15)$$

$$\bar{\psi}_{1} = \frac{1}{\sum_{i=1}^{L} |h_{1,i}|^2 \sum_{j=1}^{K+1} \beta_{j}}. \quad (16)$$

The source node then transmits its information signal, $\rho_{1}$, $\bar{\psi}_{1}$, and all relay node indexes to the first relay node. The $k$th relay node calculates the $k + 1$ relay’s PS ratio(s) as

$$\tilde{\psi}_{k+1} = \frac{1}{\sum_{i=1}^{L} \rho_{k+1,i} |h_{k+1,i}|^2} \bar{\psi}_{k}, \quad (17)$$

where $k = 1, \ldots, K - 1$ [4].

The current $k$ relay node transmits its decoded information, $\rho_{k+1}$, $\tilde{\psi}_{k+1}$, and the $K - k$ relay nodes’ indexes to the next $k + 1$ relay node.

The advantage of the centralized system is that the relay nodes do not have any computational burden with respect to the PS ratio calculation. However, the first few relay nodes would have a large amount of data bits to process and forward depending on the number of succeeding relay nodes’ PS ratios transmitted to it. The DF process may be affected if the relay nodes do not have enough memory (i.e., computational processing power). However, with the distributed system, each node receives fewer data bits for DF functions in comparison with the centralized system. The drawback of the distributed system is that the relay needs to compute variables $\rho_{k+1}$ and $\bar{\psi}_{k+1}$ before retransmission to the next node. The SWIPT TS technique will be more challenging to implement using a distributed method because a single node (which is the source node) calculates and implements Algorithm 1.\footnote{The node which will serve as the central node in a distributed system will need to know each internode channel gain to be able to use Algorithm 1. This is less practically feasible.}
TABLE 1. Comparison of PS and TS ratio schemes—optimal solutions.

| SWIPT PS Configuration | PS ratio Scheme | Optimal PS ratio | Distributed Method |
|-------------------------|----------------|------------------|--------------------|
| Fixed PS ratio scheme   | Centralized Method | Relay Node | Source | Relay Node |
| Communicating Node      | Source           | Relay Node      | Source | Relay Node |
| Computational Complexity | $O((K+1)J)$        | $O(J)$          | $O(J)$          |
| Transmit Bits           | $K \{t_0 \log_2 K + B + F\}$ | $K \{t_0 \log_2 K + B + F\}$ | $K_i \log_2 K + 2B + F$ |
| CSI Requirement         | Global CSIIs      | Global CSIIs    | Local CSIIs       |

TABLE 2. Comparison of PS and TS ratio schemes—fixed ratio solutions.

| SWIPT TS Configuration | TS ratio Scheme | Optimal TS ratio | Distributed Method |
|-------------------------|----------------|------------------|--------------------|
| Fixed TS ratio scheme   | Centralized Method | Relay Node | Source | Relay Node |
| Communicating Node      | Source           | Relay Node      | Source | Relay Node |
| Computational Complexity | $O(A) \times O((K+1)J)$ | $\times$          | $\times$          |
| Transmit Bits           | $K \{t_0 \log_2 K + B + F\}$ | $K \{t_0 \log_2 K + B + F\}$ | $\times$          |
| CSI Requirement         | Global CSIIs      | Global CSIIs    | $\times$          |

Next, we consider the implementation and complexity analysis for fixed PS and TS ratio schemes. With the fixed PS and TS ratio schemes, the source node calculates the minimum required energy for both SWIPT configurations as

$$E_{PS, fix}^{PS} = \sum_{k=1}^{K+1} \beta_k \alpha_k \sigma_k^2 \frac{\Gamma_{k,i}}{2},$$

(18)

and

$$E_{TS, fix}^{TS} = \sum_{k=1}^{K+1} \beta_k \alpha_k \sigma_k^2 \left(\frac{2^{R_{TH,k}} - 1}{\frac{1}{2}^k} - 1\right),$$

(19)

where $\beta_k$ and $\alpha_k$ are the fixed PS and TS ratios for each relay node, respectively. Also, the source node transmits only its information signal without performing any EH demands with the knowledge of the PS/TS ratios being the requirement of each DF-SWIPT relay. The only data transmitted to the relay nodes are the information and routing node indexes. Hence, there are no computational strains on the nodes but only the source node. However, the disadvantage with the fixed ratio schemes is that more source power is needed to successfully support communication between the source and destination node as shown in the simulation results.

A comparison between the two optimum proposed schemes, and the fixed ratio schemes are summarized in Tables 1 and 2, respectively. In the tables, $O(J)$ and $O(A)$ represent a single arithmetic operation and the implementation of an iterative algorithm, respectively. Note that $K = K - k$. Also, we assume that the actual transmitted information bit, real number bits (i.e., can be $\beta_k \alpha_k$ or $\psi_{k+1}$ value), and relay index bits broadcast from the current node to the next node to be processed are defined as $F$, $B$, and $i_0$, respectively.

VI. SIMULATION RESULTS

In this section, we evaluate the performance of the DF relaying multi-hop wireless network. To determine the validity of Algorithm 1, there is the need for use of a test of convergence. Hence, Fig. 3 is a representation of the test for that algorithm. It shows that the iterative algorithm begins to converge after 4 iterations which meets the convergence requirement - confirming that the algorithm works - of the number of iteration being greater than 2 iterations. Based on that, we present simulation results of possible practical deployment of our splitting schemes via Figs. 4 and 5. We also present plots on the behavior of the minimum source power solutions with respect to increasing system rate threshold ($R_{TH}$) in Fig. 6. Additionally, the effect of increasing source-to-destination distance (i.e., $d_T$) on the minimum source power, is shown in Fig. 7. Furthermore, our proposed scheme is compared to the fixed PS and TS ratio schemes (i.e., we set the fixed ratios as 0.5). The nodes are generated randomly, over a square...
area. With that environment, the source and destination nodes are then chosen randomly from the generated set of nodes. $\beta_k = 0.7$, error variance $= -175$ dBm, and the inter-node distance $d_k = d_T/(K + 1)$ m, where $d_T$ is the total distance between the source and the destination [15], [16]. Table 3 summarizes the various simulation parameters used in the different simulations. It presents the parameters used in our inter-node channel model as well as the number of experiments that were run. The details of the power settings for each node as well as those used for the transmitter and receiver are equally captured. The fixed splitting coefficients for our fixed scheme curves which were set to $0.5$ for both fixed TS and fixed PS. These settings aided in the generation of the results to be discussed under the subsequent sections.

A. ROUTING

Figs. 4 and 5 show various routing paths for our different DF-SWIPT schemes. The routing is done via Algorithm 2 where the maximum source power available $E_{0,\text{max}} = 30$ dBm. With each, we find the minimum source power needed for the E2E communication between the source and destination nodes for the optimal PS ratio scheme (i.e., $E_{0,\text{PS},\star}$), fixed PS ratio scheme (i.e., $E_{0,\text{PS},\text{fix}}$), optimal TS ratio scheme (i.e., $E_{0,\text{TS},\star}$), and fixed TS ratio scheme (i.e., $E_{0,\text{TS},\text{fix}}$) respectively. Finally, for the simulation topology, 50 nodes were spread over a square with dimension $(d_x \times d_y$, where $d_x = d_y = d_T$). These represent the x and y coordinate distances. From both Figs. 4 and 5, it can be observed that based on the EH scheme, the antenna configuration and channel gains, either the same or different routing paths may be selected for the information transmission. Also, as the total area increases, the minimum source power need to support communication increases. The introduction of the joint SWIPT based EH and routing functionality is a significant contribution. This is mainly due to the fact that, unlike other works which solve one problem to the neglect of the other, our work does both. The authors of [12], [14] and [36] focus exclusively on either SWIPT or energy efficiency while sticking to traditional variants of wireless routing algorithms such as the ad-hoc on demand distance vector (AODV) and other flavors of the immediate neighbor algorithm. As such the benefits accrued from the EH stage is not translated into routing decision making processes. Thus, the works that consider energy constraints tend to ignore routing altogether. Our work takes into consideration channel limitations such as pathloss and models them into our solution. It aims at mitigating their effect by offering a viable means to select the best routing path for transmissions to occur. Thus, not only is the nearest set of neighbors chosen but additionally, those that utilize the least amount of energy in transmission.

Other works [37], consider the routing problem but do not present SWIPT based EH routing, as an option. Here again our work offers a solution; not just for one scheme but for two (i.e., via PS and TS). This is very useful practically as it provides a tractable means to select the best scheme in the deployment of any such related system in a practical setting.

B. ENERGY MINIMIZATION

From Fig. 6, we notice that the minimum amount of source power needed increases with an increasing SNR.
threshold (i.e., from 0 bps/Hz to 0.14 bps/Hz). It must be noted that although some previous works have worked on problems in the wireless domain which address TS/PS based SWIPT approaches, they are mainly limited in being constrained to SISO or multi-input single-output (MISO) domains [12], [15]. This is where our work stands out by handling such benefits to the MIMO domain in a far more wieldy means via additional routing. Thus in presenting these results, two different MIMO configuration with antennas numbers of 2 and 5, are used; being bench-marked against the previously existing SISO (\(L = 1\)) PS system. The two MIMO configurations are seen to completely outperform their SISO counterpart; with an energy demand drop of about 100 dBm and 150 dBm in comparison to MIMO (\(L = 2\)) and MIMO (\(L = 5\)) respectively.

Focusing specifically on the two different MIMO setups, it is noticeable that under the same scheme for these different antenna configurations, there is an increase of about 50 dBm in transmit power demand. It is observable that an increase in antenna number results in a lower minimum energy requirement. This can be confirmed with deductions from our closed-form solutions on the required minimum source transmit power. Also noticeable is the fact that, the PS configuration in also settings needs less \(E_0\) (i.e., \(E_0^{PS}\)) to facilitate communication as compared to its corresponding TS setup. In addition, the optimal schemes outperformed their fixed ratio counterparts in terms of minimum \(E_0\) (i.e., \(E_0^{TS}\)).

Next, we discuss how the channel structure also influences the minimum \(E_0\) needed for the E2E communication in Fig. 7. The inter-node distances are known to influence the large scale fading. As such, by increasing the inter-node distances from 10 m to 30 m, we observed that the minimum \(E_0\) required also increases. Observably, the MIMO models again outperform the benchmark SISO model, with a drop of about 80 dBm between \(L = 1\) and \(L = 2\) as well as about 130 dBm between \(L = 1\) and \(L = 5\). It should be noted that TS-SWIPT routing which is introduced into the SISO domain by our work is less efficient than its PS alternative, but any such drawback could be addressed by switching to the MIMO domain addressed in addition by our work. Fig. 7, also highlights the better performance of the PS scheme in relation to the TS scheme. The plot reveals that the optimal schemes outperform their corresponding fixed ratio techniques. For example, there is about a 20 dBm increase in power demand in moving from an optimal PS scheme to its corresponding fixed ratio scheme with \(L = 5\). This can be seen from Fig. 7. Furthermore, a decrease in the number of antennas from 5 to 2 corresponds to an increase in the minimum \(E_0\) needed to support source-to-destination communication for all the schemes under consideration.

Also of interest, is the effect of the channel estimation error on the minimum energy harvested. Fig. 8 gives the result of this investigation with similar benefits of switching to optimized MIMO routing from the benchmark SISO system realized as was observed in Figs. 6 and 7. It confirms our mathematical models which make the prediction that as the channel estimation error increases, the required energy...
needed for transmission will increase as well. Physically, this could be interpreted as a having the state of channel progressively worsening, and draining up more of the resources needed for transmission. So as $\sigma_E^2$ approaches 1, the energy demands shoots towards infinity. This implies that, transmission under such circumstances will be impossible.

Fig. 9 shows a plot of the minimum transmit energy versus the number of antennas at each node. As revealed, the energy required for transmission, reduces with an increase in the number of antennas at each node. Again, each optimal protocol performs better than its corresponding fixed ratio method with. This is studied under the influence of the two different channel estimation errors being considered. The plot captures that as the channel estimation error increases from 0 to 0.3, the minimum source transmit energy needed also increases. Such consistency could be explained by the fact that, an increase in channel estimation error implies more losses. Compounded by an additional scenario of non-optimal power splitting, a greater amount of power will be needed to perform the same transmission [22]. Here again, the optimal PS outperforms its TS counterpart. These results are consistent with the mathematical formulations and analysis which were done in the previous sections.

C. ENERGY HARVESTED

To investigate the minimum amount of energy harvested at each node under the different schemes, we look at Fig. 10. For a setup having a two relay node configuration, it can be seen that, node 1 has more energy harvested than node 2 due to its greater proximity to the source. Generally, the nodal energy harvest is the same for both PS and TS; ranging between -70 dBm to 65 dBm for node 1 and -85 dBm to 65 dBm for node 2. However, the overall cumulative effect is greater in PS than TS which further explains why a greater amount of energy is require for source to destination transmission for a given threshold as was previously identified in Fig. 6.

VII. CONCLUSION

This paper has investigated a MIMO DF-SWIPT EH multi-hop relay configuration in a wireless network. The MIMO DF-SWIPT relay nodes facilitate communication between a source and a destination node using EH. First, we optimized the PS ratios with the aim of minimizing the source transmit power. We then obtained closed-form solutions for the minimum source power and the PS ratio at each DF-SWIPT relay node based MIMO SWIPT antenna configuration. In addition an iterative algorithm has been presented for the equivalent TS configuration of a similar system. Next, both the optimal PS and TS ratio schemes have been compared to their corresponding fixed TS and PS ratio fixed ratio schemes in terms of resource consumption (i.e., source power consumed and computational complexity) and overhead analysis. From our closed-form solutions, we proposed a routing algorithm based on Dijkstra’s shortest path algorithm. In this work, we consider the simple case of multi-antenna system for our initial research analysis and presentation of our DF-SWIPT PS and TS proposed communication models.

In demonstrating the novel nature of our work, we benchmarked our work by comparing it with a preexisting SISO solution [15], [16]. We further argued the uniqueness of our contribution by pointing out the impact of our new SWIPT based routing algorithm in ensuring efficient (PS/TS)-centric transmission. Additionally, it distinguishes itself as one that applies this new algorithm in the MIMO realm. Different performance metrics were presented to validate our assertions. This work sought through its different sections to re-highlight and justify the contributions outline in section I and as a result, to draw out the promising implications for further research. For instance, the current work considered a homogeneous network where all the antennas are assumed to be the same. However we could extend this to a heterogeneous multi-antenna network system with SWIPT-TS support. Additionally, we used DF in our work so an alternative protocol such as AF relay configuration could also be considered for future works. The system model used could also be adapted to wireless domains such as wireless sensor
networks (WSNs). The channel models under such architectures could focus more on the different environments and the effect of large-scale fading. Also, the computational complexity section of our work could be extended into more hardware-focused areas, e.g., to consider protocol overhead (under the assumption of packet aggregation) and the RF interface duty cycle. It is envisaged that such additional considerations could benefit other wireless domains.

**APPENDIX A**

**PROOF OF THEOREM 1**

The original problem as presented in (8) is given as

\[
\begin{align*}
\text{minimize } & E_0^{PS} \\
\text{subject to } & \psi_k^{PS} \geq \bar{\gamma}_{th}, \quad E_0^{PS} \geq 0, \\
& 0 \leq \rho_k \leq 1, \quad k = 1, \ldots, K + 1,
\end{align*}
\]

where

\[
\psi_k^{PS} = E_0^{TS} \prod_{j=1}^{k-1} (1 - \rho_j) \sum_{i=0}^{L_k} \lambda_k, \quad k = 1, \ldots, K + 1.
\]

To solve (20), we first reformulate it as

\[
\begin{align*}
\min_{\{A_k\}_{k=0}^{K+1}} & \frac{1}{Q} \\
\text{s.t. } & (A_{k-1} - A_k) \geq Q \frac{\beta_k \sigma_k^2 \bar{\gamma}_{th,k}}{\sum_{i=0}^{L_k} \Gamma_k,i}, \quad k = 1, \ldots, K + 1 \\
& A_k \leq A_{k-1}, \quad k = 1, \ldots, K + 1 \\
& Q \geq 0
\end{align*}
\]

where \(A_0 \triangleq 0, A_k \triangleq \prod_{j=1}^{k} \rho_j\) and \(Q \triangleq \frac{1}{E_0^{PS}}\).

The Lagrangian of (21) is given as

\[
\mathcal{L} \left[ Q, \{A_k\}_{k=0}^{K+1}, \{\lambda_k\}_{k=0}^{K+1} \right] = \frac{1}{Q} + \sum_{k=1}^{K+1} \lambda_{k-1} Q \frac{\beta_k \sigma_k^2 \bar{\gamma}_{th,k}}{\sum_{i=0}^{L_k} \Gamma_k,i} \\
+ \sum_{k=1}^{K+1} (A_{k-1} - A_k) \lambda_k - \lambda_0, \\
\lambda_k \geq 0, \quad \lambda_{K+1} \geq 0
\]

\[
(22)
\]

\(\lambda_k\) and \(\lambda_{K+1}\) are the dual variables of the first constraint from (21) and \(A_{K+1}\), respectively. Next, we present the Karush-Kuhn-Tucker (KKT) contractual conditions as

(a) Primal feasibility:

\[
Q \frac{\beta_k \sigma_k^2 \bar{\gamma}_{th,k}}{\sum_{i=0}^{L_k} \Gamma_k,i} - (A_{k-1} - A_k) \leq 0, \quad k = 1, \ldots, K + 1.
\]

\[
(23)
\]

(b) Dual feasibility:

\[
\lambda_k \geq 0, \quad \lambda_{K+1} \geq 0.
\]

(c) Vanishing gradient:

\[
\frac{\partial \mathcal{L}}{\partial Q} = -\frac{1}{Q} + \sum_{k=1}^{K+1} \lambda_{k-1} \frac{\beta_k \sigma_k^2}{\sum_{i=0}^{L_k} \Gamma_k,i} = 0 \\
\frac{\partial \mathcal{L}}{\partial A_k} = \lambda_{k-1} - \lambda_k = 0 \text{ for } k = 1, \ldots, K.
\]

(d) Complementary slackness:

\[
Q^* \frac{\beta_{k+1} \sigma_k^2 \bar{\gamma}_{th,k+1}}{\sum_{i=0}^{L_k} \Gamma_{k+1,i}} = (A_k^* - A_{k+1}^*), \quad A_{K+1} = 0, \quad k = 1, \ldots, K + 1.
\]

Working with (22) and following a similar series of steps as presented in [15], we obtain the optimal minimum source power \(E_0^{PS,*}\) and \(\lambda_0^*\) as

\[
E_0^{PS,*} = \frac{1}{Q^*} \sqrt{\sum_{k=1}^{K+1} \frac{\beta_k \sigma_k^2 \bar{\gamma}_{th,k}}{\sum_{i=0}^{L_k} \Gamma_k,i}}
\]

and

\[
\lambda_0^* = \sum_{k=1}^{K+1} \frac{\beta_k \sigma_k^2 \bar{\gamma}_{th,k}}{\sum_{i=0}^{L_k} \Gamma_k,i}
\]

\[
(29)
\]

respectively.

Placing (29) into (28), yields

\[
E_0^{PS,*} = \sum_{k=1}^{K+1} \frac{\beta_k \sigma_k^2 \bar{\gamma}_{th,k}}{\sum_{i=0}^{L_k} \Gamma_k,i}.
\]

Finally, fixing (29) into (20) gives \(\rho_k^*\) as

\[
\rho_k^* = \frac{1 - \prod_{j=1}^{k} \rho_j}{\sum_{i=0}^{L_k} \Gamma_k,i}, \quad \forall k, \quad k = K + 1.
\]

\[
(31)
\]

**APPENDIX B**

**PROOF OF THEOREM 2**

For the TS protocol, the original problem below is non-convex

\[
\begin{align*}
\min_{\rho_k, \alpha_k} & E_0^{TS} \\
\text{s.t. } & (1 - \alpha_k) T_k \\
& \log_2 \left( 1 + \frac{E_0^{TS} \sum_{i=0}^{L_k} \Gamma_k,i \prod_{j=1}^{k-1} \alpha_j (1 - \alpha_k)}{\beta_k \sigma_k^2} \right) \\
& \geq R_{TH,k}, \\
& 0 \leq \alpha_k \leq 1, \\
& \sum_{k=1}^{K} T_k \leq T_T
\end{align*}
\]

\[
(32)
\]
where $E_{TS}^{\alpha} = 1/Q$, and $R_{TH,k}$ is the rate threshold. Therefore, in reconstructing a convex problem from (32), certain new variables are introduced; $w_k = (1 - \alpha_k) T_k$ with its optimal value being assumed to be known as $w_k^*$. With that, $\sum_{k=1}^{K+1} w_k^2/\left(1-\alpha_k^2\right) = T_T \implies w^T a^* = T_T$. The vector $w = [w_1, w_2, \ldots, w_k]$, and $a^* = \left[\frac{1}{1-\alpha_1}, \frac{1}{1-\alpha_2}, \ldots, \frac{1}{1-\alpha_T}\right]$. Additionally, $\prod_{j=1}^{K-1} \sigma_j(1 - \alpha_k)$ is redefined as $A_{k-1} - A_k$. Thus for TS, $w_k^*$ is computed as

$$w_k^* = T_T \times \frac{|a^*|}{||a^*||}$$

Rewriting the objective function as $f(x) = \frac{1}{Q} E_{TS}^\alpha$, a reformulation of the problem then becomes

$$\min_{w_k, A_k, Q} \frac{1}{Q} s.t. w_k \log_2 \left[1 + \sum_{k=1}^{K+1} \beta_k \sigma_k \left(A_{k-1} - A_k\right)\right] \geq R_{TH,k}$$

With a little algebraic manipulation, its primal could also be rewritten as, $g_k(x) = A_k - A_k \geq \frac{Q}{\sum_{k=1}^{K+1} \Gamma_{k,i}} \left(2^{\frac{R_{TH,k}}{w_k}} - 1\right)$. Hence, the completely reformulated problem, is now given as

$$\min_{w_k, A_k, Q} \frac{1}{Q} s.t. Q \beta_k \sigma_k \left(\frac{R_{TH,k}}{w_k} - 1\right) - (A_k - A_k) \leq 0.$$  

The Lagrangian auxiliary function for (34) is given as

$$\mathcal{L} \left[Q, \{A_k\}_{k=1}^{K+1}, \{w_k\}_{k=0}^{K+1}\right] = \frac{1}{Q} + \sum_{k=1}^{K+1} \lambda_{k-1} - \sum_{i=1}^{K+1} \lambda_k \left(2^{\frac{R_{TH,k}}{w_k}} - 1\right) Q + \sum_{k=1}^{K+1} \left(\lambda_k - \lambda_k\right) A_k - \lambda_0.$$  

For brevity, let $\mathcal{L} \left[Q, \{A_k\}_{k=1}^{K+1}, \{w_k\}_{k=0}^{K+1}\right] = \mathcal{L}$. We present the KKT contractual conditions as

(a) Primal feasibility:

$$g_k(x) \leq 0 \text{ for } k = 1, \ldots, K.$$  

(b) Dual feasibility:

$$\lambda_k \geq 0 \text{ for } k = 1, \ldots, K.$$  

(c) Vanishing gradient:

$$\frac{\partial \mathcal{L}}{\partial Q} = -\frac{1}{Q^2} + \sum_{k=1}^{K+1} \lambda_k \lambda_k \left(2^{\frac{R_{TH,k}}{w_k}} - 1\right).$$  

(d) Complementary slackness:

$$\sum_{k=1}^{K+1} \lambda_k \lambda_k \left(2^{\frac{R_{TH,k}}{w_k}} - 1\right) Q = 0.$$  

From (39)

$$\lambda_0 = \lambda_1 = \lambda_2 = \ldots = \lambda_K = \lambda.$$  

Substituting (42) into (38)

$$\lambda \sum_{k=1}^{K+1} \beta_k \sigma_k \left(2^{\frac{R_{TH,k}}{w_k}} - 1\right) = \frac{1}{Q^2}(43)$$

Using condition (c) above and taking note of complementary slackness under the case of constraint (34) being active (i.e. $\lambda > 0$), we have

$$\lambda \left[\sum_{k=1}^{K+1} \left(A_k - A_k\right) - Q \sum_{i=1}^{K+1} \lambda_k \left(2^{\frac{R_{TH,k}}{w_k}} - 1\right)\right] = 0.$$  

From (45), we obtain:

$$1 = \sum_{k=1}^{K+1} \left(A_k - A_k\right) - Q \sum_{i=1}^{K+1} \lambda_k \left(2^{\frac{R_{TH,k}}{w_k}} - 1\right).$$  

Thus, the final expression for the optimal value of energy $Q^*$, obtained as

$$Q^* = \left[\sum_{k=1}^{K+1} \beta_k \sigma_k \left(2^{\frac{R_{TH,k}}{w_k}} - 1\right)\right]^{-1}.$$  

Finally, from (46), the expression for finding the optimum TS ratio at relay node $k$ is given as

$$a_k = 1 - \left[\prod_{j=1}^{K-1} \sigma_j\right]^{-1} \left[Q^* \beta_k \sigma_k \left(2^{\frac{R_{TH,k}}{w_k}} - 1\right)\right].$$  

Equations (33), (49) and (50), are each used in Algorithm 1 for our subsequent simulations to find the necessary optimal values.
APPENDIX C

DERIVATION OF $\Psi_{k}^{PS}$

We follow a similar set of steps as presented in [15] for the SISO case, to arrive at our MIMO formulation (i.e., the multiple antennas) for both $\Psi_{k}^{PS}$ and $\Psi_{k}^{TS}$. We present here, the steps for only $\Psi_{k}^{PS}$ as $\Psi_{k}^{TS}$'s derivation results from an identical procedure. Thus the derivation is as follows:

From [15] the energy harvested at relay 1 is shown to be:

$$E_{1} = \rho_{1}E_{0} \sum_{i=0}^{L_{1}} \xi_{1,i}^{2} \beta_{1,i}$$

(51)

The SNR resulting from information decoding at $\gamma_{1}^{ID}$ gives:

$$\gamma_{1}^{ID} = \frac{\sum_{i=0}^{L_{1}} E_{0} \xi_{1,i}^{2} \beta_{1,i} (1- \rho_{1})}{\sigma_{1}^{2}}$$

Assuming that $\delta^{2} \ll \sigma^{2}$

$$\gamma_{1}^{ID} = \frac{\sum_{i=0}^{L_{1}} E_{0} \xi_{1,i}^{2} \beta_{1,i} (1- \rho_{1})}{\sigma_{1}^{2}}$$

(52)

Similarly, $E_{2}$ and $\gamma_{2}^{ID}$ can be calculated respectively as:

$$E_{2} = \rho_{2} \left( \rho_{1}E_{0} \sum_{i=0}^{L_{2}} \xi_{2,i}^{2} \beta_{2,i} \right) \left( \sum_{i=0}^{L_{2}} \xi_{2,i}^{2} \beta_{2,i} \right)^{-1}$$

(53)

and

$$\gamma_{2}^{ID} = \left( \rho_{1}E_{0} \sum_{i=0}^{L_{2}} \xi_{2,i}^{2} \beta_{2,i} \right) \left( \rho_{2} \sum_{i=0}^{L_{2}} (\xi_{2,i}^{2}) \right)^{-1}$$

(54)

Using equations (52) and (54), the generalized equation for SNR is reached as:

$$\gamma_{k}^{ID} = \frac{E_{0} \prod_{j=1}^{k-1} \rho_{j} (1- \rho_{k}) \prod_{i=0}^{L_{k}} \xi_{j,i}^{2} \beta_{j,i}}{\sigma_{j}^{2} \beta_{j,i}}$$

$$= \frac{E_{0} \prod_{j=1}^{k-1} \rho_{j} (1- \rho_{k}) \prod_{i=0}^{L_{k}} \xi_{j,i}^{2} \beta_{j,i}}{\sigma_{j}^{2} \beta_{j,i}}$$

(55)

Setting the numerator to $\psi_{k}$, we have

$$\psi_{k} = E_{0} \prod_{j=1}^{k-1} \rho_{j} (1- \rho_{k}) \prod_{i=0}^{L_{k}} \xi_{j,i}^{2} \beta_{j,i}$$

$$\therefore \gamma_{k}^{ID} = \frac{\psi_{k}}{\beta_{j} \sigma_{j}^{2}}$$

(56)

From (56) and with $\Gamma_{k,i} \triangleq \prod_{j=1}^{k} \beta_{j,i} \xi_{j,i}^{2}$, both $\psi_{k}^{PS}$ and $\psi_{k}^{TS}$ can be derived as:

1) ENERGY HARVESTED AT EACH NODE - PS

$$\psi_{k}^{PS} = E_{0}^{PS} \prod_{j=1}^{k-1} \rho_{j} (1- \rho_{k}) \sum_{i=0}^{L_{k}} \Gamma_{k-1,i} \xi_{k,i}^{2}$$

(57)

2) ENERGY HARVESTED AT EACH NODE - TS

$$\psi_{k}^{TS} = E_{0}^{TS} \prod_{j=1}^{k-1} \rho_{j} (1- \rho_{k}) \sum_{i=0}^{L_{k}} \Gamma_{k-1,i} \xi_{k,i}^{2}$$

(58)

All variables are as defined previously in the paper.

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**KWADWOOD BOATENG OFORI-AMANOFO** (Member, IEEE) received the B.Sc. and M.Phil. degrees in computer engineering from the University of Ghana (UG), Ghana, in 2010 and 2014, respectively. He is currently pursuing the Ph.D. degree with the Department of Electronic and Control Engineering, Hanbat National University, South Korea. His research interests include wireless information and power transfer, physical layer security, and machine learning.

**KYOUNG-JAE LEE** (Senior Member, IEEE) received the B.S., M.S., and Ph.D. degrees from the School of Electrical Engineering, Korea University, Seoul, South Korea, in 2005, 2007, and 2011, respectively. In 2006, he interned with Beceem Communications, Inc., Santa Clara, CA, USA, and he visited the University of Southern California at Los Angeles, Los Angeles, CA, as a Visiting Student, in 2009. He was a Research Professor with Korea University, in 2011. From 2011 to 2012, he was a Postdoctoral Fellow with the Wireless Networking and Communications Group, The University of Texas at Austin, Austin, TX, USA. Since 2012, he has been with the Department of Electronic Engineering, Hanbat National University, Daejeon, South Korea, where he is currently a Professor. In 2020, he was a Visiting Professor with the University of Southern California. His research interests include communication theory, signal processing, and information theory applied to the next-generation wireless communications. He was a recipient of the Best Paper Award at IEEE VTC Fall, in 2009, the IEEE ComSoc APB Outstanding Paper Award, in 2013, and the IEEE ComSoc APB Outstanding Young Researcher, in 2013. He currently serves as an Associate Editor for Journal of Communications and Networks.

**DEREK KWAKU POBI ASIEDU** (Member, IEEE) received the B.Sc. degree in biomedical engineering from the University of Ghana (UG), Ghana, in 2011, the M.S. degree in computer engineering from the Department of Computer Engineering, UG, in 2017, and the M.Sc. and Ph.D. degrees in electronic engineering from Hanbat National University (HBNU), South Korea. He did his Post-doctoral Research Fellowship with the Wireless Intelligent Systems Laboratory, Hanbat National University, from September 2019 to December 2020. He has been a Research Assistant Professor with the Seoul National University of Science and Technology (SeoulTech), since May 2021. His research interests include wireless information and powered transfer applications in the Internet-of-Things networks, backscatter communication in next-generation wireless communication, massive MIMO, cell-free massive MIMO and full-duplex wireless communication, machine learning applications in wireless communication, physical layer security, next-generation wireless communication technologies, and biomedical wireless communication signal processing.

**ROGER KWAO AHIDORMEY** (Member, IEEE) received the B.Sc. degree in electrical/electronic engineering from the Kwame Nkrumah University of Science and Technology, Ghana, in 2012, and the M.S. and Ph.D. degrees in electronic engineering from Hanbat National University, South Korea, in 2016 and 2020, respectively. He was a Postdoctoral Research Fellow with the Department of Electronic Engineering, Hanbat National University, in 2020. He is currently a Research Assistant Professor with the Department of Information and Communication Engineering, Yeungnam University, South Korea. His research interests include physical layer security, power line communication, and massive MIMO.