Optimal Centralized Dynamic-Time-Division-Duplex Scheduling Scheme for a General Network of Half-Duplex Nodes

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Abstract

In this paper, we propose optimal centralized dynamic-time-division-duplex (D-TDD) scheduling scheme for a general network comprised of K half-duplex (HD) nodes. For this network, we propose optimal adaptive scheduling of the reception, transmission, and silence at every node such that the average sum signal-to-interference-plus-noise-ratio (SINR) of the network is maximized. To this end, the proposed scheme uses the channel gains of all links in the network to make an optimal decision of which node should receive, transmit, or be silent in a given time slot such that the average sum SINR of the network is maximized. The numerical results show that the proposed optimal centralized D-TDD scheme achieves significant SINR gains over existing centralized D-TDD schemes.

I. Introduction

In general, time-division duplex (TDD) communication between half-duplex (HD) nodes in a network can be static or dynamic. In static-TDD, each node allocates a fraction of the total number of time slots for transmission and the rest of the time slots for reception regardless of the channel conditions and the interference in the network [1]. Due to the scheme being static, the time slots in which the nodes perform reception and the time slots in which the nodes perform transmission are prefixed and unchangeable over time [2]. On the other hand, in dynamic

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(D)-TDD, each time slot can be dynamically allocated either for reception or for transmission based on the channel gains of the links in the network in order to maximize the overall network performance. Thereby, D-TDD schemes achieve a much better performance compared to static-TDD schemes. As a result, D-TDD schemes have attracted significant research interest, see [3], [4] and references therein.

D-TDD schemes can be implemented in either distributed or centralized fashion. In distributed D-TDD schemes, the individual nodes, or a group of nodes, make their decision for transmission, reception, or silence without synchronizing with rest of the nodes in the network [3]–[7]. Hence, in distributed D-TDD at the start of each transmission time slot, a node is not aware of the decisions made by the other nodes. As a result, the decisions made by the nodes can not maximize the overall network performance. On the other hand, in centralized D-TDD schemes, the decision for a node to receive, transmit or be silent in a given time slot is performed at a central processor in the network, which then informs the nodes about the decision. In this way, the receptions, transmissions, and silences of the nodes are synchronized by the central processor in order to maximize the overall network performance. To this end, centralized D-TDD schemes require full channel state information (CSI) of all links at the central processor, which is not practical. However, the performance of a centralized D-TDD is valuable since it serves as an upper bound on the performance of any distributed D-TDD scheme. Motivated by this, we investigated optimal centralized D-TDD schemes in this paper.

Centralized D-TDD schemes for a general network are investigated in [8]–[12]. The work in [8] proposes a centralized D-TDD scheme, where instead of an acting central processor, the nodes reach to a global decision using cooperation, which is a heuristic and a non-optimal solution. On the other hand, the authors in [13] use a central processor and a game-theoretic approach to achieve a global solution. However, due to difficulty of the underlying problem, the solution could only be obtained by a reinforcement learning approach, which may not lead to the optimal solution. The work in [10] proposes a centralized D-TDD scheme for a general network where the decisions for transmission and reception at the nodes are chosen from a finite and predefined set of configurations, which is not optimal and severely limits the network performance. A network comprised of two-way links is investigated in [11], where the proposed scheme has the freedom to select the transmission and the reception of the nodes in a given time slot. The difficulty of the problem also leads to a sub-optimal solution being proposed in [11].

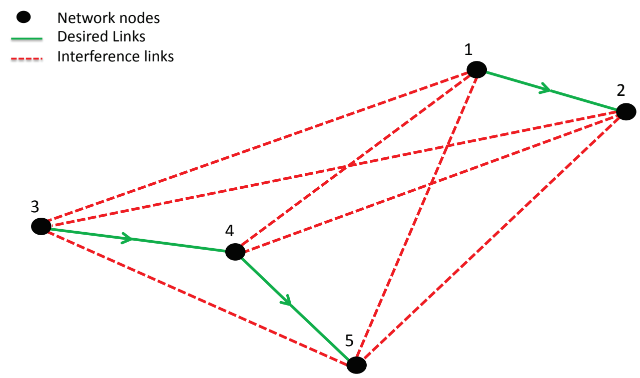

Figure 1. A general network comprised of 10 HD nodes

The work in [12] investigates a general network, where the nodes can select to transmit, receive, or be silent in a given time slot. However, the proposed solution in [12] is again sub-optimal due to the difficulty of the investigated problem. To the best of our knowledge there is no optimal centralized D-TDD in the literature, i.e., a solution to the problem of optimal scheduling of the transmissions, receptions, and silences of the nodes of a general network, which is another motivation for the work in this paper

In this paper, we propose optimal centralized D-TDD scheduling scheme for a general network comprised of K half-duplex (HD) nodes. In particular, we propose optimal scheduling of the reception, transmission, and silence at every node in a given time slot such that the performance of the network in term of signal-to-interference-plus-noise-ratio (SINR), is maximized. The simulation results show that the proposed optimal centralized D-TDD scheme achieves significant gains over existing centralized D-TDD schemes.

II. System Model and Problem Formulation

A. System Model

We consider a general network comprised of K HD nodes, where each node can wirelessly communicate with rest of the nodes in the network either as a receiver in order to receive information from the other nodes, or as a transmitter in order to send information to the other nodes. In the considered general network, we assume that there exist a link between any two nodes in the network. Each link is assumed to be impaired by independent flat fading, which is modelled via the channel gain. If the channel gain between two nodes is zero during the entire transmission time, then this means that the wireless signal sent from one of the nodes can not propagate and reach the other node. Otherwise, if the channel gain is non-zero, this means that the wireless signal sent from one of the nodes can reach the other node. Obviously, not all of the links leading to a given node carry desired information and are thereby desired. There are links which carry undesired information to the considered node, which are referred to as interference links. An interference link causes the signal transmitted from a given node to reach an unintended destination node, and acts as interference. For example, in Fig. 1, node 2 wants to receive information from node 1. However, since nodes 3 or 4 are also transmitting in the same time slot, node 2 will experience interference from nodes 3 or 4, depending on which node is transmitting in the considered time slot. Similarly, nodes 4 and 5 experience interference from node 1. It is easy to see that for node 2 it is beneficial if all other nodes, except node 1, are either receiving or silent. However, such a scenario would be harmful for the rest of the network nodes since they will not be able to receive and transmit any data.

B. Channel Model

We assume that each node in the considered network is impaired by unit-variance additive white Gaussian noise (AWGN), and that the links between the nodes are impaired by block fading. Let the transmission on the network be carried-out over $T \to \infty$ time slots, where a time slot is small enough such that the fading on all network links can be considered constant during a time slot. Hence, the fading gains are assumed to change only from one time slot to the next and not within a time slot. Let $g_{j,k}(i)$ denotes the fading coefficient of the channel between nodes j and k in the considered network.

C. Problem Formulation

The main problem in the considered general network is to find the optimal state of each node (receive, transmit, or be silent), based on global knowledge of the channel fading gains, such that the performance of the network, in terms of sum SINR, is optimized [11]. Our task here is to derive the optimal reception-transmission scheduling scheme of the network nodes which maximizes the performance of the network in term of average sum SINR .

Remark 1: Note that the optimal state of the nodes of the network (i.e., receive, transmit, or silent) in each time slot can also be obtained by brute-force. Even if this is possible for a small network, an analytical solution of the problem will provide depth insights into the corresponding problem.

Remark 2: In this paper, we only optimize the reception-transmission schedule of the nodes, and not the transmission coefficients of the nodes, which leads to interference alignment [14]. Combining adaptive reception-transmission with interference alignment is left for future work.

D. Framework For Solving the Problem

Since all nodes operate in the HD mode, in time slot i, each node can either receive (r), transmit (t), or be silent (s). To model the modes of the nodes in each time slot, we define the following binary variables for node k in time slot i

$$r_k(i) = \begin{cases} 1 & \text{if node } k \text{ receives in time slot } i \\ 0 & \text{otherwise,} \end{cases} \quad (1)$$

$$t_k(i) = \begin{cases} 1 & \text{if node } k \text{ transmits in time slot } i \\ 0 & \text{otherwise,} \end{cases} \quad (2)$$

$$s_k(i) = \begin{cases} 1 & \text{if node } k \text{ is silent in time slot } i \\ 0 & \text{otherwise.} \end{cases} \quad (3)$$

Since node k can be in one and only one mode in each time slot, i.e., can either receive, transmit, or be silent, the following has to hold

$$r_k(i) + t_k(i) + s_k(i) = 1, \ \forall k. \quad (4)$$

Note that for the purpose of simplifying the analytical derivations, it is more convenient to represent (4) as

$$r_k(i) + t_k(i) \in \{0, 1\}, \ \forall k, \quad (5)$$

where if $r_k(i) + t_k(i) = 0$ occurs, it means that the node k is silent in time slot i.

Now, using the binary variables in (1)-(3), let us define the vectors $\mathbf{r}(i)$, $\mathbf{t}(i)$, and $\mathbf{s}(i)$ as

$$\mathbf{r}(i) = [r_1(i),\ r_2(i),\ ...,\ r_K(i)], \tag{6}$$

$$\mathbf{t}(i) = [t_1(i),\ t_2(i),\ ...,\ t_K(i)], \tag{7}$$

$$\mathbf{s}(i) = [s_1(i),\ s_2(i),\ ...,\ s_K(i)]. \tag{8}$$

Hence, the k-th element of the $\mathbf{r}(i)$/$\mathbf{t}(i)$/$\mathbf{s}(i)$ vector is $r_k(i)$/$t_k(i)$/$s_k(i)$, and this element shows whether the k-th node is receiving/transmitting/silent. The three vectors, $\mathbf{r}(i)$, $\mathbf{t}(i)$ and $\mathbf{s}(i)$, show which nodes in the network are receiving, transmitting, and are silent in time slot i, respectively. Note that due to (4), the elements in the vectors in (30), (7), and (8) are mutually dependent and have to satisfy the following condition

$$\mathbf{r}(i) + \mathbf{t}(i) + \mathbf{s}(i) = \mathbf{e}, \tag{9}$$

where $\mathbf{e}$ is the all-ones vector, i.e., $\mathbf{e} = [1, 1, ..., 1]$.

Let $\mathbf{G}(i)$ denote the weighted connectivity matrix of the graph of the general network in time slot i, where the (j, k) element in the matrix $\mathbf{G}(i)$ is equal to the square of the fading coefficient of the channel between nodes j and k, $|g_{j,k}(i)|^2$, divided by the noise power at node k, $\sigma_k^2 = 1, \forall k$, and denoted as $\gamma_{j,k}(i) = |g_{j,k}(i)|^2$. Note that, since the links are impaired by fading, the values of $\gamma_{j,k}(i)$ change from one time slot to the next.

Remark 3: A central processor is assumed to collect all fading gains, $\gamma_{j,k}(i)$, and thereby construct $\mathbf{G}(i)$ at the start of time slot i. This central unit will then decide the optimal values of $\mathbf{r}(i)$, $\mathbf{t}(i)$, and $\mathbf{s}(i)$, defined in (30)-(8), based on the solution of the optimization problem developed below, and broadcast these values to the rest of the nodes. Once the optimal values of $\mathbf{r}(i)$, $\mathbf{t}(i)$, and $\mathbf{s}(i)$ are known, transmissions, receptions, and silences start at the nodes in time slot i. Obviously, the gathering of global CSI at a central processor is impossible in practice. However, this assumption will allow us to compute an upper bound on the network performance which will serve as an upper bound to the performance of any distributed D-TDD.

Let $\mathbf{W}$ denote a matrix of the desired links at each node, where the (j, k) element of $\mathbf{W}$, denoted by $w_{j,k}$, is equal to 1 if node k regards the signal transmitted from node j as a desired signal, and $w_{j,k}$ is equal to 0 if node k regards the signal transmitted from node j as an interference signal. Moreover, let $\bar{\mathbf{W}}$ denote an identical matrix as $\mathbf{W}$ but with flipped binary values. Hence, the (j,k) element of $\bar{\mathbf{W}}$ assumes the value 1 if node k regards the signal transmitted from node j as interference, and the (j,k) element of $\bar{\mathbf{W}}$ is 0 when node k regards the signal transmitted from node j as a desired signal.

Remark 4: The matrix $\mathbf{W}$, and thereby also the matrix $\bar{\mathbf{W}}$, are set before the start of the transmission in the network. How a receiving node decides from which nodes it receives desired signals, and thereby from which node it receives interference signals, is unconstrained for the analyses in this paper.

Using $\mathbf{G}(i)$, $\mathbf{W}$, and $\bar{\mathbf{W}}$, we define two matrices $\mathbf{D}(i)$ and $\mathbf{I}(i)$, as

$$\mathbf{D}(i) = \mathbf{G}(i) \circ \mathbf{W}, \tag{10}$$

$$\mathbf{I}(i) = \mathbf{G}(i) \circ \bar{\mathbf{W}}, \tag{11}$$

where $\circ$ denotes the Hadamard product of matrices (i.e., the element wise multiplication of two matrices). The elements in the matrix $\mathbf{D}(i)$ are the fading gains of the desired links which carry desired information. On the contrary, the elements in the matrix $\mathbf{I}(i)$ are the fading gains of the interference links which carry undesired information. Let $\mathbf{d}_k(i)$ and $\mathbf{i}_k(i)$ denote the k-th column vector of the matrices $\mathbf{D}(i)$ and $\mathbf{I}(i)$, respectively. The vectors $\mathbf{d}_k(i)$ and $\mathbf{i}_k(i)$ show the fading gains of the desired and interference links for node k in time slot i, respectively. For example, if the third and fourth elements in $\mathbf{d}_k(i)$ are the only non-zero element and are equal to $\gamma_{3,k}(i)$ and $\gamma_{4,k}(i)$, respectively, then this means that the k-th node receives desired signals from nodes 3 and 4 in the network via channels which have squared fading gains $\gamma_{3,k}(i)$ and $\gamma_{4,k}(i)$, respectively. Similar, if the fifth and sixth elements in $\mathbf{i}_k(i)$ are the only non-zero elements and are equal to $\gamma_{5,k}(i)$ and $\gamma_{6,k}$, respectively, it means that the k-th node receives interference signals from nodes 5 and 6 in the network via channels which have squared fading gains $\gamma_{5,k}(i)$ and $\gamma_{6,k}(i)$, respectively.

Using the above notations, we state a theorem that models the SINR at node k in time slot i.

Theorem 1: Assuming that all nodes transmit with power P, then the SINR at node k in time slot i is given by

$$SINR_k(i) = r_k(i) \frac{P\,\mathbf{t}(i)\mathbf{d}_k(i)}{1 + P\,\mathbf{t}(i)\mathbf{i}_k(i)}. \tag{12}$$

Proof: Please refer to Appendix A for the proof. ■

In (12), we have obtained a very simple and compact expression for the received SINR at each node of the network in each time slot. As can be seen from (12), the SINR depends on the fading channel gains of the network via $\mathbf{d}_k(i)$ and $\mathbf{i}_k(i)$, the transmit vectors of the network via $\mathbf{t}(i)$ and $r_k(i)$[1]. Now, note that the only variables that can be manipulated in the SINR expression of node k in time slot i, given by (12), are the values of the elements in the vector $\mathbf{t}(i)$, and the value of the element $r_k(i)$. The optimum vector $\mathbf{t}(i)$ and the optimum value of $r_k(i)$, that maximizes the average sum of the SINRs at the nodes can be obtained by using following optimization problems

$$\begin{aligned}
&\underset{\mathbf{t}(i),\mathbf{r}(i),\forall i}{\text{Maximize:}} \lim_{T\to\infty} \frac{1}{T}\sum_{i=1}^{T}\sum_{k=1}^{N} SINR_k(i)\\
&\text{Subject to :}\\
&\qquad\qquad \text{C1}: t_v(i)\in\{0,1\},\ \forall v\\
&\qquad\qquad \text{C2}: r_v(i)\in\{0,1\},\ \forall v\\
&\qquad\qquad \text{C3}: t_v(i)+r_v(i)\in\{0,1\},\ \forall v.
\end{aligned} \tag{13}$$

The solution of this problem is given in the following theorem.

Theorem 2: The optimal values of the vectors $\mathbf{t}(i)$ and $\mathbf{r}(i)$ which maximizes the average sum of the SINRs at the nodes, found as the solution of (13), are given by Algorithm 1, which is explained in details in the following.

Algorithm 1 is comprised of an inner and an outer loop. Each loop has it own index, denoted by l and n, for the inner-loop and the outer-loop, respectively.

1) The inner loop: In this loop, we compute $t_v(i)$ and $r_v(i)$, in addition to three auxiliary variables $b_{j,k}(i)$, $\lambda_t^{j,k}(i)$, and $\lambda_r^{j,k}(i)$. Since the computation process is iterative, we add the index l to denote the l'th iteration. Hence, the variables $t_v(i)$, $r_v(i)$, $b_{j,k}(i)$, $\lambda_t^{j,k}(i)$ and $\lambda_r^{j,k}(i)$, in iteration l are denoted by $t_v(i)_l$, $r_v(i)_l$, $b_{j,k}(i)_l$, $\lambda_t^{j,k}(i)_l$ and $\lambda_r^{j,k}(i)_l$, respectively.

[1]Note that SINR of node k, given by (12), is zero if $r_k(i)=0$, i.e., if the k-th node does not receive in time slot i.

The variables $t_v(i)_l$ and $r_v(i)_l$ are the updates in the l'th iteration, and they are calculated as

- $[t_v(i)_l = 1$ and $r_v(i)_l = 0]$

  if $\left[\sum_{k=1}^{N} \lambda_t^{v,k}(i)_{l-1} - X(i)_n \geq \sum_{j=1}^{N} \lambda_r^{j,v}(i)_{l-1} \right.$ and $\left. \sum_{k=1}^{N} \lambda_t^{v,k}(i)_{l-1} > X(i)_n \right]$,

- $[t_v(i)_l = 0$ and $r_v(i)_l = 1]$

  if $\left[\sum_{j=1}^{N} \lambda_r^{j,v}(i)_{l-1} > \sum_{k=1}^{N} \lambda_t^{v,k}(i)_{l-1} - X(i)_n \right.$ and $\left. \sum_{j=1}^{N} \lambda_r^{j,v}(i)_{l-1} > 0 \right]$,

- $[t_v(i)_l = 0$ and $r_v(i)_l = 0]$ if O.W. (14)

We define $X(i)_n = \sum_{k=1}^{N} u_k(i)_n \beta_k(i)_n i_{v,k}(i)$, where $u_k(i)_n$ and $\beta_k(i)_n$ are the outer loop variables, and they are treated as constants in this inner loop and will be explained in the following.

The auxiliary variable, $b_{j,k}(i)_l$, is the update in the l'th iteration and it is calculated as

- $[b_{j,k}(i)_l = r_k(i)_l]$ if $\left[\lambda_r^{j,k}(i)_{l-1} > 0 \text{ and } \lambda_t^{j,k}(i)_{l-1} = 0\right]$,
- $[b_{j,k}(i)_l = t_j(i)_l]$ if $\left[\lambda_t^{j,k}(i)_{l-1} > 0 \text{ and } \lambda_r^{j,k}(i)_{l-1} = 0\right]$,
- $[b_{j,k}(i)_l = 1]$ if $\left[\lambda_t^{j,k}(i)_{l-1} > 0 \text{ and } \lambda_r^{j,k}(i)_{l-1} > 0\right]$,
- $[b_{j,k}(i)_l = 0]$ if $\left[\lambda_t^{j,k}(i)_{l-1} = 0 \text{ and } \lambda_r^{j,k}(i)_{l-1} = 0\right]$. (15)

The auxiliary variables, $\lambda_t^{j,k}(i)_l$ and $\lambda_r^{j,k}(i)_l$ are the updates in the l'th iteration, and they are calculated as

$$\lambda_t^{j,k}(i)_l = \left[\lambda_t^{j,k}(i)_{l-1} - \delta_t^l \left(b_{j,k}(i)_{l-1} - t_j(i)_{l-1}\right)\right]^+, \tag{16}$$

$$\lambda_r^{j,k}(i)_l = \left[\lambda_r^{j,k}(i)_{l-1} - \delta_r^l \left(b_{j,k}(i)_{l-1} - r_k(i)_{l-1}\right)\right]^+, \tag{17}$$

where δ_t^l and δ_r^l are the positive step sizes, which can be selected properly, such as $\frac{1}{2l}$. In addition, The equations in (44) and (45) have to hold the following condition

$$\lambda_t^{j,k}(i)_l + \lambda_r^{j,k}(i)_l \leq u_k(i)_n d_{k,j}(i). \tag{18}$$

The condition in (18) means that any change on $\lambda_t^{j,k}(i)_l$ in (44), may cause a change on $\lambda_r^{j,k}(i)_l$ in (45) to hold (18) and vice versa. Moreover,

The process of updating the variables, $t_v(i)_l$ and $r_v(i)_l$, $b_{j,k}(i)_l$, $\lambda_t^{j,k}(i)_l$ and $\lambda_r^{j,k}(i)_l$, is repeated until convergence occurs, which can be checked by following equation

$$\sum_{k=1}^{N}\sum_{j=1}^{N}|\lambda_r^{j,k}(i)_l - \lambda_r^{j,k}(i)_{l-1}| < \epsilon, \tag{19}$$

where $\epsilon > 0$ is a relatively small constant.

The above procedure are summarized in the Algorithm 1(Lines 9-20).

2) The outer loop: In this loop, we compute two auxiliary variables, $u_k(i)$ and $\beta_k(i)$, where the computation process is iterative. To this end, we add an index for each iteration which is the outer loop index, n. As a result, the new variables are $u_k(i)_n$ and $\beta_k(i)_n$.

The variables $u_k(i)_n$ and $\beta_k(i)_n$ are the updates in the n'th iteration, and they are calculated as

$$\beta_k(i)_n = (1-\zeta^n)\beta_k(i)_{n-1} + \zeta^n \frac{r_k(i)_l \mathbf{t}(i)_l \mathbf{d}_k(i)}{1+\mathbf{t}(i)_l \mathbf{i}_k(i)}, \tag{20}$$

and

$$u_k(i)_n = (1-\zeta^n)u_k(i)_{n-1} + \zeta^n \frac{1}{(1+\mathbf{t}(i)_l \mathbf{i}_k(i))}, \tag{21}$$

respectively, where $\zeta^n \in (0,1)$ is the largest value satisfying

$$\begin{aligned} &\Big|\Big|\phi\left(\beta_k(i)_n, u_k(i)_n\right)\Big|\Big| \\ &\leq (1-\delta\zeta^n)\Big|\Big|\phi\left(\beta_k(i)_{n-1}, u_k(i)_{n-1}\right)\Big|\Big|, \end{aligned} \tag{22}$$

and $\delta \in (0,1)$. The function ϕ in (22) is defined as

$$\begin{aligned} &\phi_k(\beta_k(i)_n) = \beta_k(i)_n \left(1 + \mathbf{t}(i)_l \mathbf{i}_k(i)\right) - r_k(i)_l \mathbf{t}(i)_l \mathbf{d}_k(i), \\ &\phi_{k+K}(u_k(i)_n) = u_k(i)_n \left(1 + \mathbf{t}(i)_l \mathbf{i}_k(i)\right) - 1, \end{aligned} \tag{23}$$

for $k \in \{1, 2, ..., K\}$.

The process of updating $\beta_k(i)_n$, and $u_k(i)_n$ in (51) and (52), respectively, and feed them to the inner loop continuous until a convergence occurs, which can be checked by following equation,

$$|| \, [\phi_1, \phi_1, ..., \phi_{2K}] \, || < \delta, \tag{24}$$

where $\delta > 0$ is a small value.

The above procedure are summarized in the Algorithm 1(Lines 3-24)

Algorithm 1 Finding the optimal vectors, $\mathbf{t}(i)$ and $\mathbf{r}(i)$

1: **procedure** $\forall\, i \in \{1, 2, ..., N\}$
2: Initiate $\beta_k(i)_0$ to zero and $u_k(i)_0$ to one, $\forall k$
3: ****** Outer-loop start*****
4: **while** outer-loop-flag $==$ FALSE **do**
5: **if** (24) holds **then**
6: outer-loop-flag $\leftarrow$ TRUE
7: **else**
8: Initiate $t_v(i)_0$, $r_v(i)_0$, $b_{j,k}(i)_0$, $\lambda_t^{j,k}(i)_0$ and $\lambda_r^{j,k}(i)_0$ to zero , $\forall j, k, v$
9: ****** Inner-loop start*****
10: **while** inner-loop-flag $==$ FALSE **do**
11: l++
12: compute $t_v(i)_l$ and $r_v(i)_l$ with (41)
13: compute $b_{j,k}(i)_l$ with (42)
14: compute $\lambda_t^{j,k}(i)_l$ with (44)
15: compute $\lambda_r^{j,k}(i)_l$ with (45)
16: **if** (19) holds **then**
17: inner-loop-flag $\leftarrow$ TRUE
18: **else**
19: **go to** 11.
20: ****** Inner-loop end*****
21: n++
22: compute $\beta_k(i)_n$ with (51)
23: compute $u_k(i)_n$ with (52)
24: ****** Outer-loop end*****
25: **return** $\mathbf{t}(i)$ and $\mathbf{r}(i)$

Proof: Please refer to Appendix B for the proof. ■

III. Simulation and Numerical Results

In this section, we have used a network covering an area of D×D m^2. In this area, we place 50 pairs of nodes randomly. To this end, we randomly place one node of each pairs in the considered area, and then the other node is placed by choosing a uniformly selected random angle from $0°$ to $360°$, and a uniformly selected random distance from d=10 m to 100 m, from the first node. We assume that only the link between the paired nodes is desired for the considered pair of nodes and the other links act as interference links. The channel gain corresponding to the each link is assumed to have Rayleigh distribution fading, where the mean of the channel gains are calculated using the standard path-loss model [15] as

$$E\{|g_{j,k}(i)|^2\} = \left(\frac{c}{4\pi f_c}\right)^2 d_{jk}^{-\beta} \text{ , for } k \in \{U, D\}, \tag{25}$$

where c is the speed of light, $f_c = 1.9$ GHz is the carrier frequency, d_{jk} is the distance between node j and k, and $\beta = 3.6$ is the path loss exponent.

Benchmark Scheme 1 (Conventional scheme): This benchmark is the current approach in the TDD networks. Thereby, we divide the network nodes into two groups, denoted by A and B. In odd time slots, nodes in group A send information to the desired nodes in group B. Then, in the even time slots, nodes in group B send information to the desired nodes in group A. With this approach there will be no interference between the nodes in group A and group B since the transmissions are synchronized. However, there are interferences from group A on group B, and vice versa, because there are interference links between these two groups.

Benchmark Scheme 2 (Optimal interference spins scheme): The interference spins scheme, proposed in [11], has been considered as the second benchmark scheme.

A. Numerical Results

All of the presented results in this section are generated for Rayleigh fading by numerical evaluation of the derived results and are confirmed by Monte Carlo simulations.

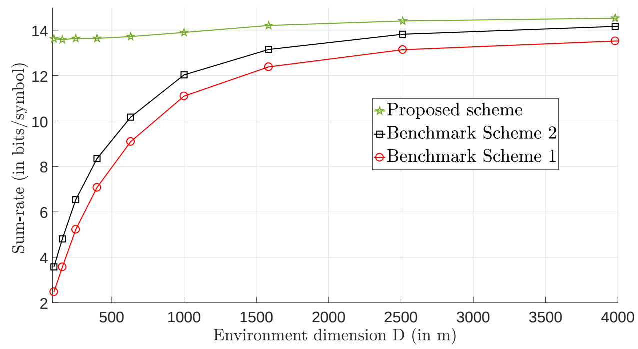

Figure 2. Sum-rate vs. dimension D of the proposed schemes and the benchmark schemes for P=20 dBm.

All of the numerical results are represented in terms of sum-rate, instead of sun SINR, for better visualization of the results. The sum-rate is given by

$$\lim_{T\to\infty} \frac{1}{T} \sum_{i=1}^{T} \sum_{k=1}^{N} \log_2(1 + SINR_k(i)), \tag{26}$$

where $SINR_k(i)$ are obtained using Theorem 2, for the proposed scheme.

In Fig. 2, the sum-rates achieved using the proposed scheme is compared with the benchmark schemes as a function of the dimension of the considered area, D. Moreover, we assume that the transmit power is fixed to P=20 dBm. Since the nodes are placed randomly in an area of D$\times$D m^2, for large D, the links become more separated and the interference has no effect. As a result, all of the schemes have close results. However, decreasing the dimension, D, causes the overall interference to increase, in which case the proposed scheme has a considerable gain over the considered benchmark schemes.

In Fig. 3, we show sum-rates achieved using the proposed scheme and the benchmark schemes as a function of the transmission power at the nodes, P. This example is for the area of 1000*1000 m^2. As can be seen from Fig. 3, for the low transmit power region, where noise is dominant, all schemes achieve a close sum-rate. However, increasing the transmit power causes the overall interference to increase, where the proposed scheme achieves a huge gain over the considered benchmark schemes. In fact, the proposed scheme has multiplexing gain of $log_2(1 + \mathrm{P})$, since the proposed scheme selects only one link and switches off the other links so as to minimize the interference, i.e, the proposed scheme always chooses the best pair in the high power region. This is a similar behaviour to the case of selecting only one transmitter to transmit when the

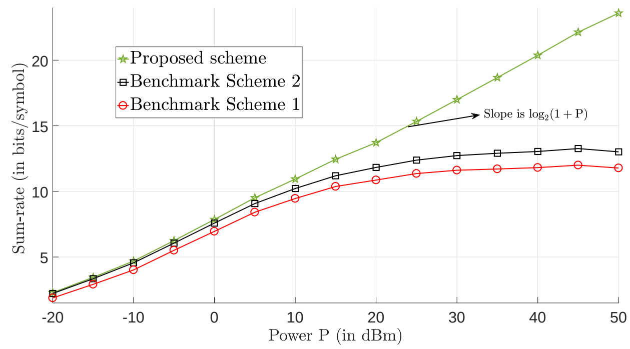

Figure 3. Sum-rate vs. transmit power P of the proposed schemes and the benchmark schemes for D=1000 m.

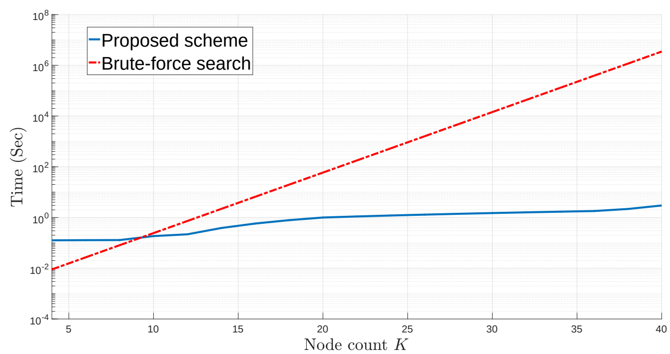

Figure 4. Complexity vs. node count of the proposed schemes and the benchmark scheme for P=20 dBm and D=1000 m.

objective is to maximize the sum-rate of the multiple-access channel (MAC) impaired by additive white Gaussian noise (AWGN) and fading [16]. The other considered benchmark schemes show limited performance, since in the high power region they can not avoid the interference.

In Fig. 4, we present the total time required by the proposed scheme to obtain the solution as a function of number of nodes in the network. For comparison purpose, we also present the total time required by a general brute-force search algorithm to search over all the possible solutions in order to to find the optimal one. To this end, we set power at nodes to P=20 dBm, and the area of example to 1000*1000 m^2. As it can bee seen from Fig. 4, the brute-force search algorithm's computation time increases exponentially, however the proposed scheme's computation time is just increased linearly, which is a huge improvement in the computational cost for achieving the optimal solution.

IV. Conclusion

In this paper, we proposed optimal centralized D-TDD scheme for a general network comprised of K HD nodes, which maximizes the average sum SINR of the network. The proposed centralized D-TDD scheme makes an optimal decision of which node should receive, transmit, or be silent in each time slot. We have shown that the proposed optimal centralized D-TDD scheme has significant gains over existing centralized D-TDD schemes.

Appendix

A. Proof of Theorem 1

The received signal at node k is

$$y_k(i) = \sum_{v\in\{\text{desired nodes}\}} \sqrt{\mathrm{P}g_{v,k}(i)}S_v(i) + \sum_{v\in\{\text{undesired nodes}\}} \sqrt{\mathrm{P}g_{v,k}(i)}S_v(i) + n_k(i), \tag{27}$$

where $S_v(i)$ is the transmitted symbol. Without loss in generality we can assume $|S_v(i)|^2 = 1$. Using (27), we can calculate the power of desired signal over the power of noise plus interference as

$$SINR_k(i) = \frac{\sum_{v\in\{\text{desired nodes}\}} \mathrm{P}g_{v,k}(i)}{\sigma_k^2 + \sum_{v\in\{\text{undesired nodes}\}} \mathrm{P}g_{v,k}(i)}. \tag{28}$$

Note that when $r_k(i) = 0$, actually we are either transmitting or silent, so in this case the value of $SINR_k(i)$ is meaningless, hence by multiplying the binary variable $r_k(i)$ with (28), we put $SINR_k(i)$ to 0, and so (27) turns to

$$SINR_k(i) = r_k(i)\frac{\sum_{v\in\{\text{desired nodes}\}} \mathrm{P}g_{v,k}(i)}{\sigma_k^2 + \sum_{v\in\{\text{undesired nodes}\}} \mathrm{P}g_{v,k}(i)}. \tag{29}$$

By substituting $\sum_{v\in\{\text{desired nodes}\}} g_{v,k}(i) = \mathbf{t}(i)\mathbf{d}_k(i)$, and also $\sum_{v\in\{\text{undesired nodes}\}} g_{v,k}(i) = \mathbf{t}(i)\mathbf{i}_k(i)$, and also assuming that $\sigma_k^2 = 1$, we can obtain (12) from (29). This completes the proof.

B. Proof of Theorem 2

In order to obtain a global solution, we first transform the non-convex objective function of the (13) into an equivalent objective function. To this end, let us define the vector $\mathbf{b}_k(i) = r_k(i)\mathbf{t}^T(i)$ as the k-th column vector of matrices $\mathbf{B}(i)$, where

$$\mathbf{b}_k(i) = r_k(i)[t_1(i),\ t_2(i),\ ...,\ t_K(i)]^T, \tag{30}$$

and rewrite (13) as

$$\underset{\mathbf{t}(i),\mathbf{r}(i),\mathbf{B}(i),\forall i}{\text{Maximize:}} \sum_{k=1}^{K} \frac{\mathbf{b}_k^T(i)\mathbf{d}_k(i)}{1+\mathbf{t}(i)\mathbf{i}_k(i)}$$

$$\begin{aligned} &\text{Subject to :} \\ &\qquad \text{C1} : t_v(i) \in \{0,1\},\ \forall v \\ &\qquad \text{C2} : r_v(i) \in \{0,1\},\ \forall v \\ &\qquad \text{C3} : t_v(i) + r_v(i) \in \{0,1\},\ \forall v \\ &\qquad \text{C4} : \mathbf{b}_k(i) = r_k(i)\mathbf{t}^T(i). \end{aligned} \tag{31}$$

The optimization problem in (31) is equivalent to (13). Now, we relax constraint C1, C2, and C3, such that $0 \leq t_v(i) \leq 1$, $0 \leq r_v(i) \leq 1$, and $0 \leq t_v(i) + r_v(i) \leq 1$, $\forall v$, respectively. Moreover, we relax the equation in C4 such that $0 \leq b_{j,k}(i) \leq r_k(i)$, and $0 \leq b_{k,j}(i) \leq t_j(i)$. Now, using Theorem 1 in [17], we transform the objective function in (31) into an equal form as

$$\underset{\mathbf{t}(i),\mathbf{r}(i),\mathbf{B}(i),\mathbf{u}(i),\boldsymbol{\beta}(i),\forall i}{\text{Maximize:}} \sum_{k=1}^{N} u_k(i)\left(\mathbf{b}_k^T(i)\mathbf{d}_k(i) - \beta_k(i)\left(1+\mathbf{t}(i)\mathbf{i}_k(i)\right)\right)$$

$$\begin{aligned} &\text{Subject to :} \\ &\qquad \text{C1} : 0 \leq t_v(i) \leq 1,\ \forall v \\ &\qquad \text{C2} : 0 \leq r_v(i) \leq 1,\ \forall v \\ &\qquad \text{C3} : 0 \leq t_v(i) + r_v(i) \leq 1,\ \forall v \\ &\qquad \text{C4} : 0 \leq b_{j,k}(i) \leq r_k(i),\ \forall j,k\ , \\ &\qquad \text{C5} : 0 \leq b_{j,k}(i) \leq t_j(i),\ \forall j,k \\ &\qquad \text{C6} : u_k(i)\left(1+\mathbf{t}(i)\mathbf{i}_k(i)\right) - 1 = 0,\ \forall k \\ &\qquad \text{C7} : \beta_k(i)\left(1+\mathbf{t}(i)\mathbf{i}_k(i)\right) - \left(\mathbf{b}_k^T(i)\mathbf{d}_k(i)\right) = 0,\ \forall k. \end{aligned} \tag{32}$$

The optimization problem now can be divided in two steps: first step (inner-loop) is to find the optimal $\mathbf{t}(i)$, $\mathbf{r}(i)$, and $\mathbf{B}(i)$, in (32) for given $(\mathbf{u}(i), \boldsymbol{\beta}(i))$, and the second step (outer-loop) is to find the optimal $\left(\mathbf{u}^*(i), \boldsymbol{\beta}^*(i)\right)$ satisfying C6 and C7.

1) Inner-loop: In the following, we will first discuss the finding of optimal $\mathbf{t}(i)$, $\mathbf{r}(i)$, and $\mathbf{B}(i)$, for a given $(\mathbf{u}(i), \boldsymbol{\beta}(i))$.

The optimization problem to find the optimal $\mathbf{t}(i)$, $\mathbf{r}(i)$, and $\mathbf{B}(i)$, for given $(\mathbf{u}(i), \boldsymbol{\beta}(i))$ can be written as

$$
\begin{aligned}
&\underset{\mathbf{t}(i),\mathbf{r}(i),\mathbf{B}(i),\forall i}{\text{Maximize:}} \ \sum_{k=1}^{N} u_k(i) \left(\sum_{j=1}^{N} b_{j,k}(i) d_{j,k}(i) - \beta_k(i) \left(1 + \sum_{j=1}^{N} t_j(i) i_{j,k}(i) \right) \right) \\
&\text{Subject to :} \\
&\qquad \text{C1} : 0 \le t_v(i) \le 1, \ \forall v \\
&\qquad \text{C2} : 0 \le r_v(i) \le 1, \ \forall v \\
&\qquad \text{C3} : 0 \le t_v(i) + r_v(i) \le 1, \ \forall v \\
&\qquad \text{C4} : 0 \le b_{j,k}(i) \le r_k(i), \ \forall j, k \\
&\qquad \text{C5} : 0 \le b_{j,k}(i) \le t_j(i), \ \forall j, k \ ,
\end{aligned} \tag{33}
$$

which is a convex optimization problem, and can be solved by Lagrangian dual method. Upon rearranging terms, the Lagrangian can be written as

$$
\begin{aligned}
\mathcal{L} = &- \sum_{k=1}^{N} \sum_{j=1}^{N} u_k(i) b_{j,k}(i) d_{j,k}(i) + \sum_{k=1}^{N} \sum_{j=1}^{N} u_k(i) \beta_k(i) t_j(i) i_{j,k}(i) - \sum_{k=1}^{N} u_k(i) \beta_k(i) \\
&- \sum_{v=1}^{N} \lambda_1^v(i) t_v(i) - \sum_{v=1}^{N} \lambda_2^v(i) \left(1 - t_v(i)\right) - \sum_{v=1}^{N} \lambda_3^v(i) r_v(i) - \sum_{v=1}^{N} \lambda_4^v(i) \left(1 - r_v(i)\right) \\
&- \sum_{v=1}^{N} \lambda_5^v(i) \left(t_v(i) + r_v(i)\right) - \sum_{v=1}^{N} \lambda_6^v(i) \left(1 - t_v(i) - r_v(i)\right) \\
&- \sum_{k=1}^{N} \sum_{j=1}^{N} \lambda_7^{j,k}(i) b_{j,k}(i) - \sum_{k=1}^{N} \sum_{j=1}^{N} \lambda_r^{j,k}(i) \left(r_k(i) - b_{j,k}(i)\right) \\
&- \sum_{k=1}^{N} \sum_{j=1}^{N} \lambda_t^{j,k}(i) \left(t_j(i) - b_{j,k}(i)\right),
\end{aligned} \tag{34}
$$

where $\lambda_r^v(i) \ge 0$, $r \in \{1, 2, 3, 4, 5, 6\}$, $\lambda_7^{j,k}(i) \ge 0$, $\lambda_r^{j,k}(i) \ge 0$, and $\lambda_t^{j,k}(i) \ge 0$, are the Lagrangian multipliers. We can solve the above dual problem iteratively by maximizing over state-selection variables, $\mathbf{t}(i)$, $\mathbf{r}(i)$, $\mathbf{B}(i)$, $\lambda_r^{j,k}(i)$ and $\lambda_t^{j,k}(i)$. In the following, we will discuss this process in detail.

The Lagrangian function, $\mathcal{L}$, given by (34) is bounded below if

$$-\lambda_1^v(i)+\lambda_2^v(i)-\lambda_5^v(i)+\lambda_6^v(i)-\sum_{k=1}^{N}\lambda_t^{v,k}(i)+\sum_{k=1}^{N}u_k(i)\beta_k(i)i_{v,k}(i)=0,\forall v \tag{35}$$

$$-\lambda_3^v(i)+\lambda_4^v(i)-\lambda_5^v(i)+\lambda_6^v(i)-\sum_{j=1}^{N}\lambda_r^{j,v}(i)=0,\forall v. \tag{36}$$

Let us define $X(i)=\sum_{k=1}^{N}u_k(i)\beta_k(i)i_{v,k}(i)$. Now, we find the system selection schemes for the three different available cases as follows:

$t_v(i)=1$: Since $t_v(i)=1$, we set $r_v(i)=0$. As a result, we have $\lambda_1^v(i)=0$, $\lambda_4^v(i)=0$, and $\lambda_5^v(i)=0$ (by complementary slackness in KKT condition), which using them we can rewrite (35) and (36), as

$$\lambda_2^v(i)+\lambda_6^v(i)-\sum_{k=1}^{N}\lambda_t^{v,k}(i)+X(i)=0, \tag{37}$$

$$-\lambda_3^v(i)+\lambda_6^v(i)-\sum_{j=1}^{N}\lambda_r^{j,v}(i)=0, \tag{38}$$

respectively. We can easily derive $\sum_{k=1}^{N}\lambda_t^{v,k}(i)-\sum_{j=1}^{N}\lambda_r^{j,v}(i)\geq X(i)$, and $\sum_{k=1}^{N}\lambda_t^{v,k}(i)\geq X(i)$.

$r_v(i)=1$: Since $r_v(i)=1$, we set $t_v(i)=0$. As a result, we have $\lambda_2^v(i)=0$, $\lambda_3^v(i)=0$, and $\lambda_5^v(i)=0$, which using them we can rewrite (35) and (36), as

$$-\lambda_1^v(i)+\lambda_6^v(i)-\sum_{k=1}^{N}\lambda_t^{v,k}(i)+X(i)=0, \tag{39}$$

$$\lambda_4^v(i)+\lambda_6^v(i)-\sum_{j=1}^{N}\lambda_r^{j,v}(i)=0, \tag{40}$$

respectively. We can easily derive $\sum_{k=1}^{N}\lambda_t^{v,k}(i)-\sum_{j=1}^{N}\lambda_r^{j,v}(i)\leq X(i)$, and $\sum_{j=1}^{N}\lambda_r^{j,v}(i)\geq 0$.

$t_v(i)=0$, and $r_v(i)=0$: For other conditions we can choose this system state.

Based on (37)-(40), we propose following optimal state-selection scheme for a dynamic TDMA network as

- $[t_v(i) = 1 \text{ and } r_v(i) = 0]$ if $\left[\sum_{k=1}^{N} \lambda_t^{v,k}(i) - X(i) \geq \sum_{j=1}^{N} \lambda_r^{j,v}(i) \text{ and } \sum_{k=1}^{N} \lambda_t^{v,k}(i) > X(i)\right]$,
- $[t_v(i) = 0 \text{ and } r_v(i) = 1]$ if $\left[\sum_{j=1}^{N} \lambda_r^{j,v}(i) > \sum_{k=1}^{N} \lambda_t^{v,k}(i) - X(i) \text{ and } \sum_{j=1}^{N} \lambda_r^{j,v}(i) > 0\right]$,
- $[t_v(i) = 0 \text{ and } r_v(i) = 0]$ if O.W. (41)

Also, in order to maximize (34), we use the Lagrangian variable, $\lambda_r^{j,k}(i)$, and $\lambda_t^{j,k}(i)$, to determine the value of $b_{j,k}(i)$, $\forall j, k$, as following

- $[b_{j,k}(i) = r_k(i)]$ if $\left[\lambda_r^{j,k}(i) > 0 \text{ and } \lambda_t^{j,k}(i) = 0\right]$,
- $[b_{j,k}(i) = t_j(i)]$ if $\left[\lambda_t^{j,k}(i) > 0 \text{ and } \lambda_r^{j,k}(i) = 0\right]$,
- $[b_{j,k}(i) = 1]$ if $\left[\lambda_t^{j,k}(i) > 0 \text{ and } \lambda_r^{j,k}(i) > 0\right]$,
- $[b_{j,k}(i) = 0]$ if $\left[\lambda_t^{j,k}(i) = 0 \text{ and } \lambda_r^{j,k}(i) = 0\right]$. (42)

Note that because $b_{j,k}(i) \geq 0$, we can omit the Lagrangian variable $\lambda_7^{j,k}(i)$.

For calculating the $\mathbf{t}(i)$, $\mathbf{r}(i)$, and $\mathbf{B}(i)$, we have required $\lambda_r^{j,k}(i)$ and $\lambda_t^{j,k}(i)$, which in the following we derive the equations for obtaining $\lambda_r^{j,k}(i)$ and $\lambda_t^{j,k}(i)$.

To find $\lambda_r^{j,k}(i)$ and $\lambda_t^{j,k}(i)$, the subgradient method can be used since the dual function is differentiable. In the following we will derive the subgradient update equations.

To this end, first we note that the Lagrangian function, $\mathcal{L}$, given by (34) is bounded below if

$$\lambda_r^{k,j}(i) + \lambda_t^{k,j}(i) = u_k(i) d_{k,j}(i), \forall k, j \ . \tag{43}$$

As a result, the Lagrangian variables $\lambda_r^{j,k}(i)$ and $\lambda_t^{j,k}(i)$ are linked to each other by (43). So, increasing the $\lambda_r^{j,k}(i)$, causes a decrement for $\lambda_t^{j,k}(i)$, and vice versa. Using (34), the subgradient update equations are given by

$$\lambda_t^{j,k}(i)_{l+1} = \left[\lambda_t^{j,k}(i)_l - \delta_t \left(b_{j,k}(i) - t_j(i)\right)\right]^+, \tag{44}$$

$$\lambda_r^{j,k}(i)_{l+1} = \left[\lambda_r^{j,k}(i)_l - \delta_r \left(b_{j,k}(i) - r_k(i)\right)\right]^+. \tag{45}$$

However, (44) and (45) have to hold (43) in each update, i.e., none of them can become larger than $u_k(i)d_{k,j}(i)$, and while the sum of $\lambda_t^{j,k}(i)_l$ and $\lambda_r^{j,k}(i)_l$ are less than $u_k(i)d_{k,j}(i)$, increasing one causes a decrement for the other one, and vice versa. Moreover, δ_t and δ_r are the positive step sizes, which can be selected properly. The process of computing the state-selection variables, $\mathbf{t}(i)$, $\mathbf{r}(i)$, and $\mathbf{B}(i)$, and subsequently updating $\lambda_r^{j,k}(i)$ and $\lambda_t^{j,k}(i)$, is repeated until convergence, which is defined in (19), indicating that the dual optimal point has been reached.

2) Outer-loop: In the following we introduce an algorithm to iteratively update $(\mathbf{u}(i), \boldsymbol{\beta}(i))$ satisfying C6 and C7 in (32). To this end, we define functions

$$\phi_k(\beta_k(i)) = \beta_k(i)\left(1 + \mathbf{t}(i)\mathbf{i}_k(i)\right) - \mathbf{b}_k^T(i)\mathbf{d}_k(i) \tag{46}$$

and

$$\phi_{K+k}(u_k(i)) = u_k(i)\left(1 + \mathbf{t}(i)\mathbf{i}_k(i)\right) - 1 \tag{47}$$

for $k \in \{1, 2, ..., K\}$. It is shown in [17] that the unique optimal solution $(\mathbf{u}^*(i), \boldsymbol{\beta}^*(i))$ is obtained if and only if $\phi(u_k(i), \beta_k(i)) = [\phi_1, \phi_2, ..., \phi_{2K}] = 0$. Thus, the well-known damped Newton method can be employed to update $(\mathbf{u}(i), \boldsymbol{\beta}(i))$ iteratively. In particular, in the n-th iteration, $\mathbf{u}^{n+1}(i)$ and $\boldsymbol{\beta}^{n+1}(i)$ can be updated as

$$\boldsymbol{\beta}^{n+1}(i) = \boldsymbol{\beta}^n(i) + \zeta^n q_{1:K}^n, \tag{48}$$

and

$$\mathbf{u}^{n+1}(i) = \mathbf{u}^n(i) + \zeta^n q_{K+1:2K}^n, \tag{49}$$

respectively, where $q^n = -[\phi'\left(\mathbf{u}(i), \boldsymbol{\beta}(i)\right)]^{-1}\phi\left(\mathbf{u}(i), \boldsymbol{\beta}(i)\right)$ and $\phi'\left(\mathbf{u}(i), \boldsymbol{\beta}(i)\right)$ is the Jacobian matrix of $\phi\left(\mathbf{u}(i), \boldsymbol{\beta}(i)\right)$. ζ^n is the largest ϵ^l satisfying

$$||\phi\left(\boldsymbol{\beta}^n(i) + \epsilon^l q_{1:K}^n, \mathbf{u}^n(i) + \epsilon^l q_{K+1:2K}^n\right)|| \le (1 - \delta\epsilon^l)||\phi\left(\boldsymbol{\beta}^n(i), \mathbf{u}^n(i)\right)||, \tag{50}$$

where $l \in \{1, 2, ...\}$, $\epsilon^l \in (0, 1)$, and $\delta \in (0, 1)$. The equations (48) and (49), can also be rewritten component-wisely as

$$\beta_k^{n+1}(i) = (1 - \zeta^n)\beta_k^n(i) + \zeta^n \frac{\mathbf{b}_k^T(i)_n \mathbf{d}_k(i)}{1 + \mathbf{t}(i)_n \mathbf{i}_k(i)}, \tag{51}$$

and

$$u_k^{n+1}(i) = (1-\zeta^n)u_k^n(i) + \zeta^n \frac{1}{(1+\mathbf{t}(i)_n \mathbf{i}_k(i))}, \tag{52}$$

respectively. The damped Newton method converges to the unique solution $(\mathbf{u}^*(i), \boldsymbol{\beta}^*(i))$ satisfying C6 and C7 in (32) for the outer-loop problem and the convergence is checked with (24). This completes the proof.

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