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Joint Energy-Bandwidth Allocation for Multi-User Channels with Cooperating Hybrid Energy Nodes

Vaneet Aggarwal, Mark R. Bell, Anis Elgabli, Xiaodong Wang, and Shan Zhong

Abstract-In this paper, we consider the energy-bandwidth allocation for a network of multiple users, where the transmitters each powered by both an energy harvester and conventional grid. access the network orthogonally on the assigned frequency band. We assume that the energy harvesting state and channel gain of each transmitter can be predicted for K time slots a priori. The different transmitters can cooperate by donating energy to each other. The tradeoff among the weighted sum throughput, the use of grid energy, and the amount of energy cooperation is studied through an optimization objective which is a linear combination of these quantities. This leads to an optimization problem with $O(N^2K)$ constraints, where N is the total number of transmitter-receiver pairs, and the optimization is over seven sets of variables that denote energy and bandwidth allocation, grid energy utilization, and energy cooperation. To solve the problem efficiently, an iterative algorithm is proposed using the Proximal Jacobian ADMM. The optimization sub-problems corresponding to Proximal Jacobian ADMM steps are solved in closed form. We show that this algorithm converges to the optimal solution with an overall complexity of $O(N^2K^2)$. Numerical results show that the proposed algorithms can make efficient use of the harvested energy, grid energy, energy cooperation, and the available bandwidth.

Index Terms—Energy Harvesting, Conventional Grid, Multiuser network, Proximal Jacobian ADMM.

I. INTRODUCTION

The rapid development of energy harvesting technologies leads to a new paradigm of wireless communications powered by renewable energy sources [2, 3]. By their nature, some renewable energy technologies (wind, solar, and run-of-river hydro) provide intermittent generation. Thus, hybrid energy sources with a mix of energy from the grid and renewable energy sources become important. Further, the grid allows different nodes to share energy with each other. Although energy harvesting can potentially enable sustainable and environmentally friendly deployment of wireless networks, it requires efficient utilization of energy and bandwidth resources [4, 5]. In this paper, we consider optimizing the weighted sum throughput of a multi-user network while minimizing both the energy from the grid and energy cooperation between the nodes.

In the absence of conventional energy, a number of works addressed energy scheduling with non-causal channel state information. A single-user channel is considered in [6-10].

For multiple users, novel scheduling algorithms have been proposed for multiple-access channels [11, 12], relay channels [13–15], broadcast channels [16, 17], and interference channels [5, 18–21]. Recently, the authors of [5, 19] considered joint allocation of energy and bandwidth for multi-user networks with renewable energy. Cooperation between nodes has been studied for a relay channel in [22]. Hybrid energy supply at the transmitter has been studied in [23-25], where there is a single transmission node. Cooperation for hybrid energy supply for cellular networks has been recently considered in [26–29]. However, these papers do not consider the aspect of limited capacity of battery capacity, nor the maximum transmission power constraint, which will be taken into account in this paper. Limited battery capacity helps mitigate the energy supply variations in time and space. For example, at any given slot, a node with sufficient energy can either share it with other nodes with insufficient energy, or store it for future use. The maximum power constraint on the transmitting node encourages cooperation to avoid energy wastage, reduces the need of grid energy, while making a part of the incoming energy prone useless and thus has to be discharged. In this paper, we consider the cost for the use of additional grid energy, and possible energy cooperation between nodes which brings new challenges to optimize the system throughput for a multi-user system.

This paper considers seven degrees of freedom for the design which include bandwidth allocation, transmission energy allocation, local harvested energy allocation, donated energy allocation, donated energy usage allocation, grid energy allocation, and discharged energy allocation. The problem is jointly convex, but has $O(N^2K)$ variables and $O(N^2K)$ constraints for N users scheduling over K time slots which makes it hard for a generic convex solver. This is mainly due to the donation of energy between two users in a time-slot need to be decided, which contributes to these many variables/constraints. In this paper, we give the optimal solution with complexity $O(N^2K^2)$. In the prior work [12], since the incoming energy was stored in battery, used, or discharged which helped finding the energy discharge in each time slot by a greedy algorithm. The existence of energy cooperation between nodes makes such greedy algorithm for energy discharge no longer optimal. Without energy cooperation and grid energy, the problem reduces to that in [19]. This paper gives a different optimal algorithm in this case, with the same computational complexity of $O(NK^2)$, and also provides convergence rate.

The Alternating Direction Method of Multipliers (ADMM) is a widely used algorithm for solving separable convex optimization problems with linear constraints for two sets of

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This paper was presented in part at the IEEE International Conference on Communications, May 2017 [1].

variables. Global convergence of ADMM was established in the early 1990s by Eckstein and Bertsekas [30] while studying the algorithm as a particular instance of a Douglas-Rachford splitting method. This relationship allowed them to use the monotone operator theory to obtain their global convergence guarantees. The interest in ADMM has exploded in recent years because of applications in signal and image processing, compressed sensing [31], matrix completion [32], distributed optimization and statistical and machine learning [33], and quadratic and linear programming [34]. Extensions to more than two blocks have been recently considered. For example, an ADMM-type algorithm is introduced in [35], where during each iteration a randomly selected subset of blocks is updated in parallel. The method incorporates a backward step on the dual update to ensure convergence. Hong and Luo [36] present a convergence proof for the n-block ADMM when the functions are convex, but under many assumptions that are difficult to verify in practice. The work in [37] shows that ADMM is convergent in the *n*-block case when the separable functions are strongly convex. The separable functions in the proposed problem in this paper are not strongly convex limiting the use of this algorithm. Recently, different extensions of ADMM like Jacobian ADMM [38], Flexible ADDMM [39], Proximal Jacobian ADMM [40], etc. have been considered which give different conditions on the guarantees for convergence.

In this paper, we show that recent results of Proximal Jacobian Alternating Direction Method of Multipliers (Proximal Jacobian ADMM) for any number of variables can be used to give a convergence speed in terms of the residual error as o(1/k) for k iterations [40]. As this algorithm is based on ADMM, it solves convex optimization problems by breaking them into smaller, easier to handle pieces which can be solved in parallel, and is thus useful in distributed scenarios [33]. This algorithm uses Jacobi-type scheme that helps convergence of the algorithm and adds proximal terms to get a convergence rate of o(1/k). Further, the conditions of the convergence of the algorithm are conservative, and do not require strong convexity of the separable functions.

The challenge of the non-separable objective function is handled through pairing a set of variables into a single variable.

The proposed algorithm reveals a tradeoff between the system throughput, amount of energy consumption from the grid, and the amount of energy cooperation. The system designer can use this tradeoff region to choose an optimal operating point. The simulation results depict these tradeoffs. Further, we investigate the different interactions of incoming and outgoing energy, and their impact with changing cost of energy cooperation. An interesting observation is that with low cost of energy cooperation, a node with low energy arrivals may receive donated energy from other nodes not necessarily to consume it but to transfer it back when others need thus making efficient use of battery sizes at different nodes.

The main contributions of the paper are as follows.

1) This paper jointly considers use of grid and renewable energy with maximum battery capacity, and energy cooperation between all nodes in a multi-user network.

- Multi-variable Proximal Jacobian ADMM is used and shown to be optimal for this problem, with an efficient splitting of variables.
- 3) Unlike the prior works where the bandwidth allocation had to be assumed at least ε (for some ε > 0), and an outer loop was needed to decrease ε due to non-differentiability of the objective function at zero bandwidth allocation [5, 21], this paper uses power and bandwidth allocation as a single variable in Proximal Jacobian ADMM to show that such conditions are no longer needed.
- The seven sets of sub-problems are solved in closed form, except one of the sub-problems in which single variable equation needs to be solved.
- 5) The proposed algorithm has been used in a window-based schemes with limited prediction and the performance gap as compared to the offline strategy has been shown to decrease with increasing window size.
- 6) The proposed algorithm reveals a tradeoff between the system throughput, amount of energy consumption from the grid, and the amount of energy cooperation, and performs better than the considered causal and greedy baselines.

The remainder of the paper is organized as follows. In Sections II, we describe the system model and formulate the problem. In Section III, we solve our problem efficiently using Proximal Jacobian ADMM, and prove the convergence to the optimal solution. In Section IV, we provide numerical results for the proposed solution. Finally, Section V concludes the paper.

II. SYSTEM MODEL AND PROBLEM FORMULATION

Consider a network consisting of N pairs of transmitters and receivers with a total bandwidth of B Hz. Assume that no two transmitters can transmit in the same time slot and the same frequency band thus the channel is accessed orthogonally by sharing the total bandwidth without any overlap. We consider a flat-fading channel where the channel gain is constant within the entire frequency band of B Hz and over the coherence time of T_c seconds. Assume a scheduling period of K time slots and the duration of a time slot of T_c seconds. We denote X_{nki} as the symbol sent to the receiver of link n at instant i in slot k (a time-slot is composed of multiple time-instants). The corresponding received signal at receiver $n \in \mathcal{N} \triangleq$ $\{1, \dots, N\}$ is given by

$$Y_{nki} = h_{nk}X_{nki} + Z_{nki},\tag{1}$$

where h_{nk} represents the complex channel gain for link nin slot k, and $Z_{nki} \sim CN(0, 1/T_c)$ is the i.i.d. complex Gaussian noise (i.e., the power spectrum density of the noise is $1/T_c$). We denote $H_n^k \triangleq |h_{nk}|^2$ and denote p_n^k as the total transmission energy consumption for link n in slot k. Without loss of generality, we assume $T_c = B = 1$. Assuming that link n uses a normalized bandwidth of a_n^k in time-slot k, we use an upper bound on the achievable rate for link n, $\sum_{k=1}^{K} a_n^k \log(1 + \frac{p_n^k H_n^k}{a_n^k})$ as the system performance metric [41], where $0 \cdot \log(1 + \frac{x}{0}) \triangleq 0$. We note that in general frequency reuse may give benefits, while optimal capacity for general interference channels is an open problem [42]. Thus, we use bandwidth splitting to orthogonalize transmissions, while still being able to have multiple users transmit in the same time slot. Joint energy-bandwidth allocation has been shown to be advantageous with energy harvesting with limited capacity battery since multiple users can transmit simultaneously and avoid energy wastage [5, 21].

Assume that each transmitter is equipped with a hybrid energy source, with access to both the energy from the grid, and the energy from the energy harvesting device. The energy from the grid to transmitter n is unbounded, whose cost influences the amount of energy that can be used from the grid. For transmitter n in time-slot k, let g_n^k be the energy used from the grid, and l_n^k is the amount of local harvested energy that is used. The energy harvesting device at transmitter n harvests energy from the surrounding environment, and is equipped with a buffer battery of capacity B_n^{\max} . We denote E_n^k as the total energy harvested up to the end of slot kby transmitter n. Since in practice energy harvesting can be accurately predicted for a short period [43, 44], we assume that the amount of the harvested energy, $E_n^k - E_n^{k-1}$ in each slot kis known. Moreover, the short-term prediction of the channel gain in slow fading channels is also possible [45]. Therefore, we assume that $\{H_n^k\}$ and $\{E_n^k\}$ are known non-causally before scheduling. We will further consider a window-based scheme with limited look-ahead information of the channels and energy harvesting in Section IV.

We further assume that different transmitters can donate energy to each other. The energy donation can for instance happen through a power grid or as a wireless power transfer [23–25]. However, there is a cost to this energy cooperation which will prioritize using the locally harvested energy at each node as opposed to cooperation. Let $r_{n,m}^k$ be the amount of energy that is donated from node n to node m in time slot k, where $r_{n,n}^k = 0$. A part of the incoming donated energy $s_n^k \leq \sum_{m=1}^N r_{m,n}^k$ is used while the rest is stored in the battery. Thus, the amount of power used for communication for transmitter n in time slot k is $p_n^k = l_n^k + s_n^k + g_n^k$.

We assume that each transmitter n has a maximum per-slot transmission energy consumption, P_n , such that $p_n^k \leq P_n$ for all $k \in \mathcal{K} \triangleq \{1, 2, \dots, K\}$. Thus, all the energy may not be used and some may get wasted. Let D_n^k be the amount of energy that is discharged (or wasted) by node n in time slot k. For transmitter n, assuming that the battery is empty initially, then the battery level at the end of slot k can be written as

$$B_{n}^{k} = B_{n}^{k-1} + \left(E_{n}^{k} - E_{n}^{k-1}\right) - l_{n}^{k} - \sum_{m \in \mathcal{N}} r_{n,m}^{k} + \sum_{m \in \mathcal{N}} r_{m,n}^{k} - s_{n}^{k} - D_{n}^{k}, \qquad (2)$$

where B_n^k must satisfy $0 \le B_n^k \le B_n^{\max}$ for all $k \in \mathcal{K}$. The constraints on the battery level can be re-written as

$$0 \leq E_{n}^{k} - \sum_{t=1}^{k} l_{n}^{t} - \sum_{t=1}^{k} \sum_{m \in \mathcal{N}} r_{n,m}^{t} + \sum_{t=1}^{k} \sum_{m \in \mathcal{N}} r_{m,n}^{t} - \sum_{t=1}^{k} s_{n}^{t} - \sum_{t=1}^{k} D_{n}^{t} \leq B_{n}^{\max}.$$
(3)

Moreover, we denote $\mathcal{P} \triangleq \{\boldsymbol{p}_n \mid \boldsymbol{p}_n \triangleq [p_n^1, p_n^2, \dots, p_n^K], n \in \mathcal{N}\}$ as the transmission energy allocation, $\mathcal{A} \triangleq \{\boldsymbol{a}_n \mid \boldsymbol{a}_n \triangleq [a_n^1, a_n^2, \dots, a_n^K], n \in \mathcal{N}\}$ as the bandwidth allocation, $\mathcal{L} \triangleq \{\mathcal{L}_n \mid \boldsymbol{l}_n \triangleq [l_n^1, l_n^2, \dots, l_n^K], n \in \mathcal{N}\}$ as the local harvested energy allocation, $\mathcal{R} \triangleq \{\boldsymbol{r}_{n,m} \mid \boldsymbol{r}_{n,m} \triangleq [r_{n,m}^1, r_{n,m}^2, \dots, r_{n,m}^K], n \neq m, n, m \in \mathcal{N}\}$ as the donated energy allocation, $\mathcal{S} \triangleq \{\boldsymbol{s}_n \mid \boldsymbol{s}_n \triangleq [s_n^1, s_n^2, \dots, s_n^K], n \in \mathcal{N}\}$ as the donated energy allocation, $\mathcal{G} \triangleq \{\boldsymbol{g}_n \mid \boldsymbol{g}_n \triangleq [g_n^1, g_n^2, \dots, g_n^K], n \in \mathcal{N}\}$ as the grid energy allocation, and $\mathcal{D} \triangleq \{\boldsymbol{D}_n \mid \boldsymbol{D}_n \triangleq [D_n^1, D_n^2, \dots, D_n^K], n \in \mathcal{N}\}$ as the discharged energy allocation. A system model is described in Figure 1, where we consider four transmitters, each equipped with a battery. For transmission, a part of grid energy is used. All the arriving energy that could not be used in a time slot is saved in the battery. The centralized controller makes all decisions of the different allocations for each node in each time slot.



Fig. 1. System model for four transmitters depicting different energy arrivals at a node.

We wish to maximize the weighted sum rate of all links while minimizing the use of grid energy and energy cooperation. Thus, the objective is to maximize

$$=\sum_{n=1}^{N} W_n \sum_{k=1}^{K} a_n^k \log(1 + \frac{p_n^k H_n^k}{a_n^k}) - \lambda \left(\sum_{k=1}^{K} \sum_{n=1}^{N} g_n^k\right) - \mu \left(\sum_{k=1}^{K} \sum_{n=1}^{N} \sum_{m=1, m \neq n}^{N} r_{n,m}^k\right), \qquad (4)$$

where $\lambda \ge 0$ and $\mu \ge 0$ are parameters that impact the cost of using energy from the grid, and cooperation, respectively, and $\mathcal{W} \triangleq \{W_n, n \in \mathcal{N}\}$ is the *weight set*, which determines the weight (or priority) of different links. Increasing λ would mean that the energy from the grid will be used less since it gets more expensive. Similarly, increasing μ would make energy cooperation more expensive. The values of λ and μ can be chosen by the system designer to choose a tradeoff point between the system throughput, amount of energy cooperation, and the use of grid energy. We thus have the following problem to optimize the system resources:

$$\max_{\mathcal{P},\mathcal{A},\mathcal{L},\mathcal{R},\mathcal{S},\mathcal{G},\mathcal{D}} C_{\mathcal{W}}(\mathcal{P},\mathcal{A},\mathcal{L},\mathcal{R},\mathcal{S},\mathcal{G},\mathcal{D}),$$
(5)

subject to

$$\begin{cases} 0 \leq E_{n}^{k} - \sum_{t=1}^{k} l_{n}^{t} - \sum_{t=1}^{k} \sum_{m \in \mathcal{N}} r_{n,m}^{t} \\ + \sum_{t=1}^{k} \sum_{m \in \mathcal{N}} r_{m,n}^{t} - \sum_{t=1}^{k} s_{n}^{t} - \sum_{t=1}^{k} D_{n}^{t} \leq B_{n}^{\max}, \\ p_{n}^{k} - l_{n}^{k} - s_{n}^{k} - g_{n}^{k} = 0, \ s_{n}^{k} \leq \sum_{m \in \mathcal{N}, m \neq n} r_{m,n}^{k}, \\ \sum_{i=1}^{N} a_{i}^{k} = 1, p_{n}^{k} \leq P_{n}, \\ a_{m}^{k}, p_{n}^{k}, l_{n}^{k}, r_{n,m}^{k} \text{ for } n \neq m, s_{n}^{k}, g_{n}^{k}, D_{n}^{k} \geq 0, \end{cases}$$
(6)

for all $k \in \mathcal{K}, m, n \in \mathcal{N}$.

Remark 1. We note that the energy donated from one node to another may lead to an energy transfer loss (e.g., propagation loss), which can be easily incorporated into the model by adding an efficiency parameter to the received energy. This will not change any of the results in this paper, and is thus ignored for the rest of this paper.

We note that the problem is convex with respect to each set of variables. However, it is not separable in all the variables. Further, the objective is not differentiable at $a_n^k = 0$ which limits the applicability of a generic convex solver. In addition, the complexity of a generic convex solver is exponential in the number of constraints [46], which in this case is $O(N^2K)$. Thus, this paper proposes an algorithm that exploits the problem structure to give a computationally efficient solution.

III. OPTIMAL ALGORITHM

There are seven sets of variables in the problem - bandwidth allocation \mathcal{A} , transmission energy allocation \mathcal{P} , local harvested energy allocation \mathcal{L} , donated energy allocation \mathcal{R} , donated energy usage allocation \mathcal{S} , grid energy allocation \mathcal{G} , and discharged energy allocation \mathcal{D} . We note that the proposed problem in (5)-(6) is jointly convex in all variables. We use the Proximal Jacobian Alternating Direction Method of Multipliers (Proximal Jacobian ADMM) technique to solve this problem [40]. The Proximal Jacobian ADMM algorithm solves convex optimization problems by breaking them into smaller and easier pieces which can be run in parallel and is thus useful for large-scale distributed convex optimization. Since the standard Proximal Jacobian ADMM does not allow inequalities, we add additional variables to only have equality constraints.

$$\begin{split} & \Gamma(\mathcal{P}, \mathcal{A}, \mathcal{L}, \mathcal{R}, \mathcal{S}, \mathcal{G}, \mathcal{D}, \mathcal{U}) = -C_{\mathcal{W}}(\mathcal{P}, \mathcal{A}, \mathcal{L}, \mathcal{R}, \mathcal{S}, \mathcal{G}, \mathcal{D}) + \\ & \sum_{n=1}^{N} \sum_{k=1}^{K} \left(I(u_{1,n}^{k}) + I(u_{2,n}^{k}) + I(u_{3,n}^{k}) + I(u_{4,n}^{k}) + I(p_{n}^{k}) + I(p_{$$

where $\mathcal{U} \triangleq \{(\boldsymbol{u}_{1,n}, \boldsymbol{u}_{2,n}, \boldsymbol{u}_{3,n}, \boldsymbol{u}_{4,n}) | \boldsymbol{u}_{i,n} \triangleq [u_{i,n}^1, u_{i,n}^2, \dots, u_{i,n}^K], n \in \mathcal{N}, i \in \{1, 2, 3, 4\}\}$ are the auxiliary variables that help remove inequalities in the

constraints, and $I(\cdot)$ is the indicator function which represents I(x) = 0 for $x \ge 0$ and is infinite otherwise. Thus, the problem in (5)-(6) becomes

$$\min_{\mathcal{P},\mathcal{A},\mathcal{L},\mathcal{R},\mathcal{S},\mathcal{G},\mathcal{D},\mathcal{U}} \Gamma(\mathcal{P},\mathcal{A},\mathcal{L},\mathcal{R},\mathcal{S},\mathcal{G},\mathcal{D},\mathcal{U}),$$
(7)

subject to

$$\begin{cases} \sum_{t=1}^{k} l_{n}^{t} + \sum_{t=1}^{k} \sum_{m \in \mathcal{N}, m \neq n} r_{n,m}^{t} + \sum_{t=1}^{k} D_{n}^{t} + u_{1,n}^{k} \\ -\sum_{t=1}^{k} \sum_{m \in \mathcal{N}, m \neq n} r_{m,n}^{t} + \sum_{t=1}^{k} s_{n}^{t} = E_{n}^{k}, \\ \sum_{t=1}^{k} l_{n}^{t} + \sum_{t=1}^{k} \sum_{m \in \mathcal{N}, m \neq n} r_{n,m}^{t} + \sum_{t=1}^{k} D_{n}^{t} - u_{2,n}^{k} \\ -\sum_{t=1}^{k} \sum_{m \in \mathcal{N}, m \neq n} r_{m,n}^{t} + \sum_{t=1}^{k} s_{n}^{t} = E_{n}^{k} - B_{n}^{\max}, \\ p_{n}^{k} - l_{n}^{k} - s_{n}^{k} - g_{n}^{k} = 0, p_{n}^{k} + u_{3,n}^{k} = P_{n}, \\ s_{n}^{k} + u_{4,n} = \sum_{m \in \mathcal{N}, m \neq n} r_{m,n}^{k}, \sum_{i=1}^{N} a_{i}^{k} = 1, \end{cases}$$
(8)

for all $k \in \mathcal{K}, m, n \in \mathcal{N}$.

Let the augmented Lagrangian ψ be defined as in Equation (9). The Proximal Jacobian ADMM updates variables (p_n^k, a_n^k) , l_n^k , $r_{m,n}^k$, s_n^k , g_n^k , D_n^k , and u_n^k for all m, n, and k in sequence, whose steps are summarized in Algorithm 1. Note that the objective function is not separable in p_n^k and a_n^k), which is why (p_n^k, a_n^k) is taken as a single variable.

Remark 2. Algorithm 1 is a distributed parallel algorithm. In particular, the variables associated with different (n, k) can be updated independently and in parallel.

We note that there are seven sets of arg-mins in Algorithm 1. All these problems are convex problems (since the indicator functions are equivalent to linear constraints). The detailed solutions to these problems are given in Appendix, where the problems are solved in closed form, except the first where the solution is in terms of a solution to a single variable equation. The next theorem states the optimality of Algorithm 1.

Theorem 1. Algorithm 1 optimally solves the problem in (5)-(6), and converges with an error rate of o(1/b) after b iterations when the ADMM parameters are chosen such that

$$\tau > 4K\rho\left(\frac{9NK + N^2K}{2 - \gamma} - 1\right),\tag{10}$$

for $0 < \gamma < 2$, and $\rho > 0$.

Proof. The objective function $\Gamma(\mathcal{P}, \mathcal{A}, \mathcal{L}, \mathcal{R}, \mathcal{S}, \mathcal{G}, \mathcal{D}, \mathcal{U})$ is separable in all the variables (p_n^k, a_n^k) , l_n^k , $r_{m,n}^k$, s_n^k , g_n^k , D_n^k , and u_n^k for all m, n, and k, and the constraints are linear equalities. The problem is convex optimization and all the separable functions are closed proper convex, which satisfies the assumptions for the optimality of Proximal Jacobian ADMM in [40]. Further, the choice of parameters in (10) satisfy the parameter conditions in [40] for the $9NK + N^2K$ number of variables ($(p_n^k, a_n^k), l_n^k, r_{m,n}^k, s_n^k g_n^k, D_n^k$, and u_n^k for all m, n, and k), and that each variable is in at-most 4K constraints with absolute multiplicative coefficient of 1 in the problem (5)-(6).

The next result gives the computational complexity of the proposed algorithm.

Theorem 2. Each iteration of Algorithm 1 has $O(N^2K^2)$ computational complexity.

$$\begin{split} \psi(\mathcal{P}, \mathcal{A}, \mathcal{L}, \mathcal{R}, \mathcal{S}, \mathcal{G}, \mathcal{D}, \mathcal{U}, \mathcal{Y}) &= \Gamma(\mathcal{P}, \mathcal{A}, \mathcal{L}, \mathcal{R}, \mathcal{S}, \mathcal{G}, \mathcal{D}, \mathcal{U}) \\ &+ \sum_{k,n} y_{1,n}^{k} \left(\sum_{t=1}^{k} l_{n}^{t} + \sum_{t=1}^{k} \sum_{m \in \mathcal{N}, m \neq n} r_{n,m}^{t} - \sum_{t=1}^{k} \sum_{m \in \mathcal{N}} r_{m,n}^{t} + \sum_{t=1}^{k} s_{n}^{t} + \sum_{t=1}^{k} D_{n}^{t} + u_{1,n}^{t} - E_{n}^{k} \right) \\ &+ \sum_{k,n} y_{2,n}^{k} \left(\sum_{t=1}^{k} l_{n}^{t} + \sum_{t=1}^{k} \sum_{m \in \mathcal{N}, m \neq n} r_{n,m}^{t} - \sum_{t=1}^{k} \sum_{m \in \mathcal{N}} r_{m,n}^{t} + \sum_{t=1}^{k} s_{n}^{t} + \sum_{t=1}^{k} D_{n}^{t} - u_{2,n}^{k} - E_{n}^{k} + B_{n}^{\max} \right) \\ &+ \sum_{k,n} y_{3,n}^{k} \left(p_{n}^{k} - l_{n}^{k} - s_{n}^{k} - g_{n}^{k} \right) + \sum_{k,n} y_{4,n}^{k} \left(p_{n}^{k} + u_{3,n}^{k} - P_{n} \right) + \sum_{k,n} y_{5,n}^{k} \left(s_{n}^{k} + u_{4,n}^{k} - \sum_{m \in \mathcal{N}, m \neq n} r_{m,n}^{k} \right) \\ &+ \frac{\rho}{2} \sum_{k,n} \left(\sum_{t=1}^{k} l_{n}^{t} + \sum_{t=1}^{k} \sum_{m \in \mathcal{N}, m \neq n} r_{n,m}^{t} - \sum_{t=1}^{k} \sum_{m \in \mathcal{N}} r_{m,n}^{t} + \sum_{t=1}^{k} s_{n}^{t} + \sum_{t=1}^{k} D_{n}^{t} + u_{1,n}^{k} - E_{n}^{k} \right)^{2} \\ &+ \frac{\rho}{2} \sum_{k,n} \left(\sum_{t=1}^{k} l_{n}^{t} + \sum_{t=1}^{k} \sum_{m \in \mathcal{N}, m \neq n} r_{n,m}^{t} - \sum_{t=1}^{k} \sum_{m \in \mathcal{N}} r_{m,n}^{t} + \sum_{t=1}^{k} s_{n}^{t} + \sum_{t=1}^{k} D_{n}^{t} - u_{2,n}^{k} - E_{n}^{k} + B_{n}^{\max} \right)^{2} \\ &+ \frac{\rho}{2} \left(\sum_{n} a_{n}^{k} - 1 \right)^{2} + \frac{\rho}{2} \sum_{k,n} \left(p_{n}^{k} - l_{n}^{k} - s_{n}^{k} - g_{n}^{k} \right)^{2} + \sum_{k} y_{6}^{k} \left(\sum_{n} a_{n}^{k} - 1 \right). \end{split}$$

$$(9)$$

Algorithm 1 - Proximal Jacobian ADMM for Solving Proposed Problem in (5)-(6)

1: Initialization: $i = 0, (\mathcal{P}, \mathcal{A}, \mathcal{L}, \mathcal{R}, \mathcal{S}, \mathcal{G}, \mathcal{D}, \mathcal{U}, \mathcal{Y})^0 = (0, 0, 0, 0, 0, 0, 0, 0)$ Specify the ADMM parameters ρ, τ , and γ , and the convergence threshold η 2: ADMM Iteration: **REPEAT** $(p_n^k, a_n^k)^{i+1} \leftarrow \operatorname{argmin}_{p_n^k, a_n^k} \psi((\mathcal{P}, \mathcal{A} \setminus p_n^k, a_n^k), p_n^k, a_n^k, \mathcal{L}^i, \mathcal{R}^i, \mathcal{S}^i, \mathcal{G}^i, \mathcal{D}^i, \mathcal{U}^i, \mathcal{Y}^i) + \frac{1}{2}\tau(p_n^k - (p_n^k)^i)^2 + \frac{1}{2}\tau(a_n^k - (a_n^k)^i)^2, \forall k, \text{ and } n$ $(l_n^i)^{i+1} \leftarrow \operatorname{argmin}_{h_n^k, m} \psi(\mathcal{P}^i, \mathcal{A}^i, \mathcal{L}, (\mathcal{R} \setminus h_n^k)^i, h_n^k, \mathcal{R}^i, \mathcal{G}^i, \mathcal{D}^i, \mathcal{U}^i, \mathcal{Y}^i) + \frac{1}{2}\tau(h_n^k - ((h_n^k)^i)^2, \forall k, \text{ and } n, n \neq m$ $(s_n^k)^{i+1} \leftarrow \operatorname{argmin}_{h_n^k, m} \psi(\mathcal{P}^i, \mathcal{A}^i, \mathcal{L}^i, \mathcal{R}^i, \mathcal{G}^i, \mathcal{D}^i, \mathcal{U}^i, \mathcal{Y}^i) + \frac{1}{2}\tau(s_n^k - (s_n^k)^i)^2, \forall k, \text{ and } n$ $(g_n^k)^{i+1} \leftarrow \operatorname{argmin}_{g_n^k} \psi(\mathcal{P}^i, \mathcal{A}^i, \mathcal{L}^i, \mathcal{R}^i, \mathcal{S}^i, \mathcal{G}^i, \mathcal{D}^i, \mathcal{U}^i, \mathcal{Y}^i) + \frac{1}{2}\tau(g_n^k - (g_n^k)^i)^2, \forall k, \text{ and } n$ $(g_n^k)^{i+1} \leftarrow \operatorname{argmin}_{g_n^k} \psi(\mathcal{P}^i, \mathcal{A}^i, \mathcal{L}^i, \mathcal{R}^i, \mathcal{S}^i, \mathcal{G}^i, \mathcal{D}^i, \mathcal{U}^i, \mathcal{Y}^i) + \frac{1}{2}\tau(g_n^k - (g_n^k)^i)^2, \forall k, \text{ and } n$ $(u_{j,n}^k)^{i+1} \leftarrow \operatorname{argmin}_{u_n^k, n} \psi(\mathcal{P}^i, \mathcal{A}^i, \mathcal{L}^i, \mathcal{R}^i, \mathcal{S}^i, \mathcal{G}^i, \mathcal{D}^i, \mathcal{U}^i, \mathcal{Y}^i) + \frac{1}{2}\tau(Q_n^k - (Q_n^k)^i)^2, \forall k, \text{ and } n$ $(u_{j,n}^k)^{i+1} \leftarrow (y_{n,n}^k)^i + \gamma \rho(\sum_{k=1}^k l_n^k + \mathcal{S}^k, \mathcal{G}^i, \mathcal{D}^i, (\mathcal{U} \setminus u_{j,n}^k)^i, u_{j,n}^k, \mathcal{Y}^i) + \frac{1}{2}\tau(u_n^k - (u_n^k)^i)^2, \forall k, n, \text{ and } j = 1, 2, 3, 4$ $(y_{1,n}^k)^{i+1} \leftarrow (y_{n,n}^k)^i + \gamma \rho(\sum_{k=1}^k l_n^k + \mathcal{S}^k, \mathcal{G}^i, \mathcal{D}^i, (\mathcal{U} \setminus u_{j,n}^k)^i, u_{j,n}^k, \mathcal{Y}^i) + \frac{1}{2}\tau(u_n^k - (u_n^k)^i)^2, \forall k, n, \text{ and } j = 1, 2, 3, 4$ $(y_{2,n}^k)^{i+1} \leftarrow (y_{3,n}^k)^i + \gamma \rho(\sum_{k=1}^k l_n^k + \mathcal{S}^k, \mathcal{G}^k, \mathcal{G}^k, \mathcal{T}^k, m - \mathcal{S}^k_{k=1} \sum_{m \in \mathcal{N} \mathcal{T}^k_{m,n}} + \sum_{k=1}^k s_n^k + \sum_{k=1}^k D_n^k + u_{k,n}^k - \mathcal{E}^k_n + B_n^{max})^{i+1} \forall k, \text{ and } n$ $(y_{3,n}^k)^{i+1} \leftarrow (y_{3,n}^k)^i + \gamma \rho(p_n^k - u_{3,n}^k - P_n^k)^{i+1} \forall k, \text{ and } n$ $(y_{3,n}^k)^{i+1} \leftarrow (y_{3,n}^k)^i + \gamma \rho(\mathcal{S}^k, \mathcal{H}^k, \mathcal$

Proof. We note that the detailed steps the sub-problems are given in the Appendix. Problem 1 for each n and k involves solving a single-variable equation and is thus O(NK) computational complexity. Problem 2 for each n and k needs a sum over v from k to K and thus has $O(NK^2)$ complexity. Problem 3 is for energy cooperation which for every m, n, and k requires O(K) time, and has $O(N^2K^2)$ complexity. We assume that for each n and k, $\sum_{m \neq n} r_{m,n}^k$ can be computed and stored which is $O(N^2K)$ complexity. Using this, Problem 4 has $O(NK^2)$ complexity. Similarly, Problem 5 has O(NK) complexity. Problem 6 has $O(NK^2)$ complexity. Having stored values of $\sum_{m \neq n} r_{m,n}^k$ and $\sum_{m \neq n} r_{n,m}^k$ for each n and k, Problem 7 has a complexity of $O(NK^2)$. Thus, the

overall complexity is dominated by the complexity of Problem 3, and is $O(N^2K^2)$.

Remark 3. Without any energy cooperation, $r_{m,n}^k = 0$ and the overall complexity of the proposed algorithm is $O(NK^2)$.

We further note that this problem was considered without the energy cooperation and grid energy in [21] and the proposed algorithm in [21] has the same computational complexity of $O(NK^2)$. However, the algorithm in [21] performs the first step of calculating the optimal discharge allocation. However, in the presence of grid energy and cooperation, such allocation cannot be found since the energy can be transferred to other nodes rather than discharging. Having removed the discharge variables, there were only two variables for power and bandwidth left, which could be solved using an alternating minimization based approach in [21]. However, we have many more sets of variables. In order to use Proximal Jacobian ADMM, we had to use the power and bandwidth as the variables in a single block. Rather than performing an alternating minimization over these variables, the joint optimization is solved in this paper. Thus, this paper gives an alternate way of solving the algorithm in [21] with the same complexity. In addition, the proposed algorithm in this paper works for the energy cooperation and grid energy parameters while the approach of [21] do not extend easily.

We finally note that the cooperation may involve a loss due to efficiency of transfer which can be easily incorporated in the given constraints without changing the problem structure or the approach. In order to keep the expressions simpler, we have not included the efficiencies for energy transfer as well as battery charging or discharging.

IV. SIMULATION AND RESULTS

In this section, we will evaluate the proposed algorithm in different scenarios.

A. Impact of Grid Energy Cost

We consider N = 5 users with a scheduling period of K = 5 time slots. The weights of all the users are taken to be identical, $W_n = 1$. We assume that the maximum power constraints is $P_n = 20W$, and maximum battery capacity is $B_n^{\max} = 20W$. The channel gains $\{h_n^k\}$ are distributed as CN(0, 1). For the energy arrival $E_n^k - E_n^{k-1}$, a truncated Gaussian distribution is used which is given by the maximum of zero and a Gaussian random variable with mean Δ_n and variance 4. Let $\Delta_n = \Delta$, independent of *n*. The Proximal Jacobian ADMM parameters are $\rho = 10^{-3}$, $\gamma = 1$, $\tau = 0.5$, and the convergence threshold for the iterative loop is chosen to be $\eta = 10^{-6}$. Let the cooperation cost to be $\mu = 0.2$. The grid energy cost λ is chosen as a variable.

The results are averaged over 12 runs with different realizations of channel gains and energy arrivals. Figure 2 shows the decrease of system throughput (in nats) with increasing grid energy cost, λ , for four different values of $\Delta = 5, 10, 15,$ and 20J. We note that when $\lambda = 0$, the system throughput is independent of Δ since the energy from grid can be taken up to the maximum power constraint in the chosen bandwidth. Thus, the problem in this case becomes a bandwidth allocation problem with each node using the maximum energy constraint in each time slot. Due to similar channel gains for all links, assuming equal bandwidth for all links, and ignoring the random effect of channel gains give the system rate as $5 \times \log(1 + 20 \times 5) \approx 23$ nats. Thus, the result at $\lambda = 0$ is almost equal to this. As the use of grid energy becomes more expensive, the system throughput reduces. For $\Delta = 20$ J, more energy arrives at each node and thus there is little decrease in throughput with increasing λ as compared to the case where grid energy is free. However, for smaller value of Δ , the system throughput decreases significantly with λ . An optimal operating point can be chosen based on the system design requirements.

B. Impact of Energy Cooperation Cost

We consider N = 5 users with $\Delta_n = 5n$ J, $n = 1, \dots, 5$. The maximum battery capacity of each node is chosen to be the same $B_n^{\max} = B_{\max}$. The grid energy cost $\lambda = 0.1$, and μ is a variable. All other parameters are same as those in Sect. IV-A. Figure 3 plots the system throughput with respect to μ for different values of B_{\max} . We note that the system throughput decreases with μ since the donation across nodes is more expensive. Figure 4 demonstrates that the amount of energy that is discharged and thus not used also increases with the increase in μ . This is because different nodes have different average incoming energy and by penalizing donation, the energy does not get evenly distributed.

C. Energy Arrival and Utilization

We will now compare the amounts of energy that enters a node, and that leaves a node including the power consumption for communication transmission. The grid energy cost $\lambda =$ 0.01, $B_n^{\max} = 10W$, and all other parameters are the same as those in Section IV-B. For a given realization of channel gains and energy arrivals, we find the total amount of incoming energy at each node and separate it into the amount of energy harvested \mathcal{L} , the amount of energy donated by other nodes \mathcal{R} (incoming part), and the amount of grid energy \mathcal{G} . We also find the amount of energy that leaves the node and separate it into the amount of energy used for communication transmission \mathcal{P} , the amount of energy donated to other nodes \mathcal{R} (outgoing part), and the amount of energy discharged \mathcal{D} . We consider two donation cost values, $\mu = 0.01, 0.1$, in Figures 5 and 6 respectively. The first three nodes (with lower harvested energy arrival) have incoming donated energy, while the nodes with higher harvested energy have outgoing energy when μ is small. This is because the later nodes can store energy in the first nodes to avoid going over the battery which can be transferred back in future time slots, and this impact is higher at smaller values of μ . It is easier to donate energy at lower value of μ and thus external grid energy used is lower, and there is less discharge as compared to higher value of μ . At lower μ , more energy can be used by the users with less harvested energy. Finally, we note that the total amount of outgoing energy is slightly less than the total amount of incoming energy in some nodes. This is because a residual amount of energy is stored in the battery.

D. Comparison with Baseline Schemes

We consider three baseline schemes. The first is a windowbased scheme where at each time, each node only has the information of the energy arrival in its current and the next T < Knumber of time slots. At each time *i*, we perform the optimization for min(T + 1, K - i + 1) time-slots using the proposed Proximal Jacobian ADMM strategy and use these decisions for the current time slot. Even though the complexity of the algorithm at each time is lower $(O(N^2(T + 1)^2))$, the process is repeated at each time (thus having overall complexity of $O(N^2T^2K)$). The second is equal bandwidth strategy, where the bandwidth is equally divided among all transmission links, and the remaining variables are optimized using the Proximal Jacobian ADMM algorithm. The third is a greedy bandwidth



Fig. 2. Decrease in system throughput with increasing λ for different values of Δ .



Fig. 5. Incoming and outgoing energy for different nodes, $\mu = 0.01$. TABLE I

CONVERGENCE SPEED FOR VARYING IV.			
N	Iterations to converge	Time / iteration (ms)	System throughput
5	3715	88.5	21.4
10	4004	189.7	25.2
15	4008	299.7	28.1
20	4050	426.6	29.8
25	4014	573.7	31.0
30	4085	733.8	31.9

scheme, which assigns all available bandwidth to the link with the highest channel gain. Given such bandwidth allocation, the rest of the variables are optimized based on the proposed Proximal Jacobian ADMM strategy.

We consider N = 5 users, K = 5 time units, $\Delta_n =$ $\Delta~=~10$, and variance of energy arrival in each time slot as 36. Let $\mu = 0.8$ and all other parameters be the same as those in Section IV-A. Figure 7 depicts the weighted sum rate (or the system throughput) for the proposed algorithm as compared to the different base-lines for varying λ . For window-based schemes, we consider T = 0 and T = 1. As T increases, the performance improves, and will reach optimal when T = K - 1. When T = 0, the algorithm is causal since it does not use any future information. However, the algorithm does not try to save for future (since the optimization is performed only for the current time-slot). Thus, there is a bigger difference between T = 0 and T = 1, while there is diminishing return since there is not a big difference between T = 1 and T = 4 (offline scheme). We note that the closeness between T = 1 and T = 4 are for the particular parameters chosen, while the diminishing returns in T should hold in general. Thus, with limited prediction, window-based schemes can potentially be used where in each window, the proposed algorithm is used for system optimization. We also note that the proposed strategy significantly outperforms the greedy







Fig. 6. Incoming and outgoing energy for different nodes, $\mu = 0.1$.



Fig. 4. Increase of discharged energy with increase in cost of donation, μ , for different values of battery capacity B_{max} .



Fig. 7. System throughput of proposed ADMM algorithm, as compared with the different baseline schemes.

 $\mu = 0.1.$

and equal bandwidth strategies thus depicting that the joint optimization over all variables is necessary.

E. Convergence with Increasing Number of Users

We consider increasing the number of users N, for the parameters as in Section IV-D, and $\lambda = 0.01$. The results are presented in Table I. The test was carried out on a 64-bit desktop with 3.5 GHz quadcore processor and 20 GB RAM. We see that the number of iterations to converge to a value lower than the chosen threshold $\eta = 10^{-6}$ generally increases with N, since the number of variables is growing in the expanding system. On the other hand, the time taken per iteration increases as well. At these parameters, the complexity seems to increase slightly more than linearly with N even though theoretically, the complexity scales as N^2 . This is because the only step that takes N^2K^2 complexity is the update of variables $r_{n,m}^k$, which potentially do not take that dominant time at the considered parameters, and all other updates are $O(NK^2)$. The system throughput increases as the number of users increase. However, we see diminishing gains with increasing number of users. We note that the parallelization of the algorithm for different (n, k) can significantly reduce the time per iteration in practice.

V. CONCLUSIONS

We have treated the energy-bandwidth allocation problem for multiuser network where each node is powered with both renewable and grid energy, nodes can cooperate, and each node has a limited battery capacity and finite transmission power. The objective is to maximize the weighted sum throughput, and minimize the use of grid energy and the amount of energy cooperation. An iterative algorithm based on the Proximal Jacobian ADMM is proposed and proved to be optimal. Numerical results demonstrate the different tradeoffs in the optimal solution. Extension of the results with a data buffer at the transmitter is an open problem. Using stochastic information of the energy arrivals and the channel gains to come up with optimal online algorithms is an interesting future direction. Incentive based mechanisms to help increase users' willingness to donate energy is left for the future.

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VI. APPENDIX: SOLVING SEVEN OPTIMIZATION PROBLEMS

For primal updates, we have seven sets of problems. We now consider solving these problems one by one. Note that we will ignore the iteration numbers, accounting that the last values of the other variables are used.

Problem 1: Updating $(\mathcal{P}, \mathcal{A})$

$$(p_n^k, a_n^k) = \operatorname*{argmin}_{p_n^k \ge 0, a_n^k \ge 0} \left(-W_n a_n^k \log(1 + p_n^k H_n^k / a_n^k) \right. \\ \left. + y_{3,n}^k p_n^k + y_{4,n}^k p_n^k + y_{6,n}^k a_n^k + \frac{\rho}{2} \left(p_n^k - l_n^k - s_n^k - g_n^k \right)^2 \right. \\ \left. + \frac{\rho}{2} \left(p_n^k - P_n + u_{3,n}^k \right)^2 + \frac{\rho}{2} (a_n^k + \sum_{j,j \ne n}^N a_j^k - 1)^2 \right. \\ \left. + \frac{1}{2} \tau (p_n^k - (p_n^k)^i)^2 + \frac{1}{2} \tau (a_n^k - (a_n^k)^i)^2 \right).$$
 (11)

This optimization is for a jointly convex function that is not differentiable at $a_n^k = 0$ at which $p_n^k = 0$. The KKT conditions for $a_n^k > 0$ are as follows.

$$-\frac{W_nH_n^k}{1+p_n^kH_n^k/a_n^k}+y_{3,n}^k+y_{4,n}^k+\rho\left(p_n^k-l_n^k-s_n^k-g_n^k\right)$$

$$+\rho \left(p_n^k - P_n + u_{3,n}^k \right) + \tau (p_n^k - (p_n^k)^i) = 0, \tag{12}$$

$$-W_n \log(1 + p_n^k H_n^k / a_n^k) + \frac{\eta_n p_n H_n / a_n^k}{1 + p_n^k H_n^k / a_n^k} + y_{6,n}^k$$
$$+\rho(a_n^k + \sum_{i,j \neq n}^N a_j^k - 1) + \tau(a_n^k - (a_n^k)^i) = 0.$$
(13)

 $\begin{array}{l} \text{From (12), we can solve } a_n^k \text{ as } a_n^k = p_n^k H_n^k / \\ \left(\frac{W_n H_n^k}{y_{3,n}^k + y_{4,n}^k + \rho(p_n^k - l_n^k - s_n^k - g_n^k) + \rho(p_n^k - P_n + u_{3,n}^k) + \tau(p_n^k - (p_n^k)^i)} - 1 \right), \end{array}$ which can be substituted in (13) where we get an equation with a single variable which can be solved. If there is a solution (p_n^k, a_n^k) with $p_n^k \ge 0$, and $y_{3,n}^k + y_{4,n}^k + \rho \left(p_n^k - l_n^k - s_n^k - g_n^k \right) + \rho \left(p_n^k - P_n + u_{3,n}^k \right) + \tau (p_n^k - (p_n^k)^i) < W_n H_n^k$, this is the required solution. Else, $a_n^k = p_n^k = 0$.

Problem 2: Updating \mathcal{L} Let $\beta_n^{k,v} = \sum_{t=1,t\neq k}^v l_n^t + \sum_{t=1}^v \sum_{m\in\mathcal{N},m\neq n} r_{n,m}^t - \sum_{t=1}^v \sum_{m\in\mathcal{N}} r_{m,n}^t + \sum_{t=1}^{v} s_n^t + \sum_{t=1}^v D_n^t - E_n^v$ for $k \leq v \leq K$ and $n \in \mathcal{N}$.

$$\begin{split} l_{n}^{k} &= \operatorname*{argmin}_{l_{n}^{k} \geq 0} \left(\left(\sum_{v=k}^{K} \left(y_{1,n}^{v} + y_{2,n}^{v} \right) - y_{3,n}^{k} \right) l_{n}^{k} \right. \\ &+ \frac{\rho}{2} \sum_{v=k}^{K} \left(l_{n}^{k} + \beta_{n}^{k,v} + u_{1,n}^{v} \right)^{2} \\ &+ \frac{\rho}{2} \sum_{v=k}^{K} \left(l_{n}^{k} + \beta_{n}^{k,v} - u_{2,n}^{v} + B_{n}^{\max} \right)^{2} \\ &+ \frac{\rho}{2} \left(p_{n}^{k} - l_{n}^{k} - s_{n}^{k} g_{n}^{k} \right)^{2} + \frac{1}{2} \tau (l_{n}^{k} - (l_{n}^{k})^{i})^{2} \right). \end{split}$$
(14)

This is a quadratic equation. By differentiating it we obtain

$$l_{n}^{k} = \frac{1}{\rho(2(K-k)+3)+\tau} \max\left(0,\tau(l_{n}^{k})^{i} - \left(\sum_{v=k}^{K} \left(y_{1,n}^{v} + y_{2,n}^{v}\right) - y_{3,n}^{k} + \rho \sum_{v=k}^{K} \left(\beta_{n}^{k,v} + u_{1,n}^{v}\right) + \rho \sum_{v=k}^{K} \left(\beta_{n}^{k,v} - u_{2,n}^{v} + B_{n}^{\max}\right) - \rho \left(p_{n}^{k} - s_{n}^{k} - g_{n}^{k}\right)\right)\right).$$
(15)

Problem 3: Updating \mathcal{R}

For m = n, $r_{m,n}^k = 0$. Otherwise, let For m = n, $r_{m,n}^{*} = 0$. Otherwise, let $\nu_{m,n}^{k,v} = \sum_{t=1}^{v} l_{m}^{t} + \sum_{t=1, \cdots, v, b \in \mathcal{N}, (t,b) \neq (k,n), b \neq m} r_{m,b}^{t} - \sum_{t=1}^{v} \sum_{b \in \mathcal{N}} r_{b,m}^{t} + \sum_{t=1}^{v} s_{m}^{t} + \sum_{t=1}^{v} D_{m}^{t} - E_{m}^{v}$, and $\gamma_{m,n}^{k,v} = \sum_{t=1}^{v} l_{n}^{t} + \sum_{t=1}^{v} \sum_{n \in \mathcal{N}} r_{n,b}^{t} - \sum_{t=1, \cdots, v, b \in \mathcal{N}, (t,b) \neq (k,m), b \neq n} r_{b,n}^{t} + \sum_{t=1}^{v} s_{n}^{t} + \sum_{t=1}^{v} D_{n}^{t} - E_{n}^{v}$ for $k \leq v \leq K$ and $n, m \in \mathcal{N}, n \neq m$. Then, the optimization for \mathcal{R} reduces as

$$r_{m,n}^{k} = \underset{r_{m,n}^{k} \ge 0}{\operatorname{argmin}} \left(\left(\mu + \sum_{v=k}^{K} \left(y_{1,m}^{v} - y_{1,n}^{v} + y_{2,m}^{v} - y_{2,n}^{v} \right) \right. \\ \left. - y_{5,n}^{k} \right) r_{m,n}^{k} + \frac{\rho}{2} \sum_{v=k}^{K} \left(r_{m,n}^{k} + \nu_{m,n}^{k,v} + u_{1,m}^{v} \right)^{2} \\ \left. + \frac{\rho}{2} \sum_{v=k}^{K} \left(-r_{m,n}^{k} + \gamma_{m,n}^{k,v} + (u_{1,n}^{v}) \right)^{2} \\ \left. + \frac{\rho}{2} \sum_{v=k}^{K} \left(r_{m,n}^{k} + \nu_{m,n}^{k,v} - u_{2,m}^{v} + B_{m}^{\max} \right)^{2} \\ \left. + \frac{\rho}{2} \sum_{v=k}^{K} \left(-r_{m,n}^{k} + \gamma_{m,n}^{k,v} - u_{2,n}^{v} + B_{m}^{\max} \right)^{2} \\ \left. + \frac{\rho}{2} \left(s_{n}^{k} + u_{4,n} - \sum_{b \in \mathcal{N}, b \neq n, b \neq m} r_{b,n}^{k} - r_{m,n}^{k} \right)^{2} \\ \left. + \frac{1}{2} \tau (r_{m,n}^{k} - (r_{m,n}^{k})^{i})^{2} \right).$$

$$(16)$$

This is a quadratic equation. By differentiating it we obtain

$$r_{m,n}^{k} = \frac{1}{\rho(4(K-k)+5)+\tau} \max\left(0,\tau(r_{m,n}^{k})^{i} - (\mu + \sum_{v=k}^{K} (y_{1,m}^{v} - y_{1,n}^{v} + y_{2,m}^{v} - y_{2,n}^{v}) - y_{5,n}^{k} + \rho \sum_{v=k}^{K} (\nu_{m,n}^{k,v} + u_{1,m}^{v} - \gamma_{m,n}^{k,v} - u_{1,n}^{v}) + \rho \sum_{v=k}^{K} (\nu_{m,n}^{k,v} - u_{2,m}^{v} + B_{m}^{\max} - \gamma_{m,n}^{k,v} + u_{2,n}^{v} - B_{n}^{\max}) - \rho \left(s_{n}^{k} + u_{4,n} - \sum_{b \in \mathcal{N}, b \neq n, b \neq m} r_{b,n}^{k} \right) \right) \right).$$
(17)

Problem 4: Updating S

 $\begin{array}{lll} \underset{v \leq K}{\operatorname{Let}} & \beta_n^{k,v} &= \sum_{t=1}^v l_n^t + \sum_{t=1}^v \sum_{m \in \mathcal{N}, m \neq n} r_{n,m}^t - \\ \sum_{t=1}^v \sum_{m \in \mathcal{N}} r_{m,n}^t + \sum_{t=1, t \neq k}^v s_n^t + \sum_{t=1}^v D_n^t - E_n^v \text{ for } k \leq v \\ \end{array}$

$$s_{n}^{k} = \underset{s_{n}^{k} \geq 0}{\operatorname{argmin}} \left(\left(\sum_{v=k}^{K} \left(y_{1,n}^{v} + y_{2,n}^{v} \right) - y_{3,n}^{k} + y_{5,n}^{k} \right) s_{n}^{k} + \frac{\rho}{2} \sum_{v=k}^{K} \left(s_{n}^{k} + \beta_{n}^{k,v} + u_{1,n}^{v} \right)^{2} + \frac{\rho}{2} \sum_{v=k}^{K} \left(s_{n}^{k} + \beta_{n}^{k,v} - u_{2,n}^{v} + B_{n}^{\max} \right)^{2} + \frac{\rho}{2} \left(p_{n}^{k} - l_{n}^{k} - s_{n}^{k} - g_{n}^{k} \right)^{2} + \frac{1}{2} \tau (s_{n}^{k} - (s_{n}^{k})^{i})^{2} + \frac{\rho}{2} \left(s_{n}^{k} + u_{4,n} - \sum_{m \in \mathcal{N}, m \neq n} r_{m,n}^{k} \right)^{2} \right).$$
(18)

This is a quadratic equation. By differentiating it we obtain

$$s_{n}^{k} = \frac{1}{\rho(2(K-k)+4)+\tau} \max\left(0,\tau(s_{n}^{k})^{i} - \left(\sum_{v=k}^{K} \left(y_{1,n}^{v} + y_{2,n}^{v}\right) + \rho \sum_{v=k}^{K} \left(2\beta_{n}^{k,v} + u_{1,n}^{v} - u_{2,n}^{v} + B_{n}^{\max}\right) - y_{3,n}^{k} + y_{5,n}^{k} - \rho\left(p_{n}^{k} - l_{n}^{k} - g_{n}^{k}\right) + \rho\left(u_{4,n} - \sum_{m \in \mathcal{N}, m \neq n} r_{m,n}^{k}\right)\right)\right).$$
(19)

Problem 5: Updating G

$$g_{n}^{k} = \operatorname{argmin}_{g_{n}^{k} \geq 0} \left(\lambda g_{n}^{k} - y_{3,n}^{k} g_{n}^{k} + \frac{\rho}{2} \left(p_{n}^{k} - l_{n}^{k} - s_{n}^{k} - g_{n}^{k} \right)^{2} + \frac{1}{2} \tau (g_{n}^{k} - (g_{n}^{k})^{i})^{2} \right).$$
(20)

This is a quadratic equation. By differentiating it we obtain

$$g_n^k = \frac{1}{\rho + \tau} \max\left(0, -\lambda + y_{3,n}^k + \rho\left(p_n^k - l_n^k - s_n^k\right) + \tau(g_n^k)^i\right).$$
(21)

Problem 6: Updating \mathcal{D} Let $\beta_n^{k,v} = \sum_{t=1}^v l_n^t + \sum_{t=1}^v \sum_{m \in \mathcal{N}, m \neq n} r_{n,m}^t - \sum_{t=1}^v \sum_{m \in \mathcal{N}} r_{m,n}^t + \sum_{t=1}^v s_n^t + \sum_{t=1, t \neq k}^v D_n^t - E_n^v$ for $k \leq v \leq K$ and $n \in \mathcal{N}$.

$$D_{n}^{k} = \underset{D_{n}^{k} \ge 0}{\operatorname{argmin}} \left(\left(\sum_{v=k}^{K} \left(y_{1,n}^{v} + y_{2,n}^{v} \right) \right) D_{n}^{k} + \frac{\rho}{2} \sum_{v=k}^{K} \left(D_{n}^{k} + \beta_{n}^{k,v} + u_{1,n}^{v} \right)^{2} + \frac{1}{2} \tau (D_{n}^{k} - (D_{n}^{k})^{i})^{2} + \frac{\rho}{2} \sum_{v=k}^{K} \left(D_{n}^{k} + \beta_{n}^{k,v} - u_{2,n}^{v} + B_{n}^{\max} \right)^{2} \right).$$
(22)

This is a quadratic equation. By differentiating it we obtain

$$D_n^k = \frac{1}{2\rho(K - k + 1) + \tau} \max\left(0, -\left(\sum_{v=k}^K \left(y_{1,n}^v + y_{2,n}^v\right) + \rho\sum_{v=k}^K \left(2\beta_n^{k,v} + u_{1,n}^v - u_{2,n}^v + B_n^{\max}\right)\right) + \tau(D_n^k)^i\right).$$
(23)

Problem 7: Updating \mathcal{U}

The optimization for each of $u_{i,n}^k$ is a quadratic problem, and thus the solutions for these problems are as follows.

$$\begin{aligned} u_{1,n}^{k} &= \frac{1}{\rho + \tau} \max\left(0, -y_{1,n}^{k} - \rho \sum_{t=1}^{k} l_{n}^{t} - \rho \sum_{t=1}^{k} \\ &\sum_{m \in \mathcal{N}, m \neq n} r_{n,m}^{t} + \rho \sum_{t=1}^{k} \sum_{m \in \mathcal{N}} r_{m,n}^{t} - \rho \sum_{t=1}^{k} s_{n}^{t} \\ &- \rho \sum_{t=1}^{k} D_{n}^{t} + \rho E_{n}^{k} + \tau (u_{1,n}^{k})^{i} \right), \end{aligned}$$
(24)
$$\begin{aligned} u_{2,n}^{k} &= \frac{1}{\rho + \tau} \max\left(0, y_{2,n}^{k} + \rho \sum_{t=1}^{k} l_{n}^{t} + \rho \sum_{t=1}^{k} \\ &\sum_{m \in \mathcal{N}, m \neq n} r_{n,m}^{t} - \rho \sum_{t=1}^{k} \sum_{m \in \mathcal{N}} r_{m,n}^{t} + \rho \sum_{t=1}^{k} s_{n}^{t} \\ &+ \rho \sum_{t=1}^{k} D_{n}^{t} - \rho E_{n}^{k} + \rho B_{n}^{\max} + \tau (u_{2,n}^{k})^{i} \right), \end{aligned}$$
(25)
$$\begin{aligned} u_{3,n}^{k} &= \frac{1}{\rho + \tau} \max\left(0, -y_{4,n}^{k} - \rho p_{n}^{k} + \rho P_{n} \\ &+ \tau (u_{3,n}^{k})^{i} \right), \end{aligned}$$
(26)

$$u_{4,n}^{k} = \frac{1}{\rho + \tau} \max\left(0, -y_{5,n}^{k} - \rho s_{n}^{k} + \rho \sum_{m \in \mathcal{N}, m \neq n} r_{m,n}^{k} + \tau (u_{4,n}^{k})^{i}\right).$$
(27)