UC Berkeley
Working Papers

Title
Blockchains for Decentralized Optimization of Energy Resources in Microgrid Networks

Permalink
https://escholarship.org/uc/item/80g5s6df

Authors
Munsing, Eric
Mather, Jonathan
Moura, Scott

Publication Date
2017-03-14

Blockchains for Decentralized Optimization of Energy Resources in Microgrid Networks*

Eric Munsing[1], Jonathan Mather[2], and Scott Moura[1]

Abstract— We present an architecture for peer-to-peer energy markets which can guarantee that operational constraints are respected and payments are fairly rendered, without relying on a centralized utility or microgrid aggregator. We demonstrate how to address trust, security, and transparency issues by using *blockchains* and *smart contracts*, two emerging technologies which can facilitate decentralized coordination between non-trusting agents. While blockchains are receiving considerable interest as a platform for distributed computation and data management, this is the first work to examine their use to facilitate distributed optimization and control. Using the Alternating Direction Method of Multipliers (ADMM), we pose a decentralized optimal power flow (OPF) model for scheduling a mix of batteries, shapable loads, and deferrable loads on an electricity distribution network. The DERs perform local optimization steps, and a smart contract on the blockchain serves as the ADMM coordinator, allowing the validity and optimality of the solution to be verified. The optimal schedule is securely stored on the blockchain, and payments can be automatically, securely, and trustlessly rendered without requiring a microgrid operator.

I. INTRODUCTION AND MOTIVATION

The energy production landscape is being reshaped by distributed energy resources (DERs) — photovoltaic panels, electric vehicles, smart appliances, and battery storage systems, which provide low-voltage energy services and are often remotely controllable as part of the Internet of Things. When used intelligently, these DERs can reduce cost, improve reliability, and integrate renewable resources in the electric grid — features which have led regulators to introduce policies promoting their adoption [1], [2].

However, payments for DER services must be negotiated with electric utilities, monopolies who may be invested in preserving conventional generation systems. As a result, the deployment of DERs has often been met with animosity by utilities, which may bar the participation of DERs or seek monopoly rents in return for access to the distribution infrastructure [3], [4].

Local distribution markets for energy services have been proposed as a means of efficiently incentivizing and dispatching DERs, much as is done at the transmission scale [5], [6]. However, such a local distribution market would need to address both the monopoly incentive issues highlighted

[1]Eric Munsing and Scott Moura are with the Department of Civil and Environmental Engineering, University of California at Berkeley, USA e.munsing@berkeley.edu
[2]Jonathan Mather is with the Department of Mechanical Engineering, University of California at Berkeley, USA jonathan.mather@berkeley.edu

above, and also the abuses of market power observed in wholesale energy markets [7], [8]. These issues would be particularly pertinent in microgrid operation, which may not benefit from the scrutiny given to a larger utility [9].

Engineering literature has examined control schemes for providing energy services with DERs in distribution grids and microgrids [10], but has typically assumed operation is managed by a benevolent aggregator or cooperative utility. It is unclear how these proposed control systems would work in the face of incentive issues or regulatory shortcomings.

To address these issues, we leverage an emerging technology which has been developed to allow decentralized consensus between non-trusting agents: blockchains and smart contracts. Despite extensive use in financial applications for addressing trust issues [11], blockchains have seen limited deployment in the energy space [12] and have not been considered for the direct coordination of DERs [13].

We examine how a blockchain architecture can be used to distribute the aggregator's role across all devices on a microgrid network. This integrated architecture is demonstrated on a blockchain platform controlling a microgrid simulation, and demonstrates how to address incentive issues while respecting operational constraints.

We structure the remainder of the paper as follows: Section II provides a brief overview of blockchains and smart contracts. Section III provides a survey of previous literature on dispatch of DERs in microgrids, decentralized optimization techniques, and blockchain use in energy applications. Section IV presents the formulation of the optimal power flow problem with DERs and its ADMM equivalent, and Section V describes the algorithm for utilizing a blockchain for securing our decentralized problem. We present results from a simulation network, discuss limitations, and conclude by highlighting additional research opportunities.

II. BLOCKCHAINS AND SMART CONTRACTS

Blockchains are an emerging technology for decentralized computation and data storage, secured by a combination of cryptographic signatures and a distributed consensus mechanism. Participants on the blockchain network are able to come to universal agreement on the system state σ^t at each time step t, even in the presence of cyberattacks, communication dropouts, and participants joining/departing the network. This is in stark contrast to conventional architectures where a central coordinator defines the state of the system, but may be subject to attack or malfeasance.

The general architecture of blockchains is described in [14] and illustrated in Fig. 1. Participants on the peer-to-peer
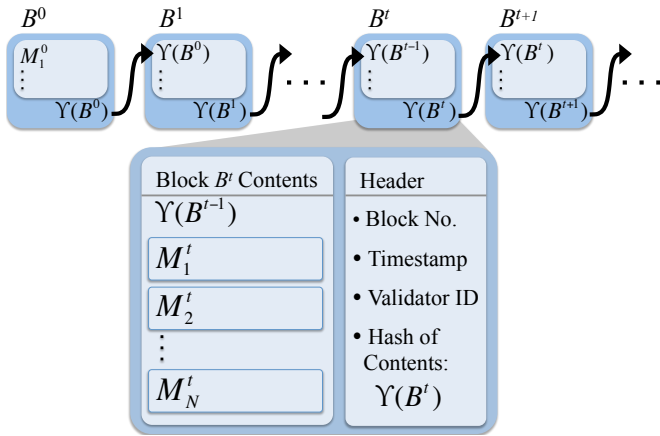
Fig. 1. Symbolic representation of the data in a blockchain, showing blocks B^0 to B^{t+1} with detail of block B^t. Blocks are linked by their cryptographic hashes $\Upsilon(B^t)$, securing the contents from alteration and allowing transparent auditing of system history. Messages M_i^t contain information about changes to the system state, such as energy transfers or payments.

Fig. 2. Comparison of an efficient market in which the optimal quantity $Q*$ is cleared at price $P(Q*)$, and a market operated by a monopoly who is able to charge separate prices for generation and consumption. In this model, the monopoly restricts output to Q_M, purchasing energy at $C(Q_M)$ and charging consumers $P(Q_M)$.

network broadcast messages $M_i^t, i \in (1, \ldots, N_m)$. These messages contain commands which affect the state of the system (control actions, account withdrawals, etc), and the feasibility of each message can be checked by each node using a validation function $\pi(\sigma^{t-1}, M_i^t)$.

Participants listen to the network and collect a set of messages into the contents of the next block B^t. A block header H is formed which contains the timestamp, a concise *cryptographic hash* $\Upsilon(B^{t-1})$ of the contents of the previous block, and the results of a verification test that is computationally or economically difficult to forge. The new block is broadcast to the network, where its validity is checked and nodes reach consensus on the updated state of the system $\sigma^t = \Pi(\sigma^{t-1}, B^t)$. The utility of blockchains can be significantly expanded when the state transition function $\Pi(\cdot)$ can execute computer code embedded in the transmissions M_i. These *smart contracts* can be transparently inspected and audited, and are guaranteed to be faithfully executed on the network.

Recursively linking the contents of blocks, verifying new blocks with peer-to-peer consensus, and using cryptographic signatures to verify communication are the pillars of blockchain architecture. Together, they provide an immutable and robust representation of system state- without requiring the intervention of a trusted central authority. While this architecture introduces some computational overhead, it offers immutability, transparency, and verifiability which can make the system well suited for coordination between parties who do not trust each other. We refer the reader to [13], [15], [11] for additional details on the security, architecture, and applications of blockchains and smart contracts.

III. PRIOR LITERATURE

This work draws on three bodies of research: control of distributed energy resources, the economics and regulation of microgrids, and research on blockchains and smart contracts.
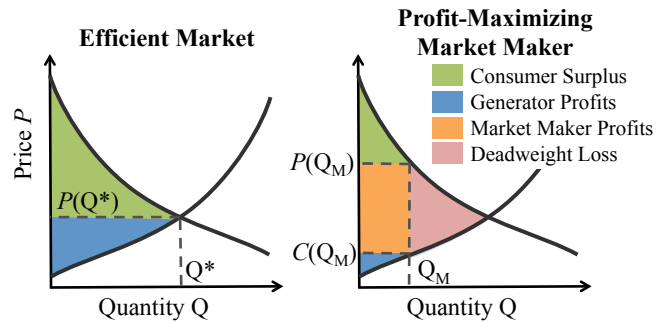
We provide a brief summary of relevant literature from each domain.

A. DER Control

Microgrids are electricity networks which can be controlled autonomously, and may operate in both grid-connected and self-sufficient modes [16]. Without the benefit of a large balancing territory, loads and generation must be coordinated carefully and the role of DERs becomes particularly important. Surveys of approaches to microgrid management can be found in [17], [10].

Conventionally, generation resources have been centrally controlled by a utility or system operator — but these centralized approaches do not scale well to large numbers of DERs, and recent research has focused on decentralized algorithms with low computational overhead. Decentralized algorithms have been explored for coordinating electric vehicles [18], [19], smart inverters [20], and for fleets of diverse DERs [21], [22], [23].

Constraints on network voltage and power power flows can become significant at high DER penetrations, and decentralized models for power flow in distribution systems have been explored in [24], [25], [26]. As the underlying AC optimal power flow problem (OPF) problem is nonconvex, each of these examines different assumptions or relaxations which grant computational tractability.

B. Microgrids and Monopoly Economics

In prior literature, DERs are compensated for providing energy services by an aggregator or a utility: a central authority who is trusted to act fairly in scheduling generators, satisfying loads, and rendering payments.

Like conventional electrical utilities, a microgrid operator faces a set of competing demands: minimizing consumer costs, investing in reliability and long-term capacity, and providing a return for shareholders [27]. Even without owning any assets, such a monopoly aggregator can have strong incentives to shift the market away from a cost-minimizing equilibrium and towards a profit-maximizing monopoly outcome, as shown in Figure 2. These conflicts of interest are typically controlled through regulatory intervention, where

auditors scrutinize market outcomes and regulate customer fees [28].

However, when regulatory efforts are expensive, a small degree of market inefficiency may be less burdensome than regulatory costs [29]. This can create distrust between the microgrid operator and producers/consumers, who cannot assess whether their bills reflect monopoly profits or justified costs [9], [1].

This trust issue is already visible in the integration of rooftop photovoltaic systems in distribution networks [3], [4], and can be expected to be a greater problem in microgrids if regulatory scrutiny cannot be efficiently implemented for small systems — for example, if regulation has a high fixed cost (such as for retaining auditors) [29].

C. Blockchains and Energy

Blockchain research is still a new field, with most existing work focused on security and scalability [13], [11] and few applications for controlling physical devices [15], [30]. Although blockchains rely on a distributed consensus mechanism to provide security, the parallels with decentralized consensus algorithms in engineering control and optimization research have not yet been explored.

Existing applications in the energy space have only used blockchains as secure databases for tracking energy generation and consumption, typically in the form of tokens representing renewable energy credits [31], [32], [33].

While blockchains have been discussed for use in coordinating DERs in transactive energy markets [34], [35], these works have not considered physical constraints on DER operation – instead treating DERs as idealized financial assets. In reality, any coordination system must consider the DER's own constraints as well as the constraints of the distribution network. Prior literature has not considered methods for addressing these constraints in blockchain applications.

D. Novel Contributions

With this background, we see blockchains and smart contracts holding unexplored potential for eliminating trust issues with microgrid operators, and as a natural platform for coordinating the decentralized optimization schemes described above. The following contributions extend prior literature:

- Distributed optimal power flow algorithm with batteries, shapable loads, and deferrable loads
- Recovery of distributed locational marginal prices from a decentralized OPF problem
- Use of a blockchain for coordinating devices with operational constraints
- Use of a blockchain to facilitate the aggregator step of a decentralized optimization algorithm

IV. OPTIMAL DISPATCH FORMULATION

We consider a microgrid with a dispatchable central generator, uncontrolled plug loads, non-dispatchable renewable energy resources, shapable loads (e.g. electric vehicles), deferrable loads (e.g. appliances), and batteries. We consider a day-ahead scheduling problem, with the objective of minimizing cost of energy provision subject to the operational constraints of the DERs and of the distribution network.

Note that in formulating the equations our variables are italicized, constants are non-italicized, and sets are denoted by calligraphy.

A. Network Model

The distribution network is modeled as an undirected radial graph $\mathcal{G}(\mathcal{N}, \mathcal{E})$, consisting of a set of nodes $\mathcal{N}$ and a set of distribution lines (a.k.a. edges) $\mathcal{E}$ connecting these nodes. Using the notation described in [36], we index the nodes in $\mathcal{N}$ by $i = 0, 1, \ldots, n$, where node 0 represents the root node (substation) and other nodes in $\mathcal{N}$ represent branch nodes. We also denote a line in $\mathcal{E}$ by the pair (i, j) of nodes it connects where j is closer to the feeder 0. We call j the parent of i, denoted by $\pi(i)$, and call i the child of j. Denote the child set of j as $\delta(j) := \{i : (i, j) \in \mathcal{E}\}$. Thus a link (i, j) can be denoted as $(i, \pi(i))$.

For each line $(i, \pi(i)) \in \mathcal{E}$, let $z_i = r_i + ix_i$ be the impedance of the line, let I_i be the complex current flowing from nodes i to $\pi(i)$, and $S_i = P_i + iQ_i$ be the complex power flowing from nodes i to $\pi(i)$. On each node $i \in \mathcal{N}$, let V_i be the complex voltage, and $s_i = p_i + iq_i$ be the net complex power injection. We assume the complex voltage V_0 at the substation node is given and fixed. We define $l_i := |I_i|^2$, $v_i := |V_i|^2$.

We model power flow on the network using the branch flow equations, first proposed in [37], which reflect a balanced single-phase radial network.

$$p_i = P_i - \sum_{k \in \delta(i)} P_k + r_i l_i, \quad i = 0, \ldots, n \tag{1a}$$

$$q_i = Q_i - \sum_{k \in \delta(i)} Q_k + x_i l_i, \quad i = 0, \ldots, n \tag{1b}$$

$$v_i = v_{\pi(i)} + 2(r_i P_i + x_i Q_i) - (r_i^2 + x_i^2) l_i, i = 1, \ldots, n \tag{1c}$$

$$l_i = \frac{P_i^2 + Q_i^2}{v_i}, \quad i = 1, \ldots, n \tag{1d}$$

where $S_0 = 0 + i0$ at the slack bus. Equations in (1) define a system in the variables $(P, Q, l, v) := (P_i, Q_i, l_i, v_i, \forall i \in \mathcal{N})$, which do not include phase angles of voltages and currents. Given (P, Q, l, v), phase angles can be uniquely determined for radial networks [38].

The final equation (1d) forms a non-convex set. It is relaxed to an inequality, which yields a second-order cone constraint:

$$l_i \geq \frac{P_i^2 + Q_i^2}{v_i} \iff \left\| \begin{array}{c} 2P_i \\ 2Q_i \\ l_i - v_i \end{array} \right\|_2 \leq l_i + v_i \tag{2}$$

In addition to the power flow equations, we also consider constraints on voltage magnitude on the network. These typically bound voltage within $\pm 5\%$ of a nominal voltage.

$$\underline{v}_i \leq v_i \leq \overline{v}_i, \quad i = 1, \ldots, n \tag{3}$$

B. Controllable DERs

We consider a set of energy resources with complex injections/withdrawals s placed at nodes i throughout the microgrid network, denoted as follows:

s_i^g	Dispatchable generators	s_i^u	Uncontrollable loads
s_i^r	Renewable generators	s_i^d	Deferrable loads
s_i^b	Stationary batteries	s_i^s	Shapable loads

The net complex injection at a node i in period t is

$$s_i(t) = s_i^g(t) - s_i^l(t), \quad i = 0, \ldots, n \tag{4}$$

where

$$s_i^l(t) = s_i^u(t) + s_i^d(t) + s_i^s(t) - s_i^b(t) - s_i^r(t) \tag{5}$$

Dispatchable generators (e.g. microturbines, diesel generators, fuel cells) are considered to have quadratic increasing cost, which may be time-varying:

$$C_{i,t}(s_i^g(t)) = \alpha_{i,t} s_i^g(t)^2 + \beta_{i,t} s_i^g(t) + \gamma_{i,t} \tag{6}$$

Power injection from renewable generators is considered to be deterministic and have no marginal cost $C_{i,t}(s_i^r(t)) = 0$. Power withdrawals due to uncontrollable loads (lights, plug loads) are considered deterministic, inflexible, and inelastic. We do not model thermostatically controlled loads or smart inverters, though those can be added to the formulation using the approaches in [39] and [26] respectively.

Stationary batteries are modeled as dispatchable loads which can be controlled to withdraw power ($s_i^b < 0$) or inject power ($s_i^b > 0$). We assume charging efficiency $\eta_{i,\text{in}}$, and discharging efficiency $\eta_{i,\text{out}}$. We assume that the battery should not undergo a net discharge of more than ε over the course of the dispatch period.

$$\forall t = 1 \ldots T:$$

$$s_i^b(t) = d_i^b(t) - c_i^b(t) \tag{7a}$$

$$0 \leq c_i^b(t) \leq P_{i,\text{charge}}^b \tag{7b}$$

$$0 \leq d_i^b(t) \leq P_{i,\text{discharge}}^b \tag{7c}$$

$$E_{b,\min} \leq E_b(t) \leq E_{b,\max} \tag{7d}$$

$$E_i^b(t) = E_i^b(t-1) + c_i^b(t)\Delta t \eta_{i,\text{in}} - d_i^b(k)\Delta t / \eta_{i,\text{out}} \tag{7e}$$

$$(1+\varepsilon)E_i^b(1) \leq E_i^b(T) \leq (1-\varepsilon)E_i^b(1) \tag{7f}$$

Shapable loads (e.g. electric vehicles with continuous charging levels, continuously variable fans) are modeled as having net energy demand $E_{i,\text{demand}}^s$, and must be charged between times $t_{i,\text{startby}}$ and $t_{i,\text{endby}}$:

$$P_{i,\min}^s \leq s_s(t) \leq P_{i,\max}^s \quad \forall t = 1 \ldots T \tag{8a}$$

$$\sum_{t=1}^{T} s_s(t) = E_{i,\text{demand}}^s \tag{8b}$$

$$s_i^s(t) = 0 \quad \forall t = 1, \ldots, t_{i,\text{startby}} \tag{8c}$$

$$s_i^s(t) = 0 \quad \forall t = t_{i,\text{endby}}, \ldots, T \tag{8d}$$

Deferrable loads are considered to have some flexibility in their start time, but a defined load profile $l(\tau) \, \forall \, \tau = 1, \ldots, L$ once started (e.g. appliances, manufacturing equipment).

Following on the work in [22], we model the minimal starting time of the load as an arrival process $a(t)$, and the actual starting time as a departure process $d(t)$, where each of these variables takes the value 0 until the time of the request arrival/departure, at which point it takes the value 1. If the device can be started at most ζ time steps after the arrival request, we can formulate the constraints on our decision variable $d(t)$ as

$$\forall t = 1 \ldots T:$$

$$0 \leq d_i(t-1) \leq d_i(t) \leq a_i(t) \tag{9a}$$

$$a_i(t-\zeta) \leq d(t) \tag{9b}$$

$$d_i(t) \in (0,1) \tag{9c}$$

Following [22] to formulate a matrix Φ which convolves the departure process $d(t)$ into a power consumption profile $s_d = \Phi d$, we can relax the binary constraint to allow scheduling to be expressed as a linear problem.

C. Optimal Power Flow

We consider the problem of maximizing social welfare in the network over a day, which amounts to scheduling the controllable loads to minimize generation cost, while respecting network constraints. This problem is commonly known as *economic dispatch*, one of a family of optimal power flow (OPF) problems. It is formulated as follows:

$$\min \sum_{t=1}^{T} \sum_{i=1}^{n} C_{i,t}(s_i^g(t)) \tag{10a}$$

$$\text{s.t. } (1a), (1b), (1c), (2), (3), (4), \quad t = 1, \ldots, T \tag{10b}$$

$$(7)_i, (8)_i, (9)_i, \quad i = 1, \ldots, n \tag{10c}$$

$$\text{over } s_i^g(t) \in [\underline{s_i^g}, \overline{s_i^g}], i = 0, \ldots, n, t = 1, \ldots, T$$

$$(P_i, Q_i, l_i, v_i)(t), i = 1, \ldots, n, t = 1, \ldots, T$$

where constraints $(7)_i, (8)_i, (9)_i$, are specific to each node $i = 1, \ldots, n$, depending on the resources at that node.

In order to compensate the DER operators for their services and charge consumers for withdrawals, we want to compute nodal clearing prices, known as *distributed locational marginal prices* (DLMPs). The DLMP at a node represents the marginal cost to supply an additional unit of real power at that node. We denote the DLMP at node i as λ_i, and they can be found as the dual variables associated with the real power balance constraint (1a). As described in [36], the DLMP can be decomposed into contributions from energy, line losses, and voltage congestion.

D. Decomposition with ADMM

The Alternating Direction Method of Multipliers (ADMM) has gained popularity as a tool for decomposing difficult convex optimization problems into a set of simpler subproblems, coordinated through an aggregator step [40]. While convergence may be slow, the simplicity of the aggregator step and the guarantee of global optimality make the algorithm compelling for DER coordination. For examples of ADMM applications in various models of optimal dispatch problems, see [23], [41], [26], [25].

In the canonical ADMM problem, we consider a minimization problem with separable objectives and constraints in vectors x and z:

$$\min_{x,z} \quad f(x) + g(z)$$
$$\text{s. to:} \quad x \in \mathcal{K}_x, \; z \in \mathcal{K}_z$$
$$Ax + Bz = c$$

We can form the augmented Lagrangian:

$$L_\rho(x,z,\xi) := f(x) + g(z) + \xi^\top(Ax + Bz - c) + \frac{\rho}{2}\|Ax + Bz - c\|^2$$

This then decomposes into the general form of ADMM:

$$x^{k+1} = \arg\min_{x \in \mathcal{K}_x} L_\rho(x, z^k, \xi^k) \tag{11a}$$
$$z^{k+1} = \arg\min_{z \in \mathcal{K}_z} L_\rho(x^{k+1}, z, \xi^k) \tag{11b}$$
$$\xi^{k+1} = \xi^k + \rho(Ax^{k+1} + Bz^{k+1} - c) \tag{11c}$$

When decomposing a problem into subproblems for solution with ADMM, it is useful to think of x and z in the above as *local* and *global* variables respectively. Local variables only pertain to their respective subproblems, whereas global variables couple subproblems together and must be agreed upon at the global optimum, reaching a distributed consensus among subproblems. An intuitive way to formulate this is to give each subproblem its own copy of any coupling variables, and then try and make these copies agree.

The economic dispatch problem of (10) can be reformulated in this way by forming an individual subproblem at each node, whose solutions are made to coincide at the global optimum through copied local coupling variables. Each subproblem has its own copy of the relevant global coupling variable, and consensus on their value is achieved among subproblems through the ADMM algorithm. The subproblem of node i takes the following form, where for clarity we have omitted the time index from each nodal variable.

$$\min \sum_{t=1}^{T} C_{i,t}(s_i^g(t)) \tag{12a}$$

$$\text{s.t. } p_i = P_i - \sum_{k \in \delta(i)} P_k + \mathrm{r}_i l_i, \quad t = 1, \ldots, T \tag{12b}$$

$$q_i = Q_i - \sum_{k \in \delta(i)} Q_k + \mathrm{x}_i l_i, \quad t = 1, \ldots, T \tag{12c}$$

$$v_i = v_{\pi(i)} + 2(\mathrm{r}_i P_i + \mathrm{x}_i Q_i) - (\mathrm{r}_i^2 + \mathrm{x}_i^2)l_i, \; t = 1, \ldots, T \tag{12d}$$

$$l_i \geq \frac{P_i^2 + Q_i^2}{v_i} \tag{12e}$$

$$(7)_i, (8)_i, (9)_i \tag{12f}$$

over $s_i^g \in [\underline{s_i^g}, \overline{s_i^g}], s_i^b, s_i^d, s_i^s$
$(P_i, Q_i, l_i, v_i), (P_{\delta(i)}, Q_{\delta(i)}, v_{\pi(i)})$

We first define a set of global variables $z := [P^\top, Q^\top, v^\top]^\top \in \mathbb{R}^{3n}$, a set of private local variable $x_i := [s_i^g, s_i^b, s_i^d, s_i^s, l_i]^\top$, and a set of coupling local variables

$\tilde{x}_i = [P_i^\top, Q_i^\top, v_i^\top, P_{\delta(i)}^\top, Q_{\delta(i)}^\top, v_{\pi(i)}^\top]^\top$. We see that each subproblem i is coupled to other subproblems through the coupling local variables $\tilde{x}_i$, each of which is a selection of the components of the global variable z. Using notation from [40], the mapping from local variable indices into the global variable index can be written as $g = \mathcal{G}(i,j)$, which means that local variable component $(\tilde{x}_i)_j$ corresponds to global variable component z_k. Achieving consensus between the local variables and the global variable means that

$$(\tilde{x}_i)_j = z_{\mathcal{G}(i,j)}, \forall i, j \tag{13}$$

We can equivalently define a selection matrix B_i, such that, $\tilde{z}_i = B_i z$, and at the optimum

$$\tilde{x}_i - B_i z = \tilde{x}_i - \tilde{z}_i = 0 \tag{14}$$

At each iteration k, each node i, receives $\tilde{z}_i^k$ from the central aggregator, and solves

$$\min \sum_{t=1}^{T} C_{i,t}(s_{i,t}) + \xi_i^\top(\tilde{x}_i - \tilde{z}_i^k) + \frac{\rho}{2}\|\tilde{x}_i - \tilde{z}_i^k\|_2^2$$
$$\text{s.t. (12)} \tag{15}$$
$$\text{over } x_i, \tilde{x}_i$$

The node then sends its new $\tilde{x}_i^{k+1}$ to the central aggregator, who computes the following update for each individual global variable z_g^{k+1}

$$z_g^{k+1} := \frac{1}{k_g} \sum_{\mathcal{G}(i,j)=g} (\tilde{x}_i^{k+1})_j \tag{16}$$

where k_g is the number of local variable entries that correspond to global variable entry z_g. The update can be thought of as taking the average of all local copies of the global variable. The central aggregator then updates ξ_i as

$$\xi_i^{k+1} = \xi_i^k + \rho(\tilde{x}_i^{k+1} - \tilde{z}_i^{k+1}) \tag{17}$$

We define the stopping criteria using the following residuals

$$r_i^k = \tilde{x}_i^k - \tilde{z}_i^k, \; s^k = z^k - z^{k-1} \tag{18}$$

Defining $r^k := [r_1^k, \ldots, r_n^k]$, the algorithm is determined to have converged when the both the following conditions are met

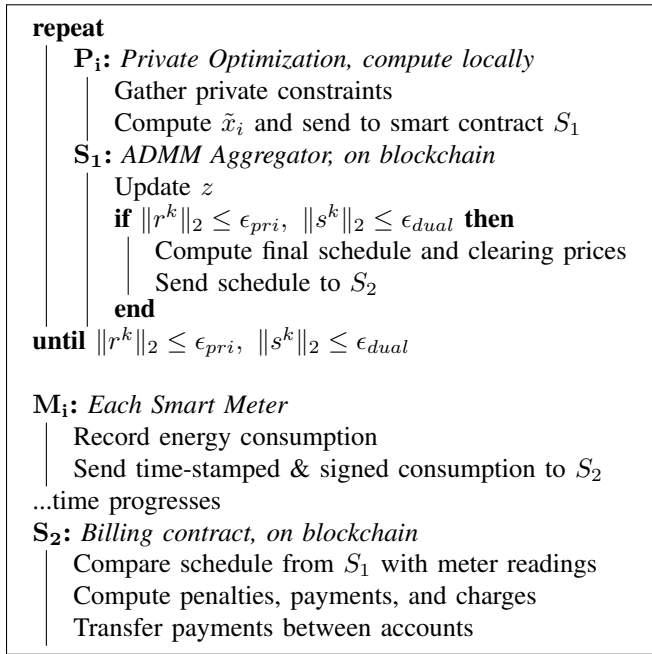$$\|r^k\|_2 \leq \epsilon_{pri}, \; \|s^k\|_2 \leq \epsilon_{dual} \tag{19}$$

where $\epsilon_{pri}, \epsilon_{dual}$ are suitably defined tolerances, and can be set using methods described in [40].

V. BLOCKCHAIN AND ADMM

We have formulated an optimal scheduling program for distributed energy resources through a decentralized algorithm. However, this only addresses part of the microgrid operation problem, and still has notable weaknesses:

- The aggregation step is not guaranteed against cyberattack or tampering by participants
- Individual DERs/consumers cannot verify that they are being paid/billed at fair prices
- Payments for actual generation/consumption will still be handled by a central utility

As an alternative, we propose to leverage the benefits of a blockchain architecture to create a fully peer-to-peer system which guarantees both operational feasibility and fair payments to all parties while taking full advantage of the decentralized structure of the problem.

---

repeat
    P_i: *Private Optimization, compute locally*
        Gather private constraints
        Compute $\tilde{x}_i$ and send to smart contract S_1
    S_1: *ADMM Aggregator, on blockchain*
        Update z
        if $\|r^k\|_2 \le \epsilon_{pri}$, $\|s^k\|_2 \le \epsilon_{dual}$ **then**
            Compute final schedule and clearing prices
            Send schedule to S_2
        end
until $\|r^k\|_2 \le \epsilon_{pri}$, $\|s^k\|_2 \le \epsilon_{dual}$

M_i: *Each Smart Meter*
    Record energy consumption
    Send time-stamped & signed consumption to S_2
...time progresses
S_2: *Billing contract, on blockchain*
    Compare schedule from S_1 with meter readings
    Compute penalties, payments, and charges
    Transfer payments between accounts

Algorithm 1: Computational elements in the microgrid control system. Function P_i is executed locally by each device participating in the market. The results are passed to the smart contract S_1, which serves as publicly verifiable ADMM aggregation step. P_i and S_1 iterate back and forth until ADMM converges, at which point the schedule is saved to the billing smart contract S_2. Smart meters send trusted meter readings to S_2, which computes payments and automatically transfers funds from consumers to generators.

As discussed in Section II, blockchains provide a method for providing a transparent, trustless platform for data storage and computation. This makes a private blockchain the perfect platform for conducting the aggregation step of ADMM, allowing all participants to audit the progress of the algorithm, the accuracy of the solution, and the veracity of their scheduled commitments. Further, ADMM is a natural fit for implementation on a blockchain, as it guarantees convergence yet has a *computationally cheap* aggregation step (minimizing the burden of verification).

Algorithm 1 provides an outline of the sequence of events in our proposed blockchain-based system. In it, we use the blockchain to (i) provide a fair computation of the ADMM aggregator update step from (16), (ii) store the resulting schedule, and (iii) compute payments and penalties for actual generation/consumption.

Any participant can verify that the schedule maximizes social benefit while respecting network constraints, removing the possibility of monopolistic price manipulation. This immutable record can also become the basis for reckoning payments when the schedule is realized, if smart meters send consumption data to a billing contract S_2 on the
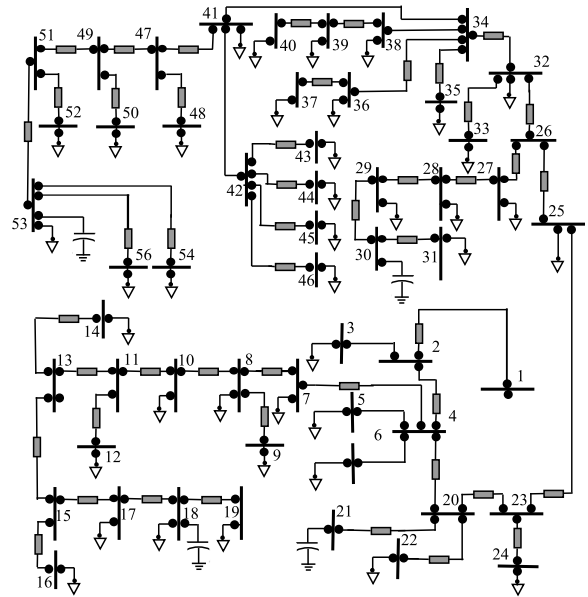

Fig. 3. The 55-bus sample microgrid test feeder used in the simulation, with a microturbine placed at Bus 1 and DERs randomly distributed throughout the network.

blockchain. After computing credits and debits for each node in the network, the updated account balance is securely saved to the blockchain. Paired with a cryptocurrency as discussed in [11], this can form a complete payment system — removing the need for a utility or microgrid operator to handle scheduling and billing.

VI. IMPLEMENTATION: TEST NETWORK

We implement the proposed algorithm on a simulated SCE 55-bus test network shown in Fig. 3 with parameters described in [42]. Bus 1 is used as the reference bus, and is equipped with a large microturbine generator with quadratic cost function (this could also represent a connection to a utility grid). Each node has a deterministic load profile, created by adding a uniform random variable to the average uncontrollable load signal seen in Figure 4. We randomly placed solar arrays at 60% of the buses, and assume a deterministic solar generation profile. We place deferrable loads at 70% of the buses, with earliest start times randomly distributed between hours 7:00-11:00; these represent appliances and industrial equipment. Shapable loads are also randomly placed at 70% of the buses, with net energy demand generated from a uniform random variable that is up to 10 times the peak power consumption of the uncontrollable loads; these are intended to represent electric vehicle loads. The time constraints are randomly generated such that the shapable loads begin self-scheduling as early as 10:00, and can continue to draw power as late as hour 24:00. Batteries are placed at each bus, with a power capacity of 50% of the peak controllable load at the bus, and with a 4 hour energy storage capacity.

We use a private Ethereum Frontier blockchain test network [43], and Python/CVXpy [44] to run the private optimization problems. Remote procedure calls through EthJ-
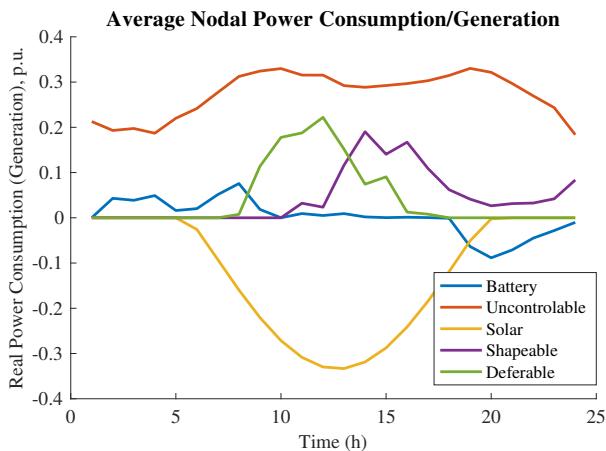
Fig. 4. Schedule of commitments generated by the ADMM algorithm and stored to the smart contract. Positive values of power indicate real power consumption, and negative values indicate generation/injections.
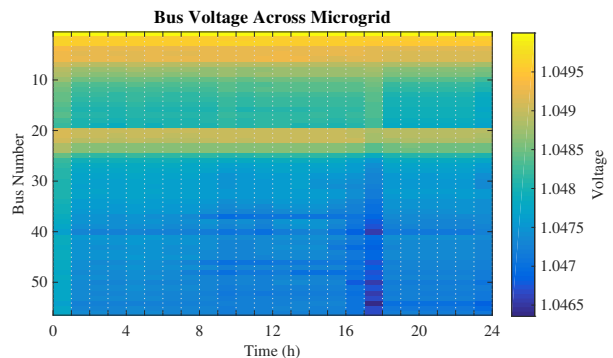

Fig. 5. Voltage magnitude at each of the buses on the test network, for each hour in the simulation. Voltages vary based on local injections, and variations in time can be seen due to the impacts of local DER scheduling.

sonRpc allow the Python scripts to communicate with the smart contracts.

A. Results and Discussion

The ADMM algorithm converged in 204 iterations, using $\rho = 100$, $\epsilon_{pri} = 10^{-3}$, $\epsilon_{dual} = 0.1$, with each iteration taking at most 1.2s to compute. The optimal cost of the distributed solution was 0.4% larger than the centralized OPF solution.

The average power consumption across all nodes is shown in Fig. 4. The power consumption profiles of individual nodes primarily differ in the temporal constraints, size of shapable load, and presence or absence of solar. The algorithm schedules deferrable and shapable loads to consume energy coincident with solar generation. Roughly speaking, the shapable loads fill gaps in the sawtooth profile of the deferrable loads. The battery charges when the net load is lowest, and discharges when net load is highest.

The impacts of network topology can be seen in the voltage of each bus during the simulation period, shown in Figure 5. Since there are no current flow constraints, at optimality the upper voltage limit at the generator bus (#1) becomes the binding constraint; the voltages at each of the other buses decrease with distance from the feeder due to line effects (the critical link between bus 4 and 20 can be clearly seen). General trends in voltage over the course of the day are visible, with a significant drop in hour 18 when the setting sun and peaking uncontrollable load leads to a spike in net load throughout the network. Upon closer inspection, the impacts of DER scheduling are also visible at some buses (e.g. 38, 48.49) as appliances and EVs switch on and off.

The distributed marginal prices are not shown here for brevity, but can be easily calculated from the net load which must be supplied by the central generator (other resources are inframarginal). We found very little variation in DLMPs between buses (variance of $<1\%$ of hourly DLMP), reflecting a lack of congestion on this small network.

VII. Limitations

We only consider a day-ahead scheduling problem here, and do not consider shorter time horizons and ancillary services. For these secondary electrical services, the communication overhead required for ADMM and the verification delay required for a blockchain may make conventional systems more appropriate. One solution could be an economic scheduling layer as we have described here, above a real-time control layer operating at much faster time scales.

The algorithm above does not consider stochasticity in generation, demand, and device constraints. We also assume that the network topology is fully known by all parties, and we do not consider changes in line impedances (e.g. due to temperature changes) or in topology (e.g. due to outages).

This paper focuses on exploring the application of blockchains for coordinating decentralized optimization, but does not attempt a rigorous examination of system security, speed, or resilience as is discussed in [45] and other blockchain literature.

VIII. Conclusions

We have shown how decentralized consensus techniques and blockchains can be used both to coordinate the scheduling of distributed energy resources on a microgrid, and to guarantee fair payments without requiring a utility or centralized microgrid aggregator. By using ADMM, we decompose our problem into a structure that naturally lends itself to a blockchain implementation, and show how blockchains and smart contracts can provide a natural solution for the trust, security, reliability, and immutability requirements of microgrid operation.

The proposed architecture can be improved with contributions from active areas of control research: examining privacy of device constraints and consumption data, addressing stochastic/uncertain data through model predictive control and robust optimization, examining resilience to network interruptions, utilizing fully distributed ADMM between nodes to reduce communication overhead, and developing fault detection algorithms to identify fraud and changes in system architecture.

While this is the first paper (to our knowledge) to examine the integration of blockchain with distributed optimization of energy systems, we expect that many other applications are possible, both within the energy sector and in other engineering realms. Blockchain's distributed consensus mechanism has proven itself in the finance world by guaranteeing robust, trustless, and transparent execution; we highlight similar benefits for controlling physical devices. We see blockchains and smart contracts as a key technology that enables distributed optimization amongst non-trusting entities, at all scales of operation.

REFERENCES

[1] New York State Energy Planning Board, "The Energy to Lead: New York State Energy Plan," tech. rep., New York State Energy Planning Board, 2015.

[2] North Carolina Clean Energy Technology Center, "Net Metering Policy Map," *DSIRE*, no. July, 2016.

[3] F. Flores-espino, "Compensation for Distributed Solar : A Survey of Options to Preserve Stakeholder Value," Tech. Rep. NREL/TP-6A20-62371, National Renewable Energy Laboratory, 2015.

[4] G. Meyers, "Black Hole Forms On Solar Net Metering In Nevada," jan 2016.

[5] Council GridWise Architecture, "GridWise Transactive Energy Framework Version 1.0," pp. 1–43, 2013.

[6] S. Chen and C.-c. Liu, "From Demand Response to Transactive Energy: the State-of-the-Art," *J. Mod. Power Syst. Clean Energy*, 2016.

[7] S. Borenstein, J. Bushnell, and F. Wolak, "Measuring Market Inefficiencies in California ' s Restructured Wholesale Electricity Market," *American Economic Review*, vol. 92.5, pp. 1376–1405, 2002.

[8] F. Wolak, "Lessons from the California Electricity Crisis," in *Electricity deregulation: choices and challenges*, ch. 4, 2005.

[9] California Public Utilities Commission, "Microgrids : A Regulatory Perspective," tech. rep., 2014.

[10] L. I. Minchala-Avila, L. E. Garza-Castañón, A. Vargas-Martínez, and Y. Zhang, "A review of optimal control techniques applied to the energy management and control of microgrids," *Procedia Computer Science*, vol. 52, no. 1, pp. 780–787, 2015.

[11] A. Killeen, *Handbook of Digital Currency*. 2015.

[12] Deutsche Energie-Agentur GmbH (dena), "Blockchain in the energy transition: A survey among decision-makers in the German energy industry," tech. rep., 2016.

[13] J. Bonneau, A. Miller, J. Clark, A. Narayanan, J. A. Kroll, and E. W. Felten, "SoK: Research perspectives and challenges for bitcoin and cryptocurrencies," *Proceedings - IEEE Symposium on Security and Privacy*, vol. 2015-July, pp. 104–121, 2015.

[14] G. Wood, "Ethereum: a secure decentralised generalised transaction ledger," *Ethereum Project Yellow Paper*, pp. 1–32, 2014.

[15] K. Christidis and M. Devetsikiotis, "Blockchains and Smart Contracts for the Internet of Things," *IEEE Access*, vol. 4, pp. 2292–2303, 2016.

[16] D. T. Ton and M. A. Smith, "The U.S. Department of Energy's Microgrid Initiative," *The electricity Journal*, vol. 25, no. 8, pp. 84–94, 2012.

[17] A. Ahmad Khan, M. Naeem, M. Iqbal, S. Qaisar, and A. Anpalagan, "A compendium of optimization objectives, constraints, tools and algorithms for energy management in microgrids," *Renewable and Sustainable Energy Reviews*, vol. 58, pp. 1664–1683, 2016.

[18] C. Le Floch, F. Belletti, and S. Moura, "Optimal Charging of Electric Vehicles for Load Shaping : a Dual Splitting Framework with Explicit Convergence Bounds," *IEEE Transactions on Transportation Electrification*, vol. 7782, pp. 1–9, 2016.

[19] C. Le Floch, F. Belletti, S. Saxena, A. M. Bayen, and S. Moura, "Distributed optimal charging of electric vehicles for demand response and load shaping," *Proceedings of the IEEE Conference on Decision and Control*, vol. 2016-Febru, no. Cdc, pp. 6570–6576, 2016.

[20] O. Sondermeijer, R. Dobbe, D. Arnold, and C. Tomlin, "Regression-based Inverter Control for Decentralized Optimal Power Flow and Voltage Regulation," in *Power & Energy Society General Meeting. IEEE*, 2016.

[21] S. Mhanna, A. C. Chapman, and G. Verbic, "A Fast Distributed Algorithm for Large-Scale Demand Response Aggregation," *IEEE Transactions on Smart Grid*, vol. 7, no. 4, pp. 2094–2107, 2016.

[22] S. C. Tsai, Y. H. Tseng, and T. H. Chang, "Communication-efficient distributed demand response: A randomized ADMM approach," *IEEE Transactions on Smart Grid*, vol. PP, no. 99, pp. 1–11, 2015.

[23] Y. Wang, L. Wu, and S. Wang, "A Fully-Decentralized Consensus-Based ADMM Approach for DC-OPF With Demand Response," *IEEE Transactions on Smart Grid*, pp. 1–11, 2016.

[24] E. Dall'Anese, H. Zhu, and G. B. Giannakis, "Distributed Optimal Power Flow for Smart Microgrids," *IEEE Transactions on Smart Grid*, vol. 4, no. 3, pp. 1464–1475, 2013.

[25] Q. Peng and S. H. Low, "Distributed Algorithm for Optimal Power Flow on an Unbalanced Radial Network," *53rd IEEE Conference on Decision and Control*, no. Cdc, pp. 0–7, 2015.

[26] P. Sulc, S. Backhaus, and M. Chertkov, "Optimal Distributed Control of Reactive Power Via the Alternating Direction Method of Multipliers," *IEEE Transactions on Energy Conversion*, vol. 29, no. 4, pp. 968–977, 2014.

[27] S. Borenstein and J. Bushnell, "The U.S. Electricity Industry after 20 Years of Restructuring," *Annual Review of Economics*, vol. 7.1, pp. 437–463, 2015.

[28] R. Hirsh, *Power Loss: The Origins of Deregulation and Restructuring in the American Electric Utility System*. Cambridge, MA: MIT Press, 2000.

[29] J. D. Hertog, "Review of economic theories of regulation," *Tjalling C. Koopmans Institute Discussion Paper Series*, vol. 10, no. 18, pp. 1–59, 2010.

[30] M. Conoscenti, A. Vetro, and J. C. De Martin, "Blockchain for the Internet of Things: a Systematic Literature Review," no. November, 2016.

[31] M. Mihaylov, I. Razo-Zapata, R. Rdulescu, S. Jurado, N. Avellana, and A. Nowé, "Smart grid demonstration platform for renewable energy exchange," *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 9662, pp. 277–280, 2016.

[32] L. P. Johnson, A. Isam, N. Gogerty, and J. Zitoli, "Connecting the Blockchain to the Sun to Save the Planet," dec 2015.

[33] Microgrid Media, ""It's Like the Early Days of the Internet," Blockchain-based Microgrid Tests P2P Energy Trading in Brooklyn," mar 2016.

[34] J. Mattila, T. Seppala, C. Naucler, R. Stahl, M. Tikkanen, A. Badenlid, and J. Seppala, "Industrial Blockchain Platforms : An Exercise in Use Case Development in the Energy Industry," tech. rep., ETLA, 2016.

[35] J. Horta, D. Kofman, and D. Menga, "Novel paradigms for advanced distribution grid energy management," 2016.

[36] N. Li, "A Market Mechanism for Electric Distribution Networks," *Conference on Decision and Control (CDC)*, no. Cdc, pp. 2276–2282, 2015.

[37] M. E. Baran and F. F. Wu, "Optimal capacitor placement on radial distribution systems.," *IEEE Transactions on Power Delivery*, vol. 4, no. 1, pp. 725–734, 1989.

[38] M. Farivar and S. Low, "Branch Flow Model: Relaxations and Convexification #x2014;Part I," *IEEE Transactions on Power Systems*, vol. 28, no. 3, pp. 2554–2564, 2013.

[39] E. M. Burger and S. J. Moura, "Generation following with thermostatically controlled loads via alternating direction method of multipliers sharing algorithm," *Electric Power Systems Research*, vol. 146, pp. 141–160, 2017.

[40] S. Boyd, "Distributed Optimization and Statistical Learning via the Alternating Direction Method of Multipliers," *Foundations and Trends® in Machine Learning*, vol. 3, no. 1, pp. 1–122, 2010.

[41] P. Scott and S. Thiébaux, "Dynamic Optimal Power Flow in Microgrids using the Alternating Direction Method of Multipliers," *CoRR*, pp. 1–8, 2014.

[42] Q. Peng and S. Low, "Optimal Branch Exchange for Distribution System Reconfiguration," *Arxiv Preprint*, p. 12, 2013.

[43] Ethereum Foundation, "Ethereum Frontier Guide," 2016.

[44] S. Diamond and S. Boyd, "{CVXPY}: A {P}ython-Embedded Modeling Language for Convex Optimization," *Journal of Machine Learning Research*, vol. 17, no. 83, pp. 1–5, 2016.

[45] S. Barber, X. Boyen, E. Shi, and E. Uzun, "Bitter to Better How to Make Bitcoin a Better Currency,"