Blockchain Design and Implementation for Decentralized Optimal Power Flow

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Abstract

We consider decentralized Energy Markets whose underlining power grid topology consists of generators, consumers, and transmission lines, and which is divided into regions. In the absence of a central System Operator, the Market Location Prices should be computed with coordination between the regions. The local regions perform local Optimal Power Flow (OPF) steps which are subsequently clued together with respect to certain operational constraints using the Alternating Direction Method of Multipliers (ADMM). This problem leads itself to a decentralized coordination problem and the Blockchain Technology seems to be its proper and effective backbone. The regions communicate through an Ethereum distributed application (dApp). The Proof of Authority (PoA) consensus algorithm is used, and blocks are created when an optimal global solution has been found. The integration of the Blockchain Technology in the ADMM algorithm is the main contribution of this paper.

Keywords: Energy, Markets, Blockchain, Smart Grid

2010 MSC: 00-01, 99-00????

1. Introduction

In a competitive Electricity Market, all participants would enjoy its advantages: There are no limits to enter the Market, everyone is able to trade electricity, every participant determines how much is willing to pay for the electricity commodity. A market equilibrium is obtained when the social welfare is maximized: the electricity prices correspond to the participants' (generators and consumers) best profit.

However, electricity is a special commodity. Generators and consumers are part of a power transmission topology. When energy is transmitted from one point to another, it obeys to some physical laws. For that reason, the concept of the System Operator is introduced. The System Operator is responsible to balance supply and demand in a given energy system (obeying the power flow laws), maximizing in parallel the social welfare. His role can be described as an auctioneer who guarantees legitimate power flows in the topology. The literature indicates that the System Operator solves Optimal Power Flow Problems to achieve his goal, which consist of complex non-linear problems. However, this procedure is a fully centralized one which could arise concerns concerns about the incentives behind System Operator's role, e.g. price manipulation for his own benefit. The need of decentralizing the Energy Market is also strengthened if the whole topology is not available to the System Operator, e.g. the system is divided into autonomous regions.

The main challenge of decentralization is to distribute the Optimal Power Flow (OPF) problem into the regions; decentralized System Operators. With the integration of the Alternating Direction Method of Multipliers (ADMM), the *fully* decentralization of the system is achieved. The regions solve local OPF problems and communicate with each other in order to find a globally optimal solution - which maximizes the total social welfare.

The computation part of the decentralized algorithm is solved by the ADMM, however proper communication between the regions is a key point. In this paper, it will be shown how Blockchain Technology could be utilized in order to provide a trustful and secure communication. In particular, a private Ethereum network is used as the communication backbone, which is suitably modified for the adaption on the ADMM algorithm. Using the Blockchain Technology together with the ADMM algorithm for OPF problems was the paper's main contribution.

Experiments of this paper's implementation are provided and analyzed. The quality of the solution is tested, alternating different kind of parameters, and blockchain metrics are also discussed. Additional research opportunities and similar researches are also highlighted.

2. Optimal Power Flow and Energy Markets

The traditional power system consists of the physical infrastructure for electricity generation, transport and use on one hand, and an organized electricity market on the other [1].

The physical grid, that is, the flow of electricity, consists of electricity generators and electricity-transport systems, which are usually subdivided into systems for transmission over long distances and systems for distribution to residential and industrial consumers of electricity. The electricity market, that is the flow of money, consists of electricity suppliers, consumers, transmission system operators (TSO), distribution network operators (DSO), regulators.

In this paper's study, **generators**, **consumers** or **loads** will be the key components of the electricity system. As decentralization of the system will be introduced later, various authority-forms of the electricity system will be absent. System Operators will be part of the system but their behavior will be drastically changed due to the decentralization induced.

Subsequently, the definition and some characteristics of *Competitive* Electricity Markets is presented as it is stated in [2, 3].

> A competitive market includes open access with unrestricted entry by new participants willing to absorb ordinary business risks. The ideal case of the competitive market presumes a large number of competitors with no barriers to entry or exit. However, the ideal case provides the simple benchmark where participants do not have market power in the sense of being able to maintain sustained and substantial profits that would disappear with significant new entry. Ultimately the competitive market model must be examined as to

the degree of workable competition that is feasible in the electricity market.

In this paper we restrict ourselves to structure of the Electricity Market of Figure 1. This competitive wholesale market structure is illustrated that follows this traditional three-part segmentation and emphasizes competition in the generation market [2, 3]. The key elements of these structures are:

Genco: Operates and maintains existing generating plants. The Gencos interact with the short term market acting on behalf of the plant owners to bid into the short-term power pool for economic dispatch. There are many participants with existing plants and no barriers to entry for construction of new plants.

Poolco: Dispatches existing generating plants and operates a short-term market. Operates a system providing long-term transmission compensation contracts. System control interactions require monopoly operation or close coordination. This segment is regulated to provide open access, comparable service and cost recovery.

Gridco: Constructs and maintains the network of transmission wires. Network interaction and scale economies call for monopoly provision and entry barriers. This segment is regulated to provide non-discriminatory connections, comparable service and cost recovery.

Disco: Provides services to final customers including connection and billing. There are many potential entrants and no barriers to entry.

It is to be noted that in this paper, the transmission and distribution components coincide. This produces more simplicity without affecting the final results of the implemented decentralization. Most cases that are experimented do not dissociate these two components. We continue this chapter with the following very accurate and elucidating statement by Hogan [4].

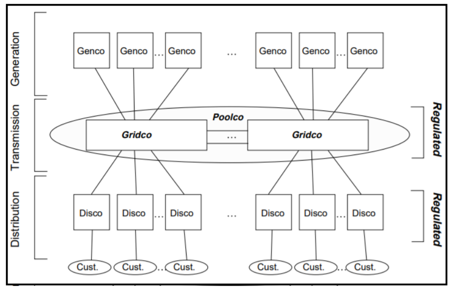


Figure 1: Wholesale Competitive Market.

A pool-based, short-term electricity market coordinated by a system operator provides a foundation for building a system that provided economic dispatch. Coordination through the system operator is unavoidable, and spot-market locational prices define the opportunity costs of transmission that would determine the market value of the transmission rights without requiring physical trading and without restricting the actual use of the system.

Economic Dispatch

A Market Equilibrium in an Energy Market is achieved if the total Load Demand -assuming it is non-dispatchable- will be met by the cheapest generators. This leads us to the Optimal Power Flow Problem: The goal of the Optimal Power Flow is to minimize an objective function (examples in [5, 6, 7]) while solving the Power Flow Problem. Generators' power and voltages are not fixed -in contrast with the classical power flow problem-, but input variables and they have to be determined like the node voltages [8]. The objective function combined with the power flow equations forms an optimization problem for the system, [8]. Of course, the solution methods performance depends on the nature of the given system model or topology, e.g. on the type of nonlinearities, on the type of constraints, on the number of constraints, etc.

A lot of literature (e.g. [9]) implies that in order to achieve an economic dispatch of an Energy Markets, the generators costs should be minimized. The operational costs can be quadratic or picewise linear. For example, in the case of quadratic costs the cost function for Generator k is:

$$F_k(P_k) = a_k * P_k^2 + b_k * P_k + c_k,$$

where a_i, b_i, c_i are predefined for every generator.

Then the objective function becomes:

$$F(P) = \sum F_k(P_k)$$

and the optimized solution is obtained by:

$$Minimize \quad F(P)$$

2.1. Physical Load Flow/Equality Constraints

From the Power Flow Problem [10] we have for every node i:

$$P_i(V,\theta) = P_i^G - P_i^L = V_i \sum_{j=1}^{n} V_j (G_{ij} \cos\theta_{ij} + B_{ij} \sin\theta_{ij})$$
$$Q_i(V,\theta) = Q_i^G - Q_i^L = V_i \sum_{j=1}^{n} V_j (G_{ij} \cos\theta_{ij} - B_{ij} \sin\theta_{ij})$$

2.2. Operational Limits/Inequality Constraints

The input variables are limited and should not be exceeded for a stable, secure operation [8] [7]:

- Limits on active power of a PV node (generator k) :

$$P_{low_k} \leq P_{PV_k} \leq P_{high_k}$$

- Limits on voltage of a PV or PQ node :

$$|V|_{low_i} \leq |V|_i \leq |V|_{high_i}$$

- Limits on voltage angles of nodes :

$$\theta_{low_i} \leq \theta_i \leq \theta_{high_i}$$

- Limits on voltage angles between nodes :

$$\Theta_{low_{ij}} \leq \Theta_i - \Theta_j \leq \Theta_{low_{ij}}$$

- Limits on reactive power generation of a PV node (generator k) :

$$Q_{low_k} \leq Q_{PV_k} \leq Q_{high_k}$$

- For simplicity we will omit transmission line limits (these limits are responsible for transmission congestion), transformers and shunt capacitances and reactances.

The OPF formulation will be rephrased. For simplicity the system's variables will be divided into *control* variables $\mathbf{u}$ (Active power and Voltage magnitude of a PV node) and *state* variables $\mathbf{x}$ (Voltage magnitude and angle at all nodes) as described in [7], [11]. We denote

$$\mathbf{X} = \begin{bmatrix} \boldsymbol{u} \\ \boldsymbol{x} \end{bmatrix}$$

where $\mathbf{X}$ is the vector of the variables of the system (whole set).

2.3. Optimal Power Flow Problem Formulation

The Problem is formulated related to the $\mathbf{x}, \mathbf{u}$ *state* and *control* variables as:

$$minimize \quad \boldsymbol{F(x, u)}$$

subject to:

$$\boldsymbol{g(x, u) = 0},$$

where $\boldsymbol{g}$ represents the equality constraints as described in Section 2.1.

$$\boldsymbol{h(x, u) \leq 0},$$

where $\boldsymbol{h}$ represents the inequality constraints as described in Section 2.2.

This symbolization is common in most related literature, and will be used throughout the paper. The OPF Problem is well defined by the above equations and the objective function.

3. Decentralized Optimal Power Flow

Relying on a centralized System Operation is a natural monopoly and the operator could distort both dispatch and expansion. The introduction of a decentralized approach towards this matter would reinforce trust among the participants and the system. Trust suggests lack of individual incentives, making the investment on energy markets more appealing [12]. Furthermore, to facilitate the application of optimal control to large-scale systems, the overall problem may be decomposed into subproblems which are solved in a coordinated way. This also complies with the above mentioned fact that the task of controlling a system might be shared by several entities (e.g. distinct areas) of which each is in charge for a dedicated part of the system [13].

The ADMM algorithm ([14] [15]) can be applied to OPF problems which are completely distributed/decentralized, i.e., do not require any form of central coordination, and are applicable to any network. The solution is based upon a region-based (local) optimization process, where a limited amount of information is exchanged only between neighboring regions in a (locally) broadcast fashion [16]. Similar algorithm can be found in [17, 18, 19] but their disadvantages are that they are not *fully* decentralized or they can assure convergence under only some certain assumptions.

3.1. ADMM in Optimal Power Flow

The OPF Formulation for Distributed ADMM follows the methodology in [20]. This formulation is also implemented in the experiments of this paper. One specification of this formulation is that it does not take into consideration the transmission line constraints. A lot of literature also omits the presence of transmission constraints, making the computation part simpler. Congestion is not so often in real-time electricity systems, so in most cases, transmission constraints are never violated. Different OPF formulations for distributed ADMM can be found in [15, 16, 21, 22, 23, 24, 25].

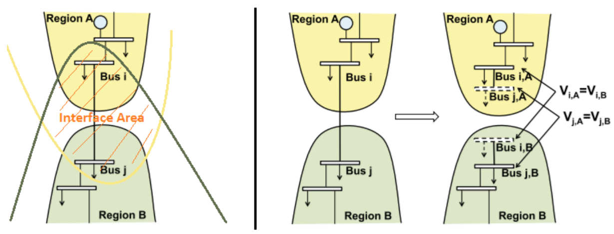


Figure 2: Duplicating voltages at boundaries of regions.[20]

The OPF problem is decomposed into regions. Each region does not have information about the topology/buses/constraints/costs of the other regions, it only needs to interact with its neighbors. A globally optimal solution will be given by the ADMM. In order for that to happen, neighbor regions need to exchange information. Tielines, i.e connecting transmission lines between two neighbors, are treated like in Figure 2 :

Duplicating the voltages on region boundaries results in that the tielines are removed and the regions are totally separated. As it was explained in Section **??**, each region's OPF problem consists of the following equations :

$$minimize \quad f(P) \ \text{ - i.e. the total generators' costs within the region.}$$

$$subject\,to: \ \text{equality and inequality equations as described in Sections 2.1, 2.2.}$$

Because of the interface voltages decomposition (Figure 2), two more equality constraints are added for region A, which has region B as a neighbor - bus i and bus j are their interface buses respectively (more neighbors would add more voltage equality constraints of the same form) [20]:

$$V_{i,A} - V_{j,A} = V_{i,B} - V_{j,B}$$

$$V_{i,A} + V_{j,A} = V_{i,B} + V_{j,B}$$

We define:

$$z_k = ({z_{i,j}}^-, {z_{i,j}}^+) = (\ \beta^-(V_{i,A} - V_{j,A}),\ \beta^+(V_{i,A} + V_{j,A})\ )$$

where β^- and β^+ are scaling factors. Constant β^- is set to be larger than β^+ to give more weight to $V_{i,A} - V_{j,A}$, which is strongly related to the line flow through tie line ij, [26].

and, the feasible region of all the zs associated with tie lines is defined as

$$Z = \{(z^-, z^+)| \ \ z^-_{i,j} = -z^-_{j,i} \ , \ z^+_{i,j} = z^+_{j,i} \ , \ \ \forall(i,j) \in \text{ inter-region tielines}\}$$

And the problem is reformulated using the $x_k = \{(P_i, V_i, Q_i, \theta_i)|\forall \text{ bus } i\}$ variable (the set of control *and* state variables of k region for every regional bus i - containing the duplicated neighbor ones. We have for *each* k region (omitting transmission limits) :

$$minimize \qquad f_k(x_k)$$

subject to:

$A_k x_k = z_k,$ i.e. the boundary voltages in respect of x_k

$g(x_k) = 0,$ i.e. the power flow equality constraints.

$x_{k_{min}} \leq x_k \leq x_{k_{max}},$ i.e. operational limit inequality constraints.

$z_k \in Z,$ i.e equalities in boundary voltages between neighbors.

For simplicity, we express the constraints $\{ \ g(x_k) = 0 \ , \ x_{k_{min}} \leq x_k \leq x_{k_{max}} \ \}$ as $x_k \in X_k$. Because of the limitation $z_k \in Z$, it is obvious that information needs to be exchanged between neighbor regions, it is the only constraint that does not depend totally on region k. An important property of problem above is that if z is fixed, then the problem can be decomposed into subproblems where each subproblem only contains the local variables x_k . This property enables distributing the computations of ADMM to solve the whole problem.

The ADMM algorithm minimizes the Augmented Lagrangian function ([27, 28]) of the problem, which is given as follows for region k:

$$L_k(x_k, z_k, \lambda_k) = f_k(x_k) + +{\lambda_k}^T(A_k x_k - z_k) + \frac{1}{2}\|A_k x_k - z_k\|^2_{\rho_k}$$

The vector ρ is a vector of penalty parameters whose entries are increased during the iterative process [20] to ensure convergence of ADMM [15]. The *(v+1)*-th iteration of the local ADMM consists of the following steps:

$$x_k^{v+1} = \underset{x_k}{\operatorname{argmin}}\, L_k(x_k, z_k^v, \lambda_k^v)$$

$$z_k^{v+1} = \underset{z_k}{\operatorname{argmin}}\, L_k(x_k^{v+1}, z_k, \lambda_k^v)$$

$$\lambda_k^{v+1} = \lambda_k^v + diag(\rho_k^v)(A_k x_k^{v+1} - z_k^{v+1})$$

Notes: The parameter ρ is updated for faster convergence according to [20]. In the problem formulation some other parameters exist also which tuned optimally according to [29, 30]. As a convergence guidance, the regional primal residue $\Gamma_k^{v+1} = \left\| A_k x_k^{v+1} - z_k^{v+1} \right\|_\infty$ is used.

To enhance the performance of ADMM on non-convex problems, the penalty parameter ρ is usually updated to make the Augmented Lagrangian function convex near the solution. Specifically, for any region k, ρ_k is updated as follows [26]:

$$\rho_k^{\sim v+1} = \begin{cases} \left\|\rho_k^v\right\|_\infty \mathbf{1}, & \text{if } \Gamma_k^{v+1} \leq \gamma \Gamma_k^v \\ \tau \left\|\rho_k^v\right\|_\infty \mathbf{1}, & \text{otherwise} \end{cases}$$

with constants $0 < \gamma < 1$ and $\tau > 1$, and with $\mathbf{1}$ denoting the all-ones vector.

$$\rho_{k,i,j}^{v+1} = \max\{\rho_{k,i,j}^{\sim v+1}, \rho_{l,j,i}^{\sim v+1}\}$$

meaning that we select the maximum ρ from $\{\rho_k, \rho_l\}$ for each tieline (i, j) between regions k and l.

A detailed procedure of the distributed ADMM algorithm for region k is illustrated in Figure 3.

A general way to check the convergence of is to check whether the primal residue $(\Gamma_k, \forall k)$ is smaller than some ϵ. Convergence is declared when both the primal residue and the maximum bus power mismatch (after voltage averaging) fall below ϵ [20, 26].

Algorithm 1: Distributed OPF in Region k.

1: **Initialization** Initialize x_k^0, $z_k^0 = 0$, $\lambda_k^0 = 0$, $\rho_k^0 = \rho_0 \mathbf{1}$, $\nu = 0$
2: **while** Not converged **do**
3: $\nu \leftarrow \nu + 1$
4: Update x_k by solving the local OPF

$$x_k^\nu = \underset{x_k \in \mathcal{X}_k}{\operatorname{argmin}} f_k(x_k) + \lambda_k^{\nu-1\top}(A_k x_k - z_k^{\nu-1}) + \frac{1}{2}\|A_k x_k - z_k^{\nu-1}\|^2_{\rho_k^{\nu-1}}$$

5: Prepare messages $m_k^\nu = A_k x_k^\nu$
6: Broadcast m_k^ν to neighboring regions and receive m_l^ν from each neighboring region $l \neq k$
7: Update z_k using

$$z_{i,j}^{-\nu} = \frac{1}{2}(m_{k,i,j}^{-\nu} - m_{l,j,i}^{-\nu})$$

$$z_{i,j}^{+\nu} = \frac{1}{2}(m_{k,i,j}^{+\nu} + m_{l,j,i}^{+\nu})$$

8: Update λ_k using

$$\lambda_k^\nu = \lambda_k^{\nu-1} + \operatorname{diag}(\rho_k^{\nu-1})(A_k x_k^\nu - z_k^\nu)$$

9: Calculate the primal residue Γ_k^ν for each region k
10: Check convergence
11: Compute $\tilde{\rho}_k^\nu$
12: Broadcast $\tilde{\rho}_k^\nu$ to neighboring regions and receive $\tilde{\rho}_l^\nu$ from each neighboring region $l \neq k$
13: Update ρ_k
14: **end while**

Figure 3: Distributed ADMM for OPF. [20]

4. Blockchain Optimal Power Flow Design and Implementation

4.1. Blockchain in Energy Markets and Smart Grids

Blockchain technology ([31**?**]) is becoming more and more popular. Decentralized payments are a hot trend nowadays, getting integrated also in Smart Grids. The appearance of blockchain in these energy grids is more and more frequent and indicates that payments and energy trading among participants can be secure, decentralized and immediate. There are various proposal in the literature about how blockchain technology can develop Energy Markets and Grids. A lot of them have been studied and a common direction between them has been found. Most of these proposals integrate Blockchain for financial transactions facilitation. Some of these proposals can be found in [32, 33, 34].

Moreover *smart contracts* ([35]) can organize autonomously energy schedules in long term energy agreements. They are used to activate payments between the agreeing parties when energy actually is traded, and not beforehand. Smart contracts can also behave as auctioneers which gather the asks and bids by generators and consumers and find the optimal clearing price. As the smart contract is public and immutable, no manipulation to the final schedule is feasible.

It has to be mentioned that new decentralized digital currencies have been introduced. An example is [36] and is used for buying and selling green energy in the smart grid. This currency is generated by injecting energy into the grid. Another example is [37], used in a localized peer-to-peer (P2P) electricity trading model for locally buying and selling electricity among plug-in hybrid electric vehicles (PHEVs) in smart grids. Participants are rewarded - in currency tokens - for discharging their PHEVs to balance local demand.

4.2. Blockchain in decentralized Optimal Power Flow

The main idea of the proposals is that the Blockchain in an Energy Market provides immediate payments among participants and schedules energy trades. However, all these proposals do not consider the Power Flow Problem - i.e. transmission lines are absent in the system.

In this paper, the Blockchain Technology will be used as a *decentralized Application* in order to solve the Optimal Power Flow problem. A centralized System Operator is absent from this system. Decentralized System Operators (e.g. regions) will coordinate between them in order to find the optimal locational clearing prices for the system. The purpose is not to concentrate completely on payment and schedule issues, but to propose an alternative use of blockchain, as it will be the backbone of communication between the regions.

A private Ethereum network ([35]) is set for the communication between the regions. An input topology is given in PYPOWER-caseformat [38], which is divided into regions. Each region sets its own local optimal power flow problem (Section 3.1), having information only about the neighboring interface. The solution to each ADMM iteration is obtained by the PYPOWER Interior Point Solver [39, 40, 41]. After each iteration, neighbor values of the solution are encoded as Ethereum transactions and through RPC-calls to the Ethereum nodes, they are broadcasted these transactions to the network. Transactions are gathered in the transaction pool - common for all. The neighbor regions update their local problem based on these solutions and continue to a new

ADMM iteration. Authorized miners in the network inspect continuously the transaction pool. When convergence of the problem has been remarked, a new block is created containing every transaction exchange between the regions.

In Figure 4A an decentralized Optimal Power flow problem is illustrated. For simplicity, the problem contains 3 regions and a few buses. In Figure 4B , the post-actions of each region (here of Region 3) are illustrated. The post-actions express the preparation of the algorithm - i.e. the actions each region needs to do, before executing the ADMM algorithm.

In Figure 5 the execution of the ADMM-OPF algorithm is illustrated (for example for Region 3 following the problem in Figure 4). The figure presents the steps of the algorithm and which component of the architecture is responsible for each step.

5. Experimental Analysis

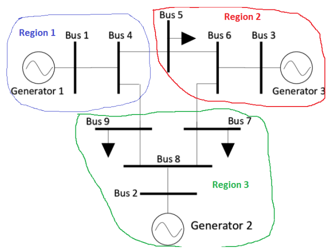
In the next section, different experiments are presented in order to test the quality, the convergence and other characteristics of the algorithm. Experiments vary on the initial values and the algorithm's parameters.

5.1. Quality and Convergence of Solution

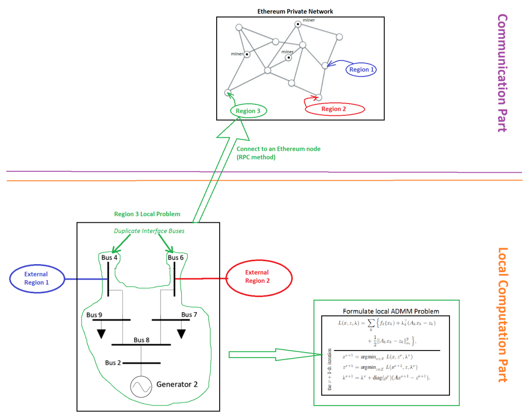
The primal residual for the next cases is selected to be 10^{-3}. Flat Start indicates that the initial values for the ADMM problem are random. On the other hand, Warm Start indicates that values close to the solution are used for initialization.

In this section, we test the 30-Bus IEEE Case, 39-Bus IEEE Case, a 2-region *modified* 118-Bus IEEE Case (Flat Starts) and the 39-Bus IEEE Case (Warm Start) - Figure 6. The results are plotted in Figures 7, 8 and are summarized in Table 1.

As it can be seen by the results, the convergence time does not depend totally on the number of buses, but the complexity of the topology (compare the 30-bus with the 39-bus). The biggest deviations appeared on the 30-bus



(a) A given Optimal Power Flow Problem (Adapted from here).



(b) Preparation actions of each region (e.g. Region 3) Schema.

Figure 4: Preparation of the algorithm per region for a given problem. (Images adaptations from [20], here)

case due to the algorithm's lack of considering transmission line limits. The other cases did not have binding constraints so the Locational Marginal prices were close the optimal solution. When we start the algorithm warmly much less iterations occur, but bigger deviation may appear (here -in 39-bus case- the slack bus deviated the most).

5.2. *Blockchain - Gas Usage*

The nodes in the Ethereum network need to consume *gas* in order to be able to send transactions. The ADMM algorithm demands exchangeable information between the regions, meaning that the nodes in the network who "represent" the corresponding regions need to have the necessary gas resources. For the normal

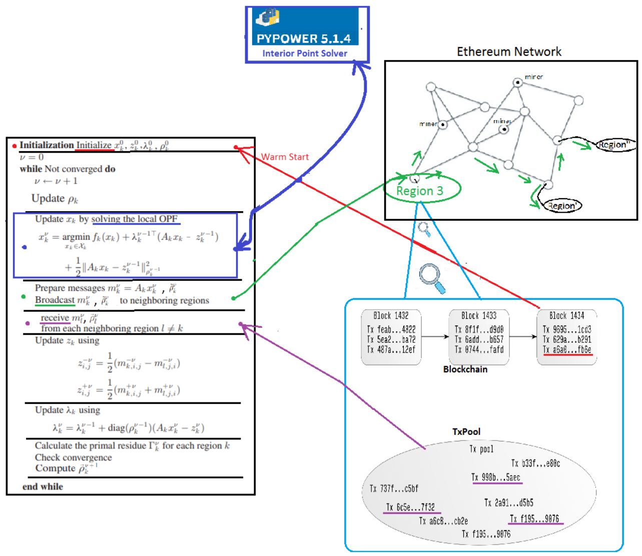


Figure 5: Algorithm Implementation in the Architecture. (Images adaptations from [20], here)

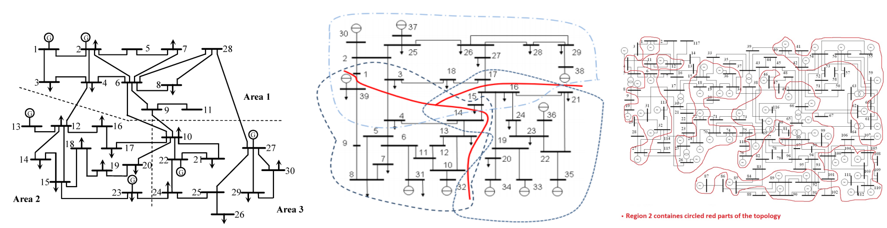


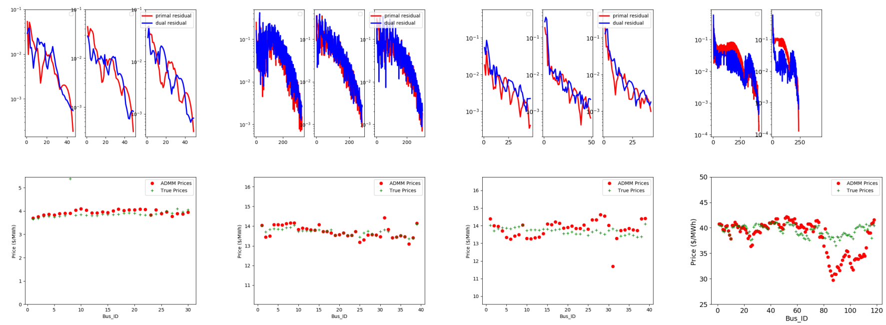
Figure 6: From left to right: The IEEE 30-Bus Test Case (Source), the 39-Bus Case (Source), the 118-Bus Case (Adapted from here).

operation of the Ethereum network, every node is supplied with unlimited gas. However, a Gas Usage Analysis is done for a better understanding (Figure 9).

5.2.1. *Expected Gas Used*

The interface values are encoded into hex-values in order to be sent through transactions in an Ethereum network. The gas needed in order to send one transaction with some data is (given the default Ethereum values):

$$gas \approx 2100 + 68 * DataByteLength$$



(a) 30-Bus (b) 39-Bus (c) 39-Bus (Warm) (d) 118-Bus

Figure 7: Iterations until convergence per region (top plots) and Locational Prices at the Buses (bottom plots) for the Test Cases.

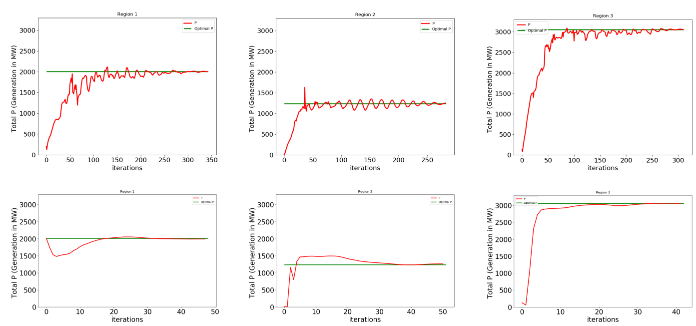


Figure 8: Active Power Generation between the Decentralized and Centralized solution of the 39-Bus Case: Flat Start on the top plots, Warm Start on the bottom plots .

he $DataBytesPerTransaction$ needed for one transaction from region i to region j are affected by the following values :

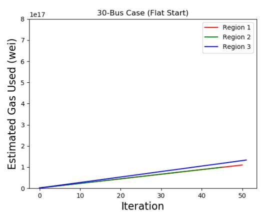
The total neighbor regions nb_i for region i, the total tielines tl_{ij} - i.e. interfaces - between region i and its neighbor region j, the total number of regions $nreg$ and how the information is encoded into its hex values - without emphasizing more.

So, the total gas used by region i until convergence is given by:

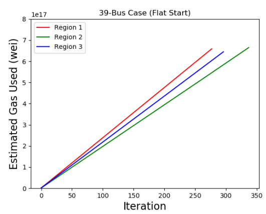
$$Gas_i \approx iterations_i * (\sum_{j}^{nb_i} 2100 + 68 * DataBytesPerTransaction]$$

Cases	Convergence Time (secs)	Average Time per ADMM iteration (secs)	Objective Function Value ($/h)	Gap in Objective Function (%)
30-Bus	45.6	0.023	573	0.66
39-Bus (Flat Start)	521.7	0.209	41889	0.06
39-Bus (Warm Start)	32.0	0.022	41880	0.04
118-Bus	659.9	0.265	131845	1.68

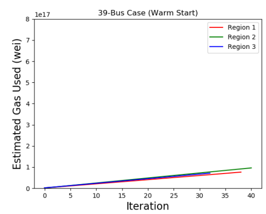
Table 1: Metrics on different Cases.



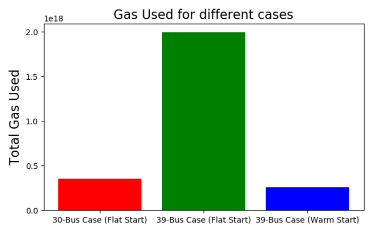
(a) 30-Bus



(b) 39-Bus (Flat)



(c) 39-Bus (Warm)



(d) Gas Usage per case

Figure 9: Estimated Gas until Convergence for different Cases.

5.2.2. Block creation

Network miners are examining constantly the Transaction Pool. If the problem has reached convergence, blocks will be created with all the transaction history. However, in the Ethereum private network the block creation depends on how much *gas* was used, what the *gas price* or the *gas limit* is.

Continuing as before, we define:

$nreg$: Total number of regions

$Convergence\_t$: Total time until the ADMM algorithm has converged for a given problem.

BlockPeriod: The time period for block creation. It is declared in the *genesis block*.

Gas_Price: It is set by the node that sends the transaction. We will assume every node/regions have a common gas price set for every transaction.

Gas_i : It is the total gas used by each region i until convergence. Details were given in the previous subsection.

$Block\_GasLimit_\tau$: Gas Limit defines how much Gas Cost -i.e. number of transactions - can fit into a single block. It is not constant and it changed through time. Details can be found in [35]. So, we suppose that we know the Gas Limit value at time τ.

The total time needed to include every transaction into blocks at time τ is given *approximately* by:

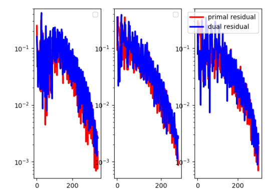
$$Convergence\_t + \left\lceil (\sum_{i}^{nreg} Gas_i * Gas\_Price)/Block\_GasLimit_\tau \right\rceil * BlockPeriod$$

5.3. Convergence Robustness

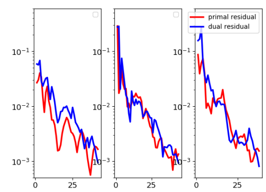
The convergence time and the number iterations are dependent on the initial values and parameters of the ADMM problem. One important parameter is ρ, which accelerates the convergence [26]. If the initial values are far from the solution, a small ρ should be selected. On the other hand, larger ρ needs much less iterations.

The experiments continue with the 39-bus case but the load/demands at the buses will be changed. In a real balanced system, the loads do not change dramatically from time to time, but small input differences are applied. This is the case that is tested in Figure 10. It is shown that with small input differences, the algorithm converges fast enough (due to the Warm Start) and the deviations from the centralizes solution remain in acceptable intervals.

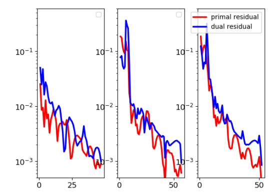
In Figure 11 different initial selection of ρ are tested for Flat Starts. The deviation results indicate the one should be careful on the ρ selection: Every case has an optimal ρ that combines the best performance with the smallest deviations.



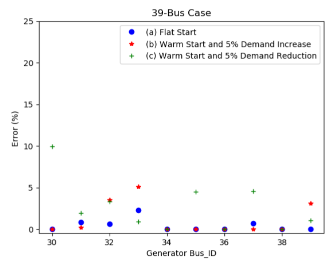
(a) Flat Start



(b) Warm Start and 5% Demand increase

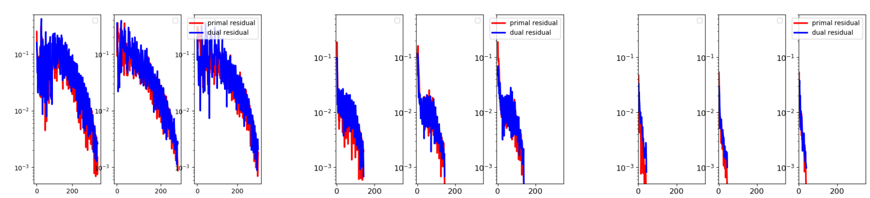


(c) Warm Start and 5% Demand reduction



(d) Power Generation Deviations for different Demands

Figure 10: Convergence with different Demands in the 39-Bus Case (top plots) and their deviations (bottom plot).



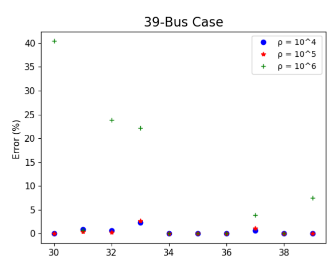


Figure 11: Iterations until convergence based on initial ρ selection in the 39-Bus Case (top plots) and their deviations (bottom plot). $\rho = 10^4, 10^5, 10^6$ from top left to top right.

The blockchain is a huge database. This characteristic can help System Operators to select the suitable initialization values for better convergence robustness. As every block is timestamped, the Operators could select starting points for the topology based on time, period, season, etc.

6. Related Work

To the best of our knowledge the only work that combines Energy Markets with Blockchain Technologies, respecting the Power Flow limits, can be found in [22]. This is also an architecture which solves decentralized optimal power flow problem with the ADMM method, using as communication backbone the blockchain technology.

6.1. Differences

- Fully decentralized vs Partly decentralized
- No Smart Contract vs Smart Contract

This paper's implementation guarantees verified results under a *fully* decentralized model. That means that the region need to know only their regional topology, having no information about the "outer" topology.

On the other hand, in [22] it is stated that:

> "We assume that the network topology is fully known by all parties, and have not considered changes in line impedances (e.g. due to temperature changes) or in topology (e.g. due to outages)."

Moreover, the presence of a smart contract as an ADMM Aggregator indicates that if a different topology is given as an input, a new smart contract must be created for the new problem. This limitation sets a barrier on the automated operation of the blockchain. Finally, it has to be noted that every computation in a smart contract uses extra gas and depends on the computation's complexity. Unfortunately, gas usage comparison cannot be done between the two implementations, because it depends strongly on the transactions' nature - and this information is not available.

7. Synopsis and Research Plans

An architecture which divides an Economic Dispatch problem into regions, solving OPF problems with the ADMM was designed. The regions were representing nodes in an Ethereum private network. In this network, the information exchange is more than feasible and every Economic Dispatch solution is stored in a blockchain. Experimental Analysis indicated satisfying results of this architecture. Similar research and future research are also highlighted.

Future Work will include the following improvements: The first one is the ability of the implementation to consider line transmission constraints- binding constraints affect the Locational Prices and limit the power transmission from cheap generators. The second would integrate automated payments by every consumer for the power consumed. The blockchain technology provides naturally this possibility - smart contracts could take care of the billing between the participants, collaborating with smart meters in order to ascertain the actual consumed. It is natural to think that some fraud detection algorithms should also be developed.

Blockchain seems to work for our problems but it not clear how well it will scale in real cases. For this it is worth to investigate new public ledger technologies that are based on more general structures. For example IOTA addresses the shortcoming of scalability and high transaction fee which is not suitable for machine economy like the case in our study. Please note that the lack of smart contract capability which is a major drawback currently on IOTA does not have an impact of our approach.

We close with the following rather philosophical comments. Our efforts for decentralization do not really focus on developing an excellent dApp platform for next generation energy markets. It mainly concerns about sharing energy in a socially correct and effective way. It is to find the most optimal way to evolve as a community that follows social and physical laws at the same time. Its after all about the root essence of what energy and money means, to the people.

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