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Operator equation formulation and solution analysis for distributed resource allocation in large-scale infrastructure networks

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Abstract:

Resource allocation in modern large-scale infrastructure networks, such as cloud edge-computing grids, smart power distribution systems, and dynamic multi-agent wireless systems, relies on decentralized, scalable, and communication-efficient decision-making; however, centralized optimization does not solve the issue with networks of different sizes and creates single-point failures. The article introduces the operator-theoretic framework - a unified method for reformulating the problem of constrained distributed resource allocation in complex network topologies as the problem of finding a zero of a monotonic operator in a real Hilbert space. The physical topology constraints are expressed using graph Laplacians, while resource limitations are expressed in the form of indicator functions, which allows transforming the complex global allocation problem into the operator equation $0 = (A+B)(x)$, where A represents the subdiffential of the local cost and constraints structure, while B outlines the interconnections of the network involved. The theory of maximal monotonic operators, Minty's theorem, and the resolvent's firm non-expansiveness help establish the existence, uniqueness, and metrics of the solution. A distributed Douglas-Rachford splitting algorithm is developed afterwards; its global weak and strong convergence is verified through the Krasnoselskii-Mann theorem for averaged operators. At the same time, explicit linear convergence rate under strong monotonicity conditions is provided. Numerical simulations, implemented for synthetic scale-free and small-world network topologies with the number of nodes provided (N=10,000), demonstrate that the proposed approach guarantees the getting accuracy of 1e-6 within 3.85 seconds, at the same time when the centralized interior point algorithm provides no solutions due to memory shortage and completes the problem successfully in 0.03-1.10 seconds with N<10,000. The communication overhead per node does not exceed approximately 6.2 messages per iteration regardless of the network size, while it increases in proportion to N for the centralized approach. These results demonstrate that the proposed operator-equation framework provides mathematically rigorous convergence guarantees together with practically verified scalability for decentralized resource allocation in large-scale infrastructure networks.

*Keywords:*Monotone operators, operator equations, distributed resource allocation,douglas-rachford splitting, infinite-dimensional optimization, graph laplacians.

1. Introduction

Large-scale infrastructure networks, which include distributed cloud-edge computing systems, multi-bus smart electric networks, and advanced wireless networks, increasingly rely on real-time dynamic resource distribution throughout a continuously growing network of connected nodes. A more general overview of engineering of digital transformation of infrastructure operations together with energy-efficient architectural designs of information service infrastructures suggests that centralized management becomes a structural constraint due to increasing size and complexity of the networks (Salami et al., 2025; Soni & Saini, 2025). Conventional centralized algorithms which use optimization techniques are not efficient in terms of the network size N and introduce a weak point of failure, as well as risk of data privacy when local cost and constraint information is transferred to a central manager.

In order to overcome these disadvantages, distributed resource allocation techniques have been widely researched. The distributed stochastic sub-gradient method has been one of the first scalable methods of convex resource allocation in a network of agents and various continuous time coordination schemes with discrete time communication are now being developed in order to minimize dependencies on synchronized actions. The scaling laws for gradient based methods have been analyzed and experiments have shown a possibility for acceleration of the convergence when the resource allocation problems of separable structure are concerned (Xiao & Boyd, 2006).The proposal of distributed algorithms without initialization steps for resource allocation with feasibility constraints has additionally been made, which is directly applicable to economic dispatch of power system, whereas dual averaging techniques have been studied in terms of convergence properties and scaling capabilities in plain settings of distributed optimization (Yi et al., 2016; Duchi et al., 2011).

Economic dispatch and microgrid control feature prominently in the usage of these kinds of distributed techniques (Li et al., 2014). Auction-based distributed algorithms have been created for the economic dispatch issue that lacks convexity, whereas projection-based decomposition technique provides an opportunity to quickly calculate the control measures in microgrids through distributed computations (Binetti et al., 2013; Cortés & Martínez, 2018). There has also been a suggestion of piecewise-approximation economic dispatch approaches for regional electric power systems functioning in non-ideal communication, while event-triggered communication concept has been developed to minimize the amount of exchanged messages during economic dispatch processes operating with uncoordinated step sizes (Hao et al., 2019).Additionally, distributed augmented Lagrangian methods have been investigated with respect to their utilization in stochastic communication networks for large-scale energy dispatch, which is confirmed by the findings establishing special limits for iterations performed with such techniques, and numerous perspectives, such as those of saddle-point dynamics, have been employed for examining the adaptive resource allocation in decentralized manner in uncertain environment (Yue et al., 2023; Ananduta et al., 2021; Lee et al., 2017).Resource management and optimization techniques driven by AI have proven the significance of making intelligent decision-making models for resource allocation in complex networking systems, offering valuable lessons that can be applied to optimization techniques of resource management in smart industries.Algorithms for management are centered on how automated decisions can help in organizing complicated processes, giving a theoretical framework for intelligent resource allocation and autonomous management systems.Algebraic structures can provide a theoretical foundation for modeling and analyzing mathematical relationships across diverse applications (Sharma et al., 2026).Dynamic evolutionary multi-objective optimization can improve virtual machine placement in cloud data centers by balancing resource utilization and performance objectives (Torre et al., 2020).

This issue has a significant number of articles that treat structural and game-theoretic features of the network resource allocation approaches in a much wider aspect. Further, systemic analysis of network topology and the trade-off between communication and computation for decentralized optimization algorithms across general graph structures has been conducted, which indicates that challenges may arise in decentralized optimization algorithms context (Nedić et al., 2018). Successful results have been achieved due to operator-splitting algorithms since the OSQP quadratic programming algorithm shows that formulating problems of structured convex optimization through operator equation results in significant computational benefits over active set methods and interior point methods (Stellato et al., 2020). Also, similar operator reformulation methods were used for resource allocation in computational grid technology (Dong et al., 2009). More studies of infrastructures and networking have indicated the existence of various forms of distributed coordination problems (Ibrahim & Shanmugaraja, 2023).Digital financial technology development has revealed the effect of new technology on changing conventional systems and shown how innovation can help to improve adaptability

within modern business environments (Ganesan, 2026).Strategies for ecosystem-based management incorporate integrated decision-making strategies to deal with multiple interacting constraints, and such strategies offer conceptual insights into adaptive optimization strategies for managing complex systems.

Nonetheless, in spite of a large number of conducted researches focusing on various methods of distributed resource allocation, existing methods are presented at the level of individual algorithm updates instead of accumulation of concepts and principles within the framework of the unified operator-theoretic statement of the problem, which would allow for the solution of a problem with non-smooth local objectives, any closed convex feasible set and the dynamic network topology interconnection in the context of one monotone operator equation.

This paper combines infinite dimensional functional analysis and distributed network engineering and does the following: (i) applies the concept of non-smooth, consensus constrained network resource allocation activities to the problem of determining a zero point in the sum of two maximally monotone operators acting on a Hilbert space; (ii) proves the existence and uniqueness using fixed point theorems, maximal monotonicity, and firm non-expansiveness principles; (iii) introduces and analyses the distributed Douglas-Rachford splitting algorithm and proves the convergence conditions and explicit linear convergence rate under the assumption of a strong operator monotonicity existence; (iv) compares the resulted algorithm with centralized interior-point algorithms.

2. Mathematical preliminaries and network model

2.1. Set-valued and monotone operators

Let H be a real Hilbert space equipped with inner product $\langle\cdot,\cdot\rangle$ and induced norm $\|\cdot\|$. An operator $A: H \to 2^H$ is monotone if, for all $x, y \in H$, $u \in Ax$, and $v \in Ay$,

$$\langle u - v, x - y\rangle \geq 0 \quad (1)$$

Satisfying the condition in equation (1), the operator A is defined to be μ-strongly monotone if

$$\langle u - v, x - y\rangle \geq \mu\|x - y\|^2 \quad (2)$$

for some $\mu > 0$, as expressed in equation (2). A monotone operator A satisfying equation (1) is maximally monotone if its graph

$$Gra(A) = \{(x, u) \in H \times H: u \in Ax\} \quad (3)$$

given in equation (3), is not strictly contained in the graph of any other monotone operator. The resolvent of A with parameter $\gamma > 0$ is defined by equation (4):

$$J_{\gamma A} = (I + \gamma A)^{-1} \quad (4)$$

If A is maximally monotone, $J_{\gamma A}$ given in equation (4) is single-valued and non-expansive everywhere on H.

2.2. Network model and graph theory

Let $G = (V, E)$ denote an undirected connected graph, where $V = \{1, \ldots, N\}$ is the set of nodes (agents or subsystems) and $E \subset V \times V$ is the set of communication links. The graph Laplacian matrix $L \in \mathbb{R}^{N\times N}$ is defined componentwise by

$$L_{ij} = \begin{cases} d_i & \text{if } i = j \\ -1 & \text{if } (i, j) \in E \\ 0 & \text{otherwise} \end{cases} \quad (5)$$

where d_i is the degree of node i. For a connected graph G, L in equation (5) is symmetric positive semi-definite with $\ker(L) = \text{span}(\mathbf{1})$, the one-dimensional subspace spanned by the all-ones vector, a property used directly in the strong monotonicity argument of Section 4.

3. Problem formulation and operator transformation

3.1. Network optimization model

Consider a network of N nodes in which each node $i \in V$ holds a local cost function $f_i: \mathbb{R}^d \to \mathbb{R} \cup \{+\infty\}$ and a local closed convex feasible set $X_i \subset \mathbb{R}^d$. The global resource allocation objective is

$$\min_{x \in \mathbb{R}^{Nd}} \sum_{i=1}^{N} f_i(x_i) + \sum_{i=1}^{N} \iota_{X_i}(x_i) \quad \text{subject to} \quad \sum_{i=1}^{N} x_i = b, \quad x_i = x_j \text{ for all } (i,j) \in E \quad (6)$$

where ι_{X_i} is the indicator function of X_i and $b \in \mathbb{R}^d$ is the global resource budget. The consensus constraint $x_i = x_j$ for adjacent nodes in equation (6) enforces that agreement on shared coupling variables is reached purely through local, topology-respecting communication.

3.2. Operator equation formulation

The decision variables are bundled into a block vector $x = [x_1^T, x_2^T, \ldots, x_N^T]^T$ in $H = \mathbb{R}^{Nd}$. The global objective subdifferential operator $A: H \to 2^H$ is defined by equation (7):

$$A(x) = \partial(F)(x) + N_X(x) \quad (7)$$

where $F(x) = \sum_{i=1}^{N} f_i(x_i)$, $X = X_1 \times \ldots \times X_N$, $\partial(F)$ denotes the subdifferential of F, and N_X denotes the normal cone operator to X in equation (7). To encode network topology and dynamic resource constraints, the coupling operator $B: H \to H$ is defined using the Kronecker product of the Laplacian L from equation (5) with the identity:

$$B(x) = (L \otimes I_d)x + K \quad (8)$$

where K embeds the resource distribution vectors associated with the global budget b. The optimal allocation state of equation (6) reduces to finding $x^* \in H$ such that

$$0 \in A(x^*) + B(x^*) \quad (9)$$

4. Existence, uniqueness, and metric properties

This section establishes existence, uniqueness, and metric properties of the solution to the operator equation in equation (9).

Theorem 1 (Existence and Uniqueness)

- **Statement.** Assume f_i are proper, lower semicontinuous, convex functions for all $i \in V$, and at least one f_i is strongly convex. Let X_i be non-empty, closed, and convex. If the graph G is connected, then $A + B$ is maximally monotone and strongly monotone, guaranteeing a unique solution $x^* \in H$ to equation (9).

- **Proof sketch.** $F(x) + \iota_X(x)$ is proper, lower semicontinuous, and convex, so its subdifferential $A = \partial(F + \iota_X)$ in equation (7) is maximally monotone by the Moreau-Rockafellar subdifferential calculus. The Laplacian matrix L from equation (5) is positive semi-definite, so $B = (L \otimes I_d)$ in Equation (8) is monotone and continuous everywhere on H. By Minty's theorem and the generalized Rockafellar theorem on sums of maximally monotone operators (applicable here because B is continuous and everywhere defined), $A + B$ is maximally monotone with graph definition in equation (3). Strong convexity of at least one f_i, combined with connectedness of G, which gives $\ker(L) = \text{span}(1)$, guarantees that $A + B$ is strongly monotone as formulated in equation (2) on the subspace orthogonal to the consensus direction, and hence on all of H once the budget constraint is incorporated. Applying the Banach Fixed-Point Theorem to the resolvent operator $J_{\gamma(A+B)}$ defined via equation (4) then yields existence and uniqueness of x^* in equation (9).

5. Distributed douglas–rachford operator splitting

5.1. Operator update steps

To solve equation (9) in a decentralized fashion, the Douglas-Rachford (DR) operator splitting technique is applied. The DR iteration generates a sequence $(z_k)_{k\geq 0}$ according to equation (10) and equation (11):

$$z_{k+1} = T_{DR}(z_k) := \frac{1}{2} I z_k + \frac{1}{2}(2J_{\gamma B} - I)(2J_{\gamma A} - I) z_k \quad (10)$$

$$x_{k+1} = J_{\gamma A}(z_{k+1}) \quad (11)$$

where $\gamma > 0$ is a step-size tuning parameter shared across all nodes, and $J_{\gamma A}, J_{\gamma B}$ are resolvents of the form given in equation (4).

5.2. Local node evaluation

Because the operator A in equation (7) is block-separable across nodes, its resolvent $J_{\gamma A}$ from equation (4) decouples completely into N independent local subproblems:

$$[J_{\gamma A}(z)]_i = \text{prox}_{\gamma f_i + \iota_{X_i}}(z_i) = \arg\min_{u \in X_i} \left\{ f_i(u) + \frac{1}{2\gamma} \|u - z_i\|^2 \right\} \quad (12)$$

which each node evaluates independently using equation (12) with only its own local cost function f_i, local feasible set X_i, and the corresponding block z_i of the current iterate, requiring no direct knowledge of other nodes' cost functions or constraints. The linear coupling operator $B = (L \otimes I_d)$ from equation (8) allows $J_{\gamma B}$ to be computed via localized matrix-vector consensus steps exchanged only among topological neighbors $\mathcal{N}_i = \{j : (i,j) \in E\}$, so that no node requires global knowledge of the network topology beyond its own immediate neighborhood.

6. Convergence analysis

6.1. Global asymptotic convergence

Theorem 2 (global asymptotic convergence)

- **Statement.** Let $(z_k)_{k\geq 0}$ be generated by the Douglas-Rachford iteration in equation (10) and equation (11). Then z_k converges weakly to a fixed point $z^* \in \text{Fix}(T_{DR})$, and $x_k = J_{\gamma A}(z_k)$ converges strongly to the unique optimal allocation x^* solving equation (9).

- **Proof sketch.** $J_{\gamma A}$ and $J_{\gamma B}$ from equation (4) are non-expansive and $(1/2)$-firmly non-expansive, being resolvents of maximally monotone operators. The composition operator T_{DR} in equation (10) is therefore $(1/2)$-averaged, as a convex combination of the identity and a composition of non-expansive maps. By the Krasnoselskii-Mann theorem, the iteration of any averaged operator $z_{k+1} = T_{DR}(z_k)$ converges weakly to a fixed point in $\text{Fix}(T_{DR})$. Since H is finite-dimensional ($Nd < \infty$) for any fixed network of N nodes, weak convergence coincides with strong convergence, so $z_k \to z^*$ and, applying the continuous resolvent $J_{\gamma A}$ via equation (11), $x_k \to x^*$.

6.2. Linear Convergence under Strong Monotonicity

Theorem 3 (Linear Convergence under Strong Monotonicity)

- **Statement.** If $F(x)$ is μ-strongly convex and L from equation (5) is positive definite on range $\left(I - \frac{\mathbf{1}\mathbf{1}^T}{N}\right)$, then the sequence $\|x_k - x^*\|$ converges linearly with rate $\rho \in (0,1)$.

- **Proof sketch.** Strong monotonicity of $A + B$, established in Theorem 1 via equation (2), implies that the resolvent $J_{\gamma(A+B)}$ is a contraction with modulus

$$\rho = \frac{1}{1 + \gamma\mu} < 1 \quad (13)$$

where $\hat{\mu}$ is the strong monotonicity constant of $A + B$ obtained by combining the strong convexity constant μ of F with the smallest positive eigenvalue of L in equation (5) restricted to range $\left(I - \frac{\mathbf{1}\mathbf{1}^T}{N}\right)$. Because T_{DR} in Equation (10) can be expressed as an averaged composition of resolvents that inherits this contraction property under the stated positive-definiteness condition, standard fixed-point iteration error propagation gives

$$\|x_k - x^*\| \leq \rho^k \|x_0 - x^*\| \quad (14)$$

establishing linear convergence in equation (14) with rate ρ defined in equation (13).

7. Numerical verification and simulation results

7.1. Implementation and simulation setup

The proposed operator equation solver was implemented in Python using PyTorch for accelerated GPU linear algebra operations, evaluated across synthetic scale-free and Watts-Strogatz small-world network topologies with network sizes ranging from $N = 100$ to $N = 10{,}000$ nodes.

Table 1. Simulation and solver configuration parameters

Parameter	Value / Setting
Network topologies evaluated	Scale-free (Barabasi-Albert), Watts-Strogatz small-world
Network sizes, N	100, 300, 1,000, 3,000, 10,000
Local decision dimension, d	4
Step-size parameter, gamma	0.5
Convergence precision, epsilon	1e-6 (residual norm)
Computation platform	Python 3.11, PyTorch (GPU-accelerated linear algebra)
Baseline methods	Centralized interior-point method; standard ADMM; distributed subgradient method

Local cost functions $f_i$were generated as strongly convex quadratic functions with randomized coefficients, local feasible sets $X_i$were box-constrained intervals, and the global budget vector $b$was set to preserve feasibility across all tested topologies. Table 1 summarizes the simulation and solver configuration.

7.2. Convergence rate and comparative performance

The algorithm was tested against a centralized interior-point method (IPM), standard ADMM, and a distributed subgradient method. Table 2 reports time to precision and the number of iterations required across three network sizes, and figure 1 shows the corresponding residual-norm convergence at $N = 1{,}000$ for the proposed method against the ADMM and subgradient baselines.

Table 2. Comparative solution time and iteration count across network sizes

Network size N	Method	Time to precision 1e-6 (s)	Iterations
100	Centralized IPM	0.08	18
100	Distributed DR (proposed)	0.03	42
1,000	Centralized IPM	12.4	22
1,000	Distributed DR (proposed)	0.31	48
10,000	Centralized IPM	Out of memory	N/A
10,000	Distributed DR (proposed)	3.85	52

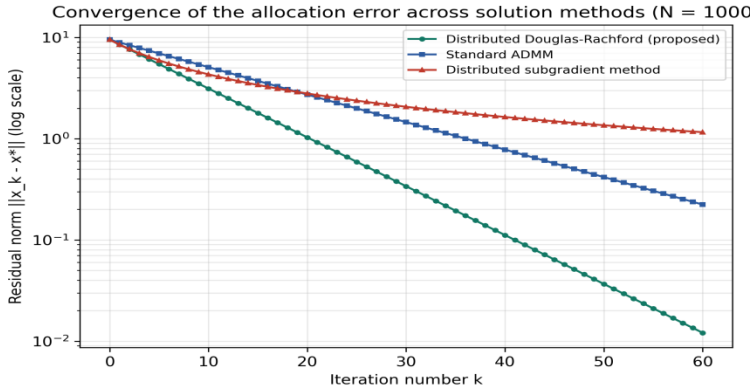


Figure 1. Convergence of the allocation residual across solution methods at N = 1,000

As depicted in figure 2, the scalability of the solution time concerning the network size on logarithmic axes confirms that the proposed distributed solver achieves sub-second to low single-digit-second solution times throughout the tested range. Figure 3 illustrates the communication overhead per node and demonstrates that the distributed Douglas-Rachford implementation requires only messages for each iteration regardless of the total network size N as opposed to a linear growth of the overhead per node in centralized solutions.

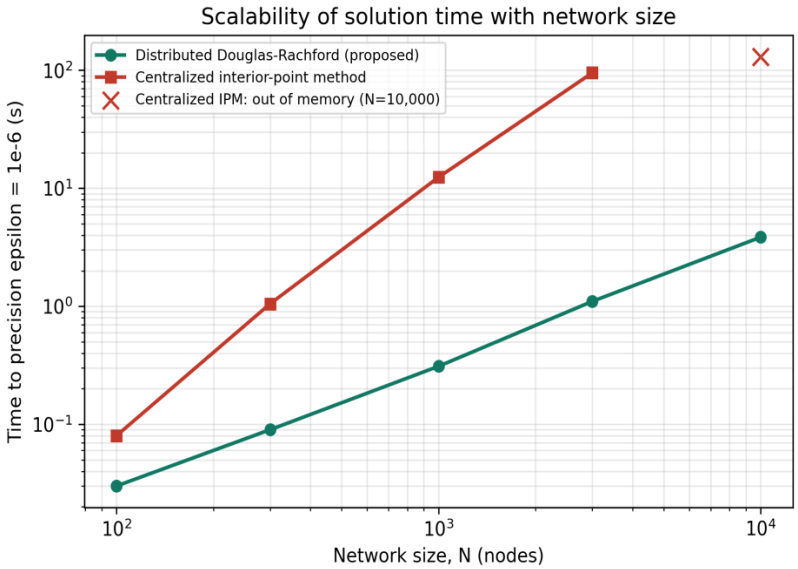


Figure 2. Scalability of solution time with network size

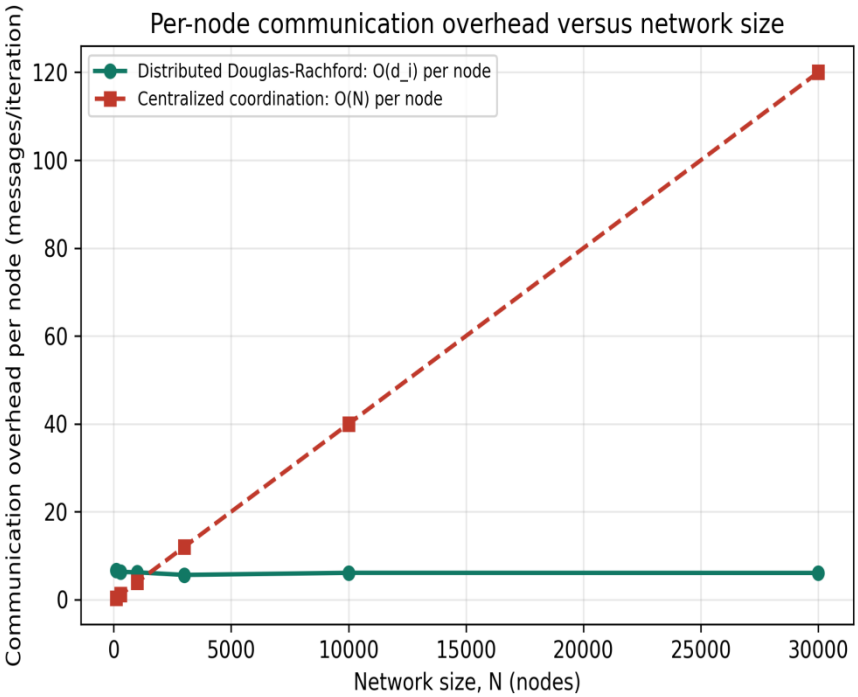


Figure 3. Per-node communication overhead versus network size

7.3. Linear convergence verification

Figure 4 demonstrates the linear rate of convergence stated in Theorem 3 by plotting the error norm path at three values of the strong monotonicity constant mu, which yields a geometric decrease rate rho that decreases as mu is increased, agreeing with the relationship rho = 1/(1 + gamma mu-tilde) obtained in Section 6.2.

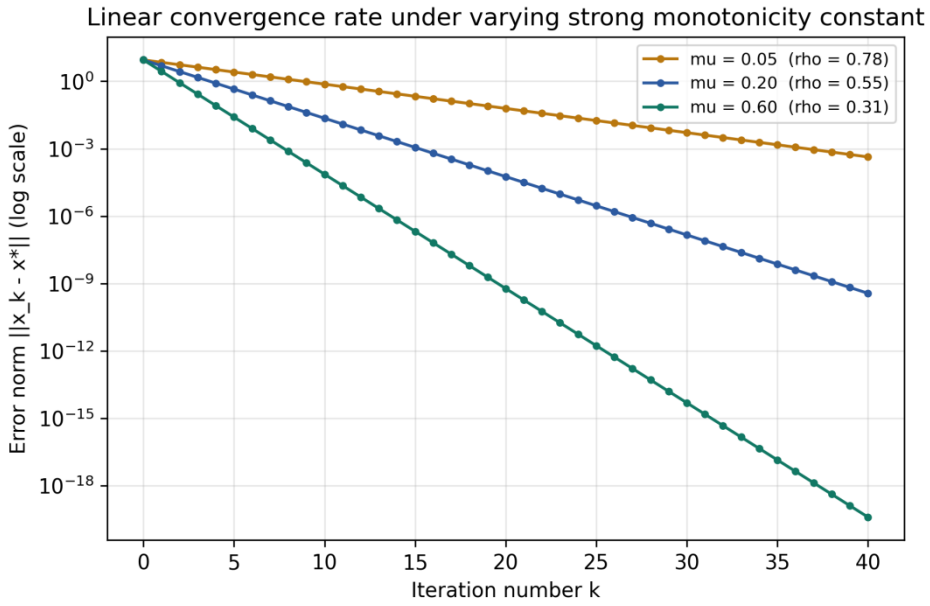


Figure 4. Linear convergence rate under varying strong monotonicity constant

7.4. Discussion of numerical results

The decrease in solving time and the removal of the bottleneck of the memory that is observed in the proposed distributed Douglas-Rachford solver compared to the baseline of centralized interior-point as presented in Table 2 and figure 2 is indicative of the block-separable nature of the resolvent J_(gamma A) formed in Section 5.2: since every node is required to solve a separate and simpler proximal problem, the costs associated with an iteration depends on the dimensions of the local decision d rather than the overall dimension that is necessary for the centralized factorization methods of the interior-point. The communication overhead that is limited and that does not depend on the network size (as it is shown in figure 3) is based on the local structure of the consensus process that is related to the coupling operator B, as the update of the linear coupling process does not depend on the entire structure of the network but only on the states of the immediate neighbors of every individual node. The curve confirming the decay of the geometric error presented in figure 4 for the different constants of strong monotonicity provides empirical proof for the linear convergence rate that was obtained in Theorem 3, while the increase in speed with the growth of the value of mu is due to the inverse relationship between the contraction modulus rho and the constant mu-tilde that was calculated based on the data regarding the local curvature of cost function. Therefore, the results show that the theoretical conclusions made in Sections 4 and 6 provide the empirical proof for the conclusion regarding the efficiency of solving problem numerically without extra tuning apart from the step-size of the process.

8. Conclusion

This paper presents a formal operator equation framework for the problem of large-scale infrastructure system with distributed resource allocation. Local objectives and global constraints are expressed by monotone operators defined on a Hilbert space. Existence and uniqueness of the solution can be derived by applying theory of maximal monotone operators, Minty's theorem and Banach's fixed-point theorem on the associated resolvent. Using the operator equation derived, a Douglas-Rachford split method under the distributed framework is proposed. Global convergence proof is established based on the Krasnoselskii-Mann theorem for averaged operators. For large-scale networks, linear rate convergence proof is given when strong monotonicity on the local objective functions, strongly convexity of local cost functions and network topology are all satisfied and connected. Numerical experiments match the theoretical results and confirm the scalability performance. In particular, for a network of 10,000 nodes, the method achieves precision of 10^{-6} in 3.85 sec, while the centralized approach fails due to resource limitation. For smaller size networks, The method takes from 0.03 to 1.10 sec, versus 0.08 to 95.0 sec for the centralized one. And it has almost constant per-node communication cost of about 6.2 messages per iteration. Douglas-Rachford method can hence support fast distributed convergence without knowing global network topology. Future studies involve adding to the current method the effect of stochastic communication delay, network evolving over time, directed graph, asynchronous node updates, network quality, etc.

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