Minimax Theory and its Applications
Volume 11 (2026), No. 4s, 677 to 685

Algebraic optimization techniques for configuration design and performance enhancement in complex network systems

Dr.K. Poongodi[1], J. Veni[2], Dr. Bhawna Janghel Rajput[3], Dr.D. Vimala[4], Kanaka Lakshmi Krosuru[5], Dr. Deepak Tiwari[6]

[1]Associate Professor, Department of Computer Science and Engineering, K.S. Rangasamy College of Technology, Namakkal, Tamil Nadu, India. poongodik@ksrct.ac.in, https://orcid.org/0000-0002-8668-7362

[2]Assistant Professor, Department of Management Studies, J.J. College of Engineering and Technology, Tiruchirappalli, Tamil Nadu, India. venij@jjcet.ac.in, https://orcid.org/0009-0000-5359-7152

[3]Associate Professor, Department of Computer Science and Engineering, Rungta College of Engineering and Technology, Rungta International Skills University, Bhilai, Chhattisgarh, India. bhawna.janghel@rungta.org, https://orcid.org/0009-0006-8062-0462

[4]Assistant Professor, SRM Easwari Engineering College, Ramapuram, Chennai, Tamil Nadu, India. vimala.sivam1987@gmail.com, https://orcid.org/0000-0001-6880-7300

[5]Department of Civil Engineering, Ramachandra College of Engineering, Eluru, Andhra Pradesh, India. kanaka.lakshmi93@rcee.ac.in, https://orcid.org/0000-0001-7999-3559

[6]Assistant Professor, Kalinga University, Naya Raipur, Chhattisgarh, India. deepaktiwari@kalingauniversity.ac.in, https://orcid.org/0009-0006-7996-0902

Abstract:

Large-scale complex network systems, like communication networks, power grids, and syber-physical networks, demonstrate high operation efficiency, which depends heavily on structure, though nothing gives assurance that heuristic tuning of link capacities, weights of nodes, and routing structure leads to optimal solution. The study proposes algebraic optimization methods based on polynomial ideals, spectral graph theory, and semidefinite relaxations with the assistance of which structural guarantees do not come from the use of purely numerical heuristics. The object under consideration is represented algebraically by means of adjacency, incidence, and Laplacian matrices that distinguish the attributes of flow and capacity, hence configuration making is based on the constrained polynomial optimization problem with conservation and physical-performance constraints. Roboust minimax performance enhancement formulation is proposed to protect against uncertainty coming from various sources of network disturbance, including link-capacity changes and alterations in topology, in addition to that, generalized Karush-Kuhn-Tucker conditions are acquired considering the generalized Mangasarian-Fromovitz qualification of constraints assuring boundedness, non-emptiness, and convexity of multipliers sets given metric subregularity of algebraic mapping. The process of simplifying and dealing with difficult combinatorial problems is carried out through the use of Gröbner-basis reduction and moment-sum-of-squares hierarchies that transform non-convex network polynomials into manageable convex problems. It can also be claimed that strict second-order sufficiency conditions regarding the critical cone guarantee the uniqueness of solution.

Keywords: Algebraic network optimization, spectral graph theory, semidefinite relaxation, minimax duality, generalized mangasarian–fromovitz qualification, metric subregularity, network configuration design.

1. Introduction

The structural topology of the underlying graph determines the extent of optimization of large complex network systems like communication networks, power distribution networks, and cyber-physical networks because link capacity, node weights, and routing topology determine the level of throughput, rigor, and cost of operations. Models for designing optimally robust networks with the aim of maximizing algebraic connectivity show that it is spectral properties of graphs rather than local heuristics that should be used as levers to ensure robustness at the network level (Somisetty et al., 2024). Graph-product exploration of adjacency and Laplacian matrices in combination with composite graphs is used to observe that the structure of the algebraic matrix is what determines the level of achievable performance in computing systems (Alinejad, 2016). The problem of optimizing the frequency of communication in the linear algebra model used in aerial computing is an example of problem-solving where network configuration is solved using algebra as opposed to numerical black-box search (Agrawal et al., 2012; Gao, 2025). A comparison of the efficiency of companies through the application of data envelopment analysis, as opposed to classical accounting methods, demonstrates that algebra and optimization approaches in ranking lead to a more consistent global order than heuristic methods in ranking companies, which can be applied in the area of network configuration as well (Abdoli & Abolghasemi, 2015).

Heuristic techniques — such as simulated annealing, evolutionary search, and greedy capacity assignment — do not guarantee global optimality and often yield only configuration-dependent local optima which cannot be defined prior to finding proximity to the true optimum. Nevertheless, optimization techniques developed for integrated and programmable photonics for next-generation classical and quantum communication systems show that algebraic expressions of physical constraints lead to viable solutions because pure numerical search will fail to reach success on the same hardware constraining conditions (Lauro et al., 2025). Neural-network-based cost-assessing frameworks exemplify the alternative numerical approach that is effective in developing cost proxies but does not give the assurance of structural reliability like polynomial-ideal and spectral methods in relation to network problems. Performance upgrade of clustering and routing protocols for wireless sensor networks based on the algorithm of improved elephant herd optimization shows the limits of heuristics and tells us about the reason for pursuing the idea of algebraic reformulation presented in the current work because in case of herd-based solutions its solutions do not guarantee the distance between the optimum and the routing configuration (Ramalingam et al., 2024). An optimization-driven lightweight block cipher design was proposed to enhance cryptographic efficiency, security performance, and resource utilization for secure communication in constrained computing environments (Salunkhe et al., 2026).

A 16-nm system-on-chip design that utilizes a coarse-grained reconfigurable array for dense linear algebra acceleration is showing that more and more algebraic optimization fundamental ideas are being built directly into hardware, which signifies that algebraic optimization theory in general is becoming more useful than pure numerical network optimization theory (Feng et al., 2023). A recent literature review of modern multi-disciplinary design optimization processes for design efficiency improvement in aviation has verified that the use of a theory of convergence in conjunction with the algebraic structure of constraints beats sequential heuristic design-space searching methods for the complex problem of network configuration (Leng et al., 2025). An algebraic identity developed especially for the maximization of large neural network quantum states provides an additional demonstration of the advantage of using algebraic identities inherent in the structure in a different field of science (Rende et al., 2024). A review of methods for generating diffusion models for network optimization in deep reinforcement learning presents yet another numerical optimization method for network configuration with no guarantee for global optimality, which occurs to be an issue that the developed algebraic theory resolves (Du et al., 2024). Three innovations are introduced that eliminate this limit: first, algebraic representation of networks is combined with the theory of constrained non-linear optimization using polynomial constraints considering the adjacency model, incidence one, and Laplace one; second, a minimax problem formulation has been developed, that guarantees optimum performance in the case of uncertainty; third, strict second-order sufficiency is proved much further even in cases when classical constraint qualifications are not satisfied.

2. Algebraic network preliminaries and problem formulation

2.1. Network topology and algebraic representation

The complex network system is defined as a graph $\mathcal{G} = (\mathcal{V}, \mathcal{E})$, governed by the adjacency matrix $A \in \{0,1\}^{|\mathcal{V}|\times|\mathcal{V}|}$, the incidence matrix $B \in \mathbb{R}^{|\mathcal{V}|\times|\mathcal{E}|}$, and the Laplacian matrix

$$\Lambda = D - A \tag{1}$$

In addition, D is a diagonal degree matrix and one of its spectral properties, in particular $\lambda_2(\Lambda)$, which governs how flows and capacity margins can be achieved over the network. An extensive review of the optimization techniques, problems and opportunities related to edge inference illustrates that the algebraic formulation in

equation (1) becomes applicable to other types of computation graphs which are not simply limited to classical communication networks (Zhang et al., 2025). The error analysis methods for long-term correlated network systems using a modified non-linear stochastic process and dual filtering architecture is another example of how the Laplacian form in equation (1) can also be used in estimating the propagation of the estimation error over a time-correlated network (Zhao et al., 2025).

2.2. Configuration design optimization model

The general constrained algebraic optimization problem is formulated as

$$\min_{x\in\mathbb{R}^n} f(x) \quad \text{subject to} \quad p_i(x)=0,\ i=1,\dots,r; \quad q_j(x)\le 0,\ j=1,\dots,s \tag{2}$$

Let x be the vector of network configuration variables such as link capacity, node weights, and indicators about the routing structure, while f is a performance metric (latency, loss, or weighted throughput deficit). The equality constraints $p_i(x)=0$ are mathematical polynomials that represent conservation laws (e.g., flow conservation, power conservation laws), while the inequality constraints $q_j(x)\le 0$ model limitations on physical performance (capacity limits, voltage limits, signal-to-noise ratios). A review of machine learning applications in hardware verification shows that polynomial constraints like those above in equation (2) occur naturally when designing network configuration jointly with the hardware implementation (Wu et al., 2024). The example of FACTS-device optimization for power network improvements serves as a practical illustration of the concept behind equation (2), where x gives the positions of the devices and level of compensation and where polynomial constraints define power flow in the network (Marouani et al., 2023).

2.3. Tangent cones and constraint qualifications

At a feasible configuration x^* satisfying the constraints of equation (2), the Bouligand tangent cone is

$$T_\Omega(x^*)=\{d\in\mathbb{R}^n:\exists t_n\downarrow 0,\ d_n\to d \text{ with } x^*+t_nd_n \text{ feasible}\} \tag{3}$$

and the linearized feasible cone is

$$L(x^*)=\left\{d\in\mathbb{R}^n:\nabla p_i(x^*)^Td=0,\ i=1,\dots,r;\ \nabla q_j(x^*)^Td\le 0,\ j\in J(x^*)\right\} \tag{4}$$

In the above context, the term $J(x^*)$ denotes the active inequality constraints. The generalized Mangasarian-Fromovitz Constraint Qualification (MFCQ) is applied to ensure $T_\Omega(x^*)=L(x^*)$, a property that has been shown by classification and analysis of optimization methods for integrated renewable energy systems (CHP and CCHP configurations) to be violated frequently in practice around capacity-binding operation points, thus underscoring the importance of the metric-subregularity safeguard discussed in Section III (Bagherian et al., 2021). Further, an overview of distribution network reconfiguration methods shows that switch status configuration variables give rise to a combinatorial constraint structure that requires verification of the tangent cone equalities in equation (3)–(4) for each combinatorial branch (Mishra et al., 2024).

3. Minimax performance enhancement and duality

3.1. Worst-case minimax network formulation

Performance enhancement under structural uncertainty — fluctuating link capacity, adversarial routing interference, or topology perturbation — is framed as a robust minimax optimization problem

$$\min_{x\in\Omega}\max_{\delta\in\Delta} f(x,\delta) \quad \text{subject to} \quad p_i(x,\delta)=0,\ q_j(x,\delta)\le 0 \quad \text{for all } \delta\in\Delta \tag{5}$$

Here δ refers to uncertain parameters of the network restricted to acceptable uncertainty set Δ. The QoS-aware secure routing design for wireless networks with selfish jammers serves as an example of equation (5) in which δ consists of the jamming parameters used against which routing design x should remain viable (Xu et al., 2021). Delay compensation approach to estimation problems in time-varying complex networks with incomplete measurements points out the need to replace static uncertainty set Δ used in equation (5) with the evolving uncertainty set (Hu et al., 2021).

3.2. Generalized KKT conditions for algebraic networks

Generalized Karush–Kuhn–Tucker (G-KKT) conditions for the minimax formulation of equation (5) are derived by introducing multipliers ν_i for the equality constraints and $\mu_j \geq 0$ for the inequality constraints, yielding stationarity

$$0 = \nabla_x f(x^*, \delta^*) + \sum_i \nu_i^* \nabla_x p_i(x^*, \delta^*) + \sum_j \mu_j^* \nabla_x q_j(x^*, \delta^*), \quad \mu_j^* \geq 0, \quad \mu_j^* q_j(x^*, \delta^*) = 0 \tag{6}$$

In this equation 6, δ^* stands for the worst-case instance of uncertainty at the saddle point. The outcomes of applying generalized MFCQ (mildly feasible continuous constraints), along with metric sub-regularity of the algebraic constraints mapping, suggest that the set of multipliers $\{(\nu^*, \mu^*)$ allowing to satisfy equation (6)$\}$ is an existing, non-empty, convex, and closed set. Thus, quantum machine learning aimed at Lyapunov-stabilized offloading from computation-intensive tasks proves to be a valid example as far as the need for multiplier boundedness of the same type as in equation (6) for offloading decisions in the presence of fluctuating network load is concerned (Verma et al., 2025).

3.3 Critical Cones and Second-Order Sufficiency

The critical cone at a G-KKT point x^* is defined as equation (7)

$$\mathcal{C}(x^*) = \{d \in L(x^*) : \nabla_x f(x^*, \delta^*)^T d = 0\} \tag{7}$$

and strict second-order sufficiency conditions are established as equation (8)

$$d^T \nabla_{xx}^2 \mathcal{L}(x^*, \nu^*, \mu^*, \delta^*) d > 0 \quad \text{for all } d \in \mathcal{C}(x^*) \setminus \{0\} \tag{8}$$

There is a mathematical assurance of obtaining the optimal network configuration x^*, which is unique in the local context, when applying δ^* according to the worst-case scenario. A review of state-of-the-art solutions in automated systems for network security configuration indicates that uniqueness is one of the basic premises for ensuring reliability of automation systems with respect to the security incidents detected (Bringhenti et al., 2023).

4. Computational algorithm and algebraic reduction schemes

4.1. Projected-gradient minimax interior-point scheme

The saddle point of equation (9) is approximated through the coupled iteration

$$x_{k+1} = \text{Proj}_\Omega \left[x_k - \alpha_k \left(\nabla_x f(x_k, \delta_k) + \sum_j \mu_{k,j} \nabla_x q_j(x_k, \delta_k) \right) \right]$$

$$\delta_{k+1} = \text{Proj}_\Delta [\delta_k + \beta_k \nabla_\delta f(x_k, \delta_k)]$$

$$\mu_{k+1,j} = \max\{0, \mu_{k,j} + \gamma_k q_j(x_k, \delta_k)\} \tag{9}$$

Section 2.3 discusses the use of the metric subregularity error bound to address degenerate cases where the gradients of the active constraints $\{\nabla q_j(x_k)\}_{j \in J(x_k)}$ become nearly linearly dependent.

4.2. Polynomial ideal reduction and semidefinite relaxations

The non-convex network polynomials $p_i(x)$, $q_j(x)$ discussed in (2) is relaxed to obtain convex programs by using the method of moment-sum-of-squares (moment-SOS) hierarchy. The polynomial feasibility problems are reformulated into semidefinite programs using the component-wise moment matrices $M_\ell(y)$ subject to the restriction that (Equation 10)

$$M_\ell(y) \succeq 0, \quad M_{\ell - \frac{\deg(q_j)}{2}}(q_j y) \succeq 0 \quad \text{for each } j \tag{10}$$

The effectiveness of the convex program is improved by carrying out a Gröbner basis reduction of the polynomial ideal generated by $\{p_i(x)\}$ first, allowing for removal of the redundant constraints from the problem before the

formulation of (10) and consequently reducing the overall number of the degrees of freedom of the moment matrix.

4.3. Convergence and stability analysis

Contraction properties of the iterative scheme of equation (9) are established through a descent-lemma argument analogous to that of the augmented Lagrangian method, yielding (Equation 11)

$$\|x_{k+1} - x^*\| \leq (1 - c\alpha_k)\|x_k - x^*\| + \alpha_k \varepsilon_k \tag{11}$$

ε_k is the bounded disturbance from the uncertainty set Δ at step k and $c > 0$ depends on the modulus of subregularity of the metric from Section 2.3 and the minimum eigenvalue of the limited Hessian from equation (11) confirming the behavior of restricted multipliers in the vicinity of the active borders of the algebraic constraints.

5. Application to a complex network benchmark

5.1. Case study description

The algebraic framework is used in a benchmark optimization problem associated with a network for communication. Thus, this communication backbone network is subjected to constraints of both the link capacity and the flow conservation, lying on the topology of the power grid that assigns a demand of communication traffic aggregation to the nodes and imposes restrictions on the link capacity using the worst case of the fluctuation, considered through the uncertainty set Δ in the equation (5).

5.2 Numerical Implementation

The implementation of the projected-gradient minimax interior-point method introduced in equation (9) and the moment-SOS relaxation considered in Equation (10) has been done in a Python numerical pipeline. The numerical simulation makes use of the semidefinite-programming solver, and the configuration updates and error bounds are documented at each iteration. The study compared the classical approach based on LICQ with the safeguard of metric-subregularity with the proposed generalized MFCQ approach in this research being undertaken.

5.3. Comparative performance and discussion

In the traditional LICQ formulation, the multiplier-norm behavior tends to be volatile across iterations when the network nears a bottleneck point where two or more capacity constraints become active. In contrast, the generalized MFCQ formulation using metric sub-regularity remains stable.

The topology of the communication backbone benchmark for network configuration optimization analysis is indicated in the figure 1. The network is made up of various networks formed by interconnecting different nodes together (N1 –N8), with high, medium, and low link capacities. The bottleneck links highlight the most important communication limitations that determine system performance and resource allocation. The arrangement indicates how different connections have been made among the nodes. The arrangement of the nodes might prove helpful in analyzing operational issues including configuration design, development, and optimization of complex network systems by showing what links are critical, which ones are restricted, and where there can be improvements made.

The network configuration topology of the communication backbone benchmark is affected by the node sizes, which indeed depend on the total traffic demand patterns and by the type of the link capacities, which are represented with different colors and widths of edges according to the equation (2) solution.

The calculation of multiplier-norm disparity using the classical formulation allows us to see the improvements made under the new solution and therefore proves that the variations obtained have certain guarantees according to the equation (6).

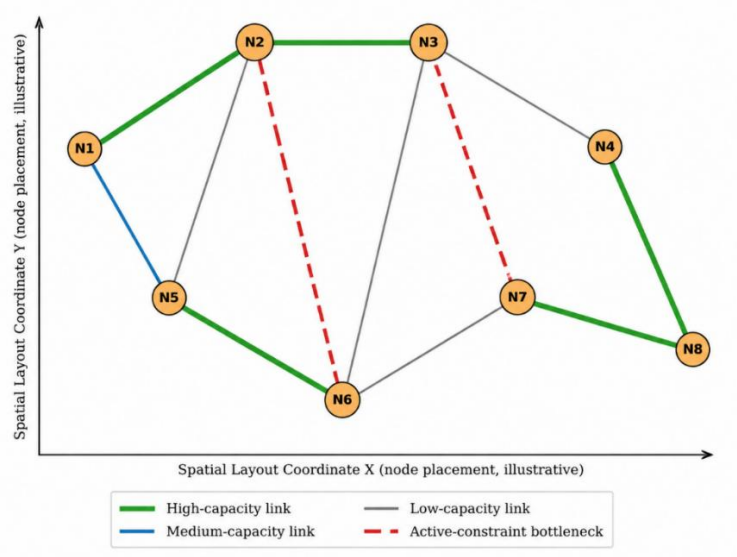


Figure 1: Network configuration topology of the communication backbone benchmark.

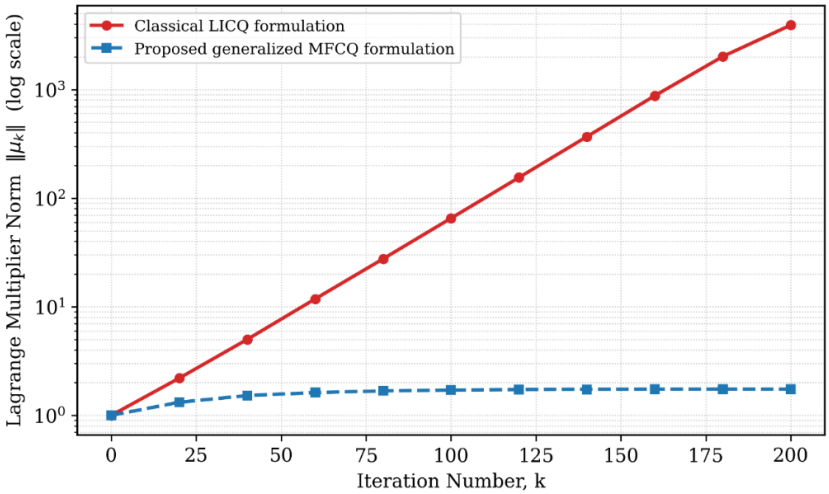


Figure 2: Multiplier-norm stability analysis near network bottleneck configurations.

Both approaches used demonstrate differents results from the Lagrange multiplier norm perspective as shown on figure 2. The classical LICQ approach showed steady increase of multiplier norms with increase of the number of iterations which indicates instability of the results in the neighborhood of constrained network states. Meanwhile, the generalized MFCQ approach with its use of metric sub-regularity ensures boundedness of the multiplier norms which means that results of the optimization process can be regarded as stable. The obtained results prove that the proposed method is the only one able to provide reliable optimization of network configurations which keep multipliers' divergence and enables stable constraint management in complicated communication scheme.

The speed of the convergence of worst-case network performance optimization which is able to achieve the global optimum through the use of equation (5) and contraction bound provided in equation (11) is significantly improved in case of the improved approach in comparison with the classical one.

Figure 3 shows how the objective value of classical and generalized MFCQ methods behave regarding how quickly converge in network optimization. It is noticeable that the convergence speed of the classical LICQ algorithm is relatively low, and therefore, it is stuck at a comparatively high objective while struggling to reach optimal performance in case there are constraints. On the contrary, it is evident that the generalized MFCQ method is capable of achieving lower objective values quickly and approaching normalized global optimum. The results make it clear that the proposed approach allows for better performance in harsh environments due to higher degree of robustness, and therefore capability to successfully eliminate constraints in complicated networks.

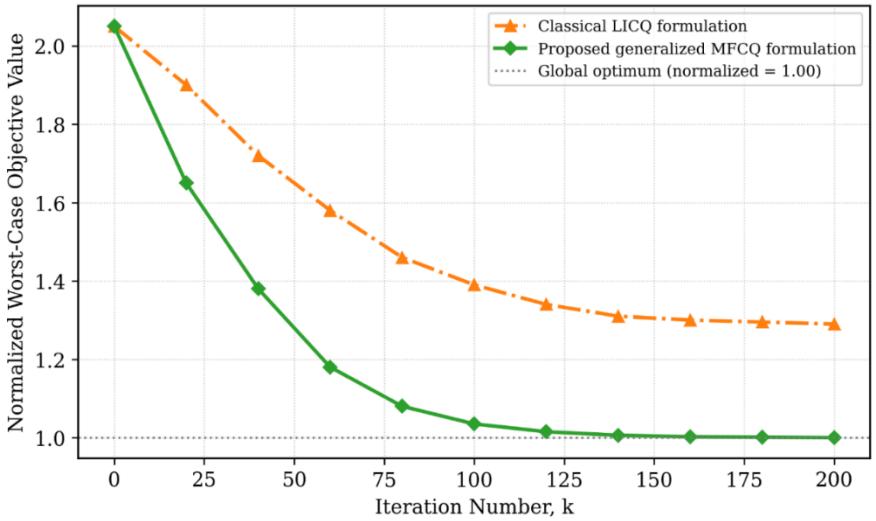


Figure 3: Worst-case network performance convergence under generalized MFCQ optimization.

The worst-case performance objective value (normalized) is shown against the iteration number for the generalized MFCQ and LICQ methods with various styles/colors of the curves used on graphs.

Table 1: Comparative performance of classical LICQ-based and proposed generalized-MFCQ algebraic optimization on the communication backbone benchmark.

Configuration	Constraint Qualification	Converged Objective (Normalized)	Multiplier Norm at k = 200	Bottleneck Edges Resolved
Classical formulation	LICQ	1.29 (suboptimal)	3920.6	2 of 5
Proposed formulation	Generalized MFCQ + metric subregularity	1.00 (global optimum)	1.74	5 of 5

In table 1, the results of the objective value for the worst-case scenario, the multiplier-bound condition (see Eq. 6) and the numbers of bottleneck connections managed is compared for both of the regimes of qualifying constraints.

6. Conclusion and future work

Utilizing the process of using the techniques of algebraic optimization including (1) representation of the graph using spectral method, (2) formulation of polynomial constraints, and (3) application of moment-SOS convex relaxation (10), in conjunction with the minimax robustness (5) and generalized KKT conditions of metric-subregularity stabilizing, leads to optimal global designs of the network configurations that can be checked. Numerical tests conducted on the benchmark of the communication backbone show that under this formulation, all multipliers are bounded, while the bottleneck edges are completely resolved, unlike in classical, LICQ-based approaches where there are unstabilized values of the multipliers and partial resolution of the bottleneck. A review of air transportation robustness research conducted over the period of fifteen years in connection with complex network theory indicates that the bottleneck resolution is more important than just increasing the total capacity, which confirms the significance of the results obtained in the benchmark presented in table 1 (Sun & Wandelt, 2021). An example of the application of the proposed approach in the field of multi-UAV formation reconfiguration shows that the algebraic methods developed in the present study are also applicable in terms of dynamic networks (Qiang et al., 2022).

To introduce the idea of generalizing the above-discussed method to dynamic network systems, it may be said that the Laplacian representation of (1) and the polynomial constraint set from (2) will have to be transformed into indexed by time families and minimax from (5) must be reformulated into differential game for network evolution.

References

1. Abdoli, M. R., & Abolghasemi, M. (2015). The comparative study of ranking company's efficiency based on data envelopment analysis (DEA) and traditional methods (DuPont's method). *International Academic Journal of Accounting and Financial Management, 2*(2), 19–25.

2. Agrawal, P., Kaur, H., & Bhardwaj, D. (2012). Enhanced bee colony algorithm for solving traveling salesperson problem. *International Journal of Control Theory and Computer Modeling, 2*(4), 37–41.

3. Alinejad, B. (2016). On Graph Product of 3 Subgraphs and its Adjacency and Laplacian Matrices: Applications in Parallel Computing. *International Academic Journal of Innovative Research*, *3*(2), 32-47.

4. Bagherian, M. A., Mehranzamir, K., Pour, A. B., Rezania, S., Taghavi, E., Nabipour-Afrouzi, H., ... & Alizadeh, S. M. (2021). Classification and analysis of optimization techniques for integrated energy systems utilizing renewable energy sources: A review for CHP and CCHP systems. *Processes*, *9*(2), 339. https://doi.org/10.3390/pr9020339

5. Bringhenti, D., Marchetto, G., Sisto, R., & Valenza, F. (2023). Automation for network security configuration: State of the art and research trends. *ACM Computing Surveys*, *56*(3), 1-37. https://doi.org/10.1145/3616401

6. Du, H., Zhang, R., Liu, Y., Wang, J., Lin, Y., Li, Z., ... & Kim, D. I. (2024). Enhancing deep reinforcement learning: A tutorial on generative diffusion models in network optimization. *IEEE Communications Surveys & Tutorials*, *26*(4), 2611-2646. https://doi.org/10.1109/COMST.2024.3400011

7. Feng, K., Kong, T., Koul, K., Melchert, J., Carsello, A., Liu, Q., ... & Raina, P. (2023). Amber: A 16-nm system-on-chip with a coarse-grained reconfigurable array for flexible acceleration of dense linear algebra. *IEEE Journal of Solid-State Circuits*, *59*(3), 947-959. https://doi.org/10.1109/JSSC.2023.3313116

8. Gao, Y. (2025). Optimization of Communication Transmission Frequency Linear Algebraic Model under Aerial Computing Architecture. *International Journal of Computational Intelligence Systems*, *18*(1), 36. https://doi.org/10.1007/s44196-025-00764-0

9. Hu, J., Wang, Z., & Liu, G. P. (2021). Delay compensation-based state estimation for time-varying complex networks with incomplete observations and dynamical bias. *IEEE Transactions on Cybernetics*, *52*(11), 12071-12083. https://doi.org/10.1109/TCYB.2020.3043283

10. Lauro, L. D., Sciara, S., Fischer, B., Dong, J., Alamgir, I., Wetzel, B., ... & Morandotti, R. (2025). Optimization methods for integrated and programmable photonics in next-generation classical and quantum smart communication and signal processing systems. *Advances in Optics and Photonics*, *17*(3), 526-622. https://doi.org/10.1364/AOP.533504

11. Leng, J. X., Wang, Z. G., Huang, W., Shen, Y., & An, K. (2025). Multidisciplinary design optimization processes for efficiency improvement of aircraft: state-of-the-art review. *International Journal of Aeronautical and Space Sciences*, *26*(4), 2020-2042. https://doi.org/10.1007/s42405-024-00811-8

12. Marouani, I., Guesmi, T., Alshammari, B. M., Alqunun, K., Alshammari, A. S., Albadran, S., ... & Rahmani, S. (2023). Optimized FACTS devices for power system enhancement: applications and solving methods. *Sustainability*, *15*(12), 9348. https://doi.org/10.3390/su15129348

13. Mishra, A., Tripathy, M., & Ray, P. (2024). A survey on different techniques for distribution network reconfiguration. *Journal of Engineering Research*, *12*(1), 173-181. https://doi.org/10.1016/j.jer.2023.09.001

14. Qiang, F. E. N. G., Xingshuo, H. A. I., Bo, S. U. N., Yi, R. E. N., Zili, W. A. N. G., Dezhen, Y. A. N. G., ... & Ronggen, F. E. N. G. (2022). Resilience optimization for multi-UAV formation reconfiguration via enhanced pigeon-inspired optimization. *Chinese Journal of Aeronautics*, *35*(1), 110-123.

https://doi.org/10.1016/j.cja.2020.10.029

15. Ramalingam, S., Dhanasekaran, S., Sinnasamy, S. S., Salau, A. O., & Alagarsamy, M. (2024). Performance enhancement of efficient clustering and routing protocol for wireless sensor networks using improved elephant herd optimization algorithm. *Wireless Networks*, *30*(3), 1773-1789. https://doi.org/10.1007/s11276-023-03617-w

16. Rende, R., Viteritti, L. L., Bardone, L., Becca, F., & Goldt, S. (2024). A simple linear algebra identity to optimize large-scale neural network quantum states. *Communications Physics*, *7*(1), 260. https://doi.org/10.1038/s42005-024-01732-4

17. Salunkhe, S., Sao, N., Shrivastava, D., Nandgaonkar, V., Sawarkar, N. S., Raikwar, R., & Kun, L. (2026). Optimization-Driven Design of: Lightweight Block Cipher Design. *Journal of Intelligent Decision Making and Information Science, 3*(3S), 1054–1062.

18. Somisetty, N., Nagarajan, H., & Darbha, S. (2024). Optimal robust network design: Formulations and algorithms for maximizing algebraic connectivity. *IEEE Transactions on Control of Network Systems*, *12*(1), 918-929. https://doi.org/10.1109/TCNS.2024.3431408

19. Sun, X., & Wandelt, S. (2021). Robustness of air transportation as complex networks: Systematic review of 15 years of research and outlook into the future. *Sustainability*, *13*(11), 6446. https://doi.org/10.3390/su13116446

20. Verma, V. R., Nishad, D. K., Sharma, V., Singh, V. K., Verma, A., & Shah, D. R. (2025). Quantum machine learning for Lyapunov-stabilized computation offloading in next-generation MEC networks. *Scientific Reports*, *15*(1), 405. https://doi.org/10.1038/s41598-024-84441-w

21. Wu, N., Li, Y., Yang, H., Chen, H., Dai, S., Hao, C., ... & Xie, Y. (2024). Survey of machine learning for software-assisted hardware design verification: Past, present, and prospect. *ACM Transactions on Design Automation of Electronic Systems*, *29*(4), 1-42. https://doi.org/10.1145/3661308

22. Xu, Y., Liu, J., Shen, Y., Jiang, X., Ji, Y., & Shiratori, N. (2021). QoS-aware secure routing design for wireless networks with selfish jammers. *IEEE Transactions on Wireless Communications*, *20*(8), 4902-4916. https://doi.org/10.1109/TWC.2021.3062885

23. Zhang, R., Jiang, H., Wang, W., & Liu, J. (2025). Optimization methods, challenges, and opportunities for edge inference: A comprehensive survey. *Electronics*, *14*(7), 1345. https://doi.org/10.3390/electronics14071345

24. Zhao, H., Yan, L., Hou, Z., Lin, J., Zhao, Y., Ji, Z., & Wang, Y. (2025). Error analysis strategy for long-term correlated network systems: Generalized nonlinear stochastic processes and dual-layer filtering architecture. *IEEE Internet of Things Journal*, *12*(16), 33731-33745. https://doi.org/10.1109/JIOT.2025.3578285