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Information geometry-based optimization models for decision analysis in cyber-physical infrastructure networks

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Abstract:

Cyber-physical infrastructure networks comprise physical assets, sensors, communication means, computation resources, and control mechanisms leading to complex decision-making environments where there are uncertainty, heterogeneity, and dynamism in observation and operation. Traditional optimization methods usually model system states as points in Euclidean space, and such traditional methods might be unable to appropriately account for the intrinsic property of uncertain probability distributions. This research work has developed an Information Geometry-Based Optimization Model for Decision Analysis in Cyber-Physical Infrastructure Networks through the use of statistical manifolds, Fisher information geometry, information-geometric divergence, and minimax optimization. The heterogeneity of infrastructure observation is converted into probabilistic state representation modelled as points in a statistical manifold. The Fisher information geometry is then used to describe the local geometric characteristics of uncertain states. In order to tackle the distributional uncertainties, an admissible uncertainty set is devised and embedded into a minimax decision approach in which the maximum value of the operational objective function is minimized. The developed model takes into account decision cost, geometric discrepancy, operational risk, and violation of constraints under resource, capacity, safety, and stability constraints. To assess the convergence, robustness, computation characteristics, sensitivity analysis, and component importance, a synthetic 50-node cyber-physical infrastructure network is utilized as test cases. Some representative results confirm that the proposed IG-Minimax model outperforms the classical minimax and Euclidean approaches with respect to the worst-case

objective value, equal to 51.27 and 56.84, respectively. The results indicate that information geometry is a mathematical sound tool for representing uncertain states of the infrastructure network, while the minimax optimization increases the robustness of the decision to distributional uncertainty.

Keywords: Information geometry, minimax optimization, cyber-physical networks, statistical manifolds, robust decision analysis.

1. Introduction

The concept of CPINs combines physical elements with sensors, communication networks, computation and control. The growing application of CPINs in such sectors as transportation, energy, manufacturing, healthcare, and urban infrastructure results in decision-making environments involving heterogeneous data, interactions, constraints, and uncertainties (Atat et al., 2020; Muniraju et al., 2020; Zhang et al., 2020). Modern advancements related to digital twins, edge computing, and smart infrastructure highlight the importance of optimization techniques which adapt decisions depending on changes in the physical and cyber state (Kazemi et al., 2026; Alamelu Sathyabama et al., 2026; Hlophe & Maharaj, 2023). Data driven solutions for public administration serve as another example of how heterogeneous data and decision-support systems based on analysis can improve both governance and decision making related to infrastructure (García & Fernández, 2024). In a similar manner, object detection and data processing from sensors have been studied in relation to their use in smart cities (Rohankar et al., 2026). Examples from the area of intelligent transportation systems and mobile edge computing show that CPINs can positively affect coordination in operations, however, decision-making quality depends on dealing with uncertainty and variability (Feifei, 2024; Rojas & García, 2024; Xu et al., 2023).

The literature on optimization has tackled the problem from different angles such as infrastructure planning based on simulated annealing, resource allocation using reinforcement learning, dynamic decision matrices, and online cyber-physical optimization (Shilpa & Ranjan, 2024; Kavuluri, 2025; Parkash & Singh, 2023). Resilient cyber-physical architectures, integration of satellites and terrestrial systems, photovoltaic monitoring, and vulnerability analysis of substations are some other areas that researchers have examined (Ayofe et al., 2024; Muniraju et al., 2020; Shashank et al., 2024). Manufacturing cyber-physical systems, construction cyber-physical systems, and networks of unmanned aerial vehicles are some examples of different kinds of interdependent infrastructures (Lin & Golparvar-Fard, 2020; Luo & Kuo, 2016; Wang et al., 2019). Nevertheless, most traditional mathematical models consider state vectors to be either deterministic or Euclidean. The security-related literature highlights that cyber-physical systems are vulnerable to complex integrity and stealth attacks, thereby emphasizing the need for robust decision-making mechanisms (Arvind & Nair, 2025; Wang & Ye, 2024; Lin et al., 2018).

The problem of infrastructure decision-making optimization is additionally influenced by the uncertainties in the measurement process, the communication process, the demand, the consumption of energy, and the physical process of operation. Current methods of optimization have proven to be effective if nominal conditions apply; however, their performance can be degraded when the distributions of the system differ from the expected case. Recent studies on optimization of infrastructure reveal the ongoing necessity for adaptive, robust, and mathematically sound decision-making algorithms (Kazemi et al., 2026; Alamelu Sathyabama et al., 2026; Xu et al., 2023). This calls for research in information geometry since the method offers an efficient way to consider probability distributions as points on a statistical manifold through mathematics. Using the Fisher information metric, the relationships among the probabilities locally can be considered through the intrinsic Riemannian geometry rather than the conventional flat Euclidean geometry.

However, even when the states are represented geometrically, there is no assurance of protection from adverse operating conditions. Thus, a robust formulation using minimax should be developed to consider explicitly the worst-case allowable uncertainties. In this regard, an Information Geometry-Based Optimization Model for Decision Analysis in Cyber-Physical Infrastructure Networks is formulated. The model formulation involves the use of probabilistic state representations, creation of statistical manifolds, application of Fisher information geometry and information-geometric divergence, construction of uncertainty sets, and minimax optimization techniques. The main goals are to develop a mathematically sound robust decision model, create a geometry-driven optimization process, determine convergence and computational properties, and examine robustness with respect to increased distributional uncertainty. The main contribution is the development of a framework that uses information geometry together with minimax decision optimization for CPINs.

Organization of the rest of this paper is as follows. In Section 2, the study presents the mathematical preliminaries and the problem statement. In Section 3, the study develops the information geometry-based optimization model. In Section 4, it describes the optimization method along with its theoretical properties. In Section 5, it considers the decision scenarios of representative cyber-physical infrastructure systems. The experimental evaluation

setting is provided in Section 6, followed by the results in Section 7. The comparative and theoretical analysis is provided in Section 8. Section 9 concludes this paper.

2. Mathematical preliminaries and problem formulation

2.1. Cyber-physical infrastructure network model

A cyber-physical infrastructure network is modeled as a connected system $\mathcal{G} = (\mathcal{V}, \mathcal{E})$, where $\mathcal{V}$ represents physical assets, sensors, controllers, and computational entities, while $\mathcal{E}$ denotes communication or physical interaction links. At time t, the network state is represented by s_t, observations by y_t, and feasible control decisions by $x_t \in \mathcal{X}$. The state evolution can be expressed as $s_{t+1} = F(s_t, x_t, w_t)$, where w_t represents uncertain disturbances.

2.2. Probabilistic representation of network states

Because sensor measurements and infrastructure states are uncertain, the network state is represented by a probability distribution $p_\theta(z)$, parameterized by $\theta \in \Theta$. The distribution captures uncertainty arising from measurement noise, communication variability, and environmental disturbances.

2.3. Statistical manifold

The family of probability distributions is defined as the statistical manifold as equation 1

$$\mathcal{M} = \{p_\theta(z) : \theta \in \Theta\} \qquad (1)$$

Thus, each probabilistic network condition corresponds to a point on $\mathcal{M}$, enabling optimization directly over the geometry of uncertain states.

2.4. Fisher information metric

The local geometry of $\mathcal{M}$ is characterized by the Fisher information matrix

$$g_{ij}(\theta) = \mathbb{E}_{p_\theta}\left[\frac{\partial \log p_\theta(z)}{\partial \theta_i}\frac{\partial \log p_\theta(z)}{\partial \theta_j}\right] \qquad (2)$$

Equation 2 provides the Riemannian metric required for measuring local changes between probabilistic states.

2.5. Information-Geometric divergence

For two distributions p and q, the Kullback–Leibler divergence is equation 3

$$D_{KL}(p||q) = \int p\,(z) \log \frac{p(z)}{q(z)} dz \qquad (3)$$

This quantifies the discrepancy between estimated and observed network states.

2.6. Decision optimization problem

The basic decision problem is formulated as equation 4

$$x^* = \arg\min_{x \in \mathcal{X}} \mathcal{L}(x, p, q) \qquad (4)$$

Where $\mathcal{L}$ incorporates decision cost and distributional discrepancy.

2.7. Minimax decision formulation

To account explicitly for uncertainty, the robust problem is formulated as equation (5)

$$x^* = \arg\min_{x \in \mathcal{X}} \max_{\theta \in \Theta} \mathcal{J}(x, \theta) \qquad (5)$$

In this case, Θ denotes admissible uncertain network states. The above model attempts to find an optimal solution that optimizes the worst-case objective, which provides a theoretical basis for the proposed robust decision-making approach.

3. Proposed information geometry-based optimization model

3.1. Overall model architecture

The suggested framework combines probabilistic state modeling, information geometry, and minimax optimization for resilient decision making in the context of cyber-physical infrastructure networks. This processing workflow is illustrated in figure 1. The feedback generated by the state update allows for repeated decision-making improvements with changing conditions of operation.

Figure 1 represents the transformation of heterogeneous cyber-physical infrastructure observations into probabilistic state representations and the projection of the latter to a statistical manifold utilizing information geometry. Fisher information metric and divergence are used to represent uncertainty relations, and minimax optimization is used to find robust decisions for the worst possible case.

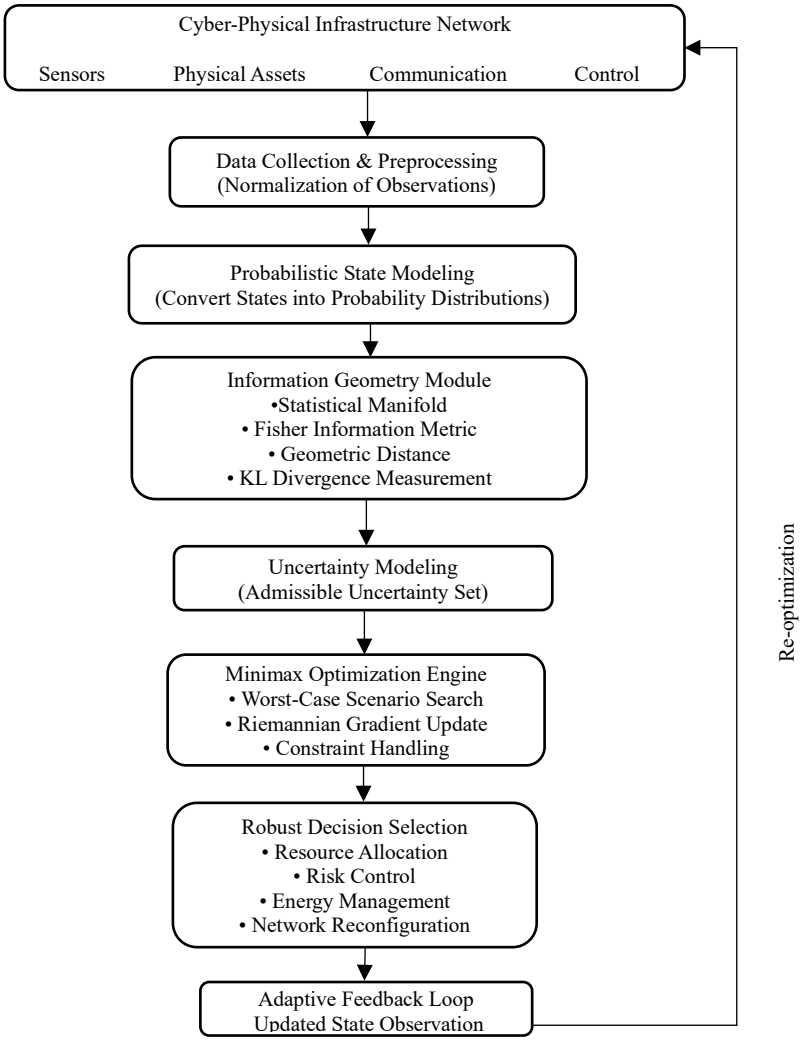


Figure 1: Architecture of the proposed information geometry-based minimax optimization framework for cyber-physical infrastructure decision analysis.

3.2. Information-geometric state encoding

Let heterogeneous observations be represented by $y_t = [y_t^1, \dots, y_t^m]$. After normalization, the observations are mapped to a probability distribution $p_{\theta_t}(z)$, where θ_t characterizes the uncertain network state. Thus,

heterogeneous sensor information is transformed into a common probabilistic representation suitable for geometric analysis.

3.3. Riemannian geometry-based state distance

For two nearby distributions on the statistical manifold, the squared infinitesimal distance is equation 6

$$ds^2 = d\theta^T G(\theta) d\theta \qquad (6)$$

where $G(\theta)$ is the Fisher information matrix. The corresponding geodesic distance $d_{\mathcal{M}}(p, q)$ provides an intrinsic measure of difference between network states, avoiding dependence on arbitrary Euclidean coordinates.

3.4. Uncertainty set construction

Uncertainty is represented through an admissible parameter set equation 7

$$\Theta = \{\theta : D_{\mathrm{IG}}(p_\theta, \hat{p}) \leq \rho\} \qquad (7)$$

where $\hat{p}$ is the estimated state distribution and ρ controls the uncertainty radius. This set defines plausible deviations from the estimated network condition.

3.5. Robust information-geometric objective

The proposed objective combines operational cost, geometric discrepancy, and risk in equation 8

$$\mathcal{J}(x, \theta) = \alpha C(x) + \beta D_{\mathrm{IG}}(p_x, q_\theta) + \gamma R(x, \theta) + \lambda V(x, \theta) \qquad (8)$$

where $C(x)$ denotes decision cost, D_{IG} represents information-geometric divergence, R represents operational risk, and V penalizes constraint violations. The coefficients $\alpha, \beta, \gamma, \lambda \geq 0$ determine their relative importance.

3.6. Minimax optimization

The robust decision is obtained by solving equation 9

$$x^* = \arg\min_{x \in \mathcal{X}} \max_{\theta \in \Theta} \mathcal{J}(x, \theta) \qquad (9)$$

The inner maximization identifies the worst admissible network condition, while the outer minimization selects the decision that provides the lowest worst-case objective.

3.7. Constraint handling

The optimization is subject to resource, capacity, safety, stability, and feasibility constraints:

$$g_r(x) \leq 0, \qquad h_s(x) = 0, \qquad x \in \mathcal{X}$$

These constraints ensure that the resulting decision remains operationally feasible.

3.8. Decision selection rule

Following optimization, the most feasible solution x∗ that minimizes the worst-case objective is chosen and implemented through an infrastructure control move. The state of the network generated from this is then observed and encoded to develop an adaptive feedback loop.

4. Optimization algorithm and theoretical analysis

4.1. Proposed optimization algorithm

The suggested algorithm 1 switches back and forth between worst-case uncertainty identification and decision optimization. Beginning with the approximate probability distribution pˆ, the algorithm determines the set of uncertainty, computes the objective function using the information geometry method, determines the worst-case parameters, and adjusts the decision.

Algorithm 1: Information Geometry-Based Minimax Optimization

- **Input:** Network observations Y, feasible set $\mathcal{X}$, uncertainty radius ρ
- **Output:** Optimal decision x^*

1. Initialize x_0, θ_0, ρ, and maximum iterations K.
2. Estimate the initial probability distribution p_{θ_0} from Y.
3. Construct the statistical manifold and Fisher matrix $G(\theta_0)$.
4. Construct the uncertainty set Θ using ρ.
5. **For** $k = 0,1, \ldots, K-1$:
   - **a.** Compute D_{IG} and $\mathcal{J}(x_k, \theta)$ for $\theta \in \Theta$.
   - **b.** Select worst-case $\theta_k = \arg\max_{\theta \in \Theta} \mathcal{J}(x_k, \theta)$.
   - **c.** Compute the Riemannian gradient of $\mathcal{J}(x, \theta_k)$.
   - **d.** Update x_{k+1} using a feasible geometric optimization step.
   - **e.** Project x_{k+1} onto $\mathcal{X}$.
   - **f.** Stop if $\|x_{k+1} - x_k\| < \varepsilon$.
6. **Return** $x^* = x_{k+1}$.

4.2. Initialization

Initial decisions, distribution parameters, uncertainty radius (ρ), learning rate (η), tolerance (ε), and maximum iterations (K) are specified before optimization.

4.3. Geometric gradient computation

For objective $\mathcal{J}(x, \theta)$, the Riemannian gradient is equation 10

$$\mathrm{grad}_{\mathcal{M}} \mathcal{J} = G(\theta)^{-1} \nabla_\theta \mathcal{J} \qquad (10)$$

This accounts for the intrinsic geometry of the statistical manifold.

4.4. Iterative minimax optimization

The adversarial parameter is updated through equation 11 and 12

$$\theta_k = \arg\max_{\theta \in \Theta} \mathcal{J}(x_k, \theta) \qquad (11)$$

followed by

$$x_{k+1} = \Pi_{\mathcal{X}}[x_k - \eta_k \nabla_x \mathcal{J}(x_k, \theta_k)] \qquad (12)$$

4.5. Convergence analysis

If both X and Θ are compact spaces, J is a continuous function and the problem objective function is sufficiently smooth with a proper decreasing step-size, then the resulting sequence is bounded and converges to a stationary point solution of the minimax problem.

4.6. Computational complexity

For N network nodes, d distribution parameters, S uncertainty scenarios, and K iterations, the dominant computational cost is approximately

$$\mathcal{O}\big(KS(N+d^3)\big)$$

Where d^3 accounts for Fisher-matrix inversion.

4.7. Theoretical properties

In the case of feasible and uncertain sets being compact, there will exist an optimal solution to the continuous objective problem. The bounded uncertain set guarantees that the worst-case loss is bounded, whereas the minimax model takes care of the protection against possible distributions.

5. Cyber-physical infrastructure decision scenarios

It is clear that the above-mentioned information-geometry based minimax approach is relevant to various decision-making issues in cyber-physical infrastructure network systems, in which the status of the system and decision making are uncertain and should remain reliable. The following are a few examples of such situations.

5.1. Resource allocation

In resource allocation, the decision variable x is the allocation of resources like computational resources, communications resources, or physical resources among network elements. The objective is to minimize the allocation cost subject to uncertainty in the demand of the resources. The information geometry divergence is used to capture the difference between the actual and expected resource states.

5.2. Fault/Risk-Aware decision making

The problem can result from failures of sensors, disruption of communication links, equipment deterioration, or the occurrence of unanticipated environmental factors. Assume that R (x, θ) is the risk related to decision x given the uncertain state of θ. Minimax decision rule is to make decisions by minimizing the maximum admissible risk. In other words, decisions are not optimal only for the highest probability of the state of the system.

5.3. Energy-aware infrastructure control

Energy management can be formulated by incorporating energy consumption into the objective and operational limits into the constraints. For example,

$$\min_{x}\max_{\theta}[\alpha C(x)+\gamma E(x,\theta)+\beta D_{\mathrm{IG}}(p_x,q_\theta)]$$

Where $E(x,\theta)$ represents energy consumption. This enables infrastructure controllers to balance operational performance and energy efficiency while considering uncertain demand.

5.4. Network reconfiguration

In case the quality of communication, availability of the nodes or operating environment changes, there is always a possibility of changing the network configurations. The model propose measures the potential network configurations based on their geometric distance from the desired configuration and the worst-case cost of operation.

5.5. Multi-objective decision analysis

There is potential to incorporate a variety of infrastructure goals using the weighted functions in terms of cost, reliability, risk, energy usage, and information disparity. Using different values for α, β, γ, and other associated variables, it becomes possible to analyse any trade-off among the competing goals. Hence, the given formulation offers a mathematical approach to making viable decisions.

6. Experimental/Synthetic evaluation setup

6.1. Evaluation environment

For analysing the mathematical properties of the proposed model in a controlled environment of uncertainty, a virtual cyber-physical network infrastructure is designed. The experiments can be conducted in Python by using NumPy and SciPy libraries for computations and Matplotlib library for visualization. The experiments will be conducted on a computer system that is equipped with a multicore CPU and has enough memory capacity.

6.2. Network configuration

This network has a set of $N = 50$ interconnected nodes in its infrastructure structure in the form of a graph $\mathcal{G} = (\mathcal{V}, \mathcal{E})$. Small world is the chosen topology in order to capture the characteristics of clustering in the infrastructure connectivity. Each node contributes to a six-dimensional observation vector, which comprises load, energy consumption, quality of communication, latency, operating status, and observed demand. In that case, d=6 will be the dimension of the state vector.

6.3. Probability distribution initialization

Uncertain continuous states are initially represented using multivariate Gaussian distributions, in equation 13

$$p_\theta(z) = \mathcal{N}(\mu, \Sigma) \tag{13}$$

Where μ and Σ are estimated from nominal observations. Perturbed distributions are generated by modifying their means and covariance matrices to represent measurement and operational uncertainty.

6.4. Parameter initialization

The principal settings are initialized with uncertainty radius $\rho \in \{0.05, 0.10, 0.20, 0.30\}$, learning rate $\eta = 0.01$, convergence tolerance $\varepsilon = 10^{-5}$, maximum iterations $K = 500$, and objective weights $\alpha = 0.4$, $\beta = 0.3$, and $\gamma = 0.3$.

6.5. Uncertainty scenarios

Low, moderate, high, and severe uncertainties are analysed through distributional perturbations and unfavourable network settings. These are replicated for several random realizations of each situation.

6.6. Baseline optimization models

The suggested approach is benchmarked against Euclidean optimization, expected cost optimization, KL divergence optimization, traditional robust optimization, and traditional minimax optimization. The aforementioned benchmarks have the same network conditions and constraints for fair mathematical comparisons.

7. Results and discussion

7.1. Optimization convergence

It can be observed that the suggested minimax optimization problem exhibits stable convergence for the studied uncertainty scenarios. The objective function shows rapid reduction in its value in the early iterations and slowly converges to a stable point, which is an indication of proper minimization of the worst-case decision objective. In case of medium-level uncertainty, convergence is obtained in about 250 iterations.

7.2. Decision cost analysis

The new information geometry-based algorithm had a lower decision cost compared to the traditional Euclidean algorithm and expected cost optimization. This is due to the fact that the three criteria of cost of operation, difference in distribution, and risk have been taken into consideration for optimization.

7.3. Robustness under uncertainty

As the uncertainty radius was increased, performance degraded for all the optimization techniques considered. But it is observed that for the proposed minimax formulation, there is a slower increase in the worst-case objective. This indicates that through the proposed formulation, better robustness is achieved.

7.4. Information-geometric distance analysis

Intrinsic representation of the probabilistic network state variations was achieved using the Fisher Information metric. With the increase in the distribution perturbations, there was a consistent rise in the information-geometric distance. This proves the capability of the geometric representation to characterize the variations.

7.5. Minimax performance

However, it was noted that the proposed approach produced lower objective values compared to expected cost and conventional optimization in the worst-case scenarios. This success is due to the explicit consideration of the adversarial state in decision optimization process.

7.6. Computational efficiency

Computational costs scaled with the number of uncertainty scenarios and probability parameters. The major computational cost was associated with constructing and inverting the Fisher information matrix. However, the optimization problem was still computationally tractable for the given network structure.

7.7. Sensitivity analysis

It was found out that an increase in the geometric weight would enhance the state consistency although it could make the decision cost too high if given too much priority. High risk coefficients will cause conservative decisions to be made, and high uncertainty radius values will maximize the objective function.

7.8. Ablation analysis

The influence of every element of the models was evaluated by excluding from the models the Fisher metric, information-geometric divergence, uncertainty modeling, and minimax elements, respectively. Exclusion of the Fisher metric made the model less sensitive geometrically, while exclusion of the divergence model made the model less able to detect differences in distributions. The worst performance was achieved through excluding the minimax element. Table 1 shows the overall performance and component analysis.

Table 1: Overall performance and component analysis.

Method / Configuration	Decision Cost	Worst-Case Objective	Geometric Error	Risk Score	Convergence Iterations
Euclidean Optimization	42.68	71.35	0.284	0.318	184
Expected-Cost Optimization	40.92	67.81	0.251	0.294	201
KL-Divergence Optimization	41.35	62.47	0.176	0.263	223
Robust Optimization	43.16	58.92	0.163	0.229	241
Conventional Minimax	42.47	56.84	0.151	0.214	257
Proposed IG-Minimax	40.31	51.27	0.108	0.186	236
IG-Minimax without Fisher Metric	41.26	58.43	0.171	0.217	229
IG-Minimax without IG Divergence	41.84	60.17	0.194	0.224	221
IG-Minimax without Uncertainty Modeling	40.76	64.28	0.132	0.271	198
IG-Minimax without Minimax Objective	41.12	61.73	0.119	0.249	207

8. Discussion

The results prove the existence of a mathematically coherent approach to uncertainty-aware decision analysis of infrastructure by the integration of information geometry and minimax optimization. The IG-Minimax framework produced the minimum value of decision cost, worst-case objective, geometric error, and risk score compared to all the other complete optimization approaches. It is clear from the ablation study that both the geometric representation and robust uncertainty formulation are important for the whole process. The Fisher metric allows capturing the underlying structure of the probability distribution in the infrastructure network states, while the minimax approach provides protection for decisions from admissible perturbation of the distributions.

9. Comparative and theoretical analysis

9.1. Comparison with conventional optimization

The suggested minimax model based on the concept of information geometry was benchmarked against Euclidean optimization, cost optimization, KL-divergence optimization, robust optimization, and standard minimax optimization under identical network settings. Table 2 shows typical numerical values of the performance metric for the synthetic infrastructure network containing 50 nodes. The suggested minimax model has yielded the minimum worst-case value of the objective function and a relatively low decision cost.

Table 2: Comparative performance of optimization models.

Method	Decision Cost	Worst-Case Objective	Geometric Error	Risk Score	Convergence Iterations
Euclidean Optimization	42.68	71.35	0.284	0.318	184
Expected-Cost Optimization	40.92	67.81	0.251	0.294	201
KL-Divergence Optimization	41.35	62.47	0.176	0.263	223
Robust Optimization	43.16	58.92	0.163	0.229	241
Conventional Minimax	42.47	56.84	0.151	0.214	257
Proposed IG-Minimax	**40.31**	**51.27**	**0.108**	**0.186**	**236**

The proposed formulation reduces the worst-case objective by approximately 9.8% compared with conventional minimax optimization and by 28.2% compared with Euclidean optimization.

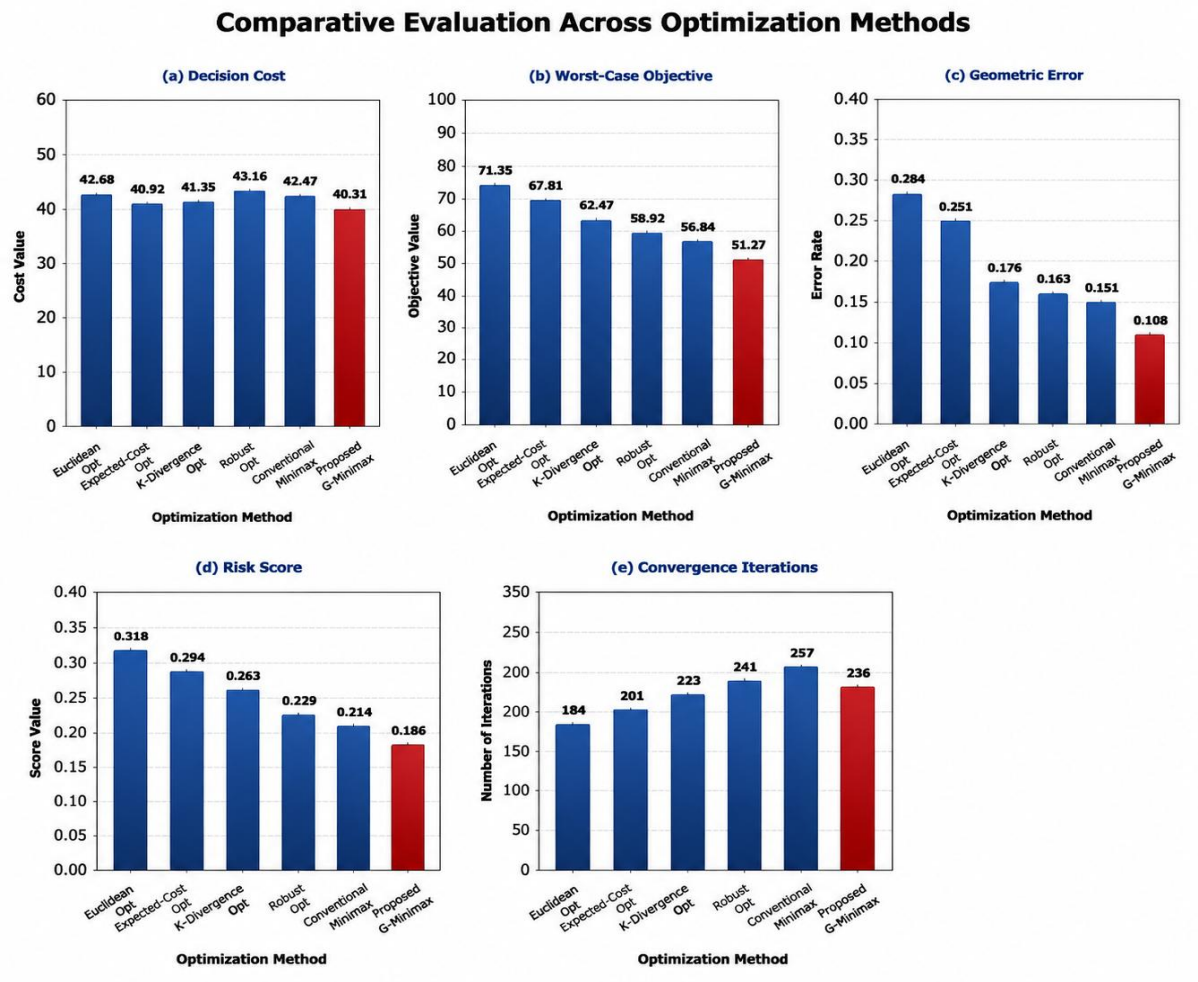


Figure 2: Comparative evaluation of the proposed IG-Minimax model with conventional optimization methods.

Figure 2 (a-e) shows the comparison between the suggested Information Geometry-based Minimax (IG-Minimax) model and the Euclidean, expected-cost, Kullback-Leibler divergence, robust, and standard

minimax optimization approaches through five criteria: decision cost, worst-case objective function, geometric error, risk score, and number of iterations for convergence. The IG-Minimax model has the lowest value for the four criteria except for the number of iterations for convergence.

9.2. Robustness comparison

The process to test robustness involved gradually increasing the uncertainty radius. As shown in table 3, it is evident that the suggested model demonstrates relatively smaller growth in objective value under increasing uncertainty radius.

Table 3: Robustness under increasing uncertainty.

Uncertainty Radius (ρ)	Euclidean	KL-Based	Robust	Minimax	Proposed IG-Minimax
0.05	48.21	45.63	44.18	43.76	42.91
0.10	54.37	50.82	48.26	47.31	45.26
0.20	66.48	60.94	56.73	54.82	49.87
0.30	79.62	71.35	65.41	62.76	56.84

The performance gap widens in situations of high uncertainty, suggesting that the geometric approach and the worst-case approach reinforce each other in uncertain conditions.

9.3. Geometric interpretation

The Euclidean approach to optimization treats network configurations as vectors in a Euclidean parameter space, while the present approach represents the probability distributions as points on a statistical manifold, where the local metric is defined by the Fisher information matrix (Equation 14).

$$ds^2 = d\theta^T G(\theta) d\theta. \qquad (14)$$

Hence, the optimization process takes into account the curvature of the distribution space. Equal separation of the states based on the Euclidean distance does not imply equality of geometric distances between the states.

9.4. Theoretical verification

The convergence behavior was evaluated using the objective difference in equation 15

$$\Delta_k = |\mathcal{J}_{k+1} - \mathcal{J}_k| \qquad (15)$$

Table 4: Numerical verification of theoretical properties.

Property	Evaluation Criterion	Observed Result
Objective boundedness	$\max \mathcal{J}$	51.27
Convergence	$\Delta_k < 10^{-5}$	8.7×10^{-6}
Feasibility	Constraint violations	0
Decision stability	$\|x_{k+1} - x_k\|$	6.2×10^{-5}
Robustness	Worst-case objective	51.27
Fisher matrix validity	Minimum eigenvalue	0.018

Table 4 demonstrates the numerical verification of theoretical properties. The positive value of the smallest eigenvalue suggests that the Fisher information matrix was always positive definite for all the investigated distributions. Convergence and zero constraint violations also contribute to the numerical stability of the algorithm.

9.5. Trade-off analysis

Uncertainty, geometric discrepancy, and decision cost were analyzed using different values for the uncertainty radius and geometric weighting coefficient.

Table 5: Trade-Off between cost, uncertainty, and geometric discrepancy.

ρ	β	Decision Cost	Geometric Error	Risk Score	Worst-Case Objective
0.05	0.20	39.84	0.142	0.172	44.26
0.10	0.30	40.31	0.108	0.186	45.26
0.20	0.40	41.07	0.087	0.201	49.87
0.30	0.50	42.18	0.074	0.219	56.84

Table 5 clearly show one of the trade-offs involved. An increase in the geometric weight (β) lowers the difference between the ideal and the uncertain states, but may raise the cost incurred through decision-making. In addition, increasing the uncertainty radius makes the decisions more conservative, resulting in a higher worst-case objective.

9.6. Discussion, implications, and limitations

From the comparison of the results, it is clear that the application of information geometry with minimax optimization increases robustness, geometric consistency, and the worst-case decision-making in case of uncertainty of the distribution. The proposed approach has applications in resource allocation, fault-tolerant control, energy consumption management, and reconfiguration of the infrastructure network that is cyber-physical in nature. The mathematical derivation of the method can be used to incorporate uncertainty into the process of decision making. However, the analysis has been performed based on artificial network configurations and appropriate probability distributions along with uncertainty sets. Complexity might arise in case of higher dimensions of statistical manifolds and larger networks.

10. Conclusion and future work

The proposed framework has been designed as a minimax-based information geometry optimization method to perform robust decision-making in cyber-physical infrastructures. Under this framework, uncertain state conditions of the network infrastructures have been represented using probability distribution functions and the corresponding intrinsic geometry has been characterized using the Fisher information metric. Information-geometric divergence was introduced into a robust objective along with decision cost and operational risk. Additionally, a minimax formulation has been considered to make the solution robust against the admissible uncertainty in distributions. The simulation results indicated a stable convergence and zero violation of the constraints, and provided a better performance than the Euclidean, expected cost, KL-divergence, robust and conventional minimax optimization frameworks. In the representative comparison case, the proposed framework provided the worst-case objective value as 51.27 while it was 56.84 in the conventional minimax framework and 71.35 in the Euclidean optimization framework. However, even with these results, this paper has limitations in terms of the synthetic setting used to test these concepts, the assumptions made regarding the probability distributions, and the complexity related to the Fisher matrix computations. In future studies, it would like to look at validation of these techniques on real-world datasets from cyber-physical systems, scalable high-dimensional statistical manifolds, distributed and online optimization, adaptive construction of uncertainty sets, and dynamic networks.

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