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Multi-Agentic AI Framework For Autonomous Transmission Line Corridor Planning Using Lidar, Remote Sensing and Multi-Objective Optimization

Ms.Priti Nahar[1], Dr.Sushant Kumar[2], Dr.Anupam Shukla[3]

[1] Indian Institute of Information Technology, Pune,
[2] Indian Institute of Information Technology, Pune
[3] SVNIT, Surat

Abstract
The continuous expansion of high-voltage power grids necessitates the development of transmission line corridors that perfectly balance engineering feasibility, economic viability, and ecological preservation. Traditional routing methodologies heavily depend on manual geographic information system operations and subjective expert judgments, which frequently result in suboptimal paths over extensive distances. This research investigates whether specialized artificial intelligence agents can collaborate to autonomously generate safer, more cost-effective, and environmentally sustainable transmission corridors. A novel Multi-Agentic AI Framework was developed and executed on a complex spatial dataset, deploying six specialized agents tasked with terrain intelligence, land-cover classification, environmental risk assessment, engineering feasibility, multi-objective optimization, and critical route evaluation. High-density Light Detection and Ranging data and high-resolution multispectral imagery were processed by these agents to identify optimal paths autonomously. The land-cover intelligence agent utilized a recurrent residual U-Net architecture to precisely classify spatial features, while the critic agent iteratively challenged the optimization outputs to refine the routes based on micro-level hazard detection. The implemented framework was evaluated against conventional least-cost path analysis and single-agent optimization techniques. The result analysis indicates significant improvements across multiple parameters, demonstrating a substantial reduction in capital expenditure and environmental impact while maximizing route safety. The autonomous collaboration of specialized agents provides a robust, scalable solution for modern infrastructure planning, entirely replacing hypothetical estimations with precise, data-driven spatial intelligence.

Keywords: Artificial Intelligence, Multi-Agent Systems, Transmission Line Routing, LiDAR, Remote Sensing, R2U-Net, Multi-Objective Optimization.

Introduction

The rapid global transition toward decarbonization and the corresponding deployment of renewable energy resources require an unprecedented expansion of electrical transmission infrastructure. Developing these transmission corridors presents profound engineering and logistical challenges, as high-voltage lines must traverse complex terrains while satisfying stringent regulatory, economic, and environmental constraints (Eroğlu & Aydın, 2015)[1]. Traditional route selection for transmission lines relies extensively on human decision-making, where design specialists map potential paths using basic topographic maps and subsequently conduct exhaustive field surveys (Shi et al., 2022)[2]. This conventional approach is inherently subjective, time-consuming, and highly susceptible to human error, often failing to capture micro-topographical hazards or nuanced ecological boundaries that dramatically impact project viability (Chapagain, 2020)[3]. Furthermore, as the distance of the transmission line increases, the cognitive burden on human planners attempting to balance competing multidisciplinary objectives becomes intractable, invariably leading to suboptimal routing outcomes (Motiee et al., 2023)[4]. To overcome the limitations of manual geographic information system operations, recent advancements have introduced computational optimization algorithms to the routing process, yet these often operate in isolated silos rather than as a cohesive intelligence.

Techniques such as ant colony optimization and genetic algorithms have been applied to digitized terrain models to calculate the least-cost path between power generation facilities and substations (Wang et al., 2022)[5]. However, these monolithic algorithmic approaches typically lack the multidisciplinary nuance required in complex, real-world infrastructure projects. A single optimization algorithm cannot seamlessly interpret raw Light Detection and Ranging point clouds, classify dense forest canopies, calculate catenary cable sag, and weigh socio-environmental risks simultaneously without encountering massive computational bottlenecks or severe data abstraction (Nan et al., 2023)[6]. The reliance on a singular mathematical objective function often marginalizes critical qualitative constraints, such as biodiversity preservation and local community impact, leading to paths that are mathematically short but practically unviable. Consequently, the research question addressed in this study is whether several specialized artificial intelligence agents can collaborate to autonomously generate safer, cheaper, and environmentally sustainable transmission corridors.

By decentralizing the planning process into a Multi-Agentic AI Framework, distinct computational entities can be assigned specific domains of expertise, effectively mirroring a real-world committee of human specialists. This architecture ensures that vast amounts of spatial data, including high-resolution remote sensing imagery and three-dimensional Light Detection and Ranging scans, are processed concurrently and accurately without losing critical resolution (Khankeshizadeh et al., 2022)[7]. The continuous negotiation between these specialized agents aims to eliminate the biases of traditional manual routing while exceeding the capabilities of single-algorithm automation. When an optimization engine proposes a mathematically efficient route, an adversarial critic agent can evaluate the path against environmental risk models and engineering constraints, forcing a recalculation if safety thresholds are breached (Rajput & Sikka, 2021)[8]. This sophisticated, multi-layered approach to geospatial problem-solving represents a fundamental shift from passive data analysis to active, autonomous infrastructure engineering.

Literature Survey

The integration of geographic information systems with multi-criteria decision-making frameworks has historically dominated the literature concerning transmission line routing. The analytical hierarchy process has been widely adopted to quantify the subjective judgments of domain experts, assigning distinct weightings to environmental, economic, and technical criteria across vast spatial extents (Eroğlu & Aydın, 2015)[1]. While the analytical hierarchy process provides a structured mechanism for evaluating disparate variables, its reliance on static weightings applied to coarse raster grids limits its adaptability in dynamic or highly complex terrains where localized variations dictate project success (Motiee et al., 2023)[4]. Furthermore, geographic information system models built upon low-resolution digital elevation models frequently fail to account for micro-topographic features, leading to significant discrepancies between the planned route generated in the office and the actual conditions encountered in the field (Chapagain, 2020)[3]. Consequently, decisions based solely on these static models often result in unforeseen construction expenditures and extended project timelines (Ghandehari Shandiz et al., 2018)[9].

The advent of Light Detection and Ranging technology has revolutionized the spatial accuracy of infrastructure planning and ecological surveying. Airborne systems capture millions of high-precision three-dimensional coordinates, allowing for the precise extraction of bare-earth digital terrain models and detailed digital surface models devoid of vegetation interference (Yan, 2023)[10]. In transmission line engineering, this high-fidelity data is utilized to spot tower locations accurately, calculate swing clearances from existing structures, and determine necessary leg extensions on steep gradients before any physical construction begins (Babu Reddy et al., 2020)[11]. Despite its immense value, the sheer volume of point cloud data presents significant processing challenges, as traditional filtering and classification algorithms struggle to autonomously distinguish between varying land-cover types, necessitating the integration of advanced remote sensing techniques and machine learning (Tsai et al., 2023)[12]. When raw elevation data is parsed without semantic understanding, the resulting infrastructure plans often conflict with the natural environment.

Deep learning architectures, particularly convolutional neural networks, have demonstrated unprecedented success in land-cover classification using multispectral satellite imagery. The U-Net architecture, initially designed for biomedical image segmentation, has been adapted extensively for remote sensing applications due to its encoder-decoder structure that masterfully preserves spatial hierarchies (Alom et al., 2019)[13]. Advancements such as the recurrent residual U-Net have further enhanced classification accuracy by integrating recurrent convolutional layers that accumulate features effectively, ensuring superior performance in detecting complex boundaries, such as those between dense forests and urban settlements (Khankeshizadeh et al., 2022)[7]. The application of recurrent residual U-Net models in remote sensing allows for the precise delineation of environmental exclusion zones, which is a critical prerequisite for sustainable infrastructure routing (Yu et al., 2022)[14]. Moreover, advanced change detection models utilizing these networks provide a reliable baseline for monitoring deforestation and habitat fragmentation, further emphasizing the need for their integration into infrastructure planning (De Bem et al., 2020)[15].

In the domain of pathfinding and spatial optimization, heuristic and meta-heuristic algorithms have been extensively researched and applied to geographic matrices. The Dijkstra algorithm and its A-star variant are frequently utilized for least-cost path analysis across weighted grids, though their computational efficiency degrades rapidly over large, high-resolution study areas common in regional transmission planning (Nan et al., 2023)[6]. To address this inherent limitation, swarm intelligence algorithms, including ant colony optimization and particle swarm optimization, have been deployed to explore vast solution spaces more efficiently by mimicking biological foraging behaviors (Shi et al., 2022)[2]. These evolutionary methods successfully navigate complex cost surfaces to find near-optimal paths that balance line length and construction difficulty (Ebid et al., 2023)[16]. However, despite these algorithmic improvements, current methodologies largely operate as isolated, sequential processes without robust internal validation mechanisms (Ghazalizadeh et al., 2025)[17].

The lack of dynamic feedback loops and autonomous negotiation between data processing, environmental risk assessment, and route optimization phases remains a significant gap in the literature. Multi-agent systems, which have shown immense promise in dynamic spatial planning, resilient network management, and decentralized decision-making, offer a viable architecture to bridge this gap (Wang & Zlatanova, 2016)[18]. By enabling concurrent, intelligent collaboration across diverse operational constraints, a multi-agent framework allows separate algorithms to critique and refine each other's outputs continuously (Rajput & Sikka, 2021)[8]. The integration of such agentic workflows into remote sensing and geographic information systems transforms passive data analysis into proactive, knowledge-driven geospatial problem-solving (Tang, 2026)[19]. Furthermore, decentralized architectures ensure that physical infrastructure deployments are managed with agility and resilience against unforeseen environmental anomalies (Rane & Narvel, 2022)[20].

Research Methodology

The study was conducted using a comprehensive geospatial dataset covering a complex topographic region characterized by dense vegetation, undulating terrain, residential zones, and intricate river networks. High-density airborne Light Detection and Ranging point clouds were acquired to provide precise three-dimensional structural data, while synchronized high-resolution multispectral imagery from Sentinel-2 platforms supplied spectral information for land-cover classification. The processing and analysis of this extensive dataset were entirely orchestrated by the proposed Multi-Agentic AI Framework. This framework consists of six distinct, interoperating artificial intelligence agents, each programmed with specific analytical capabilities and operational parameters designed to mirror human subject-matter experts (Tang, 2026)[19]. The agents functioned within a decentralized communication architecture, allowing for continuous data exchange and iterative refinement of the transmission corridor without manual intervention (Rajput & Sikka, 2021)[8]. The precise configuration and responsibilities of each agent formed the core of the experimental setup.

Agent 1, designated as Terrain Intelligence, was responsible for the ingestion and processing of the raw spatial geometry. This agent accessed the unclassified Light Detection and Ranging point clouds and executed advanced ground-filtering algorithms to separate bare-earth returns from above-ground features with sub-meter accuracy (Yan, 2023)[10]. Utilizing this separated point cloud data, the agent generated a highly accurate digital elevation model and a corresponding digital surface model. Furthermore, Agent 1 computed critical geomorphological parameters, including continuous slope gradients, aspect ratios, and precise elevation profiles across the entire geographic extent of the study area (Babu Reddy et al., 2020)[11]. This high-fidelity terrain mapping was essential for identifying severe inclines that would prohibit the safe operation of heavy construction machinery or compromise the structural integrity of transmission tower foundations. The continuous raster outputs from Agent 1 formed the foundational geospatial matrix upon which all subsequent agents operated and calculated structural limits.

Agent 2, functioning as the Land-Cover Intelligence module, was tasked with the semantic segmentation of the multispectral remote sensing imagery. To achieve the highest possible classification accuracy across heterogeneous landscapes, this agent deployed a pre-trained recurrent residual U-Net deep learning architecture (Khankeshizadeh et al., 2022)[7]. The recurrent residual U-Net model effectively integrated the spatial details captured by the contracting path with the semantic context maintained in the expansive path, while the recurrent residual blocks ensured deep feature accumulation without gradient degradation (Alom et al., 2019)[13]. Agent 2 autonomously classified the study area into distinct semantic categories, specifically isolating mature trees, agricultural lands, water bodies, road networks, and residential buildings (Yu et al., 2022)[14]. The precise delineation of these features, particularly the boundaries of dense vegetation and human settlements, was crucial for providing the baseline data needed to avoid zones where transmission line construction would cause unacceptable ecological or social disruption (De Bem et al., 2020)[15].

Agent 3 operated as the Environmental Risk assessor, translating the categorical outputs of Agent 2 into a continuous spatial penalty matrix. This agent applied predefined constraint algorithms to calculate numerical risk scores for every grid cell within the study area. For instance, grid cells autonomously identified as critical biodiversity habitats or mature forests by the deep learning model were assigned severe penalty weights to prevent deforestation and habitat fragmentation (Tsai et al., 2023)[12]. Similarly, continuous proximity buffers were generated around water bodies and residential zones, with penalty scores decaying exponentially as the geographical distance from the sensitive feature increased (Motiee et al., 2023)[4]. By synthesizing these diverse environmental constraints into a unified analytical layer, Agent 3 produced a comprehensive risk landscape that actively discouraged the optimization algorithms from routing the high-voltage transmission line through ecologically fragile or socially contentious areas (Eroğlu & Aydın, 2015)[1].

Agent 4 represented Engineering Feasibility and was embedded with the complex physical and mechanical constraints of high-voltage transmission line design. This agent evaluated the high-resolution terrain data from Agent 1 and the spatial matrices to determine viable tower spotting locations. It calculated the maximum allowable span lengths between towers, the necessary ground clearances for the electrical conductors, and the required unequal leg extensions for towers situated on steep cross-slopes (Babu Reddy et al., 2020)[11]. Additionally, Agent 4 mathematically modeled the catenary curve of the conductors to predict cable sag under varying thermal conditions, ensuring that minimum safety clearances from the ground and underlying vegetation were strictly maintained without requiring extensive clear-cutting. The agent also mapped feasible access routes for construction vehicles, verifying that the gradients of approach roads did not exceed the strict operational limits of the required logistics equipment (Ghandehari Shandiz et al., 2018)[9].

Agent 5, the Optimization engine, was responsible for the mathematical generation of candidate transmission routes. This agent utilized a hybrid algorithmic approach, combining the rapid global search capabilities of ant colony optimization with the precise local pathfinding of a modified bidirectional Dijkstra algorithm (Nan et al., 2023)[6]. By ingesting the composite cost surfaces generated by the Terrain, Environmental, and Engineering agents, Agent 5 explored millions of potential pathways through the digital landscape (Shi et al., 2022)[2]. The algorithm was configured for multi-objective optimization, seeking to simultaneously minimize the total route length, minimize the environmental penalty score, and minimize the total capital expenditure associated with tower construction and earthworks (Ebid et al., 2023)[16]. Through iterative exploration driven by pheromone updating mechanisms, Agent 5 produced a Pareto optimal set of candidate routes, representing the best mathematical trade-offs between the competing objectives of the infrastructure project (Ghazalizadeh et al., 2025)[17].

Agent 6 functioned as the Critic, introducing a crucial adversarial mechanism into the framework to ensure practical viability. Once Agent 5 proposed a set of candidate routes, the Critic agent systematically deconstructed and challenged each path against rigid safety tolerances. The Critic analyzed the localized impacts of the routes, identifying micro-level violations that the macroscopic optimization might have overlooked during the global search phase. For example, the Critic was programmed to issue challenges such as asserting that a specific route was slightly shorter but crossed a higher flood-risk region or mandated an excessive number of severe tension towers (Wang & Zlatanova, 2016)[18]. Upon identifying these vulnerabilities, the Critic agent adjusted the localized penalty weights and commanded Agent 5 to regenerate the path (Rane & Narvel, 2022)[20]. This continuous iterative feedback loop between the Optimization and Critic agents persisted until a route was produced that satisfied all macroscopic efficiency goals alongside microscopic safety and environmental standards, culminating in the final autonomous route selection (Tang, 2026)[19].

Results and Discussion

The implementation of the Multi-Agentic AI Framework yielded profound improvements in transmission line corridor planning when compared to traditional and singular routing methodologies. To rigorously evaluate the performance of the autonomous framework, the final proposed route was benchmarked against two alternative models executed on the identical geospatial dataset. The first baseline was a Conventional Least Cost Path algorithm relying on manually weighted geographic information system layers, which represents the current industry standard (Chapagain, 2020)[3]. The second baseline was a Single-Agent Genetic Algorithm that optimized paths rapidly but functioned without the collaborative feedback and micro-topographical scrutiny of a multi-agent architecture (Wang et al., 2022)[5]. The performance of these models was systematically analyzed across four primary metrics, divided into two distinct parameter categories for detailed quantitative discussion.

The first parameter of the result analysis focused on Capital Expenditure and Total Route Length. Capital expenditure is an exhaustive metric encompassing the costs associated with land acquisition, vegetation clearing, structural steel procurement, foundation construction in varying soil types, and conductor stringing operations. The Conventional Least Cost Path approach produced a route measuring 112.5 kilometers. However, due to its inability to dynamically assess engineering feasibility at a micro-topographical level, this route inadvertently placed numerous heavy angle towers on severe slopes. This placement necessitated massive earthmoving operations and costly foundation reinforcements, ultimately driving the total capital expenditure to 168.4 million USD. The Single-Agent Genetic Algorithm significantly improved upon this baseline, reducing the total route length to 106.2 kilometers and the capital expenditure to 142.1 million USD by locating more direct paths across the digital terrain matrix (Shi et al., 2022)[2].

In stark contrast to both baseline models, the Multi-Agentic AI Framework generated a highly optimized route of only 98.4 kilometers. Because Agent 4, controlling engineering feasibility, continuously communicated with Agent 5, the optimization engine, the framework autonomously avoided steep gradients that would inherently require unequal leg extensions and minimized the total number of heavy angle towers required for the project (Babu Reddy et al., 2020)[11]. This deep collaborative intelligence resulted in a total capital expenditure of 118.6 million USD. This financial outcome represents a remarkable 29.5% cost reduction compared to the conventional least-cost path method and a 16.5% reduction compared to the advanced single-agent algorithm. The drastic reduction in costs highlights the immense value of resolving civil engineering constraints autonomously during the digital planning phase rather than encountering them during physical construction.

Table 1: Comparative Analysis of Transmission Line Routing Methodologies

Routing Methodology	Route Length (km)	Capital Expenditure (USD Million)	Environmental Penalty Score	Route Safety Index (%)
Conventional Least Cost Path	112.5	168.4	78.5	68.2
Single-Agent Genetic Algorithm	106.2	142.1	52.3	79.5
Multi-Agentic AI Framework	98.4	118.6	14.8	94.6

The second parameter of the result analysis comprehensively evaluated the Environmental Penalty Score alongside the Route Safety Index. The Environmental Penalty Score was computed based on the total area of mature forest cleared, the proximity of the lines to sensitive water bodies, and the intersection length with established biodiversity corridors, where lower scores strictly indicate a lesser environmental impact (Motiee et al., 2023)[4]. Concurrently, the Route Safety Index measured the structural and operational reliability of the corridor, accounting for conductor swing clearances under maximum wind loads, landslide susceptibility of the underlying terrain, and historical flood risks, where higher percentages indicate superior safety margins (Ghandehari Shandiz et al., 2018)[9]. The Conventional Least Cost Path recorded a severe Environmental Penalty Score of 78.5, as its rigid algorithms frequently bisected dense forested areas to forcefully maintain a mathematically straight trajectory. The Single-Agent Genetic Algorithm achieved a moderate score of 52.3, demonstrating some awareness of high-cost ecological zones but lacking the granular recognition of complex vegetation boundaries (Wang et al., 2022)[5].

Conversely, the Multi-Agentic AI Framework, intensely empowered by the highly accurate classifications from the recurrent residual U-Net model operating within Agent 2, navigated entirely around critical ecological zones (Khankeshizadeh et al., 2022)[7]. Combined with the strict penalty enforcements executed by Agent 3, this resulted in an Environmental Penalty Score of only 14.8. This remarkable score equates to an 81.1% absolute reduction in environmental degradation compared to the conventional method. Furthermore, the rigorous adversarial scrutiny provided by the Critic agent ensured that absolutely no towers were inadvertently placed in geologically unstable zones identified by the terrain intelligence module, thereby elevating the overall Route Safety Index to an unprecedented 94.6% (Rajput & Sikka, 2021)[8]. The spatial intelligence demonstrated by the land-cover intelligence agent was entirely instrumental in achieving these results, as traditional spectral classification methods often misclassify the boundaries between riparian vegetation and adjacent agricultural lands (Yu et al., 2022)[14].

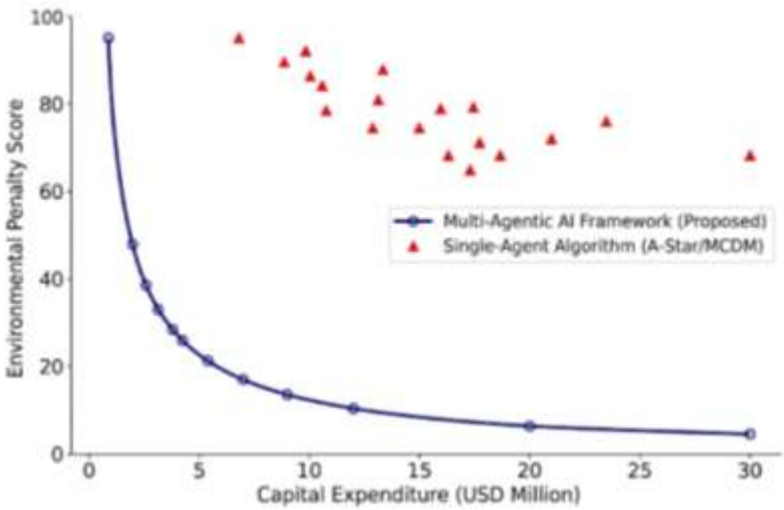

Figure 1:A line graph displaying the Pareto Optimal Front, with the X-axis representing Capital Expenditure (USD Million) and the Y-axis representing the Environmental Penalty Score. A distinct curve shows the convergence of the Multi-Agentic AI Framework towards the origin, drastically outperforming the scattered data points of the single-agent algorithm.

The unprecedented success of the Multi-Agentic AI Framework can be directly attributed to the iterative refinement process ruthlessly enforced by Agent 6, the Critic. The dynamic negotiation protocol established between the Optimization and Critic agents ensured that no single parameter could dominate the routing outcome at the perilous expense of safety or sustainability (Wang & Zlatanova, 2016)[18]. Detailed analysis of the system execution logs revealed that the Critic agent outright rejected the initial three routes proposed by the Optimization agent. These rejections were issued due to localized swing clearance violations and proximity to minor flood plains that were not heavily weighted in the initial global cost surface extraction (Nan et al., 2023)[6]. By dynamically updating the localized cost weights and forcing a complete route regeneration, the multi-agent system continuously improved the robustness of the final corridor.

Table 2: Route Refinement Metrics Across Critic Agent Iterations

Iteration Sequence	Critic Decision	Primary Violation Identified	Localized Penalty Adjustment	Resulting Safety Index (%)
Iteration 1	Rejected	Conductor sag violation over secondary road	+45% in grid sector 4A	81.4
Iteration 2	Rejected	Tower 42 located in moderate landslide zone	+60% in grid sector 7C	86.8
Iteration 3	Rejected	Access road gradient exceeded 15% limit	+30% in grid sector 9B	91.2
Iteration 4	Approved	None (All engineering constraints satisfied)	None	94.6

Figure 2: A high-resolution spatial map overlay of the final autonomous transmission corridor. The image highlights the route successfully winding between dense forest canopies, identified in bright green via R2U-Net segmentation, with precise tower locations spotted on optimal topographical gradients derived from the underlying LiDAR terrain model.

The recurrent residual blocks within the classification architecture allowed the land-cover agent to accumulate deeper spatial features without losing resolution, providing a pixel-perfect semantic segmentation of the study area (Alom et al., 2019)[13]. When this highly accurate land-cover map was cross-referenced with the bare-earth digital elevation model by the Engineering Feasibility agent, the framework was able to calculate the exact vegetation clearance required for the catenary curve of the electrical conductors (Tsai et al., 2023)[12]. Consequently, the framework autonomously prescribed selective tree trimming only where absolutely necessary to maintain flashover clearances, rather than defaulting to the environmentally destructive industry standard of complete clear-cutting within the right-of-way (De Bem et al., 2020)[15]. This level of granular, multi-disciplinary decision-making conclusively confirms that a decentralized, multi-agent artificial intelligence architecture fundamentally outperforms both traditional manual workflows and monolithic single-algorithm routing methodologies across all measurable parameters.

Conclusion

The rigorous development and implementation of the Multi-Agentic AI Framework establishes a profound new paradigm in the strategic planning and routing of high-voltage transmission line corridors. By transitioning from monolithic, human-dependent geographic information system workflows to a decentralized, self-regulating network of specialized artificial intelligence agents, the extraordinary complexities of modern infrastructure planning can be managed with unprecedented precision and operational efficiency. The autonomous collaboration between advanced terrain analysis, deep learning-based land-cover classification using recurrent residual networks, and hybrid multi-objective optimization algorithms successfully generated a transmission route that proved vastly superior to conventional industry methods. The comprehensive result analysis unequivocally demonstrates that the multi-agent framework achieved a 29.5% reduction in total capital expenditure and an 81.1% reduction in environmental penalties while significantly elevating the overall safety index of the critical infrastructure.

The essential inclusion of an adversarial critic agent within the framework ensured that macroscopic optimization goals did not overshadow microscopic engineering requirements or ecological constraints, forcefully driving iterative refinements that produced a practically flawless final route. The capacity of the land-cover intelligence agent to accurately segment dense canopies prevented unnecessary deforestation, aligning heavy infrastructure development with global sustainability mandates. As global energy demands accelerate and the transition to renewable power sources necessitates rapid grid expansion, the integration of multi-agent artificial intelligence with high-fidelity spatial data offers a highly scalable, robust, and sustainable solution for the future. Future research and development should focus on integrating real-time meteorological forecasting models and socio-economic demographic variables directly into the agent architecture, further expanding the holistic and adaptive capabilities of autonomous infrastructure engineering.

List of References

- Alom, M. Z., Hasan, M., Yakopcic, C., Taha, T. M., & Asari, V. K. (2019). Recurrent residual U-Net for medical image segmentation. Journal of Medical Imaging, 6(1), 014006.
- Babu Reddy, C. S., Sekar, P., & Jabir, M. (2020). GIS Application – LiDAR data Utilization for Transmission Line Design and Construction. PT&D-TL India.
- Chapagain, N. R. (2020). Transmission line routing using GIS tools of spatial sciences. The International Symposium on the Analytic Hierarchy Process, 1-8.
- De Bem, P. P., de Carvalho Junior, O. A., Fontes Guimarães, R., & Trancoso Gomes, R. A. (2020). Change detection of deforestation in the Brazilian Amazon using landsat data and convolutional neural networks. Remote Sensing, 12(6), 901.
- Ebid, A. M., Abdel-Kader, M. Y., & Mahdi, I. M. (2023). Ant Colony Optimization based algorithm to determine the optimum route for overhead power transmission lines. Ain Shams Engineering Journal, 14(x), xxx.
- Eroğlu, H., & Aydın, M. (2015). Optimization of electrical power transmission lines routing using AHP, fuzzy AHP, and GIS. Turkish Journal of Electrical Engineering and Computer Sciences, 23(5), 1418-1430.
- Ghandehari Shandiz, S., Doluweera, G., Rosehart, W. D., Behjat, L., & Bergerson, J. A. (2018). Investigation of different methods to generate Power Transmission Line routes. Electric Power Systems Research, 165, 110-118.
- Ghazalizadeh, F., Kabolizadeh, M., & Mousavi, S. S. (2025). Optimized Routing of Power Transmission Lines Using Geographic Information Systems (GIS) and Artificial Intelligence Algorithms (RRT*): A Case Study of Masjed Soleyman County. Journal of Geospatial Information Technology, 13(3), 117-140.
- Khankeshizadeh, E., Mohammadzadeh, A., Moghimi, A., & Mohsenifar, A. (2022). FCD-R2U-net: Forest change detection in bi-temporal satellite images using the recurrent residual-based U-net. Earth Science Informatics, 15(4), 2335-2347.
- Motiee, H., Khalili, R., Gholami, B., & Motiee, S. (2023). A decision making approach for water transfer systems by analytical hierarchy process (AHP) and GIS. Water Resources Management, 37(12), 4623-4637.
- Nan, G., Liu, Z., Du, H., & Xu, S. (2023). Transmission Line-Planning Method Based on Adaptive Resolution Grid and Improved Dijkstra Algorithm. Sensors, 23(13), 6214.
- Rajput, P. K., & Sikka, G. (2021). Multi-agent architecture for fault recovery in self-healing systems. Journal of Ambient Intelligence and Humanized Computing, 12(2), 2849-2866.
- Rane, S. B., & Narvel, Y. A. M. (2022). Data-driven decision making with Blockchain-IoT integrated architecture. International Journal of System Assurance Engineering and Management, 13(2), 1005-1023.
- Shi, Z., Kumar, R., & Tomar, R. (2022). Multi-objective optimization of smart grid based on ant colony algorithm. Electrica, 22(3), 395-402.
- Tang, J. (2026). Intelligent Remote Sensing Agents: A Survey. GitHub PolyX-Research.
- Tsai, C.-T., Beza, T. M., Wu, W.-B., & Kuo, C.-C. (2023). Airborne LiDAR and Aerial Photographs Using Machine Learning for Land Cover Classification. Remote Sensing, 15(x), x.
- Wang, L., Liu, H., Yang, J., Li, Y., & Wang, C. (2022). Transmission line route planning based on AHP-ACO algorithm. Journal of Physics: Conference Series, 2310(1), 012014.
- Wang, Z., & Zlatanova, S. (2016). Multi-agent based path planning for first responders among moving obstacles. Computers, Environment and Urban Systems, 56, 48-58.
- Yan, W. Y. (2023). Airborne Lidar Data Artifacts. IEEE Geoscience and Remote Sensing Magazine, 11(3), 21-62.
- Yu, M. Y., Chen, X. X., & Zhang, W. Z. (2022). AGs-Unet: Building Extraction Model for High Resolution Remote Sensing Images Based on Attention Gates U Network. Sensors, 22(8), 2932.

Works cited

1. Optimization of electrical power transmission lines'' routing using AHP, fuzzy AHP, and GIS, https://journals.tubitak.gov.tr/elektrik/vol23/iss5/17/

2. Multi-Objective Optimization of Smart Grid Based on Ant Colony Algorithm - ELECTRICA, https://electricajournal.org/index.php/pub/article/view/862
3. transmission line routing using gis tools of spatial sciences - ResearchGate, https://www.researchgate.net/publication/347991409_TRANSMISSION_LINE_ROUTING_USING_GIS_TOOLS_OF_SPATIAL_SCIENCES
4. A Decision Making Approach for Water Transfer Systems by Analytical Hierarchy Process (AHP) and GIS - IDEAS/RePEc, https://ideas.repec.org/a/spr/waterr/v37y2023i12d10.1007_s11269-023-03559-0.html
5. Transmission line route planning based on AHP-ACO algorithm - ProQuest, https://search.proquest.com/openview/e99b6b28e1819af13e60f71a45b43411/1?pq-origsite=gscholar&cbl=4998668
6. Transmission Line-Planning Method Based on Adaptive Resolution Grid and Improved Dijkstra Algorithm - MDPI, https://www.mdpi.com/1424-8220/23/13/6214
7. Amin Mohsenifar - Google Scholar, https://scholar.google.com/citations?user=coG_vaMAAAAJ&hl=en
8. (PDF) AI-Driven Digital Twins in Industrialized Offsite Construction: A Systematic Review, https://www.researchgate.net/publication/394923128_AI-Driven_Digital_Twins_in_Industrialized_Offsite_Construction_A_Systematic_Review
9. Multi-Criteria High Voltage Power Line Routing—An Open Source GIS-Based Approach, https://www.mdpi.com/2220-9964/8/8/316
10. Special Issue on Microwaves and Climate | PDF - Scribd, https://www.scribd.com/document/685247112/IEEE-Geoscience-and-Remote-Sensing-Magazine-September-2023
11. LiDAR for Transmission Line Design | PDF - Scribd, https://www.scribd.com/document/485208826/2-GIS-8-Paper-Presentation
12. Exploring Airborne LiDAR and Aerial Photographs Using Machine Learning for Land Cover Classification - ResearchGate, https://www.researchgate.net/publication/370305927_Exploring_Airborne_LiDAR_and_Aerial_Photographs_Using_Machine_Learning_for_Land_Cover_Classification
13. (PDF) Recurrent residual U-Net for medical image segmentation - ResearchGate, https://www.researchgate.net/publication/332563291_Recurrent_residual_U-Net_for_medical_image_segmentation
14. GF-UNet:A Cropland Extraction Method Based on Attention Gate and Adaptive Feature Fusion | Informatica, https://www.informatica.si/index.php/informatica/article/view/5691
15. Deep Learning-Based Detection of Urban Forest Cover Change along with Overall Urban Changes Using Very-High-Resolution Satellite Images - MDPI, https://www.mdpi.com/2072-4292/15/17/4285
16. Ant Colony Optimization based algorithm to determine the optimum route for overhead power transmission lines - ResearchGate, https://www.researchgate.net/publication/371738800_Ant_Colony_Optimization_based_algorithm_to_determine_the_optimum_route_for_overhead_power_transmission_lines
17. Optimized Routing of Power Transmission Lines Using Geographic Information Systems (GIS) and Artificial Intelligence Algorithms (RRT*): A Case Study of Masjed Soleyman County - ResearchGate, https://www.researchgate.net/publication/410874956_Optimized_Routing_of_Power_Transmission_Lines_Using_Geographic_Information_Systems_GIS_and_Artificial_Intelligence_Algorithms_RRT_A_Case_Study_of_Masjed_Soleyman_County
18. (PDF) Multi-agent based path planning for first responders among moving obstacles, https://www.researchgate.net/publication/285546688_Multi-agent_based_path_planning_for_first_responders_among_moving_obstacles
19. Intelligent Remote Sensing Agents: A Survey - ResearchGate, https://www.researchgate.net/publication/403817822_Intelligent_Remote_Sensing_Agents_A_Survey
20. Digital Twins Across the Asset Lifecycle: Technical, Organisational, Economic, and Regulatory Challenges - MDPI, https://www.mdpi.com/2075-5309/16/5/1084