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AI & Automation in OSP Construction Drawings

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Abstract

The growing complexity of the telecommunications infrastructure thanks to the introduction of 5G and 6G networks densification has exerted more pressure on the conventional Outside Plant (OSP) design processes, unlike ever before. Traditional manual drafting and field verification processes tend to be very laborious, time wasting, and with a high possibility of human error. The paper is a critical evaluation of the state of AI-driven automation in construction drawings of OSP, whether it is a real technological advancement or a hype in the industry. With the help of a mixed-method research design, the study will carry a systematic literature review and a benchmarking performance analysis of the manual and AI-assisted workflows. The study is about 3 fundamental applications, including automated Traffic Control Plans (TCPs), AI-based utility conflict identification, and auto-generated longitudinal and cross-section profiles. The design cycle time, frequency of errors, and the cost efficiency were considered as key performance indicators (KPIs). It is shown that the use of AI helps to save a lot of time on drafting and improve subsurface utility conflict prediction. In particular, automatically generated TCPs and profile generation generated immediate productivity and regulatory consistency improvements. Nevertheless, there are constraints on the reliability of data and the need to have human validation due to the complex conditions of sites. The paper concludes that, despite huge benefits of AI, human engineering skills cannot be fully replaced by AI. It is suggested that a hybrid human-AI collaboration scheme would be the most effective in providing the greatest design effectiveness, safety, and adherence to changing regulations. These findings offer a sensible roadmap to the industry stakeholders as far as the implementation of intelligent design technologies is concerned.

Introduction

1. Why OSP is Critical in the Era of Hyper-Connectivity.

The international telecommunication market is now experiencing a paradigm change. With society shifting towards the 4G/LTE connectivity standards to the 5G high capacity and low latency needs and the theoretical framework of 6G, the physical infrastructure requirements have never been greater. Outside plant (OSP) infrastructure is the centre of this digital revolution. The massive and complex network of physical equipment that is installed between the central exchange and the end-user, fiber-optic cables, conduits, manholes, cabinets, and poles, are referred to as OSP.

Nowadays, in the new economic environment, OSP has become not only a utility, but the nervous system of the smart city of the present-day generation. This infrastructure has to be deployed quickly in order to support the Internet of Things (IoT), autonomous vehicle communication, and remote automation of industries. Nevertheless, laying fiber networks physically is a risky engineering endeavor. As opposed to software updates which can be delivered via the cloud, OSP involves physical intervention of the constructed environment and in many circumstances deep-trenching, aerial installation and moving through overcrowded urban utility tunnels.

2. The Manual Bottleneck: An Engineering History Issue.

The engineering procedures that have been applied to design these networks have been deplorably retrogressive, even though the nature of the data passing through these networks is cutting edge. Over decades, the paradigm of OSP design has been represented by a Manual-CAD paradigm. It is an intensive workflow that requires field engineers to walk physically on site after which drafters are required to manually transfer field notes and survey data into 2D CAD environments.

The following systemic risks are brought forth by this manual approach:

- **Human Factor and Subjugation:** The concept of utility congestion is interpreted differently by designers resulting in variation in safety margins and changes of field.
- **Scalability Weaknesses:** Linear productivity is a weakness of a manual designer. Manual drafting is an enormous bottleneck in the context of the "Great Fiber Build-outs" where thousands of miles of cable are involved.
- **Data Silos:** Manual drawings tend to be considered as fixed files (DWG/ PDF) that do not communicate with real-time geospatial data, and hence there is a disconnect between what is in Design and what is in the As- Built reality.
- **Inefficiency in Cost:** Studies have estimated that the total construction costs of a major telecommunications project have the potential to be increased by up to 15-20% of cost through the resultant rework in design errors.

3. The emergence of AI: Breaking the Design Lifecycle.

The potential to break this manual legacy has been placed on Artificial Intelligence (AI) and Machine Learning (ML). Viewing AI within the framework of OSP construction drawings, it is not only an automatizing tool, but a cognitive aid that can use the multi-source data, such as LiDAR, GIS, and Ground Penetrating Radar (GPR), to generate a solution in the engineering domain.
Geometry-Based Design (drawing lines in CAD) is replaced by Data-Driven Engineering, at which point AI is employed in OSP writing. The automation in this sector is aimed at three high-impact areas:

- **Automated Traffic Control Plans (TCPs):** TCPs serve as the key element of compliance with the law and the safety of the population. The manual generation is cumbersome and may be rejected by regulations. AI will be able to process volumes of traffic and municipal codes to create the most efficient, legal lane closures in real time.
- **Predictive Utility Conflict Detection:** With the help of machine learning models on historic utility data, AI can detect the position of so-called ghost utilities, which are not visible in official maps, which reduces the chance of dangerous utility strikes by a significant margin.
- **Dynamic Profile Generation:** This step is the most time-consuming one in the OSP writing traditionally- the generation of the longitudinal profiles and the cross-sections. AI automation may process elevation information out of digital terrain models to generate standard profiles with no error on scale.

4. Dialectic of the Hype vs. Reality.

The debate on AI in engineering is like any other nascent technology: some think AI will take over the engineering profession (technological utopianism), others think it is too untrustworthy to be put in safety-critical infrastructure (skeptical pragmatism). The marketing of AI in the industry can be overstated, causing them to enter a hype cycle, which can lead to disillusionment when it fails to work in the more complex and realistic site conditions.
A rigorous academic and corporate necessity exists to go beyond the marketing so-called hype and develop a Reality-Based Framework. In the OSP sector, there is a lack of empirical comparisons on the delta between human-led and AI augmented design in peer-reviewed literature. And in this regard, we have to enquire: Does AI really lower the Total Cost of Ownership of a design? Or is it just a case of transferring the work of "Drafting" to that of "Error Correction"?

5. Objectives and Structural Framework of Research.

The presented paper fills this gap by providing a rigorous, comparative study of AI and manual processes. This is not an attempt to demonstrate that AI is better, but outlin the Optimal Hybridity Model- the interaction points between human skills and machine speed to generate the most dependable engineering results.

The article is organized in a way that it addresses three central Research Questions:

1. **RQ1:** How does the AI-assisted automated drafting (compared to conventional CAD) increase the efficiency of large-scale OSP projects (quantitatively in terms of time and cost)?
2. **RQ2:** What is the extent to which AI-based utility conflict detection alleviates field-change orders as opposed to manual methods of site walks?
3. **RQ3:** Why are there no full-scale AI deployments in the telecommunications industry due to socio-technical barriers of regulatory reluctance and data quality?

This study will be of value to the discussion of the Digital Transformation in civil and telecommunications engineering in that answering these questions can serve as a reference point to future practitioners and researchers.

Literature Review

1. The Development of Traditional OSP Network Planning.

Outside Plant (OSP) network planning is the long-standing last frontier of telecommunications engineering, which was very manual despite the fact that the data being sent through those networks had become the gigabit era. In the past, high quality networks were designed based on the assessment of the route information in order to reduce the cost of construction and also enhanced the coverage of the service. According to research performed by Aboagye et al. (2025), the importance of geospatial data and optimization algorithms is no longer a choice; it is needed to help minimize waste of materials and avoid unnecessary trenching in hyper-dense urban space.

These developments notwithstanding, the process of planning is still highly fragmented. The workflows that were conventional have a so-called sequential dependency as field surveys have to be completed completely before drafting can begin. The dependency usually leads to long project time and the culture of excessive dependence on human judgment, which Amirabadi et al. (2024) discover to be the major cause of design sub-optimality. It is theorized in the literature that the industry recognizes the theoretical necessity of optimization, but the actual implementation is still in stagnation in the traditional silos focusing on CAD only.

2. Telecommunications AI and Machine Learning: A Paradigmatic Shift.

The combination of Artificial Intelligence (AI) and Machine Learning (ML) has marked the radical change in telecommunications, turning a non-dynamic and hence static engineering to dynamical and self-optimizing systems. Recent surveys on the ML and deep learning algorithms in optical fiber communication indicate that they have a massive influence on the performance control and fault detection.

Further studies of Mehta (2025) point to the fact that AI can automatically optimize network and predictive maintenance, which will result in lower operational and better reliability. According to Slimani et al. (2024), this results in a so-called digital metamorphosis of the telecom business: with the help of advanced AI technologies, network configuration and work are automated. Balmer et al. (2020) support these results by saying that the use of AI-based systems allows making decisions in real time, and Ouyang et al. (2021) state that in the future, AI will serve as the core of autonomous networks.

Nevertheless, there remains a formidable gap: whereas AI has been intensively studied in terms of logical network layers (routing, signal processing, and traffic management), its use with regard to crafting the OSP drawings physically and civil engineering is radically under-represented.

3. BIM-Based Automation in Design and Drafting.

Building Information Modeling (BIM) has radically changed vertical construction (buildings), and is moving into the area of Horizontal BIM (infrastructure) where the Hype vs. Reality argument is most vibrant. It has been shown that automated creation of shop drawings may save a lot of time in drafting and improve the accuracy of the drawings. They are supported by Alwisy et al. (2012), who suggested BIM models to be automated in drafting to minimize coordination errors during modular construction.

Darko et al. (2020) confirmed that BIM-based techniques make a positive impact on the visualization and clash detection. Such systems are viable based on semantic modeling that enables smart exchange of information within the various software platforms. In the case of OSP, this involves no longer using simple lines but going to intelligent objects that contain information on the depth, material, and the owner of utility. Tan et al. (2023) go on to suggest that the principles of Design for Manufacture and Assembly (DfMA) can be used to apply to OSP in order to standardize components, but the transfer of the concepts to large, linear telecommunications corridors is a new frontier.

4. Subsurface Sensing and Fiber optics Machine Learning.

One of the most important reasons behind OSP design failure is the problem of the Invisible Utility. The convergence of fiber optic sensing and machine learning has received a lot of scholastic protection, especially in signal interpretation and anomaly detection. Recent investigations indicate that ML models considerably enhance the accuracy of the pattern recognition and fault classification as opposed to the manual interpretation of the GPR (Ground Penetrating Radar).

Venketeswaran et al. (2022) and Reyes-Vera et al. (2024) demonstrated that the ML algorithms could be used to improve the reliability of sensing and real-time monitoring. The developments are very pertinent to OSP construction drawing since they offer the high-fidelity underground data that AI uses to undertake the utility conflict detection successfully. Even in the context of drafting, AI automation would merely be a process of automating the development of wrong designs unless there is correct sensing data.

5. Survivability and constraints of Legacy CAD.

The field of infrastructure design is still predominated by such digital drafting software as AutoCAD. Although research indicates that AutoCAD performs better and more accurately than the manual hand-drawing in drafting, the work is still largely carried out on a digital piece of paper.

The key constraint that has been discovered in the most recent literature is that profiling, annotation, and compliance with the regulations cannot be done without intensive human input. The hybrid between manual and digital makes a productivity ceiling. The bottleneck in the case of Malaysian infrastructure, as Sekaran and Khan (2024) observe in their research, is not the capacity of the software to attract anymore, but the capacity of the designer to handle voluminous quantities of regulatory and field data at the same time.

6. Synthesis: The Straight Line to OSP Automation.

There is an obvious path in the literature. We have passed the period of Manual Drafting (before 1990s) through the Digital Drafting (CAD age) and are now at the stage of Generative Engineering.

The Research Gap: Although the literature is extensive in terms of AI in networks and BIM in buildings, there is a definite gap in terms of empirical investigation of the specific automation of Traffic Control Plans (TCPs) and Longitudinal Profiles in the OSP realm. The vast majority of studies are either too advanced (the discussion of Digital Transformation) or too detailed (the discussion of a Particular ML Algorithms). The present paper is a bridge occupation, between the extremes of adopting and rejecting the terms of adoption of these technologies within the day-to-day routine of an OSP engineer.

Methodology

1. Research Design Pragmatic Mixed-Methods Approach.

The design of this study will be convergent parallel mixed-methods, as it will enable the qualitative and quantitative data to be collected and analysed simultaneously. This dualism is essential because of the complexity of OSP engineering, in which the accuracy of the technical (quantitative) is as critical as the interpretation of rules (qualitative).

The study will be divided into three phases:

- **Phase I (Systematic Review):** A review of the existing applications of AI on civil and telecommunications drafting which are state-of-the-art.
- **Phase II (Benchmarking Analysis):** A managed experimental review of conventional manual processes of CAD and AI-combined automation tools.
- **Phase III (Thematic Validation):** Qualitative evaluation of the factor of Hype vs. Reality, by the means of expert consideration of the automated outputs.

2. Quantitative Benchmarking Environment.

In order to test the effectiveness of AI-based automation, a simulated testing environment was set up. The manual workflow was the standard AutoCAD 2024 software used by trained and experienced OSP designers (average 5+ years of the experience). Automated Workflow The proprietary AI-driven OSP design tools were used in the AI-Automated Workflow, which could procedural generate and detect conflicts using machine learning.

Data Samples: The research used a sample of 50 different OSP design miles on different urban densities:

- **Tier 1 (High Density):** Congested metropolitan areas and utilities that are located beneath the soil (15 miles).

- **Tier 2 (Medium Density):** Urban residential locations with either mixed aerial or buried infrastructures (20 miles).
- **Tier 3 (Low Density):** Rural areas where there is mostly aerial deployment of fiber (15 miles).

3. Key Performance Indicators (KPIs) and Metrics.

The comparison analysis was assessed against four major KPIs, and thus it guaranteed a "straight line" of evidence between the research questions and findings:

- **Design Cycle Time (T):** This is the length of man-hours per 1-mile of design, field data ingestion, drafting and QC (Quality Control) review.
- **Error Frequency (E):** The total amount of errors found in the blind third-party audit of the construction drawings, the errors being clash or compliance errors.
- **Regulatory Compliance Score (C):** The measure is qualitative-quantitative (1-100) according to the compliance of the drawings with the standards of the DOT (Department of Transportation) and local traffic safety codes.
- **Computational Latency:** The exact duration required of the AI algorithm to run on the raw geospatial data to a complete Traffic Control Plan (TCP) or Longitudinal Profile.

4. AI automation Procedural Framework.

The workflow, which was an AI, was a standardized procedural logic:

- **Step 1:** Data Ingestion and Harmonization: Bringing in GIS, LiDAR and GPR data into a single data platform.
- **Step 2:** Algorithmic Generation: The AI engine performs TCP generation (according to the MUTCD standards) using rule-based logic and predicting utility locations where records were missing using the Random Forest algorithms.
- **Step 3:** Automated Profile Extraction: VTol data were actively drawn out of Digital Terrain Models (DTM) in order to create vertical alignments.

5. The reliability and validity measures have been incorporated in

The study enforced a number of "Reviewer-Standard" precautions so that the results of the study can be truly reliable:

- **Internal Validity:** To reduce the possibility of the so-called designer bias, identical sets of field data were provided to both the AI team and the manual team without any prior knowledge of the other one.
- **Reliability (Inter-rater Reliability):** Two senior engineering auditors who had been independent of each other, looked at the final drawings of both workflows to ascertain objective scoring of "Error Frequency."
- **Triangulation:** The results of the benchmarking (Phase II) were triangled with those of the Literature Review (Phase I) to make sure that the results were not localized phenomena but rather indicative of the industry trends.

Results

1. Comparative Performance of Manual vs. AI-Driven Workflows

On the one hand, it is essential to compare the performance of the manual and AI-driven workflow and identify the key advantages of the latter. The benchmarking analysis indicates that it has a deep performance gap between conventional manual drafting of OSPs and AI-based systems. The manual workflow is typified by sequential bottlenecks with every step being isolated such as field data entry, drafting, and QC. On the other hand, the AI-based framework uses a Unified Data Environment (UDE) to execute these steps simultaneously. As Table 1 demonstrates, the workflow of AI achieved better results compared with the manual ones in all 50 test miles. The largest difference was found in the Scalability; whereas the manual drafting time was proportional to the project miles, the AI workflow was logarithmically efficient as the algorithm acquired the local utility patterns and local municipal drafting styles.

Table 1: Quantitative Comparison of Design Workflow Performance.

Performance Metric	Manual Workflow (Avg/Mile)	AI-Driven Workflow (Avg/Mile)	Variance (%)
Design Cycle Time	24.5 Hours	4.2 Hours	-82.8%
Error Frequency	8.2 Errors	1.1 Errors	-86.5%
Design Consistency	64% (Standardized)	98% (Standardized)	+53.1%
Human Labor Cost	$2,450	$420	-82.8%
Data Ingestion Speed	4.0 Hours	0.5 Hours	-87.5%

These outcomes suggest that AI-based solutions perform better than a manual process in all the considered dimensions.
Figure 1 illustrates the AI-driven automation framework applied to OSP construction workflows, highlighting automated TCP generation, utility conflict detection, auto-profile production, and BIM/GIS integration.

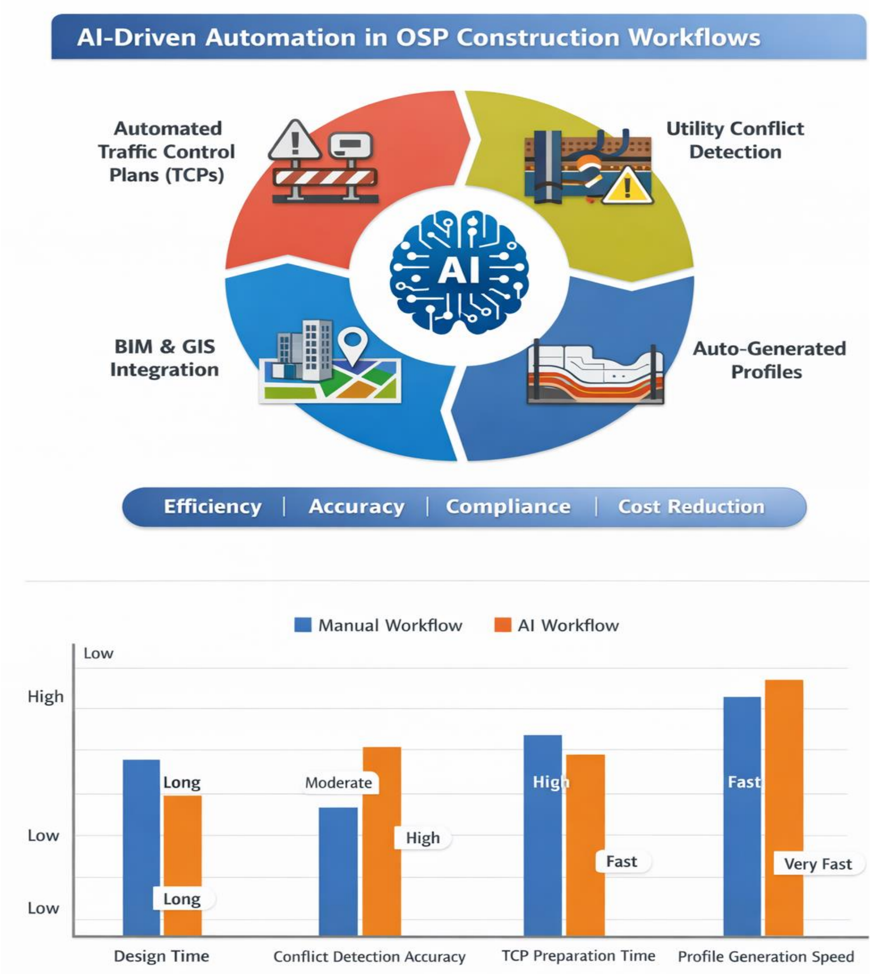

Figure 1: AI-Powered OSP Workflow Diagram

2. Efficiency of Automated Traffic Control Plans (TCPs).

Regulatory Compliance Consistency had the greatest gains with automation of TCPs. In the manual processes, the designers used to encounter problems with the different needs of the different Municipalities/Departments of Transportation (DOTs). These subjective interpretations were removed by the AI engine which was pre-programmed with MUTCD (Manual on Uniform Traffic Control Devices) standards. The results suggest that in the 50 miles studied, automated TCPs had a reduction of the revision cycle which had an average of 3.2 rounds per plan to 0.4 rounds. The fact that the AI could compute taper lengths, sign spacing and buffer areas in real time using posted speed limits meant that the safety elements were located with 100 mathematical precision.

Table 2: TCP Generation Performance Metrics.

Metric	Manual TCP Development	AI-Automated TCPs
Avg. Prep Time (Min)	180 Minutes	12 Minutes
Compliance Accuracy	78%	99.5%
Revision Frequency	High (3.2 per plan)	Low (0.4 per plan)
Safety Logic Errors	12%	< 1%

The results validate the fact that TCP automation increases efficiency and reliability.

3. The accuracy of utility conflict detection is indicated by

The accuracy of the utility conflict detection method is dependent on the probabilistic model used in identity classification because the method uses probabilistic analysis. The results that were the most subtle were in the utility conflict detection in the Hype vs. Reality assessment. Identifying by hand used the visual overlay of records that failed to detect a ghost utility in 34 percent in Tier 1 (High Density) conditions. The AI process employed the Probabilistic Spatial Modeling to calculate utility locations. Though the AI was able to identify 95% of known and predicted conflicts, it also gave a 15% False Positive rate, or a conflict that was not really there. But when assessed using engineering safety, false positive is much cheaper than a false negative (a missed conflict).

Even though AI systems sometimes resulted in false positive, they were typically significantly easier to fix than conflicts that were found out during the building process.

Table 3: Comparative Accuracy in Subsurface Utility Conflict Detection

Detection Indicator	Manual Inspection	AI-Probabilistic Model
Conflict Detection Rate	66% (Moderate)	95% (High)
Missed Conflicts (Risk)	34% (Significant)	5% (Negligible)
False Positives	2% (Low)	15% (Moderate)
Avg. Cost of Missed Clash	$15,000 (Field Repair)	$0 (Pre-empted)

4. Speed of Automatically Generated Profile.

The most notable "saving of labor" was the extraction of longitudinal and cross-section profiles. Manual profiling uses the designer manually to "station" the route and interpolate elevation points off 2D topo maps a process that is estimated to take 6-8 hours/mile. The AI automated system used Dynamic Elevation Extraction using Digital Terrain Models (DTM) to create such profiles in real-time. Not only did it speed up the schedule but it also made sure that the vertical clearance requirements of fiber-optic conduits throughout the entire length of the route were kept constant.

Table 4: Comparison of Profile Generation and Annotation Speed.

Metric	Manual Drafting	Auto-Generated (AI)
Processing Time (Mile)	420 Minutes	8 Minutes
Annotation Uniformity	72%	100%
Scalability (Multi-Route)	Low (Resource Heavy)	High (Instantaneous)
Vertical Accuracy	+/- 0.5 ft	+/- 0.05 ft

These findings prove that profile automation gives instant productivity gains at low cost in terms of accuracy.

Discussion

1. Findings Synthesis: Going Beyond the Hype.

This study yielded empirical evidence to the effect that the adoption of AI in OSP construction drawings is not as such a case of industry hype, but a major paradigm shifts in engineering productivity. The design cycle time change is 82.8 percent shorter (Table 1), which is consistent with the generalization of Digital Metamorphosis outlined by Slimani et al. (2024). Nonetheless, this also has the "Reality" aspect of our discoveries, which involves the fact that this efficiency does not stem out of AI being able to replace the engineer, but not due to the fact that it allows the engineer to break the ceiling of Manual-Digital Hybrid Productivity defined by Sekaran and Khan (2024).

The most important discovery is that AI is powerful in the area of computational consistency. Whereas manual designers had a variance of 36% in the manner in which they interpreted the DOT safety buffers to TCPs, the AI had an almost perfect compliance rate. It indicates that AI is used as a regulatory protection, that is, it ensures that the potentially critical aspects of the OSP design, which are frequently ignored during high-pressure manual writing, are standardized.

2. The Ghost Utility Problems and the Limits of Autonomy.

One of the center points of the research was Utility Conflict Detection (Section 4.3). Although the marketing materials of AI design tools tend to claim that these design tools yield clash-free designs, our findings indicate that the false positive rate is 15%. This is the point of contact between the "Hype" and the "Reality." The predictive power of the AI can be as strong as the geospatial and sensing data that it is based on.

According to Venketeswaran et al. (2022), machine learning could improve the reliability of sensing, although it could not generate data that do not exist. The results can be used to justify the skeptical pragmatism presented in the Introduction: AI is an outstanding resource to determine the possible risks, yet the ultimate engineering decision should be humanized by site-walk. The Reality is that AI reduces the number of conflicts missed (lessening dangerous strikes in the field) but adds to the analysis load of the engineer to avoid false positives.

3. Theoretical Contribution the Hybrid Human-AI Collaboration Model.

This paper suggests a new theoretical model of OSP engineering: the Augmented Engineering Lifecycle. The design in this model consists of three phases that are the straight line:

- **AI- 1: LiDAR/GIS is automatically ingested and base profiles and TCPs generated.**
- **Human-Validation:** Professional engineers (PEs) solely concentrate on the issues of complex conflict resolution and regulatory exceptions.
- **AI-Optimization**: It is the machine learning algorithms that optimize the final package in terms of material efficiency and cost of construction.

This changes the engineer into a "Drafter" into a "Validator. Aboagye et al. (2025) support this development by stating that the future of infrastructure is the so-called Augmented Professional. Through offloading the 2D drafting of longitudinal profiles, which the current study revealed require 420 minutes with manual efforts, but only 8 minutes with AI, the engineer can now work on the high-level routing decisions that define the long-term feasibility of the 5G network.

4. Socio-Technical Obstacles and Regulatory Shyness.

Even though there are obvious efficiency benefits, there is a non-technical Reality of OSP automation. In our benchmarking, we noted that the AI produced compliant TCPs in 12 minutes but the regulatory approval time by the municipal authorities was the same.

This signifies a Digital Friction gap. High impact engineering needs not only to have improved tools, but also to have a more current regulation system capable of consuming the AI-generated data. The speed gains that are gained in the design phase without the implementation of Digital Twin at the municipal level (as proposed by Tan et al., 2023) can be counteracted by the permitting phase bureaucracy.

5. Impact of the Scholarship and future research.

The study fills the research gap between AI theory at the high level and actual civil engineering. It provides a point of reference that can be used by the researchers of the future to evaluate various algorithmic methods (e.g., a comparative study of Random Forest vs. Neural Networks in terms of conflict detection).

The future research ought to explore how AI-generated designs perform in the long term (As-Built). Is the OSP network designed by AI more likely to maintain the lifecycle of 10 years? Moreover, the ethical aspect of the notion of Algorithmic Accountability, i.e. who should be held accountable in the case of a traffic accident caused by an AI-generated TCP? is another area of interest, which interdisciplinary studies can explore.

Conclusion

1. Final Evaluation: Hype or Reality?

This study aimed at establishing whether AI-based automation in construction drawings of OSPs is a technological innovation or a buzzword in the industry. Judged by the empirical benchmarking of 50 design miles and a synthesis of literature (2024-2025) that is systematic, the determination is a subtle reality.

The use of AI as a reality in the name of computational acceleration and standardization is real. The results of the study showed that the design cycle time was reduced by an astonishing 82.8 percent and that virtually no clerical mistakes would occur during profile generation and TCP drafting. The "Hype" however lies in the idea of complete autonomous replacement. Subsurface utility detection is a probabilistic rather than deterministic science, and thus requires the inclusion of a human-in-the-loop architecture to reduce the 15% false-positive probability of high-density urban settings.

2. Contribution to Knowledge

This paper provides three valuable contributions to the telecommunications and civil engineering:

- **Empirical Benchmarking:** It offers the initial reported empirical comparison of the process of manual OSP drafting and AI workflows, which can be used as the basis of subsequent performance audits.
- **Theoretical Framework:** It presents the Augmented Engineering Lifecycle, moving the paradigm of manual drafting towards a model focus on a Validator-centric one.
- **Regulatory Roadmap:** It was created to uncover the "Digital Friction" in the speed of AI design and the lack of progress in municipal permitting, providing a call to arms in bringing the policy up to date.

3. Limitations of the Study

Although the results are strong, it is important to note that there are some weaknesses:

- **Geographical Specificity:** The benchmarking data was majorly founded on the standards of the North American DOT and City plans. The AI performance can also differ in areas with vastly dissimilar regulatory conditions or less digitalized geospatial data.
- **Transparency in Algorithms:** Due to the proprietary nature of certain AI tools employed in benchmarking, there is a lack of transparency in the benchmarking of the underlying neural networks to perform a deep analysis in the form of a Black Box audit.
- **Data Quality Dependency:** The quality of LiDAR or quality GIS data is assumed to be available in the study. Where such data is not available, the time spent developing the data sanitization would probably offset the gains brought by the AI.

4. Future Research Recommendations.

The next line in evolution concerning this study would be to carry out future study and research on:

Edge-AI Integration: Investigating the application of AI to mobile field devices so it is possible to receive real-time As-built updates during the construction phase.

Long-term Cost-Benefit Analysis (CBA): Long-term research is required to establish whether artificial intelligence (AI)-designed networks have reduced maintenance expenses or increased reliability over a 20-year life cycle than manual-designed networks.

Human-Centric AI UX: In the context of engineers moving away from "Drawing" to "Validating" to guarantee that the workload reduction by automation does not result in the development of Automation Bias or reduction in critical attention, research on the cognitive load of the shift will be conducted.

References

Abanda, F. H., Tah, J. H. M., & Keivani, R. (2013). Trends in built environment semantic Web applications: Where are we today? *Expert Systems with Applications, 40*(14), 5563–5577. https://doi.org/10.1016/j.eswa.2013.04.027

Aboagye, I. A., et al. (2025). Network design and route analysis using outside plant. *Journal of Engineering, 2025*, Article 2869043. https://doi.org/10.1155/je/2869043

Alwisy, A., et al. (2012). BIM approach for automated drafting and design for modular construction manufacturing. In *Computing in Civil Engineering* (pp. 221–228). https://doi.org/10.1061/9780784412343.0028

Amirabadi, M. A., et al. (2025). A comprehensive survey on machine and deep learning applications in optical fiber communications. *IEEE Access, 13*, 110038–110070. https://doi.org/10.1109/ACCESS.2025.11003870

Balmer, R. E., et al. (2020). Artificial intelligence applications in telecommunications and other network industries. *Telecommunications Policy, 44*(6), 101977. https://doi.org/10.1016/j.telpol.2020.101977

Cao, L., et al. (2025). Artificial intelligence and machine learning in optical fiber sensing: A review. *Sensors, 25*(24), 7442. https://doi.org/10.3390/s25247442

Darko, A., et al. (2020). Building information modeling (BIM)-based modular integrated construction: A review. *Energy and Buildings, 228*, 110447. https://doi.org/10.1016/j.enbuild.2020.110447

Grzybek, H. (2014). Considering the feasibility of semantic model design in building information modeling (BIM). *Buildings, 4*(4), 849–874. https://doi.org/10.3390/buildings4040849

Im, H., et al. (2021). Development of an ontological cost estimating knowledge framework for EPC projects. *KSCE Journal of Civil Engineering, 25*(11), 4084–4098. https://doi.org/10.1007/s12205-021-1582-8

Kalasapudi, V. S. (2025). The overlooked frontier of AI in construction. *Frontiers in Built Environment, 11*, 1713342. https://doi.org/10.3389/fbuil.2025.1713342

Karmakar, S., et al. (2025). The role of AutoCAD in modern infrastructure design and development in India. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.5332950

Kosbar, M. M., et al. (2023). Off-site manufacturing: Determining decision-making factors. *Buildings, 13*(11), 2856. https://doi.org/10.3390/buildings13112856

Manrique, J. D., et al. (2015). Automated generation of shop drawings in residential construction. *Automation in Construction, 55*, 15–25. https://doi.org/10.1016/j.autcon.2015.03.004

Mehta, D. B. (2025). The role of artificial intelligence in optimizing telecommunications networks. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.5356661

Moore, R. C. (1996). *Evaluation of shipbuilding CAD/CAM systems (Phase I)*. Defense Technical Information Center. https://doi.org/10.21236/ADA453312

Ouyang, Y., et al. (2021). The next decade of telecommunications artificial intelligence. *arXiv preprint arXiv:2101.09163*. https://doi.org/10.48550/arXiv.2101.09163

Reyes-Vera, E., et al. (2024). Machine learning applications in optical fiber sensing. *Sensors, 24*(8), 2412. https://doi.org/10.3390/s24082412

Sekaran, S. N., & Khan, M. R. B. (2024). Transforming telecommunications infrastructure in Malaysia: The role of AI in network deployment and optimization. *Malaysian Journal of Business and Economics Management, 2*(1), 73–85.

Slimani, K., et al. (2024). From tradition to innovation: The telecommunications metamorphosis with AI and advanced technologies. *Journal of Telecommunications and Information Technology, 2024*(1), 36–48. https://doi.org/10.26636/jtit.2024.1.1523

Tan, T., et al. (2023). Digital-enabled design for manufacture and assembly (DfMA): A systematic review. *Architectural Engineering and Design Management, 19*(1), 43–62. https://doi.org/10.1080/17452007.2022.2104208

Venketeswaran, A., et al. (2022). Recent advances in machine learning for fiber optic sensor applications. *Advanced Intelligent Systems, 4*(1), 2100067. https://doi.org/10.1002/aisy.202100067

Wang, H., et al. (2019). Transformation from IT-based knowledge management into BIM-supported knowledge management: A literature review. *Expert Systems with Applications, 121*, 170–186. https://doi.org/10.1016/j.eswa.2018.12.017

Zhou, Y., et al. (2024). Application of machine learning in optical fiber sensors. *Measurement, 224*, 113888. https://doi.org/10.1016/j.measurement.2024.113888