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Network analysis of the Indo-Pacific: Efficiently solving a complex infrastructure engineering problem using Artificial Intelligence

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Abstract

This manuscript presents an in-person, active learning activity for civil engineering students that demonstrates how to construct and analyze complex network models. A secondary objective of the activity is to encourage students to leverage the power, popularity, and availability of artificial intelligence (AI) to efficiently and effectively support their learning process. By increasing the students' AI literacy, it may encourage the students to more critically assess the problem and propose more creative solutions. This activity is based on a lesson in an infrastructure course where students investigated air travel in the Indo-Pacific region. The exercise investigated air travel in the Indo-Pacific region using open-source data for local airports, air travel statistics, and relevant constraints. The primary objective for the students was identification of the limits of an acceptable air transportation network. Students used open-source large language model (LLM) generative AI to both write python code and execute that code "under the hood" to complete hundreds of mathematical operations with only natural text prompting. This computation would otherwise have to be coded in Python, completed by hand, or iteratively solved via Microsoft Excel or another computational tool. Instructors prompted the students to verify their answers from AI to ensure accuracy. Once the students compiled the raw data, they created a full network visualization in Google Earth using AI instead of manually drawing the network. This exercise provided students with confidence that they could construct a real-world network map using a variety of data sources and software to produce a high-quality solution. The use of AI in this in-class exercise automates the repetitive mathematical operations and the Keyhole Markup Language (KML) code writing required to map and visualize the network, providing students with more time to engineer solutions. This paper provides a unique case study for civil engineering faculty to incorporate AI into their teaching and learning. The results provide educators with a unique activity to inspire their students. This manuscript documents the design, implementation, and assessment of the network analysis activity using AI. The activity assessed student learning and perspective on the integration of AI in the in-class activity. The students successfully achieved the learning objectives as automation of the redundant processes and visualization assistance provided them with additional time to critically evaluate the network and make recommendations to improve its performance.

Introduction

Modern infrastructure systems are vast. Network nodes regularly increase in number while the links among those nodes grow denser. Modeling large transportation networks traditionally takes a great deal of time and can be a painstaking process. The level of detail and time required to map a real-world network from raw data presents a barrier to educators aiming to teach students about the fundamental components of a network and its purpose. This barrier also makes it difficult to ask students to perform to-scale real-world analysis and provide improvement recommendations. As generative artificial intelligence (AI) technology improves, industries are investigating ways to leverage these resources to more efficiently and effectively solve complex challenges. Completion of redundant calculations and complex visualizations can be automated to quickly achieve desired objectives. However, research has emphasized the importance of educating students on AI literacy, so they can maximize their learning [1]. Students may overly rely on AI to do their learning for them or lack the confidence to use AI for fear of using it incorrectly. Therefore, instructors within all disciplines must embrace AI and empower their students to use AI ethically to enhance and verify their own cognitive contributions. There are several specific documented advantages for including AI in teaching and learning activities:

1. More personalized learning [2], [3], [4], [5]
2. Independent learning [3], [4], [5]
3. Inquiry learning [4], [5], [6]
4. Access & availability [2], [5], [6], [7]

While many articles acknowledge the potential positive impact AI will have on education, others highlight barriers of entry, which have prevented widespread adoption by higher education institutions and faculty including:

1. Ethical issues (academic integrity & data privacy) [2], [3], [4], [5], [6], [8], [9], [10], [11]
2. Overreliance [3], [4], [5], [6], [7], [12], [13]
3. Lack of institutional resources & guidance [9], [11], [14], [15], [16]
4. Access & availability [2], [4], [6], [10]
5. Instructor & student expertise [3], [4], [5], [7], [9], [10], [11], [12], [13], [17]

Despite these challenges, students have stated that they want to use AI to learn, not to replace learning [18]. They believe their learning would benefit from discipline specific applications of AI in the curriculum [13], [19]. However, both students and faculty have expressed uncertainty due to the lack of policies and guidance from their institutions for concerns related to academic integrity and learning implications [15]. Just as faculty must empower their students, the institution must empower their faculty to ethically adopt AI into their curriculum while maintaining academic and scientific values, providing access to all students, and remaining flexible in an ever-changing world of political, cultural, and technological advancements [14]. Academic institutions need to provide clear and concise guidance that ensure transparency, accountability, and fairness to maximize academic freedom and minimize the risks outlined above [9].

Many colleges and universities are implementing degree, minor, or certificate programs dedicated to AI [20], [21]. The United States Military Academy at West Point has fully embraced AI in higher education by developing a required course for all 1st year students on computing, cyberspace, and AI. The institution has also created an AI and Data Engineering Sequence of three courses for non-engineering majors, and a five course AI minor [22]. The institution has encouraged its faculty to investigate opportunities to integrate AI into our individual courses and share our experiences both internally and externally. As the American Society for Engineering Education Civil Engineering Division has identified in their call for papers for 2026 and as previous researchers have stated, the profession needs to advertise educational activities that promote effective and ethical implementation of AI [16], [23], [24].

This case study investigates the development, implementation and assessment of an active learning, in-class, group assignment where students use an open-source data set and AI resources to construct and analyze a network model of a real-world infrastructure system. First, students manipulated a large open-source dataset to fit specific modeling constraints. Second, students used a large language model (LLM) to aggregate data for the construction of a real-world network provided customizable details such as airframe range. Third, students used the LLM to map that network model and display it in Google Earth. Finally, students answered a variety of scenario specific questions about the characteristics of the network that required a complete network model. The students used artificial intelligence throughout each step to assist in tedious computations and coding. There were three primary goals the authors hoped to accomplish:

1. **Provide** students with a low-stake opportunity to learn advanced AI capabilities.
2. **Verify** AI output for accuracy and relevancy.
3. **Evaluate** a complex engineering problem efficiently and critically using AI.

This manuscript includes a detailed methodology section documenting the course, the lesson on network analysis without the activity, and the revised lesson incorporating the new AI-based activity. The authors assessed the impact with and without AI on student performance on network analysis on a midterm examination. The authors also surveyed the students to evaluate the perception of the AI based activity in achieving the authors' goals listed above.

Literature Review

It is critical that students, faculty, and professionals know how to ethically and effectively implement AI resources to improve the quality of their work [25]. Faculty members play an important role in educating students on AI in their specific discipline. Research has indicated that institutions need to provide more training opportunities for faculty to learn how to use AI and how to implement it in their curriculum [9], [11], [17]. Cercone et al. proposed an activity to increase faculty use and comfort with AI by creating AI videos to enhance student learning [26]. Their survey results showed that 50% of faculty did not use AI, but almost all introduced supplemental videos into their course despite 68% stating they were uncomfortable editing videos. Using AI reduced the time to create the videos by 88%, presenting a low-threat, high-value opportunity for faculty to practice with AI.

This literature review will cover the use of custom and open-source resources tailored to engineering education to improve AI literacy and other student outcomes. Limited research is available documenting actionable case studies for faculty to implement into their curriculum. The fields of electrical engineering, robotics, computer science, and engineering lend themselves to seamless introduction of AI [27]. Narayan and Saharan propose four activities for electrical and robotics engineering instructors to implement, which promote effective and ethical use of AI: AI assisted learning (supplement out-of-class preparation), formalized verification of AI generated solutions, research-based learning to identify limitations and novel solutions, and project-based learning to enhance collaboration and creativity [28]. Although these are tailored to electrical engineering and robotics, they may be adapted to other engineering fields as well. Galos et al. developed a hands-on project to help students understand the role of AI in solving complex engineering problems by using AI to analyze large sets of material property data [29]. Manteufel and Karimi encouraged students to use AI to complete a writing assignment in a thermodynamics course [30]. They observed enhanced quality of writing. 41% of the students had not previously used AI to support their writing and 68% believed that faculty should provide formal instruction.

Specifically for civil engineering, the American Society of Civil Engineers believes that AI will provide many benefits including managing big data, remote sensing and inspection, quickly producing conceptual designs, and optimizing structural designs [31], [32]. Civil engineers must be educated on how to critically verify the results and generate new knowledge through creative design. Naser proposed creating an entire elective civil engineering course based on AI, but highlighted the need to provide all students with a platform to practice creating solutions supported by AI [33]. Plevris provided recommendations for faculty to expose their students to AI including virtual tutors, automated grading/feedback, interactive simulations, virtual labs, resources management, and curriculum development [34]. Okonkwo et al. integrated an entire AI module into a construction course to present relevant AI techniques that can be used in industry to predict construction material properties [35].

While many faculty or institutions may not have the resources to dedicate an entire program or course to AI, researchers recommend that even low-stakes assignments can help prepare students to use AI responsibly [1], [36].

Methodology

Course Description and learning objectives

The United States Military Academy at West Point's Civil Engineering program includes a course titled CE350: Infrastructure Engineering [37]. This course's objectives are:

I. **Identify**, **assess**, and **explain** critical infrastructure components and cross-sector linkages at the national, regional, and municipal levels.
II. **Calculate** the demand on infrastructure components and systems.
III. **Assess** the functionality, capacity, and maintainability of infrastructure components and systems.
IV. **Evaluate** infrastructure in the context of military operations.
V. **Prioritize** and recommend actions to improve infrastructure resilience.

CE350 is open to both engineering and non-engineering majors who have sufficient basic math and physics knowledge. The course includes blocks on infrastructure systems, water/wastewater, energy systems, and transportation. There are two lessons in the infrastructure systems block focusing on network theory and modeling. Conceptually they are largely based on the work of Barabasi and Bonabeau [38]. These lessons are foundational for8 work completed later in the course for water, energy, and transportation networks. CE350 includes the following learning objectives for students in the network modeling lesson:

I. **Construct** a network model of an infrastructure system
II. **Analyze** a network model to determine the real-world behavioral characteristics of a system.

These objectives are nested underneath course objectives I, III, IV and V, given above. An in-class exercise that walks students through these objectives was incorporated in CE350 for many years. A commonly used version of this exercise tasked students to study a map of rail lines in Ukraine and analyze critical nodes and links. The context for the assignment was to move troops and equipment towards a front line or evacuate civilians away from a front line. This example prioritized in-class time achieving the second learning objective (Analyze) at the expense of the first (Construct). The instructors provided students with a complete rail network via handout (reproduced below in Figure 1). The student completed the analysis, but did not “construct” a network independently.

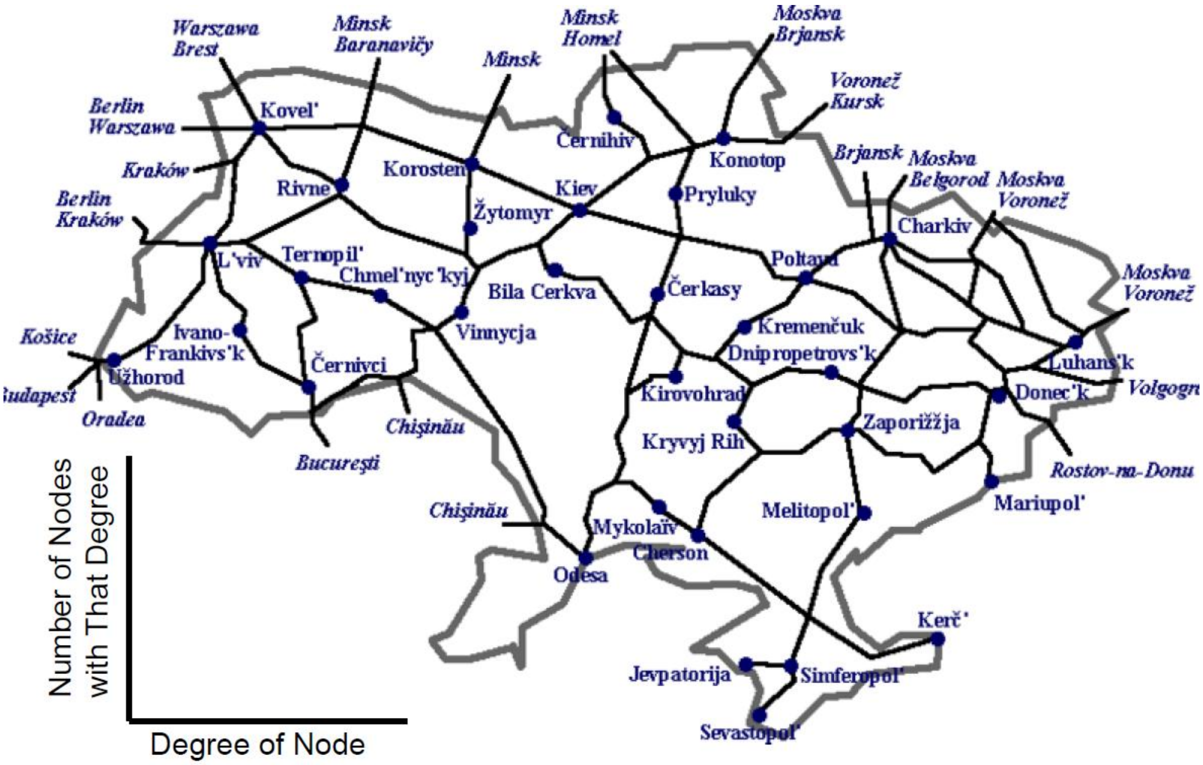

Figure 1: Example of previous in-class exercise handout, a map of the rail network in Ukraine[39]

In the fall of 2025, the instructors used a larger and more complex network to reflect the current state of intercontinental transportation networks relevant to on-going events. The context for this assignment prioritizes the relevant real-world infrastructure challenges that our cadets will face upon graduation [40]. The new assignment emphasized the learning objective for students to **construct a network model**. Instructors wanted students to work through the entire network construction and analysis in a single 55-minute class period.

The instructors chose a network of US facilities that are on the US Department of War’s Base Structure Report (BSR). This report is publicly available online in the form of a Microsoft Excel Spreadsheet, with a variety of data for each site listed and includes over 2600 locations worldwide [41]. Students used the dataset to construct the network of the locations to service a

C-130J military transport aircraft operated by the US Air Force. Instructors further narrowed the scope by providing a one-way range for the air frame and a geographic area of focus: the US Indo-Pacific (USINDOPACOM) Combatant Command Area of Responsibility (Figure 2).

Figure 2: Map of INDOPACOM [42]

The size of this network and the nature of the associated dataset presented a near-impossible challenge for undergraduate students to fully construct, visualize, and analyze the network in a single 55-minute class session. Using such a large network as a teaching exercise instead of a smaller, artificially simplified network exposed students to the sometimes-overwhelming nature of real-world problems and underscores the usefulness of AI in tackling these problems.

To facilitate completion in a time-constrained environment the students used AI LLMs to complete portions of the assignment through only natural language prompting. Reducing the students' manual effort to construct the model provided them with sufficient time to analyze the network and assess the social, economic, environmental, political, legal, and cultural impacts of the entire system [43]. The instructors designed the exercise to be completed by students with little to no experience writing code or using LLMs. The exercise aimed for students to leverage the capabilities and efficiencies of AI resources in later assignments, courses, and professional work. The instructors split students into groups of four to five to work through the exercise collaboratively.

Further sections of this paper will detail the step-by-step process to clean the data, construct, visualize, and analyze the selected network.

Cleaning the Data

Instructors cleaned the data prior to the in-class exercise to ensure that the construction and analysis of the network was the focus of available in-class time. This required instructors to review the global Base Structure Report (BSR) and extract only the installations (nodes) of interest to the exercise. The instructors selected 23 installations within the INDOPACOM theater out of the possible 2600+ in the dataset. Instructors used Google Earth to find the latitude and longitude for the airfield on each installation and provided it in both decimal degree and degree-minute-seconds formats by adding columns to the BSR. While the students could certainly complete this task on their own, instructors completed it to provide students with additional time for analysis. Figure 3 shows a screenshot of the final cleaned and modified BSR file provided to students. A majority of this data was extraneous for the exercise but was included to challenge students to identify which information was relevant.

Base Structure Report- FY25 Baseline (As of 30 Sept 2024)

Criteria: DoD sites having at least 10 acres AND $10M Plant Replacement Value; US Territory/Non-US Site having at least 10 acres OR $10M Plant Replacement Value

Country/State	Site	Component	Name Nearest City	Count Building Owne	Building Owned SqFt	Count Bldgs Leased	Bldgs Leased SqFt	Count Bldgs Other	Bldgs Other SqFt	Acres Owned	Total Acres	Plant Replacement Value ($M)
Alaska	EARECKSON AS SITE 1	Air Force Active	Shemya Station	57	1,091,579	0	0	0	0	0.00	3,520.00	$7,293.62
Alaska	EIELSON AIR FORCE BASE	Air Force Active	Eielson Air Force Base	290	4,440,346	0	0	257	2,821,758	5,398.75	24,918.91	$19,521.27
Alaska	ELMENDORF AFB SITE 1	Air Force Active	Elmendorf Air Force Base	385	6,590,146	0	0	204	1,414,037	4,976.95	7,663.52	$18,774.86
Alaska	Fort Greely	Army Active	Delta Junction	117	1,133,802	0	0	93	455,730	0.00	7,201.62	$5,031.58
Washington	Fort Lewis	Army Active	Tacoma	1,840	25,296,952	3	10,810	3,704	9,311,170	87,379.54	87,851.09	$31,897.94
Alaska	Fort Wainwright	Army Active	Fort Wainwright	379	6,394,456	0	0	733	6,597,308	3,394.54	756,371.33	$22,368.49
Hawaii	JBPHH PEARL HARBOR HI	Navy Active	Pearl Harbor	881	13,636,629	0	0	1,227	5,161,284	5,557.77	5,587.98	$41,050.03
Japan	KADENA AIR BASE	Air Force Active	Kadena Air Base Okinawa	1,240	5,360,910	0	0	820	8,883,679	0.00	4,906.00	$25,960.79
Alaska	KING SALMON AIRPORT SITE 1	Air Force Active	King Salmon	12	56,915	0	0	41	312,269	134.00	914.25	$2,279.93
Alaska	KODIAK AK	Navy Active	Kodiak	7	53,877	0	0	0	0	0.00	240.70	$140.59
South Korea	KUNSAN AIR BASE SITE 1	Air Force Active	Kunsan	376	2,585,341	0	0	62	987,264	0.00	2,548.98	$5,352.93
Marshall Islands	Kwajalein Island	Army Active	Kwajalein Atoll	497	2,511,721	0	0	2	5,618	0.00	1,361.00	$8,119.12
Japan	MCAS IWAKUNI (JA) MAIN BASE	Marine Corps Active	Iwakuni	36	117,163	0	0	891	11,423,969	0.00	7,110.64	$19,337.47
Japan	MISAWA AIR BASE	Air Force Active	Misawa Air Force Base	337	818,960	0	0	695	7,703,155	0.00	3,864.42	$16,718.44
Diego Garcia	NAVSUPPFAC DIEGO GARCIA IO	Navy Active	Unknown	549	2,335,533	0	0	2	27,750	0.00	7,000.00	$15,724.56
Guam	NSA ANDERSEN	Navy Active	Andersen Air Force Base	1,244	6,486,788	0	0	3	1,508	15,220.09	15,235.09	$27,335.26
South Korea	OSAN SITE 1	Air Force Active	Osan	344	4,802,009	0	0	81	1,647,667	0.00	1,530.93	$6,695.28
Singapore	PAYA LEBAR AIR BASE	Navy Active	Singapore	0	0	0	0	4	41,123	0.00	0.00	$43.75
American Samoa	Te'o USARC	Army Reserve	Pago Pago	10	122,436	0	0	0	0	0.00	4.68	$261.65
Northern Mariana Islands	TINIAN	Navy Active	Tinian	0	0	0	0	0	0	56,854.41	68,018.64	$4.30
California	TRAVIS AFB SITE 1	Air Force Active	Fairfield	353	6,796,591	0	0	642	2,302,218	5,129.81	6,445.73	$10,235.98
Wake Island	WAKE ISLAND AIRFIELD SITE 1	Air Force Active	Unknown	108	444,186	0	0	0	0	2,600.00	2,600.00	$3,421.99
Japan	YOKOTA AB SITE 1	Air Force Active	Yokota Air Base	115	573,964	0	0	588	9,478,081	0.00	1,749.87	$14,978.29

Figure 3: Cleaned BSR provided to students, with airfield locations in far-right columns

Network Construction

To fully understand the network within the INDOPACOM theater, students determined which installations (nodes) could be used to support travel of US forces (viable links) via the C-130J aircraft. The instructors provided the students with two assumptions to govern the network's construction. First, students used a one-way flight range of the C-130J of 2200 nautical miles (nm) based on open-source information from the manufacturer, Lockheed Martin [44]. Second, students assumed the runway at each installation met the minimum length requirements to land a C-130J.

The Haversine Formula was used to construct the network, where the distance between two points on the surface of a sphere can be calculated based on the radius of the sphere and the position of the points [45]. Modeling the network using conventional methods would first require use of the Haversine Formula to calculate all possible node lengths – a mathematically tedious operation. The instructors prompted students to use LLMs to perform the calculation, checking the output against the correct values before proceeding. Students removed node pairs separated by a distance exceeding 2200nm (the flight range of a C-130J).

The equations used for a conventional solution to the problem (and to compute the instructor-provided known values) are given below:

$$\Delta lat = latitude_2 - latitude_1 \tag{1}$$

$$\Delta long = longitude_2 - longitude_1 \tag{2}$$

$$distance = 2 \times Radius_{Earth} \times \arcsin \sqrt{\sin^2\left(\frac{\Delta lat}{2}\right) + \cos(latitude_2) \times \cos(latitude_1) \times \sin^2\left(\frac{\Delta long}{2}\right)} \tag{3}$$

This equation can be separated into distinct components to enable ease of computation:

$$a = \sin^2\left(\frac{\Delta lat}{2}\right) + \cos(latitude_2) \times \cos(latitude_1) \times \sin^2\left(\frac{\Delta long}{2}\right) \tag{4}$$

$$c = 2 \times \arcsin(a) \tag{5}$$

$$d = Radius_{Earth} \times c \tag{6}$$

The math needed to calculate these distances did not directly contribute to the lesson's objectives and was time-consuming to perform for every possible link. Performing these calculations by hand or via a programmed (i.e., student-written python script) solution for a network of just 23 nodes required computation of the length of $(23 \times 22) = 506$ different links! Demonstrating the magnitude of this challenge to the students helped reinforce the need to leverage efficient automated solutions.

LLMs such as ChatGPT 5.0 are more than capable of performing all 506 operations if the user engineers the prompt well. The in-class exercise suggested a prompt for students, reproduced from the handout in Appendix :

> "A recommendation: you can give the data to ChatGPT or other LLM to have it produce the distance from each node for you! A recommended prompt would be: "*Using this data, build me a table in .csv format that shows the distance between each location. All the rows should be each location, and each column should be each location so I can easily see the distance between any two locations in* ***nautical miles***.

The LLM produced a .csv table. "Under the hood" the LLM wrote and executed a Python script that conducted the Haversine Formula but abstracts it away from the user entirely. Table 1 includes a sample of the output from the .csv file, hereafter known as the origin-destination distance matrix (ODDM).

Table 1: Sample of initial origin-destination distance matrix

Distances, [nm]	EARECKSON AS SITE 1	EIELSON AIR FORCE BASE	ELMENDORF AFB SITE 1	Fort Greely	Fort Lewis
EARECKSON AS SITE 1	0	1375.23	1266.14	1402.57	2393.24
EIELSON AIR FORCE BASE	1375.23	0	217.74	53.85	1321.66
ELMENDORF AFB SITE 1	1266.14	217.74	0	199.58	1263.75
Fort Greely	1402.57	53.85	199.58	0	1268.2
Fort Lewis	2393.24	1321.66	1263.75	1268.2	0

After the LLM executed all 506 mathematical operations, students sorted out the links of interest and discarded the links not of interest, based on the operational range of the C-130J. Generally, the instructors observed the students used conditional formatting in Microsoft Excel to partition the links: students made links ≤ 2200 nm green, or made links > 2200 nm red. Other students sorted the links manually. Students determined that only 83 of the 506 paths were feasible. Once the students identified the feasible links, they possessed all the basic information necessary to analyze the network model. Using a LLM to assist in the computations allowed students to construct the network for a very large, real world data set during the in-class exercise and still have time for an in-depth analysis.

Network Visualization

Visualizing the network diagram makes it much easier to analyze and draw conclusions. Table 2 below shows a portion of the ODDM after conditional formatting, while useful information, it is not easy to visualize. Without preexisting knowledge of the location of each airfield relative to the others, it is difficult to truly analyze the network.

Table 2: Snippet of ODDM provided from LLM with conditional formatting to visualize routes that are acceptable given the 2200nm range constraint

Distances, [nm]	EARECKSON AS SITE 1	EIELSON AIR FORCE BASE	ELMENDORF AFB SITE 1	Fort Greely	Fort Lewis
EARECKSON AS SITE 1	0	1375.23	1266.14	1402.57	2393.24
EIELSON AIR FORCE BASE	1375.23	0	217.74	53.85	1321.66
ELMENDORF AFB SITE 1	1266.14	217.74	0	199.58	1263.75
Fort Greely	1402.57	53.85	199.58	0	1268.2
Fort Lewis	2393.24	1321.66	1263.75	1268.2	0

The students used a LLM to create high-quality visualizations. Google Earth is a free geospatial modeling program that allows users to create placemarks, routes, and other features and view them on a spherical satellite rendering of the globe instead of the flat Mercator projection [46]. Individual placemarks and routes within Google Earth are stored as a Keyhole Markup Language file (.kml). With accurate prompting, LLMs created a .kml file based on the ODDM data. This takes the product from a color-coded matrix to the visuals in Google Earth shown in Figure 4 in just a few minutes. Most importantly, it didn't require the student to learn how to construct a .kml file manually. Automating this process allowed the instructors to focus student attention on the objectives of the assignment – conducting the network analysis.

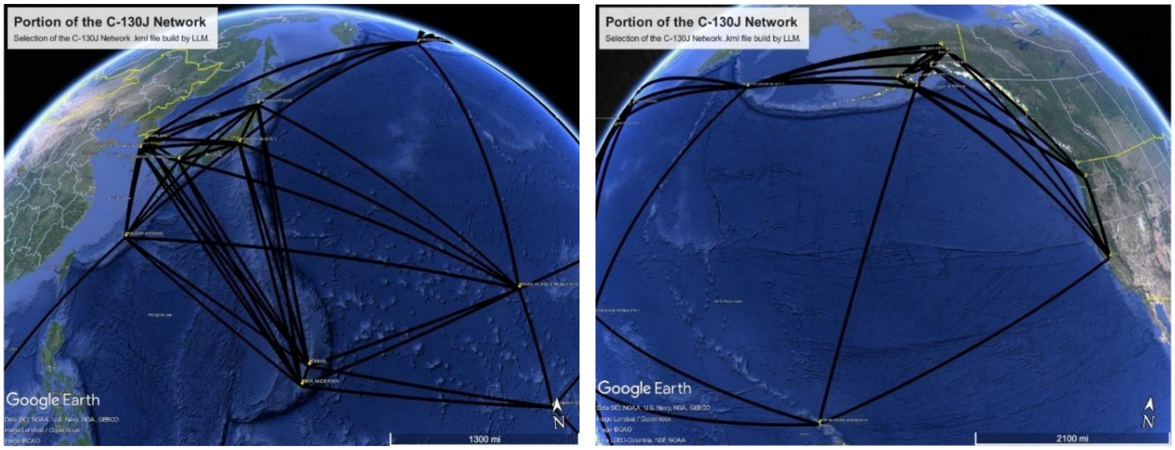

Figure 4: Portion of the C-130J Network – a) Japan, Korea, Tinian, Wake Island; b) Hawaii, Alaska, and California

However, due to time constraints, it was not feasible to clean the entire ODDM, add the latitude and longitudes, and build another table that a LLM could easily read during the short in-class exercise. Additionally, instructors found during the exercise's design that unpaid versions of LLMs did not always have the capability to complete the .kml file even if the student spent the time wrangling the data appropriately. Other research teams more knowledgeable on the use of LLMs could likely find a way to improve this step and make it more achievable for the students. The instructors coached the students on the general process and then provided the .kml file built by the instructors.

Network Analysis

Analysis of the network model was the premier objective of the exercise and where the most critical thought was expected of students. The instructors created five questions that required students to refer to both their ODDM and their Google Earth network visualization. Initially instructors planned for each group to complete each question. Due to the short class period, each group answered one question and briefed their answer to the class. Students had approximately 8-10 minutes to answer the question. This left a total of 10-12 minutes at the end of the period for each group to brief their results. The student handout with questions can be found in Appendix . Each question asked students to consider real-world events such as node failure, network expansion, hub planning, and network resilience. Each was used as an evaluation tool for the exercise's learning objective "**Analyze** a Network model to determine the real-world behavioral characteristics of a system."

Findings and Results

Assessment of Learning Objectives

The instructors assessed student knowledge of network concepts during a midterm examination administered one month after the exercise. The network test question asked students to classify a given network and identify hubs. There was not a significant change in performance (<5% difference) on the network problem between student cohorts who had experienced this version of the lesson versus previous versions of the lesson. We cannot claim any correlation between this exercise and the student's ability to answer networking problems on a test.

Survey Results

To capture the lessons learned from this exercise and the students' immediate reaction, they completed an 11-question survey at the end of the 55-minute class period. The responses were anonymous, and the students could "opt-out" if they did not want their responses analyzed. Out of 147 enrolled students, 131 responded to the survey and 109 students "opted-in" to the study.

The first five questions were 5-point Likert scale questions on the students' perception of the exercise. The Likert scale ranged from 1 = Strongly Disagree to 5 = Strongly Agree. The results are shown in Figure 5. The students had overall positive reactions to the in-class exercise. The amount of "Agree/Strongly Agree" across all answers shows that students supported the experience. 86% of students agreed or strongly agreed that they were motivated to learn from this exercise. 85% of students agreed or strongly agreed that using AI increased their ability to think creatively and take intellectual risks.

The students also provided open-ended feedback, which is shown in Table 3. The students were surprised by the LLM's ability to produce the ODDM file with distances based on the Haversine Formula and output the results in a .csv file. Furthermore, most students were unfamiliar with .kml files and did not know that LLMs could so easily map the network. The instructors heard an audible gasp from the class when they opened the .kml file on their own computers and saw the links across the Pacific Ocean. This visceral reaction from the students is consistent with their high survey response on AI inspiring future learning. One student said, "the excel data analysis is a normal use however applying it to Google Earth was new."

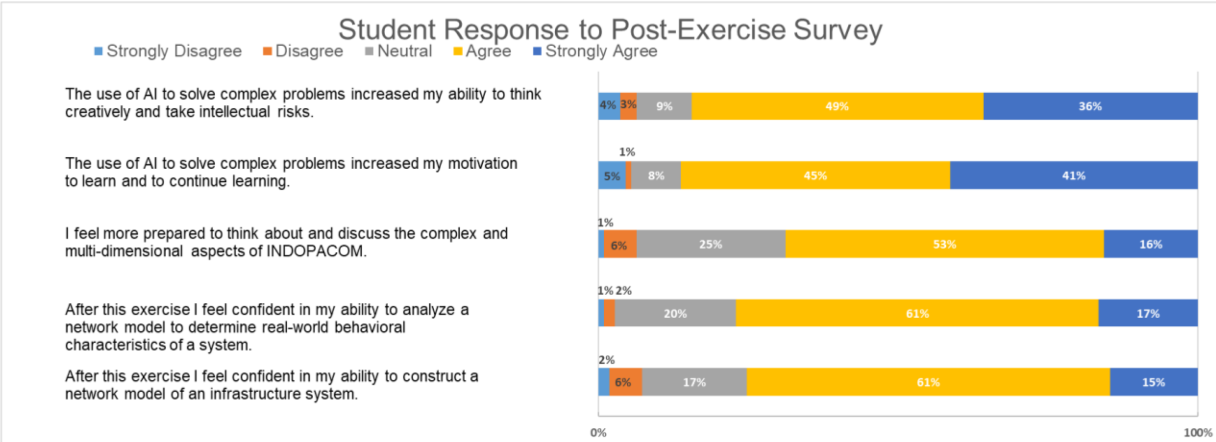

Figure 5: Post-Exercise Survey Results

Table 3: Select responses to "Please list one or more ways to improve this network analysis scenario", unedited for grammar or clarity.

Too much info for a 55 min class
There could be different areas of the world for instance the bases in Europe and the Middle East
Use microsoft copilot until chatgpt is distributed down to us.
Pre class assignment needs to have resources more easily accessible
Seeing how AI can go wrong, so how can we use critical thinking
Give more demonstration on how to prompt AI to problem solve

Instructor Feedback

The students completed the activity in small groups of four to five students with minimal interaction or guidance provided by the instructor. The instructors provided a handout containing all relevant information. The instructors took two class-wide breaks to make sure all groups were generally on track: one after approximately half of the groups created ODDM, and one after the students created or retrieved the .kml file. Individual groups completed the learning activity at different rates based on their capabilities, team dynamics, and experience. Students with previous experience with LLMs or a fully functioning paid version of an LLM completed the assignment faster and with greater ease. The instructors observed excited and surprised reactions from the students when they opened the .kml file in Google Earth. The instructors believed this "A-Ha" moment for many of them allowed them to fully understand the capabilities of a LLM in enhancing their learning. The instructors did not observe this same learning moment in previous iterations of the course either through traditional lectures or during in-class activities when the instructor provided the network diagram. Using the LLM produced the .kml files, the students assessed the network of the hubs and links in the INDOPACOM theater. This visualization tool allowed students to quickly identify the two main corridors across the Pacific, North through Alaska and South through Hawaii. They even recommended future nodes for a more robust network indicating their thorough analysis of the network model.

Limitations

The limited class time restricted the scope of the activity. The instructors allocated one 55-minute class to cover the entire assignment. Many students felt rushed. This class would be better suited over a 75-minute class or broken up into two 55-minute classes. Also, while the United States Military Academy provided students with a license for Microsoft Copilot, most students chose to use the free version or their personal paid account of ChatGPT. Many students noted the free version of ChatGPT could not produce the required .csv and .kml files due to usage quota limits. Instructors saw the same during the design of the exercise and expected this friction point. As technology improves and LLMs continue to become commoditized this will likely to be less of a problem. Additionally even the Enterprise versions of LLMs (ChatGPT and Microsoft Copilot) frequently truncated large processes to minimize compute resources used without notifying the user. For example, when creating the .kml file instructors and students would paste all 83 links and prompt for the .kml and the LLM would arbitrarily truncate the dataset and produce a smaller .kml than the full product, with no notification of the truncation. This leads to users not trusting the "black box" that LLMs can represent. When directed not to truncate the dataset users did not experience this problem, but as LLMs did not overtly warn users of the truncation it took a keen eye to recognize a need for this additional prompting.

Areas for Future work

Now that students can visualize the network, an area for future research would be to model the chance of node failure. Students understand the importance of hubs, and the susceptibility of accidental and deliberate node failure, but have not seen those variables in a real-world scenario. In the INDOPACOM theater during wartime, power failure across the island chain is a possibility. The exercise could be modified or expanded to include a stochastic simulation of power failure across the network. Since the students already have a .csv file, they could model this using a Monte-Carlo simulation in Excel.

Beyond the specific network scenario chosen here, future work should continue to utilize artificial intelligence to allow for greater depth of problem solving. This scenario was successful in the classroom because it allowed students to model a real-world network with a great number of nodes and links, but without the computational burden and repetitive coding that the LLM executed for them. Critics of artificial intelligence have suggested that it can dull the minds of students. If students are using it to get the answer that their teacher requires, it certainly may do that [47]. However, when leveraged to enable critical thought on a deeper problem, artificial intelligence can both enable and inspire students.

Conclusion

A cornerstone of the higher education model has always been to teach students problem scoping and solving techniques. Knowing how to approach and think about solving problems is often more important after graduation than a specific methodology to solve a singular problem type. When technological innovations – slide rules, digital calculators, and artificial intelligence – and the increased specialization in the workforce are considered, it becomes obvious that emphasis should be placed on teaching students how to frame problems instead of pattern matching solutions. This exercise's objectives included providing an opportunity for students to learn AI capabilities and tasking them with evaluating complex problems efficiently with AI. Both objectives directly increased student comfort with emerging technologies and honed their problem scoping abilities.

Applications of AI in education and industry will continue to expand as technology improves. This paper details just one example of an activity to improve student AI literacy and address learning objectives in a new way. It is likely that this specific problem will be able to be solved even more rapidly (skipping steps such as the ODDM production and going from initial data to .kml creation) by the time of this paper's publication. We encourage others to push students' problem scoping and solving knowledge by adding experiences that help them wrangle large and vague problems. Integration of open-source datasets can add realism and meaning to the work, while visualization tools such as Google Earth can add a level of elegance to the process that captivates attention.

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Appendix A

Student Handout

Begins on following page.

DEPARTMENT OF CIVIL AND ENVIRONMENTAL ENGINEERING
CE350: INFRASTRUCTURE ENGINEERING
IS-8: Network Modeling In-Class Example

The use of Artificial Intelligence is *authorized and encouraged* for this assignment.

Task:

You will analyze the US DOW's unclassified airfield network in the Pacific. The purpose of this assignment is to understand the constraints and multi-dimensional challenges of this operating environment at a high level. Additionally, you will make recommendations to make this network more **robust** (think: easier for the US to project power) and **resilient** (think: can absorb or mitigate hazards while providing essential services).

The source document for this assignment is the FY2025 Base Structure Report (BSR). This is provided to congress and other *stakeholders* annually by the US DOW Office of the Assistant Secretary of War for Energy, Installations, and Environment. To expedite your work, the FY2025 BSR has been trimmed. The spreadsheet you've been given is a simplified version of this document that we want you to utilize for this assignment.

A critical logistical concern for the INDOPACOM theater is Air Mobility Command's (AMC) ability to support cargo and troop movements throughout the theater. The Air Force uses 3 main airframes for this: the C-130, the C-17, and the C-5. The C-5 and C-17 have in-flight refueling capabilities and thus literally "global" range. These airframes are used largely for inter-theater travel: think from CONUS to Japan, or Germany for instance. The C-130J is smaller and better serves intra-theater travel. An example would be flying from Fort Bliss, TX to Fort Benning, GA. The C-130J can travel further than the below range but requires additional fuel tanks and may have a reduced payload.

The vast distances in the INDOPACOM theater constrain air mobility via C-130J. Use the resources and assumptions below to answer the following questions regarding the logistical support network for allied aviation assets in USINDOPACOM.

Resources:

- FY2025 BSR- On Canvas → Modules → IS-8
- Map of All Airports (ARCGIS View) – unofficial, data collated by Reddit User from https://ourairports.com/world.html
- This document (digitally with live hyperlinks on Canvas)

Assumptions:

C-130J flight range: 1800 nautical miles with normal payload Source. *However,* ***we will assume for this assignment that the C-130J can travel 2200 nautical miles***. Source*.* This assumption can be made if we place cargo restrictions on flight routes, among other things. Standard C-130Js have *no inflight refueling capability.*

Required Runway C-130J: Appx 1000m for takeoff and landing

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<u>Instructions</u>:

1. Download Google Earth Pro OR use the web browser version. **The full download will be better** to use in this assignment.
    a. Download
    b. Web Browser
2. Open the FY2025 BSR saved in the Canvas Module for this lesson. The full spreadsheet (amber tab) has over 1600 locations worldwide! You can see some interesting data as well: total buildings by site, total acreage, and (most interestingly) the estimated replacement value of the site. **Orient yourself to the green tab**, note it only has 23 nodes. The far-right columns are the latitude and longitude of the airfield at each site.
3. Construct the network using just the locations/nodes in that excel file.
    a. **For a C-130J link to exist it must be less than 2200 nautical miles**.
    b. A recommendation: you can give the data to ChatGPT or other LLM to have it produce the distance from each node for you! A recommended prompt would be: "*Using this data, build me a table in .csv format that shows the distance between each location. All the rows should be each location, and each column should be each location so I can easily see the distance between any two locations in **nautical miles**.*
    c. The output will give you a long text string of comma separated values. Save these in notepad as **<u>Distances.csv</u>** and then go open that file with Microsoft Excel. You should see a table where the diagonal will all be zero (distance from node A to node A is zero) and distances from node to node otherwise. **ChatGPT Pro** may output the file in .csv for you, saving you a step.
    d. You can eliminate routes from your network that have greater than 2200 nm separating them. An example with conditional formatting would look like this:

Distances, [nm]	EARECKS(	EIELSON A	ELMENDO	Fort Greel	Fort Lewis	Fort Wain	JBPHH PEA
EARECKSON AS SITE 1	0	1375.23	1266.14	1402.57	2393.24	1364.81	2282.56
EIELSON AIR FORCE BASE	1375.23	0	217.74	53.85	1321.66	16.72	2637.48
ELMENDORF AFB SITE 1	1266.14	217.74	0	199.58	1263.75	223.28	2421.21
Fort Greely	1402.57	53.85	199.58	0	1268.2	70.4	2608.49
Fort Lewis	2393.24	1321.66	1263.75	1268.2	0	1338.36	2310.94
Fort Wainwright	1364.81	16.72	223.28	70.4	1338.36	0	2644.24
JBPHH PEARL HARBOR HI	2282.56	2637.48	2421.21	2608.49	2310.94	2644.24	0

Figure 6: Example table (partial) after opening Distances.csv in excel and applying conditional formatting to values ≤ 2200 nm

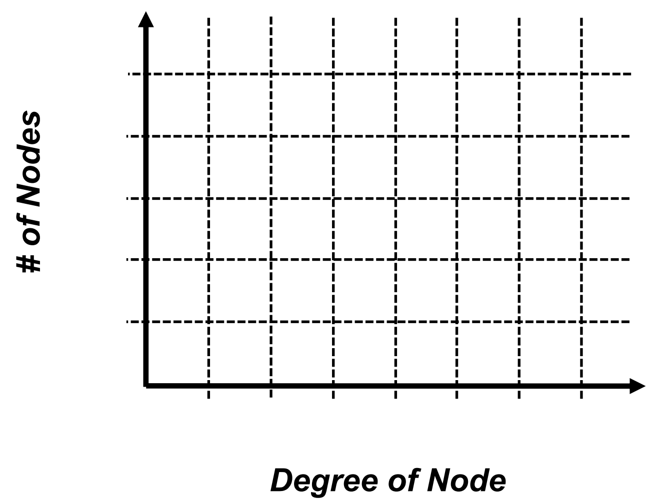
Now you can begin to answer the questions below.

DEPARTMENT OF CIVIL AND ENVIRONMENTAL ENGINEERING
CE350: INFRASTRUCTURE ENGINEERING
IS-8: Network Modeling In-Class Example

Questions: (write answers on board)

1. Classification: What is the degree of node of each of the nodes in your network? Build a table in MS Excel to calculate this. A quick way to do this is to write a COUNTIF formula for each column of your Distances.csv table. Hint: Don’t forget to address the diagonal in that calculation somehow!

2. Classification: Graph your network in Excel or below and classify it based on the distribution.



3. At this point it would be helpful to map your network (remember, only paths less than or equal to 2200nm are feasible links) in Google Earth to visualize it. Begin creating a framework for the network in excel.
   a. Format each link with six columns: From, To, Start_Lat, Start_Long, End_Lat, End_ Long. The Lat/Longs now need to be in the **decimal degree** format (on the FY2025 BSR file). Notify your instructor **when you complete three links that connect to Eareckson Station in Excel**.
      i. Practically, you could continue this procedure for all 80+ and then paste all this information into a LLM (ChatGPT or similar) and direct it to create a .kml file that you can use in Google Earth. For time purposes, we are going to provide that file to you.
      ii. There are also ways to use MS Excel and manipulate the Distances table into making this list for you, you’re encouraged to experiment with techniques to do that.

4. In Canvas, download and open in Google Earth **IS-8 AY26-1 Cadet.kml**. This file contains all nodes and all 80+ viable links given the 2200nm constraint. **It was built entirely via ChatGPT with natural language prompting!**

5. Remember, the C-130J can travel much further than 2200nm, but the base planning range we are using is 2200nm. Reference this example of one C-130J flying from Texas to Guam. Given this, which of the selected nodes would you recommend C-130Js use as a *hub* during operations in the INDOPACOM theater? Name no more than 2 nodes. Consider available life support facilities and weather patterns.

6. Where are there areas to make this network more robust? Using the Map of All Airports, pick three airfields that you would prioritize for becoming nodes (via lease or other agreement) to support C-130J traffic and add robustness to the airfield network in INDOPACOM. You can include airports that are not “C-130J ready” (need longer runways or are out of operation) but for operational security and ease of operations avoid major metropolitan commercial airports (Haneda and Narita International Airports in Tokyo would be poor examples). **Give special consideration to FVEY nations’ existing air force bases or other nation’s bases that the US has an episodic presence at**. You can find a map showing some of these sites (not all inclusive) in Figure 2 of US Defense Infrastructure in the Indo-Pacific: Background and Issues for Congress, a report prepared by the Congressional Research Service in June 2023. **Do not include any other airports in the state of Hawaii.**
    a. New Node:______________________ Currently operational?________
        i. Connects to (within 2200nm of what other nodes?)

    b. New Node: ______________________ Currently operational?________
        i. Connects to (within 2200nm of what other nodes?)

    c. New Node: ______________________ Currently operational?________
        i. Connects to (within 2200nm of what other nodes?)

7. How many nautical miles is the trip from Wake Island to Travis AFB via JBPHH? Now, assume JBPHH/other Hawaii options are removed for the network. How many nautical miles is the trip from Wake Island to Travis AFB via Eareckson and Joint Base Elmendorf-Richardson (JBER)? If JBPHH/other Hawaii options are out of service, could Henderson Field at Midway Atoll substitute if life support facilities were upgraded?

8. There are two C-130s at Tainan Airbase in Taiwan in the photo on Google Earth, repasted below. Perhaps the United States or allies intend to sell additional C-130Js to Taiwan and need to land at Tainan Airport. What nodes in your network are within the 2200nm range? Does the island of Tinian provide access that Wake Island does not in this scenario? Check this article out to help you understand the work ongoing at Tinian.

Figure 7: C-130s at Tainan Airbase (Google Earth, Snippet taken 17 AUG 2025)

9. What do the nodes in Alaska provide to this network? Specifically, Eareckson station or other potential nodes in the Aleutian Island chain.