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B2 OVERHEAD LINES
PS1 Application of Technologies, Information Technology (IT) and Artificial Intelligence (AI)

Artificial Intelligence (AI) Driven Knowledge Management for Sustained Expertise in Electrical Transmission Line Engineering

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SUMMARY

The paper addresses the critical issue of knowledge management in electrical transmission line engineering, emphasizing the challenges posed by an aging workforce and the increasing complexity of power systems. It explores how Artificial Intelligence (AI), particularly Large Language Models (LLMs), can be leveraged to capture, synthesize, and disseminate complex technical knowledge. The authors propose an AI-driven knowledge management system and evaluate its capabilities using the Gemma 27B model. The evaluation involves training the model with CIGRE B2 brochures and assessing its performance in answering questions of varying difficulty levels, simulating early, mid, and senior-career engineers. The results demonstrate that the AI model, post-training, exhibits a significant improvement in providing detailed, accurate, and practically applicable information, highlighting its potential to enhance knowledge sharing and decision-making in the power system industry.

KEYWORDS

Electrical engineering, Transmission Line Engineering, Knowledge management, Artificial Intelligence, AI, Large Language Model, LLM, Knowledge transfer

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1 Introduction

The electrical grid is often called "the most complicated machine we have ever built" [1]. While this may sound like a general statement, it effectively captures the critical importance of the electricity system in the 21st century. The power grid forms the backbone of modern civilization, comprising a vast, interconnected network of power generation, transmission, and distribution systems.

At the heart of this infrastructure lies the transmission line system. The design, construction, operation, and maintenance of transmission lines are highly complex and demanding tasks, essential to ensuring the reliable delivery of electric power [2]. Much of today's power system infrastructure was initially constructed during the 20th century, providing a strong foundation for current operations. However, the increasing age of these assets, coupled with new operational challenges, raises several pressing questions:

- What specific knowledge is necessary to operate, upgrade, and sustain the grid?
- Will there be a sufficient number of designers, operators, and linemen to meet future demands?
- How can the industry best preserve and access its accumulated expertise?
- What have been the most effective knowledge management practices in the past, and how might they evolve in the future?

Even the operation of power lines, which at first glance appears as a purely technical task, demands a vast range of interdisciplinary expertise [3]. Transmission line engineering in this context extends beyond traditional engineering education, encompassing electrical, mechanical, civil, structural, and material sciences, while also involving specialists such as foresters, legal advisors, economists, and public relations experts [3]. Similar complex systems have already been built, pushing humanity to recognize the need for systematic knowledge management. Early historical examples include the book collections of Mesopotamia around 2500 BC, the libraries of ancient Greece, and the famed Library of Alexandria, each highlighting the timeless importance of gathering, preserving, and transmitting knowledge (Figure 1) [4].

Figure 1 – Knowledge management in the past: Books from ancient Mesopotamia (left) [5]; Library of Alexandria (right) [6]

The modern era introduced new possibilities. The development of expert systems during the early computer age sought to capture and automate expertise. Today, advances in Artificial

Intelligence - particularly the rise of Large Language Models - offer powerful tools for capturing, synthesizing, and disseminating complex technical knowledge in dynamic and accessible ways. The questions are when and how we can exploit these technical opportunities.

1.1 The Aging Workforce in High-Voltage Engineering

Knowledge continuity has become a critical priority in power engineering. Two key facts highlight the urgency:

- In the United States, 31% of service engineers are over 55. As these professionals retire, the risk of losing specialized expertise grows rapidly, particularly in high-voltage engineering [6].
- A global survey of 17,000 energy professionals found that 46% identified the aging workforce and skill shortages as the industry's most pressing issue, with particular concern in the United Kingdom [8].

The sector faces a dual challenge: an aging workforce and a hiring gap. Knowledge in power line engineering is traditionally gained through decades of hands-on experience, often under the mentorship of senior professionals [9]. Much of this expertise remains undocumented, residing informally in individuals' experience rather than structured manuals or databases. This creates a serious risk: transmission lines, designed to operate for over 50 years, often outlast a single professional career. Without systematic transfer, essential knowledge about system details, operational challenges, and specific solutions risks being lost. Workforce mobility - whether from retirement or changing roles - further accelerates knowledge erosion. Additionally, regions like North America experienced limited hiring during the 1980s and 1990s, creating generational gaps within the electrical industry. Similar trends have been observed globally.

Without proactive knowledge management, the loss of essential skills is inevitable. The question is how industry can deploy scalable, efficient solutions to safeguard its technical legacy and prepare for the future.

1.2 Knowledge Management: From Future Challenge to Present Need

In response to the growing knowledge, some companies have developed structured programs to capture the expertise of departing employees, even employing oral historians to preserve critical information [9]. This highlights the need for a systematic approach to Knowledge Management (KM). Knowledge Management is the structured process of creating, organizing, sharing, and utilizing knowledge to achieve organizational goals, improve decision-making, and enhance performance. In electrical transmission lines, this knowledge includes a broad spectrum of specialized expertise, which can be broadly categorized, as shown in Figure 2.

In essence, knowledge in transmission line engineering is a dynamic mix of theoretical understanding, practical experience, and operational expertise. Continuous learning, adaptation to new technologies, and evolving regulatory frameworks are vital for ensuring grid effectiveness and sustainability. Capturing and effectively using this wide range of knowledge is essential for maintaining continuity, improving operational performance, and enhancing grid reliability. While knowledge management concepts and computer-based systems were explored decades ago, the electrical utility sector has yet to adopt a practical, scalable solution widely.

Figure 2 – Types of knowledge in power line engineering

One of the main challenges in establishing a classical knowledge management system in the power industry is the lack of properly documented knowledge. There is often a significant gap between field experience and what is formally recorded in this field. Much of the critical expertise resides with individuals rather than within company-owned resources, making it vulnerable to loss. Additionally, this knowledge is sensitive and cannot be shared on public or unsecured platforms. Therefore, new, adaptive solutions are required - approaches that not only address the technical aspects but also capture the broad spectrum of knowledge types essential for the sustainable operation of the electrical grid. Such systems must prioritize security, accessibility, and the practical realities of knowledge creation and transfer within the industry.

2 Proposed Solution: AI-driven Knowledge Retention

Over the last decade, Artificial Intelligence-based (AI-based) solutions have become key in applying complex, adaptive systems [10]. AI is the simulation of human intelligence in machines programmed to perform tasks typically requiring human cognition. These tasks include learning, reasoning, problem-solving, perception, understanding natural language, and decision-making. AI systems are designed to analyze data, recognize patterns, and make predictions or decisions with varying degrees of autonomy [10]. A critical representation of this could be the AI-based knowledge management system.

2.1 AI-driven solutions in High Voltage Engineering

Although the power system industry is a rather conservative sector, AI-supported solutions have already appeared, even in the Community of CIGRE B2. CIGRE Working Group B2.93 was established to address the emerging challenges and opportunities related to using Artificial Intelligence (AI) for power line asset management, focusing on transmission lines (Figure 3) [11]. Its core mission is to explore, evaluate, and promote AI-based methods to enhance overhead line inspection, maintenance, and operational efficiency. The group was formed in response to the increasing complexity of transmission systems, the aging workforce, and the growing demand for smarter, more resilient grid operations. A key goal is to provide a structured framework for integrating AI technologies into asset management practices, such as image recognition, machine learning, and data analytics.

Figure 3 – AI-augmented power line diagnostic system from North America [12]

Such working groups show a growing interest in using applied AI models and exploiting the opportunities offered by technology in high-voltage and power systems.

2.2 Large Language Models in Technical Fields

The rapid advancement of Artificial Intelligence (AI), particularly in Large Language Models (LLMs) and multimodal systems, presents transformative opportunities for addressing key challenges in the power industry, especially those related to knowledge management. These technologies enable the seamless integration of textual, visual, and contextual data into unified frameworks capable of capturing and organizing intricate, domain-specific knowledge with greater precision and efficiency [10]. Due to their natural capabilities, LLMs can support employees by assisting with technical inquiries, enhancing decision-making, and serving as robust platforms for managing and distributing knowledge across organizations.

However, significant challenges remain. One primary concern is the sensitive nature of utility-specific knowledge, which often cannot be made public. This precludes the straightforward use of publicly available AI platforms trained on proprietary data. A practical solution must include a secure, multi-layered system that protects access and knowledge. Furthermore, while LLMs have reached impressive levels of capability, they have not achieved general intelligence and therefore cannot fully replace human expertise. Nevertheless, an AI-augmented knowledge management system could be a powerful extension of human capability, functioning as a fast, accessible technical library. Although an AI solution will not replace engineers at this stage, it can substantially improve knowledge sharing, support better decision-making, and strengthen operational resilience across the power system industry.

3 Methodology

A technical topic was first chosen to demonstrate the LLM model's capabilities. Line uprating, specifically the transition from Aluminum Conductor Steel Reinforced (ASCR) to High-Temperature Low-Sag (HTLS) conductors, is a widely adopted practice globally [13]. This transition is essential for enhancing the capacity and efficiency of existing transmission lines.

However, practical experience with HTLS conductors varies by region, with Central Europe frequently conducting evaluation projects to assess their viability.

3.1 Input Data Preparation and Concept

To ensure a comprehensive understanding of the topic, a set of transmission line knowledge shall be collected in the field of HTLS conductors. At this stage of the demonstration only written materials were used. To have adequate and replicable AI training, the CIGRE B2 committee's published brochures (5 pieces) were selected as the primary data set. These brochures are recognized for their reliable and technically sound information, making them an ideal source for training the AI model. These documents were chosen based on the availability of appropriate transmission line knowledge. An additional criterion was that the AI model had not been previously trained with this data set, ensuring unbiased learning.

The concept of the demonstration has 3 main steps as follows.

- **Initial Evaluation (pre-training):**
  - Questions were formulated based on the content of the selected brochures.
  - The AI model, untrained on the specific data set, was asked these questions, and the responses were recorded.
- **AI Training:**
  - The AI model was trained using the CIGRE B2 brochures, which were input as text-searchable PDF files.
  - This training aimed to enhance the AI's knowledge of the domain, enabling it to provide more accurate and informed responses.
- **Post-Training Evaluation:**
  - The same set of questions was asked again after the AI had been trained with the brochures.
  - The responses were compared to those given before the training to assess the improvement in the AI's knowledge and understanding.

This kind of demonstration can highlight the AI's ability to learn from the input data and formulate knowledge based on that input. This process underscored the importance of providing accurate and truthful information for AI training.

3.2 Applied AI model and infrastructure

The Gemma 27B model was selected for this project's Artificial Intelligence testing [14][15]. This decision was made following the introduction of Gemma 3 on March 12, 2025, as it represents a significant leap forward in open-weight large language models. Boasting 27 billion parameters, Gemma 3 builds upon the research and technology of the Gemini models, achieving state-of-the-art performance across numerous benchmarks [16]. A key advancement is its enhanced multimodality, allowing it to process text and image inputs and generate text outputs. Furthermore, the larger versions feature an expanded context window of up to 128,000 tokens, enabling the processing of longer documents and more complex reasoning tasks. With support for over 140 languages, Gemma 3's robust multilingual capabilities make it a versatile tool for a wide range of global applications, including text generation, image understanding, and multimodal reasoning [14][16].

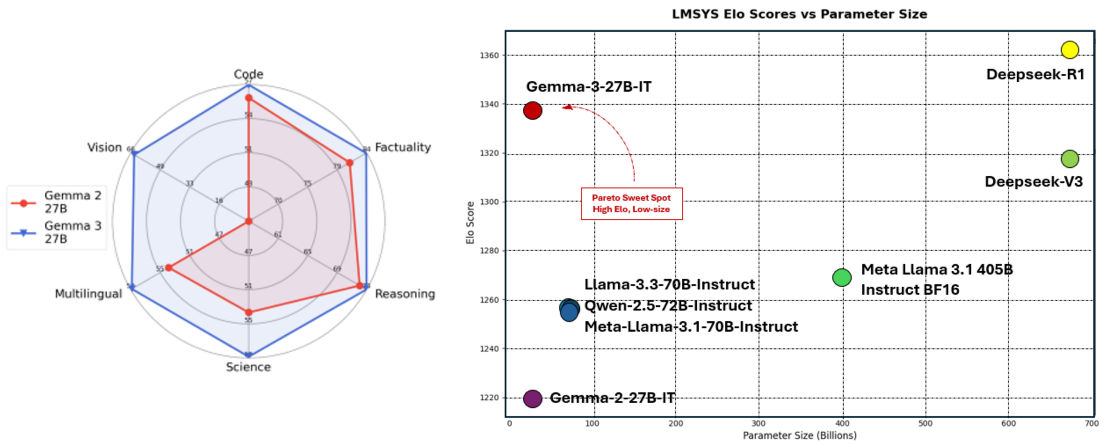

Figure 4 – Summary of the performance of different pre-trained models from Gemma 2 and 3 across general abilities (left); Gemma 3 27B is in the Pareto sweet spot (right) [14]

It is worth mentioning that the Gemma 3 model has a high Elo score while using less than 50 billion parameters (Figure 4). Adapted from chess, the Elo score ranks models by their relative performance in AI evaluation. It is calculated from pairwise comparisons, where models "compete" against each other. A higher Elo score indicates a stronger model, and the system updates scores dynamically as new comparisons are made, providing an evolving measure of model performance. The interface for interacting with the model is text-based. In this mode of communication, all input is in the form of typed text, and all responses are generated as text. This allows for a direct and focused exchange of information through written language.

Gemma 3 can also run on a powerful personal computer. Thus, the system can operate independently from the Internet and can be fully secured for privacy, data protection, and physical security reasons. A desktop computer was used for the AI evaluation with the following characteristics:

- Operating System: Microsoft Windows 10 Professional, System type x-64,
- Processor: AMD Ryzen, Threadripper, 2920X, 12 Core processor, 3500 MHz, 12 Cores, 24 Logical processors, 24 Logical Processors
- Physical Memory (RAM): 64 GB
- Two NVIDIA GeForce RTX 2080 Ti (with 11 GB of Graphical Memory) Graphics cards

3.3 Evaluation framework

The evaluation concept involves designing questions across three technical levels to test the model's understanding. The model is assessed both before and after domain-specific training. The responses are then systematically evaluated to measure accuracy, depth, and technical relevance improvements. We will simulate three distinct groups of electrical engineers based on their experience levels (Table 1):

- Early-career engineers (1-3 years of experience)

- Mid-career engineers (4-10 years of experience)
- Senior engineers (10+ years of experience)

Each group faces questions tailored to their expected knowledge and expertise. By structuring the evaluation this way, we can determine how well the AI performs in simulating knowledge retention, reasoning, and decision-making at various levels of professional development.

***Table 1* – Example questions raised to the AI model in the evaluation phase**

Group type	Experience	Question
Early-career engineer	1-3 years	Q1 - What are the benefits of using high-temperature low-sag (HTLS) conductors in line uprating?
Mid-career engineer	4-9 years	Q2 - How do different HTLS conductor types compare in terms of thermal expansion and sag performance?
Senior engineer	10+ years	Q3 - How do long-term aging effects (e.g., creep, fatigue, oxidation) influence the reliability of HTLS conductors in high-voltage power lines?

Analyzing the AI model performance for these dedicated Groups raises several benefits in the evaluation phase:

- Realistic Benchmarking: The AI's performance can be compared against typical human responses at different career stages, clearly assessing strengths and gaps.
- Progressive Difficulty: By structuring questions according to experience, we ensure that the AI's reasoning is tested in foundational and advanced knowledge areas.
- Practical Application: Engineers at different levels contribute differently to projects. Testing across experience groups helps determine if the AI can provide valuable insights for junior engineers learning the field and senior engineers making strategic decisions.

4 Results

The operation of the Gemma 3 27B LLM AI model was analyzed in 11 questions, for which the model produced nearly 40-45 pages of response documents both before and after training. This chapter presents the results for only one selected question from each category (Table 1).

4.1 Pre-Training vs Post-Training AI Performance

The model provided technically correct answers for the early-career engineer question (Q1) as presented in Table 2. It shows that the post-trained model provided more technical details and specific information than the pre-trained model. The most significant differences are listed below.

Cost-Effectiveness: The pre-trained model generally mentioned that using HTLS conductors is cheaper than building new lines. The post-trained model explained specific cost savings, such as replacing old conductors, upgrading insulators, and making minor hardware adjustments.

Reduced Sag: The pre-trained model generally mentioned that HTLS conductors have lower sag at higher temperatures. The post-trained model explained in detail how the materials and construction techniques of HTLS conductors minimize thermal expansion and why reducing sag is essential for maintaining ground clearance.

System Reliability: The pre-trained model mentioned that HTLS conductors increase grid reliability. The post-trained model provided detailed explanations of how HTLS conductors reduce line losses and increase system capacity, improving the handling of peak loads and integrating renewable energy sources.

Environmental Benefits: The pre-trained model detailed that HTLS conductors are more environmentally friendly than building new lines. The post-trained model explained how HTLS conductor installations reduce land impact, energy consumption, and carbon emissions.

Types of HTLS Conductors: The pre-trained model listed some HTLS conductors.

The post-trained model provided detailed descriptions of specific HTLS conductor types, such as ACSS, ACCR, and ACPR, and their characteristics.

Limitations and Considerations: The pre-trained model mentioned compatibility and temperature issues. The post-trained model explained insulator and hardware compatibility issues, sag calculations, and the thermal impact on nearby lines.

Table 2* – *LLM AI model answers for Q1 - What are the benefits of using high-temperature low-sag (HTLS) conductors in line uprating?

Pre-training	Post training
The model provided a broad overview of the benefits of using HTLS conductors for line uprating, highlighting key advantages such as increased ampacity, reduced sag, cost-effectiveness, and environmental benefits. It offered a good introduction to the topic but lacked detailed technical explanations and specific examples.	The model offered a more comprehensive and detailed analysis of HTLS conductors, including specific cost-saving measures, technical aspects of reduced sag, and detailed descriptions of different types of HTLS conductors. It provided a deeper understanding of the subject, making it more informative for those seeking technical insights.

Due to the paper's length constraints, a detailed explanation of the models is not provided here for the mid-career and senior engineer questions (Q2 and Q3).

For Q2, the pre-trained model provided a detailed comparison of HTLS conductor types, focusing on their thermal expansion and sag performance. It explained key concepts such as CTE, creep, and sag performance, and offers a comprehensive analysis of ACCC, ACSS, and INVAR conductors, including their advantages and disadvantages. The post-trained model also thoroughly compared HTLS conductor types, emphasizing their thermal expansion, sag performance, and creep rate. It provided specific details about the materials and construction of ACCC, ACSS, and INVAR conductors, and includes a summary table for easy reference. While both answers were technically detailed, the post-trained model provided a more structured and concise summary, making it easier to compare the conductor types at a glance. Pre-trained model offered a broader explanation of key concepts, which can help understand the technical nuances.

For Q3, the pre-trained model provided a broader explanation of key concepts and a comprehensive analysis of conductor types, including advantages and disadvantages.

The post-trained model offered a more structured and concise summary, with specific numerical values and a focus on the direct impacts of thermal expansion and sag performance. It included practical considerations for choosing the right conductor. Both answers are technically detailed, but the post-trained one focused more on providing actionable insights and a clear comparison, making it easier to understand the differences between conductor types briefly.

4.2 Early, Mid, and Professional-Level Answer Comparison

Based on the analysis of the result, the pre-trained and post-trained models provided, the following experiences are worth noting.

Improvement in Detail and Specificity:

- Early-career level: The difference between the pre-trained and post-trained models is the most pronounced. The post-trained model provides significantly more detailed and specific information than the more general overview in the pre-trained model. This suggests that the AI model's training greatly enhanced its ability to provide comprehensive and technically detailed responses.
- Mid-career level: Both answers are detailed, but the post-trained model is more structured and concise, making it easier to compare conductor types. The improvement here is in the clarity and organization of the information.
- Senior Level: Both answers are thorough, but the post-trained model offers a more structured approach to mitigation strategies and practical steps for monitoring and maintenance. The improvement is in the practical application and actionable insights provided.

Depth of Technical Understanding: The training appears to have significantly improved the AI model's depth of technical understanding. The post-trained model in all three questions demonstrates a better grasp of technical concepts and can explain them in more detail and with greater nuance.

Practical Application and Recommendations: The AI model provided more useful recommendations and actionable insights after training. This is particularly evident in the Senior-Level answers, where the post-trained model emphasizes practical steps for monitoring and maintenance. However, it is recommended that an expert check the quality of the answers.

Clarity and Organization: The trained AI (post-trained) model consistently provides more structured and organized responses. This makes the information easier to understand and compare, which is crucial for technical decision-making.

Adaptation to Audience: The trained AI model seems better at tailoring its responses to the expected knowledge level of the audience. For example, in the early-level engineer question, the post-trained model provided a more comprehensive introduction to the topic, suitable for less experienced engineers. The training has significantly enhanced the AI model's ability to provide detailed, specific, and practically useful information. The improvements are most noticeable at the Early Level, where the difference in detail and specificity is most significant.

Still, they are also evident at the mid and senior levels regarding clarity, organization, and practical recommendations.

5 Conclusion

Based on the project summarized in this paper, the developed and evaluated AI-augmented knowledge management system effectively addresses many transmission line knowledge management challenges. The evaluation proves the system is capable, robust, secure, and user-friendly. The authors suggest that the results encourage and support expanding the system for specific knowledge areas within transmission lines, like transmission structures, hardware, and system operation.

Bibliography

[1] Western Confluence. The Most Complicated Machine Ever Built [Internet]. 2017 Mar 21 [cited 2025 May 4]. Available from: https://westernconfluence.org/the-most-complicated-machine-ever-built/

[2] Farzaneh M, Farokhi S, Chisholm WA. Electrical design of overhead power transmission lines. McGraw-Hill Education; 2013.

[3] International Council on Large Electric Systems (CIGRE). CIGRE Green Books: Overhead Lines. Springer Nature; 2017. ISBN: 978-3-319-31746-5.

[4] Casson L. Libraries in the Ancient World. Yale University Press; 2001.

[5] Research Outreach. Investigating the healing arts of ancient Mesopotamia [Internet]. Available from: https://researchoutreach.org/articles/investigating-healing-arts-ancient-mesopotamia/

[6] Encyclopaedia Britannica. Library of Alexandria [Internet]. Available from: https://www.britannica.com/topic/Library-of-Alexandria

[7] Korra. The Economic Impact of Knowledge Loss Due to an Aging Workforce in Industrial Companies and How AI Can Mitigate It [Internet]. Available from: https://korra.ai/economic-impact-of-knowledge-loss/

[8] Brunel International N.V. ENERGY OUTLOOK 2023 REPORT [Internet]. Available from: https://hiring.energyjobsearch.com/Resources/energy-outlook-report

[9] CIGRE Working Group B2.39. Management guidelines for balancing in-house and outsourced overhead transmission line technical expertise. CIGRE Technical Brochure No. 744. Paris: CIGRE; 2018 Sep.

[10] Thakur K, Barker H, Pathan ASK. Artificial intelligence and large language models. 1st ed. Boca Raton (FL): CRC Press; 2024.

[11] CIGRE Working Group B2.93. Artificial Intelligence (AI) Augmented Image-Based Transmission Line Inspection and Condition Assessment TOR CIGRE; 2024

[12] Toth J, et al. Artificial Intelligence (AI) Augmented Transmission Line Inspection. Cigre Session Paris; 2020. Report No.: B2-117.

[13] Working Group B2.12. Conductors for the Uprating of Overhead Lines. WG B2-12 “Conductors for the Uprating of Overhead Lines”; 2003 Nov 1.

[14] Gemma Team. Gemma 3 technical report. arXiv [Preprint]. 2025. Available from: https://arxiv.org/pdf/2503.19786v1

[15] Google AI for Developers. Gemma 3 model overview [Internet]. 2025 [cited 2025 Apr 28]. Available from: https://ai.google.dev/gemma/docs/core

[16] Hugging Face. Welcome Gemma 3: Google's all new multimodal, multilingual, long context open LLM [Internet]. 2025 [cited 2025 Apr 28]. Available from: https://huggingface.co/blog/gemma