Application of Fine-Tuned Natural Language Processing AI Model for Plant Engineering: Utilizing In-House Technical Specifications

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1. Introduction

In a global economy dominated by major corporations, the need to manage extensive and complex technical specifications or company standard documents is increasingly becoming a pressing concern. This is also evident in large-scale endeavors such as nuclear power plant projects, where the intricacy of the engineering design, regulatory compliance, safety protocols, and operational procedures add layers of complexity. The magnitude and complexity of nuclear power plant projects exemplify the need for precise coordination and an understanding of multifaceted technical details, thereby making the management of technical documentation even more critical. This need arises from the fact that these corporations often house vast pools of technical knowledge, a significant portion of which is typically tied to specific individuals. Consequently, onboarding new hires can be a lengthy process as they need to assimilate this complex and specialized knowledge. Additionally, when key personnel have left the company, these companies face the risk of potential knowledge loss. Addressing these challenges, therefore, necessitates innovative solutions that can streamline the knowledge acquisition process and minimize the risk of losing essential expertise. This paper proposes an approach to these challenges by harnessing the capabilities of an AI model fine-tuned with in-house technical specifications or standards. It is an interactive interface service with Natural Language Processing (NLP) Artificial Intelligence (AI) models, making technical knowledge easily accessible in the form of a question-and-answer (Q&A).

2. Background

As corporations continue to evolve and expand their operations, the volume and complexity of their technical specifications or standard documents naturally increase. Especially in sectors like nuclear power plant projects, where the stakes are high and the documentation is exceptionally intricate due to safety and regulatory concerns, this escalation creates a series of challenges regarding knowledge management within these corporations. Thus, a systematic and efficient method of managing, accessing, and sharing this increasing body of knowledge within the organization becomes critical. Natural Language Processing (NLP), a subfield of artificial intelligence (AI) that endows machines with the ability to understand, interpret, and generate human language, offers a promising solution to this challenge. Natural Language Processing (NLP) has not only evolved as a theoretical concept but has also seen practical applications in diverse industries. For instance, the automation of construction specification review through the application of NLP techniques has been previously studied and proven to be effective [1]. This advancement underscores the possibility of using NLP for automating complex tasks such as the management and interpretation of intricate technical specifications. In line with this previous work, this study extends the utilization of NLP in the corporate context, aiming to make company standard documents easily accessible and understandable, not just for specialists but also for newcomers to the field. By building upon existing research, this study contributes a fresh perspective and a practical solution to the urgent need for efficient knowledge management within large corporations. One of the practical applications of NLP in recent years has been the development of chat-based AI models such as 'ChatGPT', designed to interact with humans in a natural, conversational manner. The general usage of ChatGPT involves receiving answers to questions based on pre-training data up to the knowledge cut-off date. However, by fine-tuning the AI model with company-specific technical documents, it can morph into a valuable tool for managing internal knowledge. Fine-tuning, in the context of machine learning, is a process where a pre-trained model, in this case GPT-3, is further trained on a specific dataset to improve its performance for a specific task.

3. Methods and Results

3.1. Methods

3.1.1. Data Collection

The proposed methodology employed in this study entails several distinct steps designed to leverage the full capabilities of a GPT-3 model trained on technical specifications obtained from three hypothetical companies. These companies, anonymized and referred to as AAA, BBB, and CCC, provided a basis for the dataset needed for fine-tuning the model, ensuring that the identities and sensitive data are well protected. For the clarity and simplicity of the research process, the most widely known 'pressure vessel' item was selected. The technical specifications gathered cover topics and disciplines too broad to be comprehensively covered in this single study. Consequently, a selective focus was applied to distill the information into a manageable amount. Four (4) themes; welding seam, corrosion allowance, anchor bolt, positive material identification (PMI), were chosen for structuring the information into a Q&A format dataset.

3.1.2. Data Preparation and Execution

The raw specifications were then transformed manually into a prompt-completion set, a process that entailed the careful extraction and reformulation of complex technical details into a digestible Q&A format that the GPT-3 model could learn from. If further automation of this process becomes technically possible in the future, even greater possibilities are expected. This could render the transformation process more efficient, for example by allowing raw specification native files to serve as direct input. Such a development could potentially streamline the entire procedure, subsequently enhancing the model's performance substantially. To ensure the fine-tuning process as effective as possible, the training data was enriched through a variety of methods. This includes processes such as the use of Synonym replacement, Paraphrasing, Re-structuring, Feedback and Back translation methods. This strategy, which aimed to diversify the dataset and enhance its representativeness, could be supplemented in future applications with feedback from experienced engineers and users, who could offer valuable insights to improve the model's response to previously unanswered or vaguely answered questions. The technical steps for fine-tuning include Python coding, converting the raw data sets to the JSONL format, and a validation process conducted using the GPT-3 model as well as test environments. This involves posing both new and repetitive questions to evaluate the model's responses in terms of accuracy, relevance, and consistency.

Raw Specification

5.10	SHELLS
	If shell courses have different thicknesses, the inside diameter shall be constant unless otherwise specified by the Principal.
	The minimum distance between two longitudinal seams in one course shall be 200 mm (8 in) or five times the wall thickness, whichever is the larger, as measured between the too of each weld. The minimum distance between the staggered longitudinal seams of two adjacent courses shall be 200 mm (8 in) or five times the wall thickness, whichever is the greater. However, where this cannot be achieved, the last 300 mm (12 in) of the adjacent longitudinal and the intersected circumferential seams shall be subjected to 100 % examination in accordance with (6.3) or (6.4) as applicable

Extracted Text

5.10 SHELLS

If shell courses have different thicknesses, the inside diameter shall be constant unless otherwise specified by the Principal. The minimum distance between two longitudinal seam in one course shall be 200 mm (8 in) or five times the wall thickness, whichever is the larger, as measured between the toe of each weld. The minimum distance between the staggered longitudinal seams of two adjacent courses shall be 200 mm (8 in) or five times the wall thickness, whichever is the greater. However, where this cannot be achieved, the last 300 mm (12 in) of the adjacent longitudinal and the intersected circumferential seams shall be subjected to 100% examination in accordance with (6.3) or (6.4) as applicable"

(b)

Manually Transformed Prompt-Completion Dataset

Prompt 2: What is the minimum distance between two longitudinal seams in one course, according to the AAA company specification?

Completion 2: The AAA company specification stipulates that the minimum distance between two longitudinal seams in one course should be 200 mm (8 in) or five times the wall thickness, whichever is larger, as measured between the toe of each weld.

(c)

Fig. 1. Example of Data Preparation: (a) Raw Specification, (b) Extracted Text, (C) Manually Transformed Prompt-Completion Dataset.

Step 1: Collecting Data	Collect technical specifications from 3 anonymous companies regarding engineering of pressure vessel
Step 2: Data Preparation	Raw information is split and reconstructed into a Q&A set for each detail
Step 3: Expanding Data	Diversifying the data using methods such as Synonym Replacement, Paraphrasing, Re-structuring, Feedback, Back Translation
Step 4: Developing input	Configure 'Prompt-Completion' datasets to match the format required
uatasets	Create a final input file with configured data which fit into Fine-tuning
Step 5: Fine-tune the Al model	Perform Fine-tuning using Python code
Step 6: Verification	Verify results by comparing responses to questions related to technical specifications of pressure vessel

Fig. 2. Workflow of fine-tuning the in-house technical information to the existing NLP AI model

3.2. Results

3.2.1. Optimal Creativity Setting

In the 'Playground' mode of the GPT-3.0 AI model, the response 'Temperature' setting allows for modulation of the model's response creativity. A lower temperature results in less randomness. At the default setting of temperature = 1, the model tended to produce creative yet occasionally off-mark answers. However, for accuracy-focused tasks, such as engineering applications, a temperature setting of 0.5 provided more reliable outcomes. All subsequent results were generated using this setting.

3.2.2. Assessing Fine-tuning Effects

To ascertain the impact of fine-tuning, identical questions were posed to the model before and after the fine-tuning process. In this paper, only AAA company is shown as an example.

1) Before Fine-tuning:

In the response, the limitations of the current ChatGPT model are addressed, stating that it cannot access in-house data and the answer continues with a more general discourse.

Q: "What are the specific requirements for radiographic examination or testing of seams in pressure vessels, according to AAA company's specifications?"

A: "I apologize, but the specific requirements for radiographic examination or testing of seams in pressure vessels according to the proprietary specifications of AAA company are not publicly available information. However, I can describe the general guidelines that might be followed by..."

2) After Fine-tuning:

2.1) Use of Trained Prompts:

The fine-tuned AI model's answers appeared identical to the completions used for training

Q: "What are the specific requirements for radiographic examination or testing of seams in pressure vessels, according to AAA company's specifications?"

A: "The specification requires that the last 300 mm (12 in) of adjacent longitudinal and intersected circumferential seams be subjected to 100% examination in accordance with the sections referenced in the document."

2.2) Paraphrased Prompts:

Several attempts were made to rephrase the original prompt while retaining its core meaning. Interestingly, while some paraphrased prompts resulted in accurate and consistent answers, others varied in precision or ventured into unrelated territories. The following is an example of the results of five attempts by paraphrasing the same question.

1st

Q: "According to the specifications of AAA company, what are the precise criteria for the radiographic inspection of seams in pressure vessels?"

A: "The specification requires that the last 300 mm (12 in) of adjacent longitudinal and intersected circumferential seams be subjected to 100% examination in accordance with the sections referenced in the document."

2nd

Q: "What are the detailed standards set by AAA company for radiographic analysis of seams in pressure vessels?"

A: "The specification requires that the last 300 mm (12 in) of adjacent longitudinal and intersected circumferential seams be subjected to 100% examination in accordance with the sections referenced in the document."

3rd

Q: "In accordance with AAA Company specifications, what are the exact requirements for radiographic inspection or seam testing of pressure vessels?"

A: "The specification requires that the last 300 mm (12 in) of the adjacent longitudinal and intersected circumferential seams be subjected to 100% examination in accordance with the sections referenced in the document."

4th

Q: "What are the precise requirements for pressure vessel radiography inspection or seam testing in accordance with AAA company specifications?"

A: "The specification requires that pressure vessel radiography be performed in accordance with AAA.00.10."

► Returned PMI-related completion irrelevant to the prompt

5th

Q: "What are the particular specifications set forth by the AAA company for radiographic inspection or seam testing of pressure vessels?"

A: "The AAA company mandates that the last 300 mm (12 in) of the longitudinal seam of adjacent shell rings be subjected to 100% examination. Furthermore, the minimum distances between various seams must be 100 mm (4 in) or five times the wall thickness, whichever is larger."

► The model answered correctly, but returned information about the 'positioning of the weld seam' that was not asked.

3.2.3. Observations

When the fine-tuning prompts were used without any modifications, the responses were an exact match to the learned completions.

When the original prompt was paraphrased, the model's performance exhibited variability, occasionally providing accurate answers and at other times diverging from the expected response.

Table I: Judgement for Model's Completion after fine-tuning

Type of asked question	Judgement
Trained Prompt	0
Paraphrased Prompt #1	0
Paraphrased Prompt #2	0
Paraphrased Prompt #3	0
Paraphrased Prompt #4	Х
Paraphrased Prompt #5	\bigtriangleup

(\bigcirc : Sufficient, \triangle : Partially Sufficient, X: Insufficient)

4. Discussion

The findings from this study hint at the potential applicability of the proposed approach. It is shown that the GPT-3 model, once fine-tuned, might be able to deliver answers based on the content present in the selected dataset. We need to consider how to optimize the sharing of proprietary knowledge within an enterprise or organization, and how to improve knowledge management with digital technology and artificial intelligence so that it will benefit the collation of knowledge within the nuclear industry [3]. The digitization and structuring of technical documents into an easy-to-navigate chat-bot could potentially streamline the process for new employees who need to understand these documents. Additionally, the transition of a company's technical know-how into a database might serve as a defensive strategy against the possible loss of institutional knowledge. It acts as a tool to bring people together and enhance communication and allows the organized storage and transfer of unstructured thoughts and notes, etc. [2]. Nonetheless, we should be mindful that the AI model's ability to provide accurate answers will always be tied to the information included in the dataset. Thus, it's essential to continuously update and expand the content to maintain the relevance of the responses. Depending on the global climate around nuclear power, as a company's technical specifications or regulatory requirements also evolve over time, data sets must be updated accordingly so that AI models can provide accurate and relevant answers.

5. Conclusion and Limitation

This study discusses the potential benefits of using a GPT-3 model fine-tuned on technical specifications or standards to address common challenges in knowledge management within corporations. The nature of nuclear power plant, with its strong emphasis on safety, security, and regulatory compliance, underscores the need for an efficient and precise knowledge management system. It is expected that this approach, if further developed, could simplify the onboarding process for new hires and help mitigate the risk of losing essential knowledge when key staff depart. However, several limitations must be noted. First, as previously mentioned, the model's ability to provide accurate answers is intrinsically limited to the content and scope of the dataset. This necessitates a commitment to regular updates and dataset expansion. Second, data privacy and security are key concerns that must be meticulously addressed. The fine-tuning process involves the use of potentially sensitive corporate information, and it's essential that strict measures are implemented to prevent unauthorized access or data breaches. Lastly, the current state of AI technology presents its own limitation. At the time of writing, fine tuning is

supported only up to GPT-3.0, even though the latest version of ChatGPT has been released with GPT-4.0..

The rapid progress in AI research could soon enable the fine-tuning process to be applicable to more potentially advanced models, enhancing the effectiveness and capabilities of the AI model in complex fields like nuclear power plant management. The potential improvements in areas like real-time response to safety queries, compliance tracking, and the handling of critical incidents related to nuclear operations would be significant contributions to the industry. Based on this research idea, it is hoped that more extensive and in-depth research will lead to the development of advanced and efficient knowledge management tools.

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