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LEVERAGING LARGE LANGUAGE MODELS FOR ANALYSIS AND CONTROL OF POWER TRANSMISSION NETWORKS: CASE STUDIES WITH THE LLAMA3 LLM MODEL AND PANDAPOWER

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Abstract: Use of Artificial intelligence in power systems is the mainstream theme in the scientific and engineering communities. The integration of renewable energy sources and the increasing demand for electricity have led to a significant increase in the complexity of modern power systems. To address this challenge, there is a need for advanced control and analysing techniques that can ensure the stable and efficient operation of the power grids. This paper explores the application of large language models (LLMs) for control of power transmission and distribution networks, specifically focusing on the use of an LLM-based agent in the control and analysis power system networks. The paper begins by reviewing the current state of LLMs and their potential applications in power systems. It then presents a detailed description of the proposed Llama3-based agent, which is designed to interpret and execute control commands using natural language processing (NLP) techniques. The agent can interface seamlessly with the Pandapower model, allowing it to monitor the network in real-time and make informed decisions to maintain the system's stability and efficiency. To evaluate the effectiveness of the proposed approach, the paper presents case studies using simulated power transmission and distribution network models. The results demonstrate that the LLM agent can quickly and accurately respond to changes in the system, maintaining its stability and efficiency even under challenging conditions. Second example is contingency analysis with llama3 based agent. AI agent gives recommendations for mitigation of contingencies in the predefined system. The paper also discusses the potential, limitations and challenges of using LLMs for the control and analysis of power systems and suggests directions for future research. Uncertainties of the LLMs are also interesting topic and opens the new point of view on power system problems. Overall, this paper provides insights into the potential of LLMs for control and analysis of power transmission and distribution networks and demonstrates the feasibility of using LLM agents for this purpose. It highlights the benefits of this approach, including improved system stability and efficiency, and provides a foundation for further research in this rapidly evolving field.

Keywords: Power systems, LLM, Pandapower, Power system analysis and control

INTRODUCTION

Integrating artificial intelligence (AI) and machine learning (ML) technologies into power systems has gained significant attention in recent years [1]-[2]. As power grids become more complex and dynamic, traditional control and management approaches struggle to manage vast amounts of data and rapidly changing conditions. Large Language Models (LLMs) , a subset of AI known for their impressive capabilities in natural language processing and general problem-solving, offer a promising solution to these challenges [3].

LLMs, such as GPT (Generative Pre-trained Transformer) models, have demonstrated their ability to understand and generate human-like text, perform complex reasoning tasks, and even write code. These capabilities make them potentially valuable tools for power system applications, where they could assist in tasks ranging from fault diagnosis and predictive maintenance to real-time control and optimization of grid operations.

This paper explores the current state of research and applications of LLMs in power systems and presents a practical example of how an LLM agent can be implemented for power system control. We begin with a comprehensive background on power systems and LLMs, followed by a review of existing literature on the intersection of these two fields. We then present our methodology for implementing an LLM agent using Llama 3, a state-of-the-art language model, and integrating it with a power system model developed in Pandapower, a widely used open-source tool for power system modelling and analysis.

Our practical examples illustrate how an LLM agent can be used to monitor system conditions, make decisions, and

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control various aspects of a power system. We discuss the challenges encountered during implementation, the performance of the LLM agent, and the potential implications for future power system operations.

Our aim is to contribute to the growing body of knowledge on AI-driven power systems and inspire further research and development in this exciting field by bridging the gap between theoretical studies and practical applications. Integrating LLMs into power systems can enhance grid resilience, improve energy efficiency, and support the transition to a more sustainable and intelligent energy infrastructure.

Power Systems

Power systems are complex networks designed to generate, transmit, and distribute electrical energy to consumers. These systems consist of various components, including power plants, transformers, transmission lines, substations, and distribution networks. The primary objective of a power system is to ensure a reliable and efficient supply of electricity while maintaining system stability and power quality. Key aspects of power systems include Generation, Transmission, and Distribution. Each part of the system includes control and protection mechanisms, load management, and techniques to balance electricity supply and demand, such as demand response and load forecasting. These measures contribute to grid stability, ensuring the system remains stable under various operating conditions and disturbances. The complexity of power systems has increased significantly in recent years due to factors such as integrating renewable energy sources, distributed generation, electric vehicles, and the need for greater energy efficiency. These challenges have led to a growing interest in applying advanced computational techniques, including AI and ML, to improve power system management and control.

Large Language Models

Large Language Models are a class of artificial intelligence models designed to understand, generate, and manipulate human language [4]. These models are typically based on deep learning architectures, particularly transformer models, and are trained on vast amounts of text data. Key characteristics of LLMs include:

a) Scale: LLMs often have billions of parameters, allowing them to capture complex patterns and relationships in language.
b) Self-attention mechanism: This enables the model to assess the importance of different parts of the input when processing language.
c) Transfer Learning: LLMs can be fine-tuned for specific tasks after being pre-trained on general language data.
d) Few-shot Learning: The ability to perform new tasks with minimal task-specific training examples.
e) Multi-task Capability: LLMs can perform a wide range of language-related tasks, including translation, summarization, and question-answering.

Notable examples of LLMs include GPT (Generative Pre-trained Transformer) series by OpenAI, BERT (Bidirectional Encoder Representations from Transformers) by Google, and, more recently, open-source models like Llama by Meta AI. The capabilities of LLMs extend beyond simple language processing. They have demonstrated proficiency in reasoning, problem-solving, and even code generation tasks.This versatility makes them potentially powerful tools for complex domains like power systems, where they could assist in interpreting data, making decisions, and even generating control strategies.

1. INTRODUCTION LLMS IN POWER SYSTEMS: CURRENT APPLICATIONS AND RESEARCH

The application of LLMs in power systems is an emerging field with growing interest from both academia and industry [5]. While traditional machine learning techniques have been widely used in power systems for tasks such as load forecasting and fault detection, LLMs offer new possibilities due to their ability to process and generate human-like text, understand context, and perform complex reasoning. Various processes within power systems could be driven by LLMs [6]-[7], opening significant research and engineering opportunities. Current applications and research areas of LLMs in power systems include anomaly detection and fault diagnosis, predictive maintenance, knowledge management, decision support, and more. Power systems generate vast amounts of technical documentation, standards, and operational procedures. LLMs can be used to create intelligent knowledge management systems that efficiently retrieve relevant information, answer technical questions, and provide decision support to operators and engineers. LLMs can assist in generating and analysing various scenarios for grid planning and expansion. By considering multiple factors such as load growth, renewable integration, and regulatory changes, LLMs can help planners explore different options and their potential impacts. As power systems become increasingly digitized, cybersecurity is also a growing concern. LLMs can be employed to analyse network traffic patterns, log files, and threat intelligence reports to identify potential security threats and suggest mitigation strategies. The intermittent nature of renewable energy sources poses challenges to grid stability. LLMs can be used to process diverse data sources, including weather forecasts, historical generation patterns, and grid conditions, to optimize the integration of renewable energy into the grid. LLMs can assist in interpreting and applying complex regulatory requirements. They

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can be trained on regulatory documents and standards to help ensure that power system operations comply with evolving regulations. AI also shows great potential in areas such as capacity optimization, grid mapping, asset management, and predictive maintenance.

As research in this field progresses, we can expect to see more sophisticated applications of LLMs in power systems, potentially leading to more intelligent, efficient, and resilient grid operations.

2. METHODOLOGY

Our methodology for implementing an LLM agent for power system control involves several key steps:

2.1. Power System Modelling:

We use Pandapower [8], an open-source Python library for power system modelling and analysis. Pandapower enables the creation of a realistic power system model, including generators, loads, transmission lines, and transformers. The model is easily manipulated and analysed, providing an ideal environment for testing our LLM agent.

2.2. LLM Selection and Implementation:

Developing applications using Artificial Intelligence (AI) and Large Language Models (LLMs) are mainstream in the scientific community. In this work, the Llama 3 model is used, a state-of-the-art language model developed by Meta AI [9]. Llama 3 offers an excellent balance of performance and efficiency, making it well-suited for our power system control application. For run selected model locally on PC, we use Ollama [10], an open-source tool for running Llama models locally, which provides flexibility and control over the model's deployment. Ollama is a platform designed to simplify the process of running and deploying large language models (LLMs) locally. Ollama allows users to download and run various open-source LLM models on their local machines, providing a more flexible and secure environment for interacting with AI models. It primarily focuses on enabling AI models to be used directly on personal or enterprise systems without the need for continuous cloud connectivity. Key features of Ollama include:

Local Model Execution: One of the features of Ollama is its ability to run AI models locally on user devices.

Multi-Model Support: Ollama supports various types of large language models (LLMs) that can handle tasks such as text generation, summarization, and more. Its flexible architecture enables users to easily integrate and switch between different models.

Cost-Effective: Running LLM models locally can lead to significant cost savings compared to cloud-based solutions or commercial solutions, which often involve expensive fees for computation and storage.

Offline Capability: For applications where internet connectivity is not guaranteed, such as in remote areas or high-security environments (which is often the case for large power plants), Ollama's ability to run AI models offline is highly valuable.

2.3. Agent Design:

Our LLM agent is designed to perform the following tasks:

- Monitor system conditions by interpreting Pandapower simulation outputs
- Make decisions based on predefined criteria and learned patterns
- Generate control actions to maintain system stability and efficiency
- Provide explanations for its suggestions to the operational stuff in natural language

2.4. Integration:

We developed a Python script that integrates the Pandapower model with the Llama 3 agent and the Ollama interface. This script handles the flow of information between the power system simulation and the LLM, as well as the execution of control actions. All modules are part of the Python ecosystem and run within a single script. Python modules are installed using Anaconda in a conda-managed environment [11]. The only requirement is that the Ollama server is installed and running on https://11434 local IP address [10].

3. PRACTICAL EXAMPLE 1: LLM AGENT FOR POWER SYSTEM ANALYSIS AND CONTROL

Experiments on integrating LLMs with power system control are progressing intensively [12]. Researchers are working on power system simulation cases involving LLM-based control and surveillance logic. This work focuses on optimizing power system operations, as presented in [13]. This section provides a practical example of implementing an LLM agent for power system control using Python and it's divided into three main parts: power system modelling with Pandapower, LLM agent implementation using Llama 3 and Ollama, and the integration of these components.

3.1. Power System Modelling with Pandapower

The complex configuration of the 400/110 kV power system network is selected for a practical case, represented by a single-line diagram in Figure 1. Using Pandapower, the network is modelled with large-capacity, controllable PV plants and battery storage added at several nodes to increase complexity.

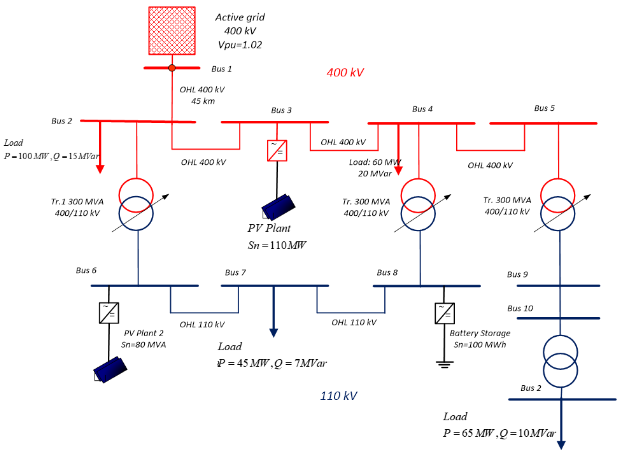

Figure 1: Single-line diagram of 400/110 kV power system

Pandapower implementation of 400/110 kV power network with additional PV plants and battery storages is on Figure 2. Network is designed with additional PV plants and battery storages for ability of injecting active and reactive power. Power system transformers are equipped with tap-changers for local voltage regulations. Loads are also positioned on buses and parametrized with reactive and active components. Initial conditions of power system is intentionally made for large overvoltages as input state for LLM agent which has task to stabilize voltages and power system in overall. Initial is 8 – 9 buses with voltages out of desired range of 1.00-1.05 per unit (p.u.) which is complicated task to stabilize with set of simultaneous actions of tap-changers and active and reactive injections of PV plants inverters and battery storages which is LLM model task.

```python
def create_network():
    net = pp.create_empty_network()
     buses = {f'bus{i}': pp.create_bus(net, vn_kv=400 if i <= 6 else 110, name=f"Bus
{i}")
             for i in range(1, 13)}

    pp.create_ext_grid(net, bus=buses['bus1'], vm_pu=1.02, name="Grid Connection")  #
Changed vm_pu to 1.02
    # Create lines
    line_data = [
        ('bus1', 'bus2', 80), ('bus2', 'bus3', 100), ('bus3', 'bus4', 70),
        ('bus4', 'bus5', 80), ('bus5', 'bus6', 90), ('bus7', 'bus8', 40),
        ('bus8', 'bus9', 50), ('bus9', 'bus10', 60), ('bus10', 'bus11', 45),
        ('bus11', 'bus12', 55)
    ]
    for from_bus, to_bus, length in line_data:
        pp.create_line(net, from_bus=buses[from_bus], to_bus=buses[to_bus],
length_km=length,
                       std_type=f"490-AL1/64-ST1A {'380.0' if int(from_bus[3:]) <= 6 else
'110.0'}")
    # Create transformers
    for hv_bus, lv_bus in [('bus2', 'bus7'), ('bus4', 'bus9'), ('bus6', 'bus12')]:
        pp.create_transformer_from_parameters(
            net, hv_bus=buses[hv_bus], lv_bus=buses[lv_bus], sn_mva=300, vn_hv_kv=380,
vn_lv_kv=110,
            vkr_percent=0.25, vk_percent=12, pfe_kw=100, i0_percent=0.1, shift_degree=0,
            tap_side="hv", tap_neutral=0, tap_min=-9, tap_max=9, tap_step_percent=1.5,
tap_pos=0)
    # Create loads
    load_data = [('bus3', 135, 27), ('bus4', 115, 23), ('bus8', 85, 17), ('bus10', 65,
13), ('bus11', 105, 21)]
    for bus, p, q in load_data:
        pp.create_load(net, bus=buses[bus], p_mw=p, q_mvar=q)
    # Create PV plants (increased capacity)
    pv_data = [('bus2', 105, 55), ('bus5', 85, 45), ('bus7', 95, 50), ('bus9', 100, 52),
('bus11', 90, 47)]
    for i, (bus, p, q) in enumerate(pv_data, 1):
        pp.create_sgen(net, bus=buses[bus], p_mw=p, q_mvar=0, name=f"PV{i}",
                       controllable=True, max_q_mvar=q, min_q_mvar=-q, max_p_mw=p,
min_p_mw=0)
    # Create battery storage systems (increased capacity)
    battery_data = [('bus3', 130, 65), ('bus6', 110, 55), ('bus8', 90, 45), ('bus10',
100, 50), ('bus12', 120, 60)]
    for i, (bus, e, p) in enumerate(battery_data, 1):
        pp.create_storage(net, bus=buses[bus], p_mw=0, max_e_mwh=e, soc_percent=50,
                          name=f"Battery{i}", max_p_mw=p, min_p_mw=-p)

    return net
```

Figure 2: Pandapower implementation of 400/110 kV system with PV plants and battery storages

3.2. LLM agent implementation

The 400/110 kV power system network model, shown in the single-line diagram in Figure 1, is created in Pandapower for further integration into the overall Python ecosystem. An AI agent based on the Llama 3 open-source LLM model is implemented via the Ollama platform to analyze and control the power network. The Llama 3-based LLM agent, by controlling the tap-changer and injecting active and reactive power, aims to stabilize the network and reduce overvoltages.

3.2.1. Presumptions for model design

In the literature [14]-[16], transformer tap-changer operations and the injection of active and reactive power from PV plant inverters and battery storage systems have been shown to stabilize voltages within the desired operational range. These are the physical and engineering assumptions used to guide the design of the Llama 3 LLM agent. The agent aims to stabilize bus voltages through a set of synchronized actions, including the manipulation of transformer tap-changers and the injection of active and reactive power from PV plant inverters.

3.2.2. Prompt design

While Llama 3 is pre-trained on a large corpus of text, it does not possess specific knowledge about

```python
prompt = f"""Given the following voltage profile in a power network:
Voltages: {voltages}
Overvoltage buses (>1.051 p.u.): {overvoltage}
Undervoltage buses (<0.998 p.u.): {undervoltage}

You are a power system control agent. Your goal is to bring all voltages within
0.9985-1.0515 p.u. in 5 actions or less.
Use all known power system theory to achieve goals.

Pandapower Network information:
Number of transformers: {network_info['num_transformers']}
Transformer indices: {network_info['transformer_indices']}
Number of PV plants: {network_info['num_pv_plants']}
PV plant indices: {network_info['pv_plant_indices']}
Number of batteries: {network_info['num_batteries']}
Battery indices: {network_info['battery_indices']}

Suggest actions to correct these violations using tap changers, active and reactive power
control of PV plants, and active power control of batteries.

Provide your response as a Python dictionary with the following structure:
{{
    'tap_changes': {{trafo_index: tap_change, ...}},
    'q_changes': {{pv_index: q_change, ...}},
    'p_changes': {{pv_index: p_change, ...}},
    'battery_changes': {{battery_index: p_change, ...}}
}}

where indices are integers within the provided ranges, tap_change is an integer (+1 for
up, -1 for down),
q_change and p_change are floats representing the change in Mvar and MW for PV plants,
respectively,
and p_change for batteries is a float representing the change in MW (positive for
discharging, negative for charging).
Make aggressive changes to correct violations quickly. Limit changes to ±1 taps, ±12 Mvar
and ±10 MW for PV, and ±8 MW for batteries per step.
Remember:
1. Injection of +MVar raises voltage in the bus, injection of -MVar decreases voltage.
2. Increasing tap changer raises voltages, decreasing tap changer decreases voltages in
nodes where transformer is connected.
3. Injecting active power of PV plants and batteries raises voltages.

All voltages after 5 steps of actions must be in range 0.99 - 1.052 p.u. as soon as
possible (0.99<= v <= 1.052), within 5 taken actions of llama agent.
In nodes with overvoltages inject -MVar or - MW
In nodes with undervoltages inject +MVar or +MW
After every step consider overall network state and consider where to inject active or
reactive power

ONLY return the Python dictionary. Do not include any explanations or additional text.
```

Figure 3: Prompt designed for llama3 agent context of power system control

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voltage stabilization. In this initial model, we provide the context through a detailed prompt, without fine-tuning or using RAG on power system operational data, technical documentation, or example scenarios. This specific prompt, as input to the LLM, helps the model understand the context and terminology specific to power systems.

3.2.3. Model execution

The Pandapower 400/110 kV transmission and distribution network is simulated with overvoltages and loaded into a Python environment, where the Llama 3 model is run via the Ollama server. Initially, nine buses in the system have voltages outside the desired range of 1.00-1.05 per unit (p.u.).

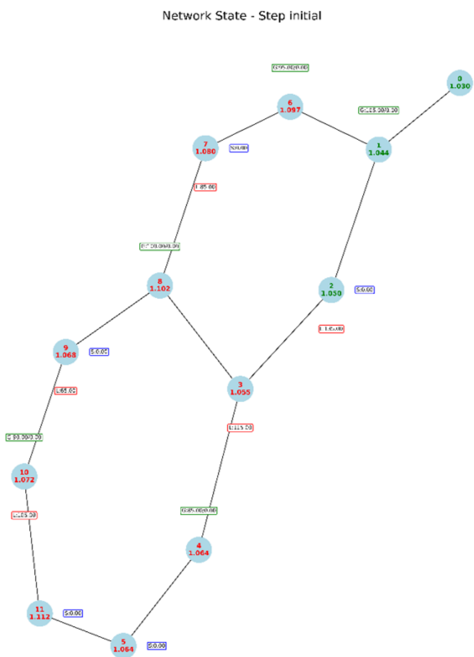

Figure 4: Initial state of the power network with overvoltages

Visualization is created using the NetworkX [17] Python library, with nodes representing buses, and overvoltage nodes are highlighted in red, as shown in Figure 4. In the model's five steps, the Llama 3 agent optimizes the Pandapower 400/110 kV network parameters. After each step, the updated network state is loaded into the LLM prompt for processing, the network parameters are modified, and power flow is recalculated to assess overall network stability. After the five-step execution, the network state is satisfactory, with only a small pair of overvoltages remaining, which can be further addressed through actions on lower voltage levels. [16].

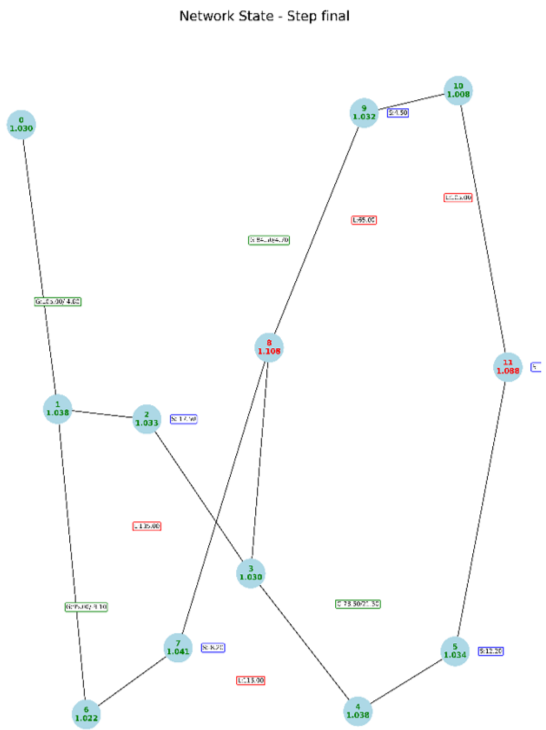

Figure 5: Power network voltage profile after execution of five action sets of llama3 agent

It is evident from Figures 4 and 5 that with each action set of the Llama 3-based LLM agent, the power system's voltage profile stabilizes within the desired range of 1.00-1.05 p.u. After five sets of actions on the tap-changers of transformers and the injection of active and reactive power from PV plants and battery storage systems, the efficiency and stability of the observed network are significantly improved, along with valuable comments and recommendations generated as LLM output.

3.2.4. Result analysis

For 20 model executions, we obtained a distribution of results as shown in Figure 6.

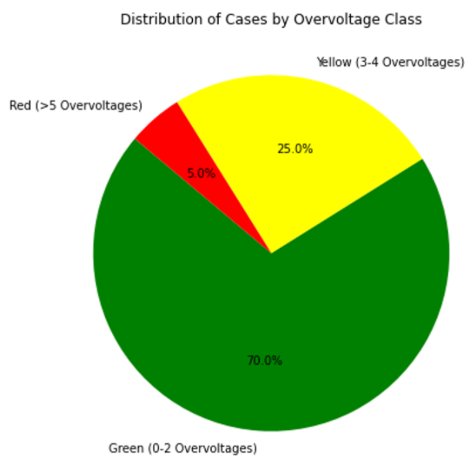

Figure 6: Analysis of model executions

Over 70% of executions produced very good results, with 0-2 overvoltages after the five-step model execution. Considering that only prompt context was used for the LLM model, without fine-tuning or the use of the Retrieval Augmented Generation (RAG) mechanism, the results are more than satisfactory for the Llama 3 open-source model.

4. PRACTICAL EXAMPLE 2: LLM AGENT FOR POWER SYSTEM ANALYSIS AND CONTROL

4.1. Power Systems Contingency analysis

Contingency analysis improves power system reliability by identifying potential risks and vulnerabilities associated with equipment failures or outages. It allows engineers to simulate various “what-if” scenarios, such as transmission line failures or generator trips, to assess the impact on system stability and security17. This process helps in developing mitigation strategies like load shedding or network reconfiguration to prevent cascading failures and ensure continuous electricity supply. Additionally, contingency analysis aids in planning and scheduling maintenance outages to minimize risks during routine maintenance. Overall, it enhances the ability to anticipate and manage disruptions, thereby maintaining grid resilience and reliability. Recent advances in contingency analysis leverage AI-driven approaches to address complex power grid challenges. As demonstrated in reference [16], which introduced a dedicated power network configuration originally analysed through reinforcement learning (RL) for optimal control strategies, this infrastructure now serves as a critical testbed for next-generation contingency management. Power system network in [16] is also modelled in Pandapower [8] simulation tool, easy to integrate in Python environment. Building

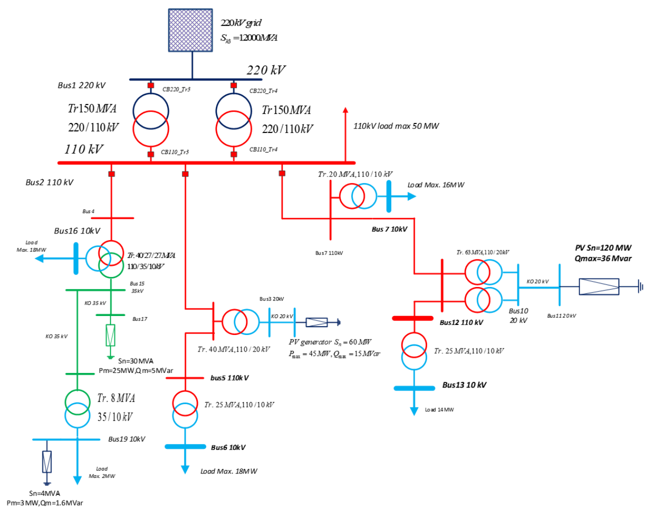

Figure 7: Power network configuration for Contingency analysis [16]

on citated paper [16] RL-optimized network topology, the current work implements a LLaMA-3 agent to perform contingency analysis, replacing traditional RL methods with large language model (LLM) capabilities. Where [16] utilized RL agents to navigate equipment failures and load imbalances through reward-based policy optimization, our approach harnesses LLaMA-3’s natural language reasoning to interpret grid states, generate human-readable diagnostics, and propose context-aware mitigation strategies.

By applying the LLaMA-3 agent to network from paper [16] validated network model, we demonstrate how LLM-enhanced analysis improves scenario generalization while maintaining compatibility with existing power flow simulation tools.

4.2. Methodology of example 2

Here’s a comprehensive explanation of the code’s key components with special focus on the LLaMA3/Ollama integration: This power grid management system combines traditional power network modelling with modern AI capabilities. The code uses Pandapower for detailed electrical network modelling (buses, transformers, lines, loads) and networkX for topology visualization. The core innovation is the integration of LLaMA-3 via a local Ollama server for AI-driven grid optimization recommendations. Ollama is a local AI server (running at http://localhost:11434) that hosts large language models. In this implementation, it serves the LLaMA-3 model - Meta’s powerful open-source LLM specifically fine-tuned for technical domains. The server acts as an AI co-pilot for grid operators, processing real-time grid data through its API endpoint (/api/generate).

```
**Ollama Server Context**
Ollama is a local AI server (running at http://localhost:11434) that hosts large language
models. In this implementation,
it serves the **LLaMA-3 model** - Meta's powerful open-source LLM specifically fine-tuned
for technical domains. The server
acts as an AI co-pilot for grid operators, processing real-time grid data through its API
endpoint (/api/generate).

**LLaMA-3 Integration Workflow**
1. **Context Preparation**: When grid violations are detected (low/high voltages,
overloads), the system compiles a
structured technical report containing:
   - Failed component details
   - Voltage violation statistics
   - Loading percentages
   - Generation/load imbalance data


2. **Prompt Engineering**: A specialized prompt template combines this technical context
with operational expertise requirements:
   ```python
   prompt = f"""
   As a senior power grid operations expert, analyze this contingency scenario:
   {context}
   Provide detailed technical recommendations to stabilize the grid, including specific
numerical values for actions.
   """
   ```
   This prompt structure forces LLaMA-3 to adopt a power engineering persona while
maintaining numerical precision.
```

Figure 7: Technical parameters of LLM Llama3

This setup and prompt design are designed for contingency analysis of power network with LLM model. Script is in folder with visualizations files produced after each contingency scenario.

4.3. Results of example 2

LLM agent's actions are denoted on graphical representation along with bolded lines on faulted or overloaded elements of analysed power system. Model generates graphical and textual representation for each scenario and saves on working folder. The Llama3 model created four scenarios for the most important contingencies on the considered power network. For each scenario, LLM results are displayed on working screen of Spyder editor as on Figure 9.

```
**Recommendations to Stabilize the Grid**

1. **Voltage Support**
To mitigate the voltage issues, I recommend injecting reactive power at strategic
locations to stabilize the voltage profile.
   * Inject 0.5 MVAR of leading reactive power at Bus 15 (high-side) to reduce the
high-voltage issue.
   * Inject 0.2 MVAR of lagging reactive power at Bus 0 (low-side) to counterbalance
the low-voltage issue.
2. **Line Flow Management**
To alleviate the overloaded line, I suggest adjusting the flow on adjacent lines to
redistribute the load and reduce congestion.
   * Increase the flow on Line A by 10% to absorb some of the excess power.
   * Decrease the flow on Line B by 5% to reduce the pressure on the overloaded line.
3. **Grid Scheduling**
To ensure a stable grid, I recommend adjusting the scheduling of generators and loads
to optimize the system's overall performance.
   * Increase the output of Generator G1 by 2 MW to compensate for the lost capacity
from Mo4_Polog.
   * Decrease the load on Load L1 by 5% to reduce the demand and alleviate pressure on
the grid.
```

Figure 8: Output of LLM Contingency analysis – Llama3 agent's actions

For each case a visualization of contingency analysis along with action list is created with NetworkX with all important information - grid topography and llama3 actions for mitigations of faults and contingencies. Agent's actions are divided into two categories - prompt actions for mitigations and strategic planning actions for the long-term securing of power system stability. Analysis of the suggested actions gives approximate 75% of quality suggestions in both categories. It can be concluded that Llama3 is a high quality LLM model which is relatively usable in power system analysis without further contextualization such as RAG or fine-tuning. Visualizations are created using the NetworkX [17] Python library for each considered scenario as on Figure 8.

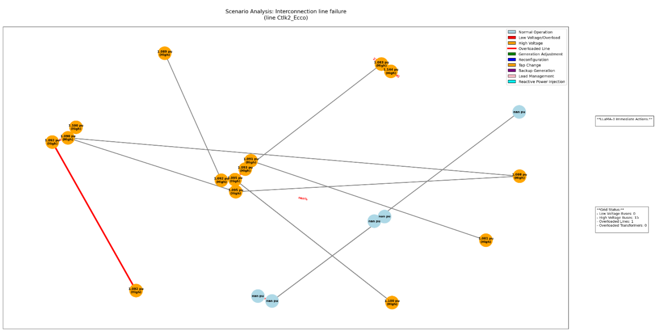

Figure 8: Output of LLM Contingency analysis of power network Fig.7

LLM agent's actions are denoted on graphical representation along with bolded lines on faulted or overloaded elements of analysed power system. Model generates graphical and textual representation for each scenario and saves on working folder.

5. CONCLUSION AND FUTURE WORK

This study has demonstrated the potential of Large Language Models in enhancing power system control and decision-making processes. The LLM agent showed remarkable capabilities in analysing complex system states, providing context-aware recommendations, and generating multi-step control strategies.

Integrating natural language processing with power system control opens new possibilities for intuitive human-machine interfaces in control rooms, automated report generation, and knowledge management in power utilities. The ability of LLMs to process and synthesize information from diverse sources could prove invaluable in managing the increasingly complex and data-rich environment of modern power grids.

However, the challenges identified in this study, particularly those related to numerical precision, real-time performance, and explainability, highlight the need for further research and development. Future work should focus on:

1. Developing hybrid systems that combine the strengths of LLMs with traditional optimization and control algorithms.
2. Investigating the use of reinforcement learning techniques to allow the LLM agent to improve its decision-making over time-based on system outcomes.
3. Developing the Retrieval Augmented Generation (RAG) mechanism to improve model accuracy.
4. Developing a multi-agent system for effective collaboration to achieve shared goals.
5. Exploring the application of LLMs in other areas of power system operation, such as long-term planning, renewable energy integration, and cybersecurity.
6. Investigating the potential of multi-modal LLMs that can process not only textual data but also visual and time-series data, which are common in power system monitoring.

Special attention will be given to the security issues associated with LLM applications in power systems [18]. In conclusion, while there are challenges to overcome, the application of Large Language Models in power systems represents a promising frontier in the ongoing digital transformation of the energy sector [19]. As these technologies continue to evolve, they have the potential to play a significant role in creating more intelligent, efficient, and resilient power grids of the future.

Recent advances in contingency analysis leverage AI-driven approaches to address complex power grid challenges. As demonstrated in [16], which introduced a dedicated power network configuration originally analysed through reinforcement learning (RL) for optimal control strategies, this infrastructure now serves as a critical testbed for next-generation contingency management with LLM agents. The current work implements a Llama3 agent to perform contingency analysis, with large language model (LLM) capabilities. our approach harnesses LLama3's natural language reasoning to interpret grid states, generate human-readable diagnostics, and propose context-aware mitigation strategies. By applying the LLaMA-3 agent to validated network model, it is demonstrated how LLM-enhanced contingency analysis improves scenario generalization with open-source power flow simulation tools.

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