Large Language Model-based Bayesian Optimization for Tokamak Stabilization

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Abstract

Nuclear fusion holds the potential to solve many of today's most pressing problems, from climate change to mass food and water production. However, modeling and operating tokamaks remain highly challenging due to distribution shifts that take place, e.g., due to hardware changes between experiments, actuator failures, and impurities in the plasma. In this work, we focus particularly on the task of predicting and mitigating tearing instabilities, which can cause the plasma to disrupt and potentially damage the tokamak. To do so, we propose a large language model-informed Bayesian optimization scheme, which aims to explore and find highly stable electron cyclotron heating configurations efficiently. Our choice of algorithm allows us to account for uncertainty in the model, which in turn helps it adapt to changes that arise due to distribution shifts. The large language model, by contrast, allows us to leverage high-dimensional prior data and to process experiment logs written by scientists and operators, which would usually be impossible with conventional Bayesian optimization tools. In preliminary offline experiments, conducted using a historical dataset from the DIII-D tokamak, our method shows promising performance compared to other baselines.

1 Introduction

Nuclear fusion holds the promise of producing high quantities of energy with minimal to no environmental impact. In fusion, energy is released through a sustained, controlled reaction in which light atoms are combined to form heavier atoms. Among the various technologies used to achieve controlled fusion, the most promising are tokamaks [Kikuchi, 2010], which utilize magnetic fields to confine high-temperature and high-pressure plasma, thereby creating conditions for the fusion reaction to occur. However, sustained tokamak control at high pressures is very challenging due to the occurrence of instabilities in the plasma. These instabilities can easily disrupt the plasma, which in turn ends the fusion process and can even severely damage the device. Electron cyclotron heating (ECH) has shown promise to mitigate instabilities [Kolemen et al., 2014]. However, understanding how to utilize ECH effectively remains unclear. This challenge is further compounded by fluctuations in the tokamak hardware, such as wall changes, sensor and actuator failures, and impurities resulting from prior experiments, which make it challenging to plan experiments solely based on prior data.

To address the aforementioned challenges, we present an LLM-based Bayesian optimization approach for tokamak control. Our approach leverages observations collected during past experiments to explore and find heating profiles that maximize the time-to-instability. Moreover, unlike classical Bayesian optimization, our LLM-based approach enables the processing of logs written by scientists between experiments. We present preliminary results obtained from a simulated Bayesian optimization setup informed by past experiments and logs.

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2 Related Work

2.1 Tokamak control and tearing instabilities

A key challenge in tokamaks is controlling neoclassical tearing modes (also referred to as tearing instabilities), which are magnetic islands that form within the plasma. These instabilities degrade plasma confinement [Sauter et al., 1997] and can grow unless suppressed, leading to plasma disruptions [Westerhof, 1990] and potentially damaging the reactor wall. Plasma disruptions are one of the major concerns for stable operations in future large tokamaks, e.g., ITER [Lehnen et al., 2015]

To counteract tearing instabilities, Electron Cyclotron Heating (ECH) is often used to create localized current drive and heating at the location of instabilities. To create these, gyrotrons are aimed at specified locations in the plasma [Kolemen et al., 2014] [Nelson et al., 2020]. Gyrotrons can also be used pre-emptively to stabilize the plasma [Bardóczi et al., 2023]. Since tokamak devices regularly undergo system upgrades, past data is potentially unreliable, thus, Bayesian optimization becomes a strong candidate for pre-emptive ECH suppression, where the tokamak is treated as a black box [Sonker et al., 2025].

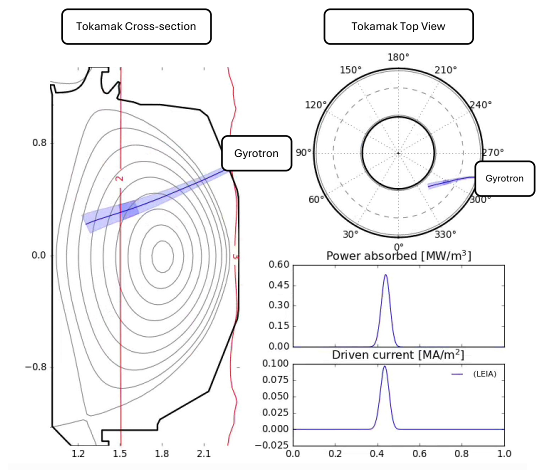

Figure 1: Gyrotron action on the Plasma inside the Tokamak. The bottom 2 curves indicate the heating power absorbed (ECH profile) and current driven in the plasma (ECCD profile) from the core to outer region of the plasma.

In this work, we adopt a similar approach to that in [Sonker et al., 2025] to mitigate tearing instabilities in plasma experiments by selecting the optimal shape of the feedforward ECH heating profile, which we approximate using a Gaussian curve. An example of the angle of the gyrotron and the resulting ECH deposition profile is shown in Fig. 1. In this paper, we focus on m/n=2/1 tearing instabilities, which are very common and highly prone to cause disruptions. We also consider experiments exclusively in a high-q$_{min}$ plasma scenario, a type of high-pressure scenario that supports long-pulse steady-state plasma operation.

2.2 LLM-Augmented Bayesian Optimization

Classical Bayesian optimization methods have been deployed for adaptive experimental design across a range of settings such as adaptive clinical trials [Berry, 2006], ecological monitoring [Diggle and Lophaven, 2006], and recently, for ECH profile optimization in tokamaks [Sonker et al., 2025]. Despite these successes, these BO methods often fail to leverage the rich task-specific prior information available to us. This has motivated a recent surge in interest using language models as a tool for more informed Bayesian optimization [Liu et al., 2024, Chang et al., 2025]. Our methodology primarily follows previous work on directly prompting the language models with prior experiment history and the observed values of the variable of interest, and prompting it to generate the next experiment [Zhang et al., 2023]. Our approach contrasts with these in that we incorporate detailed experimental logs into the experimental design observations.

3 Problem Setup

3.1 Contextual Bayesian Optimization (CBO)

We now formulate our problem in a contextual Bayesian optimization setup. Our goal is to find an ECH profile (a_{ech} that maximizes the time-to-instability given the context. The ECH profile is approximated by a Gaussian, parameterized by a 3-dimensional vector. In this work, we use the target normalized plasma pressure β_N, which strongly correlates with plasma stability and is frequently adjusted between experiments by physicists [Sonker et al., 2025]. Our goal is to perform well on any given target β_N.

The contextual decision problem is then as follows: every round t, a context $\beta_{N,t}$ is determined prior to action selection. The agent then chooses a heating profile configuration x_t and measures the (noisy) time-to-instability

$$y_t \;=\; f(x_t, \beta_{N,t}) + \varepsilon_t,$$

where f is the unknown objective, i.e., the expected time-to-instability, and ε_t is the observation noise. The goal is to learn a policy π that maps contexts to actions with high utility, i.e., $\pi(\beta_N) \approx \arg\max_x f(x, \beta_N)$. This is achieved by choosing actions that trade off exploration and exploitation over multiple rounds.

3.2 Auxiliary Feedback from experiments

In addition to the observations y_t, we also include experiment logs written down by scientists after the experiment is performed. The information presented here encompasses a wide range of specific details about the experiment and tokamak, including neutral beam failures, pellet injection, and gyrotron lag. Importantly, these logs can contain information that is impossible to express in the low-dimensional search space of traditional BO tools. Logs written during and after experiments are often written in shorthand; hence, we first pass these logs through a Llama-3-8b model to eliminate short forms and turn them into well-formed, complete sentences. Some examples are shown in table 1. Note that despite cleaning, these logs contain a lot of additional information and are very noisy by nature.

	Experiment Logs
1	The experiment began 330 seconds before the start time of 2.5 seconds with a planned current of 0.75 megaamperes, a magnetic field strength of 1.7 teslas, and a neutral beam injection power of 1 MW. The experimental plan for shot 2019-22-03 was step 6. The plasma's internal magnetic field was set to 10/40 for the entire shot duration. The gyrotrons were successfully activated, with actual delays matching the requested delays of 4500 microseconds for Luke and Leia, and 4728 microseconds for Tinman. The plasma was stable, with the current reaching the minimum value, IpMin, indicating a successful plasma formation.
2	The experiment logs indicate that a plasma shot was conducted at the DIII-D National Fusion Facility, utilizing three gyrotrons, Leia, R2D2, and Luke, to control the plasma. The gyrotrons were set to operate with a delay of 1500 microseconds, a requested power of 5000 megawatts, and an actual power of approximately 3599-3612 megawatts. The plasma was successfully initiated, and all beams were functioning as expected until a mode began to affect the beta value. The plasma shot was deemed successful, with the result being classified as "OK, good shot.
3	The last shot of the hybrid part of today's experiment was completed by increasing the plasma density to the same level as shot 155541 and maximizing the co-beam power. This shot was very successful until 4.5 seconds, when a 2/1 mode began to grow, although the plasma's betaN remained above 3.2 until the beam was turned off at 4.9 seconds. Between 3.0 and 4.5 seconds, the average plasma properties were betaN = 3.64, H89P = 2.4, and a surface loop voltage of -0.003 volts. Today's experiment consisted of 11 plasma shots, including 1 reference shot, 6 clean-up shots at two different dRsep values, and 4 successful shots with a betaN of over 3.2, three of which had a negative loop voltage at 1.0 MA.

Table 1: Examples of experiment logs which are usually written post experiment. These logs are used as auxiliary feedback in our LLM-powered Bayesian optimization method.

4 Experiment Setup

In this section, we describe our experiments.

We employ an end-to-end LLM to perform Bayesian optimization, with the difference that we include written logs in the observations. We utilize historical data from 281 past experiments carried out at the DIII-D tokamak facility between 2012 to 2023. These experiments correspond to high q_{min} plasma scenario with β_N values ranging from 2.6 to 3.9.

This data is used to simulate live experiments. At each step we sample a target plasma pressure β_N^t from the range of historical values. We then select a subset of historical experiments whose β_N lies between $[\beta_N^t - \epsilon, \beta_N^t + \epsilon]$, where $\epsilon = 0.05$. Now, the Bayesian optimization task corresponds to selecting the ECH value corresponding to any experiment in this subset. After selecting the ECH value, we treat the corresponding experiment and its time to tearing mode as an evaluated observation, which is then used to perform the posterior update. To evaluate each method, we employ contextual cumulative regret

$$\mathcal{R}_T = \sum_{t=1}^{T} \left[f^{\max} - f(x_t, \beta_{N,t}) \right] ,$$

where $f^{\max}$ denotes the maximal time-to-instability and T denotes the current round.

Methods Compared We compare the following approaches -

- **GP-EI :** Traditional Bayesian optimization with a Gaussian Process surrogate model and Expected Improvement as the Acquisition Function
- **LLM-E2E :** LLM as an end-to-end Bayesian Optimizer. Here, we provide the history of past observations, the current context and subset of ECH values to select from.
- **LLM-E2E with Aux Feedback :** Similar to LLM-E2E, along with experiment logs as auxiliary feedback for each evaluation point.

The LLM used for experiments was Llama-3.3-70B instruction-tuned model [Grattafiori et al., 2024].

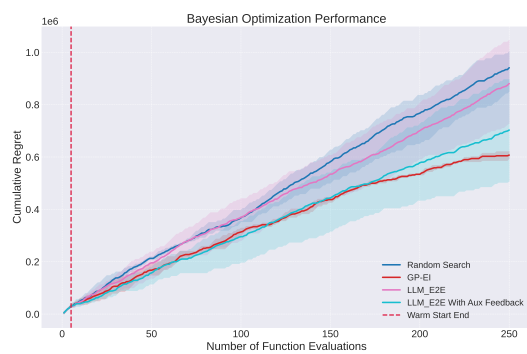

Figure 2: Cumulative Regret across different methods. GP-EI corresponds to Vanilla Contextual BO with GP and Expected improvement as Acquistion Function. LLM-E2E corresponds to BO using LLM as next query selector. LLM-E2E with Aux Feedback incorporates additional text feedback from experiments. All methods were run for 3 random seeds.

The results can be seen in fig. 2. GP-EI converges with the least cumulative regret. This is closely followed by LLM-E2E With Aux feedback which shows that including this additional information leads to substantial improvement in regret. We notice that the LLM based method matches the GP performance initially, however later on diverges. We also see that LLM-E2E method (without Aux feedback) performs better than Random Search. We attribute the advantage of GP-EI after a long horizon to the exact Bayesian updates, which do not suffer from inaccuracies for long context windows as with the LLM, ultimately driving better convergence.

5 Conclusion

We have presented an LLM-based BO approach for tokamak plasma stabilization. Our method incorporates freeform text into the optimization loop, contrasting with vanilla Bayesian optimization methods. Preliminary results using a simulated setup show promise compared to an LLM-based approach without text feedback. However, vanilla Bayesian optimization outperforms our strategy in the long run, indicating that improvements can be achieved. This motivates our future work, where we will combine both methods in a way that simultaneously leverages their advantages.

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