Computational Limits to Disruption Prediction

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A common term used within the fusion community is the term "predictive modeling". Concomitant, with this term is the often (understandably) irrational exuberance that comes with success in meeting a long-sought milestone that justifiably leads to claims of increased predictiveness, but with caveats that are not clearly conveyed, leading to widespread misunderstanding. As the theory community discusses the state-of-the-art in our knowledge of disruptions and other transients, as well as our simulation capabilities, it is an opportune time to reflect upon the meaning of "predictive modeling", in general, and as it applies to disruption prediction in particular.

An idealized, truly predictive modeling for disruptions would simulate the entire discharge as shown in Figure 1. Starting at $t=0$, the simulation would traverse through the start-up phase, enter the high performance state, detect the stability boundary for a given mode, and then use actuators to achieve a high-performance steady-state. In Figure 1, the stability boundary for the external kink is shown in terms of standard global parameters, but the boundaries will be fuzzy due to profile effects, and the steady-state will not be a stationary point, because of profile and source evolution. In this highly idealized view of computational plasma disruption prediction, we will need to understand:

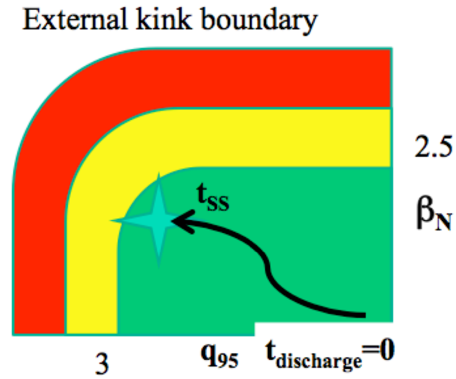

Fig.1. Schematic of obtaining a high performance plasma discharge that avoids disruptions due to external kink modes.

- Plasma transport with no free parameters, including the highly important momentum transport
- Sources, especially from the mix of RF, neutral beam, and fusion reactions expected in future reactors,
- Stability boundaries, not only for the reasonably well-understood external kink mode, but for vertical displacement events, tearing modes, resistive wall modes, etc.
- Boundary conditions, especially in the presence of 3D perturbations which can change the steady-state wall behavior.

This encompasses the entire fusion program. Each area will have limits to what is means to be predictive. Consider, for example, the results of the GLF23 flux model development [1]:

> *The average rms error for all 22 discharges is 18.4%, 13.1%, and 16.7% for Te , Ti , and vphi , respectively. ... For the entire 125 discharge dataset, the model has an rms error of 12.4% in the core thermal stored energy. The corresponding rms error in the incremental thermal stored energy is 17.4%.*

This has many excellent qualities in conveying the limits to its ability to predict transport: the error bars are quantified, the paper discusses the discharges chosen for the dataset, and the methodology is clearly outlined. This indeed was a major milestone in our predictive capability, but what is often less clearly conveyed is that the sources, sinks, magnetic geometry, and boundary conditions were all taken from experiment, and a free parameter to get the best fit for the velocity profile was used.

As a further examples of the challenges, consider this scenario for a plasma disruption:

> Tearing mode increases localized heat flux on tile → tile over temperature → tile melting or ablation → impurity influx → radiated power increase leading to H-L back-transition → p profile peaks, li increases → internal kink mode → thermal collapse and/or VDE → possible damage to PFCs

What is The Cause of the disruption in this case? As theorists who have a tendency to simplify, the real-life complexity of tokamaks and challenges of tokamak prediction and avoidance [2] can overwhelm. Thus, the idealized "predictive modeling" discussed above, is a fantasy.

Despite these challenges, theory and computation can and should play a large role in improving the disruption prediction and avoidance capabilities. Consider the experimental efforts in disruption prediction:

- Neural network on JET: 77% success rate [3]
- JET-trained neural network applied to ASDEX: 67% success rate
- ASDEX-trained neural network applied to JET: 69% success rate within 40 msec [4]
- Multi-diagnostic, hand-tuned approach (NSTX): 96.7% success rate (2.8% false positive rate) [5]

Thus, we see that the neural network approach, while successful, is less effective when applied to other machines. As we approach a new era in plasma physics research where we move from endothermic plasmas to exothermic plasmas, one can expect this neural network approach to be even less effective to a degree that is very difficult to anticipate. The success of the multi-diagnostic, hand-tuned approach shows that considering the individual causes and tailoring algorithms based on our best physics-based understanding is a better path forward.

This then gives confidence that theory and simulation can greatly contribute to an improved ability to avoid disruptions. Although "predictive modeling" is commonly used within the fusion community, the idea of using computational models to *forecast* disruptions has been less discussed. Like weather forecasting, the ability to forecast would rely on a simulation ensemble approach. Even with limiting ourselves to a 40 msec – 100 msec needed for the experimental control system times, creating such an ensemble will require a whole-device modeling approach. To develop detailed onset understanding for the long wavelength instabilities, increased cooperation (as opposed to integration) with the extended MHD codes, which have overlap in physics, will be required. Understanding how to create a forecast involving all of the actuators (sources, coils, pumps, etc) and our best understanding requires the entire theory community sub-fields (transport, RF, extended MHD, edge) to work together.

Although such an ambitious goal would undoubtedly require a large effort, the elements of such a program are well understood and would would need to include:

- Ability to include the most accurate physics modeling for core and edge transport, sources, wall physics, and extended MHD physics for mode onset;
- Ensuring that diagnostic information is optimally used by using simulation to provide guidance on precursor signatures; e.g., using synthetic diagnostics to help optimize a synthetic control system to improve the experimental control system;
- Use techniques from the applied mathematics, uncertainty quantification (UQ) community to more formalize our current uncertainty analysis and improve our projections into unknown regimes;
- Improve validation efforts by devoting experimental analysis time towards the creation of databases of cases for theorists and computation to study, including cases suitable for "blind" validation;
- Increase the efficiency of exploiting supercomputing resources for the type of ensemble simulations needed for tokamak forecasting.

The analogies between weather and tokamak forecasting are strong. For example, hurricane simulations have difficulties predicting the landfall location, however, hurricane forecasting has undoubtedly saved lives. The challenge to the fusion theory community is whether tokamak forecasting can save reactors.

[1] J. Kinsey *et al.,* Phys. Plas. **9**, 1676 (2002).
[2] P.C. de Vries, NF **49**, 055011 (2009).
[3] B. Cannas.et al. NF **47**,1559 (2007).
[4] Windsor et al. NF **45**, 337 (2005).
[5] S. Gerhardt et al. NF 53, 063021 (2013).