P&A discussion

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Discussion bullets (I)

- Thermal quench detection/prediction informing DMS trigger and strategy
    - TQ modeling is challenging (see “Consequence” session), Ip spike due to TQ difficult to reproduce
    - Unmitigated TQ simulations are scarce → predictive modeling non-existing?

- Effectiveness of predictive algorithms/forecasters, e.g. Staggered SPI scheme timescales ~ 100ms
    - Need to be conditioned to actuators response time and behavior. Are there approaches out there working in this direction?
    - Safe operating region id and disruption proximity approaches?
    - Time-to-event predictions conditioned on available actuators?

- What limits the True Positive Rate in ML algorithms for disruption prediction?
    - How extrapolable are these solutions implemented on DIII-D/KSTAR/EAST to ITER?

- Disruption rate/conditions affected by RT system, how to decorrelate effects when doing analysis at scale? (Or, rather: include the physics of the action of the PCS+actuator. E.g.1 gas puffing in rampdown to protect the divertor => plasma more prone to edge cooling; e.g.2 core power deposition to avoid impurities accumulation triggering large sawteeth and finally NTMs)

Discussion bullets (II)

- Application of ML to sensor failure: probably effective to complement the processing of plasma diagnostics (ECE for AE identification). Which are the conditions for effective predictive maintenance (statistical basis, detailed knowledge of the operation conditions...)

- From disruption prediction to avoidance. Avoidance needs more warning time and effective identification of the disruption cause to trigger the appropriate action (emergency shut down last resource in a “reactor”. Where we are on this? (eg see Steven Sabbagh, Dan Boyer presentations)
    - TM stability: experiments being run at DIII-D to regulate gradients in $J_{||}$ (current well theory) with shaping modifications (rt measurements may require faster and better constrained EFITs?). Other approaches focus on rt-DCON, AMS, data-driven discovery, ...
    - Wait till the mode locks to stabilize via modulated RF (Reimann)?

- ML approaches: better a super accurate black-box model or less reliable but more transparent/interpretable model?

Discussion: Given present successes in disruption prediction and avoidance, what are ITER needs for next steps in analysis?

- Especially important for ITER Team to provide specific guidance now
- Relevance to ITER and next step devices
  - sufficiency of early warning for (i) mitigation, (ii) avoidance. What timing is needed?
  - relevance of a disruption regarding analysis for ITER / next devices (e.g. I_p threshold)
    - what specific criteria can ITER Team give in this regard?
  - extrapolation of present analysis, models, etc. to ITER / next devices
  - sufficiency of ITER diagnostics for real-time analysis
  - ability to perform analysis in real time
- Confidence in analysis
  - event analysis correlation vs. causality to disruption VERY important !!
    - what certainty do we have in any analysis that events really cause the disruption?
  - deterministic vs. probabilistic approaches
  - physics-based vs. "black-box" AI approaches

Extra - summary slides

Physics-driven approach to DP&A on JET (Pucella)

- Temperature Hollowing and Edge Cooling (anomalous Te profiles) eventually lead to onset of 2/1 Tearing Mode (TM) in the termination phase.
    - Destabilization driven by gradient of current density profile: shrinking (EC) vs broadening of J-profile (TH)
        - Possibility of linear destabilization of 2/1 TM due to changes in J
            - Interpretative TRANSP sim show changes in J-profile reflecting changes in Te-profile
            - Linear stability analysis in p=0 approx shows delta’ to increase a positive value for destabilization to occur

- Core accumulation of high Z imp → TH, while influx of low-Z → EC, leading then to current profile deformations, leading in turn to onset of 2/1

- Baseline scenario dataset shows TH/EC indicators (volume averaged Te measurements) to be effective at detecting non-disruptive stable values (10% FP) and disruptive behaviour in the last 2s (90% accuracy)

- Characteristics time scales analyzed for baseline scenarios: time from ML to disruption depending on mode dynamics and DMV

- TH could be counteracted by increasing central additional heating (if available)

- Mitigation (gas injection) only available action for <u>EC occurring in a hollowed Te</u> profile, since it leads to an explosive growth of the TM

Disruption characterization in JET-ILW, paths in high performance scenarios with D, T and (D,T) (Alessi)

- Disruption rate and frequency of paths: Temperature Hollowing (TH) vs Edge Cooling (EC)
  - TH: High Z impurities accumulating in plasma core
  - EC: mid/high Z imp, causing loss of density ctrl

- Hybrid vs Baseline scenarios show different incidence of dominant disruption cause

- TH and EC events defined via volume averaged quantities describing core vs mid-rad vs edge region + temperature peaking + density peaking + Greenwald fraction

- JET RT control system was updated [L.Piron FED 2022] for DT operation in JET with advanced algorithms for disruption avoidance and mitigation:
  - A Temperature Hollowness detector [M.Fontana FED 2021] (saving disruptions in ramp-up)
  - RT detector based on a Generative Topographic Mapping trained with input information on density, temperature and radiation profiles [A. Pau NF 2019] -> probability of disrupting
  - RT bolometry tomography algorithm estimating the amount of radiation from different plasma regions [D.Ferreira FED 2021]

DECAF expanded to real-time in KSTAR (Sabbagh)

- Modular physics-based approach to event characterization and forecasting
  - Multi-device, integrated approach to disruption prediction and avoidance, Supporting physics analysis, experiments run to create, validate models, expand operating space
  - Island rotation dynamics forecaster model real-time available (Riquezes), utilizes DECAF rt MHD system to determine mode and critical frq then provides warning (level 3) with hundreds of ms advance time

- Physics-based “event chain” yields key understanding of evolution toward disruptions needed for confident extrapolation of forecasting, control

- Very high accuracy >99% (NSTX) and in real-time experiments on KSTAR 100% success rate
  - Controlled shutdown, MGI, disruption avoidance actuators triggered in real-time by DECAF warnings
    - Abnormal Ip and z monitored to study disruption timings (current quench spikes) across (spherical) tokamaks (Zamkovska)

- Causality vs correlation between warnings and the disruption

ML pervasively aiding fusion data analysis, experiments, and discovery of operational boundaries

- NN estimators for current centroid and growth rate (EAST/KSTAR/DIII-D)
  - Xiao, Barr
  - Real-time estimation of plasma vertical position, fast Z control
- Offline plasma equilibrium reconstruction via NN
- Offline boundary and current profile reconstruction based on Bayesian inference from magnetic diag
  - Joint reconstruction of density and current profile with HCN and POINT improves accuracy on current profile
- Sensor failures (DIII-D/NSTX)
  - Jalalvaland, Kolemen
  - Ex: Predicting circuit breaking lifetime on JET - Predictive maintenance to avoid/control sensors faults
  - NN-based AE detector: instead of reconstructing spectrograms and identifying patterns in frequency domain, a Reservoir Computing Network (RCN) chews on raw ECE data
    - TPR 91%, FPR 7% in classifying different modes
    - Smooth output label improves detection wrt SME
    - Degradation of model performance shown to depend on location of ECE signal
  - NN-based AE localizer: spectrograms used to extract the probability of AE modes per ECE channel per time step.

MAST camera data to identify disruptions caused by filamentary eruptions

- Eulerian Video Magnification (EVM) video processing technique capable to magnify subtle periodic variations

- Spectrograms subjected to EVM to target frequency of interest, e.g. long lived modes, tearing modes, ...
  - Filamentary disruptions related to ~ 100 ms ballooning activity, could challenge P&A

➢ Concerns about general applicability to a neutron rich reactor environment in which camera data may not be readily available

➢ Could EVM be combined with other tools, like DECAF or spectrogram cleaning for AE detectors?

Ctrl and ML algorithms for disruption avoidance and proximity control (Boyer)

- Limited actuation and time-varying constraints impact the effectiveness of actual predictive algorithms for disruptions

- Model Predictive Control includes controller limits and continuous changes to make up for actuators' unavailability
  - The core of MPC can be based off TRANSP simulations
  - Opportunities to accelerate nonlinear physics models (NubeamNet) or improve through empirical ones (can be based off ML/DL/RL algorithms)

- Constraints could be provided by fast simulations of ML-based predictors
  - Disruptivity vs distance from disruption boundary (SORI)
  - SORI to enable active optimization of controllable parameters to avoid disruptions

Prox ctrl (Barr): continuous monitoring and adjustment of targets away from stability/control limits

- Vertical Displacement Events (VDEs) + Additional VDE stability metric assessment on KSTAR
- Unintended H-L back-transitions
- Tearing Modes
- ML informed stable operating space

Preset settings for each problem/instability handler: modifiable thresholds for intervention.

- How extrapolable are these solutions implemented on DIII-D/KSTAR/EAST to ITER?
- Is dzmax a metric handled by prox controller? Is it independent?
- H-L back transitions, handled via input power adjustments: is the time needed for beams to have effect in plasma taken into account? What if it's too late to recover? Is the metric providing time-to-event predictions?

ML methods for Disruption Prediction (I)

- CNN / LSTM use plasma eq parameters + magnetics + radiation measurements (Xiao, EAST)
  - TPR > 87%, FPR ~ 6–15%, mean alarm time 46–60ms
- Hybrid (CNN+LSTM) approaches: CNN used for feature extraction, LSTM for warning, performances increase > 95% [Xiao (EAST), Zhu (EAST/DIII-D/C-Mod)]
  - Cross-device prediction via HDL (Zhu et al) shows general knowledge can be extracted from disruptive data while non-disruptive is device-specific.
  - Need to focus on ITER-relevant scenarios (AND disruptions) to improve prediction performance.
- LSTM / RF based algorithms being used in closed-loop experiments [Xiao (EAST), Rea (DIII-D,EAST)]
  - TPR 92-95%, FPR ~8-10%
  - RF installed in RT PCS (EAST for high density disruptions, DIII-D agnostic to disruption type)
- XGBoost Looking at impurity driven disruptions, statistical analysis underway (Xiao, EAST)

ML methods for Disruption Prediction (II)

- Transfer Learning to future devices (Zheng): Many efforts focus on “mixing” rather than transferring learnt information to new devices/regimes
  - Examples include HL-2A LP+HP, and HDL scenario adaptive study by J.X. Zhu
  - Transfer learning from existing machine to target (e.g., from J-TEXT to EAST) using CORAL (correlation alignment), pre-train & fine-tune
  - More data is needed for domain generalization.
  - With data from more tokamaks, the pre-train model will learn more general knowledge of disruption, easier on transferring to target machine.
  - More machine does not necessarily mean more data, as the model needs diagnostics that is present on all machines.

- Centroid method (Vega): ML/Ip increases when the rotation of a mode slows down or locks or the amplitude of the mode increases.
  - ML/Ip installed in JET RT network, SR > 90%, FA ~4%

- GTM + CNN (Sias/Aymerich) use equilibrium params + profiles (Peaking factors vs full profiles)
  - Pre disruptive phase length determined via statistical tools, SR > 90%, FA ~4%

- CNN + LSTM (Guo): scoping of metal wall DP on EAST using non-metal wall data
  - Convolution attention blocks increase accuracy (AUC ~ 0.84), baseline non-metal wall performances TPR ~95% FPR 8%