Identification of characteristic ELM evolution patterns with Alfven-scale measurements and unsupervised machine learning analysis

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Characteristic edge localized mode (ELM) evolution patterns are measured at Alfven timescales with a multi-point beam emission spectroscopy (BES) diagnostic on NSTX/NSTX-U, and parameter regimes corresponding to the characteristic ELM evolution patterns are identified. Understanding the nonlinear dynamics of ELM-induced heat and particle transport is a critical issue for ITER. The linear peeling-ballooning stability boundary expresses an onset condition for ELMs, but ELM saturation mechanisms, filament dynamics, and multi-mode interactions require nonlinear models. Also, heuristic ELM classification schemes (Type I, III, etc.) based on extrinsic ELM properties, like secular edge emission and inter-ELM pedestal evolution, do not capture the nonlinear dynamics and Alfven-scale evolution of ELM events. Validation of nonlinear ELM models requires fast measurements on Alfven timescales, and successful models should reproduce the complex evolution patterns observed during ELM events.

Recently, we investigated Alfven-scale evolution patterns in ELM events captured by BES measurements on NSTX [1]. Unsupervised machine learning algorithms identified two or three groups of ELMs with distinct time evolution characteristics. The identified ELM groups exhibited similar stored energy loss, but the groups occupy distinct regimes for several ELM-relevant parameters. The observed evolution patterns and associated parameter regimes suggest genuine variation in the underlying physical mechanisms that influence the evolution of ELM events and motivate nonlinear MHD simulations. Here, we review the previous results for ELM evolution patterns and parameter regimes from Ref. 1, and we report on a new effort to explore the identified ELM groups with nonlinear MHD simulations. Finally, we discuss opportunities to leverage machine learning tools in the data-rich fusion science field.

We identified 51 ELM events with BES measurements from the NSTX data archive in Ref. 1. BES measurements capture the Alfvenic nonlinear evolution of ELM events in contrast to conventional filterscope measurements or Thomson scattering profiles. The ELM events show stored energy losses up to 16%, and the ELM database in this investigation most likely includes only Type I ELMs due to the ELM selection criteria. Measurements on Alfven time-scales inherently capture the nonlinear dynamics and saturation mechanisms of ELM events,

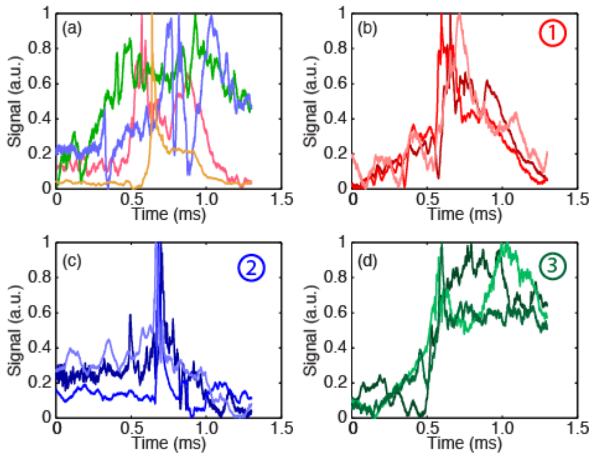

Figure 1: (a) Examples of diverse evolution dynamics for ELM events. Unsupervised cluster analysis of time-series similarity metrics identified three groups of ELMs with similar time-series evolution. (b-d) Examples of ELM events with similar time-series evolution from (b) group 1, (c) group 2, and (d) group 3 [1].

and Figure 1a shows examples of diverse evolution dynamics for ELM events in the database. To identify common evolution patterns in the ELM database, we implemented hierarchical and k-means clustering algorithms from the unsupervised machine learning domain. The clustering algorithms were applied to time-series similarity metrics like maximum time-lag cross-correlation, dynamic time warping, and maximum time-lag cross-correlation of wavelet-transformed signals. For example, Figure 2 shows groups of ELMs with similar time-series evolution as determined by hierarchical clustering and a cross-correlation dissimilarity metric. The results from the analysis point to two or three groups of ELMs with distinct evolution patterns, as shown in Figures 1b-d. Also, the clustering results were robust with respect to computation options such as linkage formula, similarity metric, and benchmark designation (for k-means clustering). Notably, the identified ELM groups occupy distinct parameter regimes for several ELM-relevant parameters. For example, Figure 3 shows that the identified ELM groups segregate in terms of plasma current, elongation, magnetic balance, and density pedestal height. The distinct evolution patterns and parameter regimes suggest genuine variation in the underlying nonlinear dynamics. The observed evolution patterns will be augmented with new measurements from the recently upgraded 2D BES system on NSTX-U.

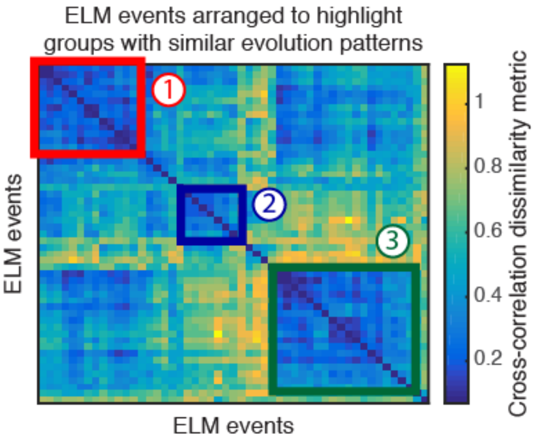

Figure 2: The reordered dissimilarity matrix from hierarchical clustering illustrates groups of ELMs with similar evolution patterns. Groups of ELMs along the diagonal with low dissimilarity (blue) are ELMs with similar evolution patterns [1].

Motivated by the identification of distinct evolution patterns and parameter regimes, we will also report on a new effort to investigate the characteristic ELM evolution patterns with nonlinear MHD simulations. Finally, we will describe opportunities for data-driven discovery in fusion science with machine learning techniques. For example, unsupervised learning techniques can identify common time-series patterns for disruptions, the LH transition, or Alfven eigenmode events. Also, classification techniques can automate the labeling of events in real-time or archived data.

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[1] "Evolution patterns and parameter regimes in edge localized modes on the National Spherical Torus Experiment," D. R. Smith et al, in press, Plasma Phys. Control. Fusion (2015)

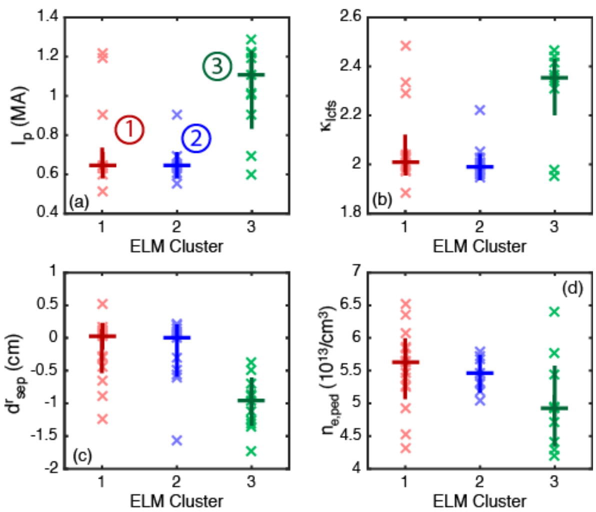

Figure 3: The ELM groups exhibit distinct parameter regimes for (a) plasma current, (b) elongation, (c) magnetic balance, and (d) pedestal density height. Solid bars denote 20th, median, and 80th percentile values, and small x's denote values for individual ELMs [1].