Predicting the Failure of Engineered Systems

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Predicting failures of engineered systems is crucial because our society increasingly hinges on the smooth functioning of engineering infrastructures. Despite the long struggle with system failures in the history of human civilization, the missing a generic understanding of the physics of failure hinders a generally effective methodology of failure prediction. Here we discover that the system failure is strongly correlated with critical transition phenomenon, which can be predicted by early warning signals, e.g. the critical slowing down and the deviation of skewness, in a variety of engineered systems. The applicability of such indicators suggest that the losing of resilience generally reflects the physics of failure in engineered systems. Our findings open a new path to forecast failures of engineered systems with a generic method and provide supporting evidence for the universal existence of critical transition in dynamical systems at multiple scales.

Engineered systems | critical transition | failure | prediction | critical slowing down

The struggle with system failure has been a fundamental theme in the history of human civilization since the invention of machines (*1*). The failure of engineered systems may incur disastrous impacts since the operation of modern society hinges on their smooth functioning. One example is the tragic Eschede high-speed train accident (*2*), which was caused by the fatigue-induced crack of a wheel, happened in 1998. Precise failure prediction of engineered systems is, however, a worldwide challenge. Although these systems are designed to offer well-defined behaviors, the complex interactions within their components and with the working environment tend to be too complex for an exhaustive analytical modeling of various idiosyncrasies in the system (*3*). Even if the system dynamics approaching failure can be approximately derived through reliability analysis (*4*), the missing a generic understanding of the physics of failure in engineered systems hinders a generally effective methodology of failure prediction.

Critical transition (*5*), i.e. the dramatic shift of state in complex dynamical systems (*6*), is increasingly recognized as a vital concern for its potentially disastrous impacts in many social-ecological systems (*7*). The existence of such tipping points is the result of the nonlinearity and stochasticity inherent in the complex dynamical systems (*8*). In spite of the vastly diverse mechanisms leading to regime shift, recent years witnessed scientific progresses in identifying early-warning signals, which can be generalized as indicators for the loss of resilience (*9,10*), for critical transitions (*11-13*). For example, Critical Slowing Down (CSD) (*11*) and other indicators like the changing skewness (*14*) have been found to be present in a wide spectrum of complex systems ranging from ecosystems (*15,16*), neurons in mammalian cortices (*17*) and climates (*18*) to financial markets (*19*) when approaching the tipping point. Likewise, engineered systems such as jet engines, locomotives, and bearings also demonstrate strong nonlinear behaviors and stochastic fluctuations under the complex interplay of internal and environmental factors (*20*). Intuitively, sudden failures in engineered systems, e.g., the abruptly accelerated worsening of cracking till the final derailment in the Eschede high-speed train accident, bear significant similarity to the critical transitions in social-ecological systems.

Motivated by the similarity of the critical transition and the system failure, we investigated representative engineered systems to explore the underlying connections. Here we discover that early-warning signals reflecting the loss of resilience can serve as the effective precursors of failures in the engineered systems. Our findings offer strong evidence for the correlation between failures in engineered systems and critical transitions in dynamical systems. Considering the prevalent existence of the critical transition phenomenon as well as the respective early warning signals at multiple scales in both social–ecological systems and engineered systems, we anticipate that the losing of resilience is the generic mechanism of the physics of failure for potentially all dynamical systems. Our findings pave the way toward a generic methodology to predict and prevent potential disasters caused by the failure of engineered systems. The discovery complements the pursuit in foreseeing the behaviors of complex systems (*5,21*) by proving that the critical transition phenomenon ubiquitously exists at multiple scales ranging from the basic engineering building block to highly complex networked systems.

We investigated four different engineered systems, an airbrake system of diesel locomotive (a pneumatic system), a Turbofan engine (a mechatronic system), an Insulated-Gate Bipolar Transistor (IGBT, a power electronic system), and a rolling bearing (a mechanic system), which are operated in dramatically diverse physical domains, to testify if the early warning indicators for critical transitions are applicable for engineered systems. The airbrake dataset is gathered from a commercially operating locomotive, while the remaining three are public prognostics benchmarks made available by NASA Prognostics Center of Excellence (PCoE) (*22*). In the NASA PCoE datasets, the Turbofan engine data are generated with an industry-strength simulation

Significance Statement

The failure of engineered systems can be disastrous as the human society increasingly depends on the engineered infrastructure. Predicting system failures, nonetheless, is extremely challenging due to the growing complexity in system design and interactions with the environment. Here we discover that the early warning signals, e.g. the critical slowing down and the deviation of skewness, which reflects the loss of resilience in dynamical systems, can effectively predict the failure of engineered systems. Our findings not only open a new path to forecast catastrophes of technical systems with a generic method, but also provide supporting evidence for the universal existence of critical transition in dynamical systems at multiple scales.

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This article contains supporting information

(*23*), whereas the IGBT and bearing datasets are ugh aging experiments (*24,25*). All the datasets are nultivariate time series sensor data collected during a ı-to-failure process. We derive the variance,

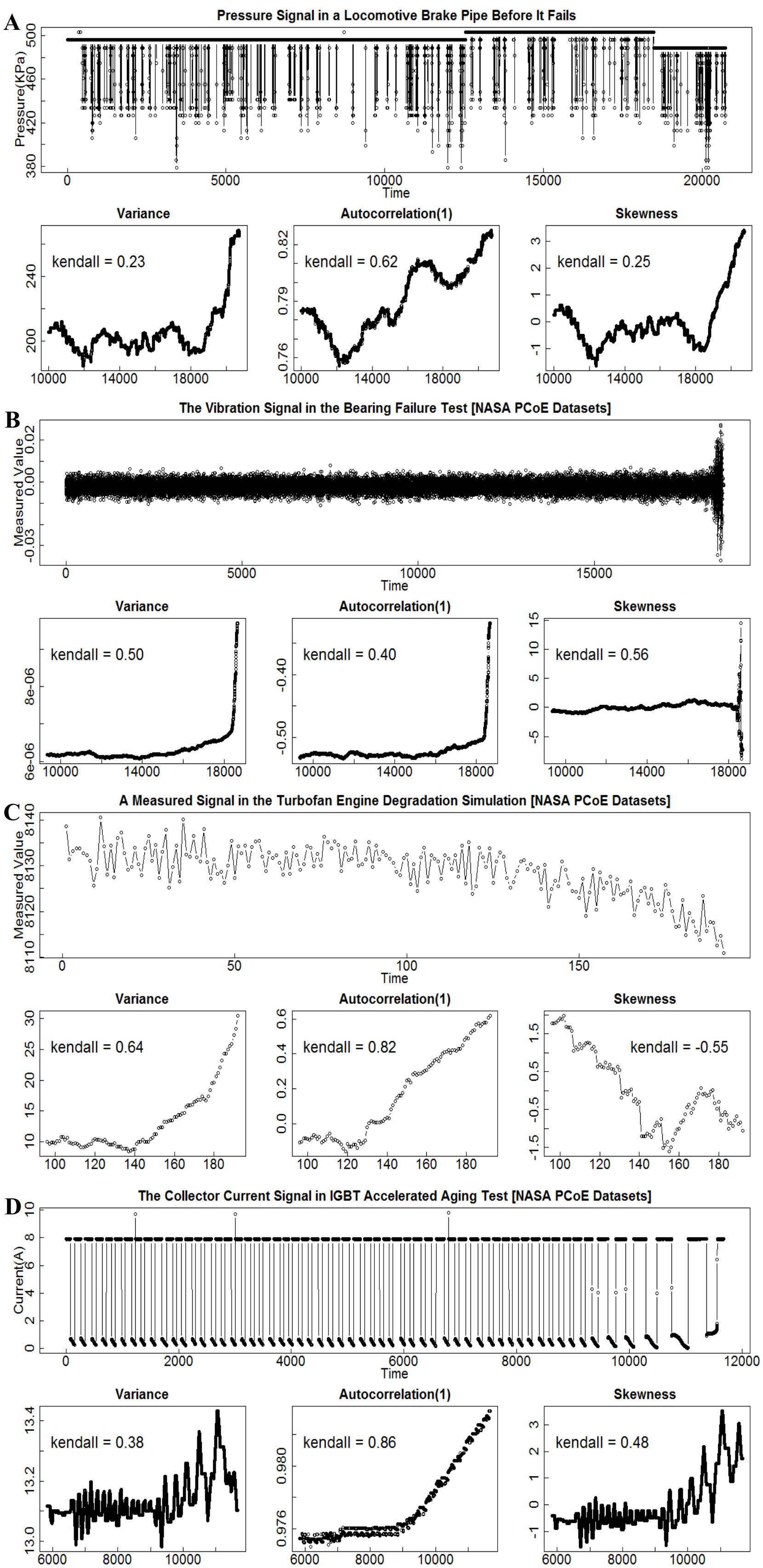

Fig. 1. The presence of early warning signals in terms of the CSD (*i.e.*, increasing variance and autocorrelation) and deviating skewness in four representative engineered systems. (**A**) The air pressure signal in the brake pipe of a locomotive collected by the Train Control/Management System (TCMS) of the locomotive every second in the period of two days before the failure of un-recoverable pressure loss and the corresponding analyzed indicators. It was preprocessed by eliminating the data corresponding to the parking states. **(B)** The vibration signal from a bearing test platform collected by NASA PCoE while the bearing is operating until breaking down and the corresponding analyzed indicators. **(C)** An unspecified signal in the Turbofan engine degradation simulation collected by NASA PCoE while the engine runs to failure and the corresponding analyzed indicators. **(D)** The collector current signal of a power IGBT during accelerated aging tests collected by NASA PCoE and the corresponding analyzed indicators. The sliding window to compute variance, autocorrelation and skewness is chosen as 50% of the span of time series for all the four systems. There are strong evidences of CSD (i.e., the increasing trend in both variance and lag 1 autocorrelation) and deviating skewness in all the four systems when they approach system failures. Despite the clear trend, strong fluctuations on the variance, autocorrelation and skewness are observed in all the cases, suggesting systematic disturbances existing in the original time-series.

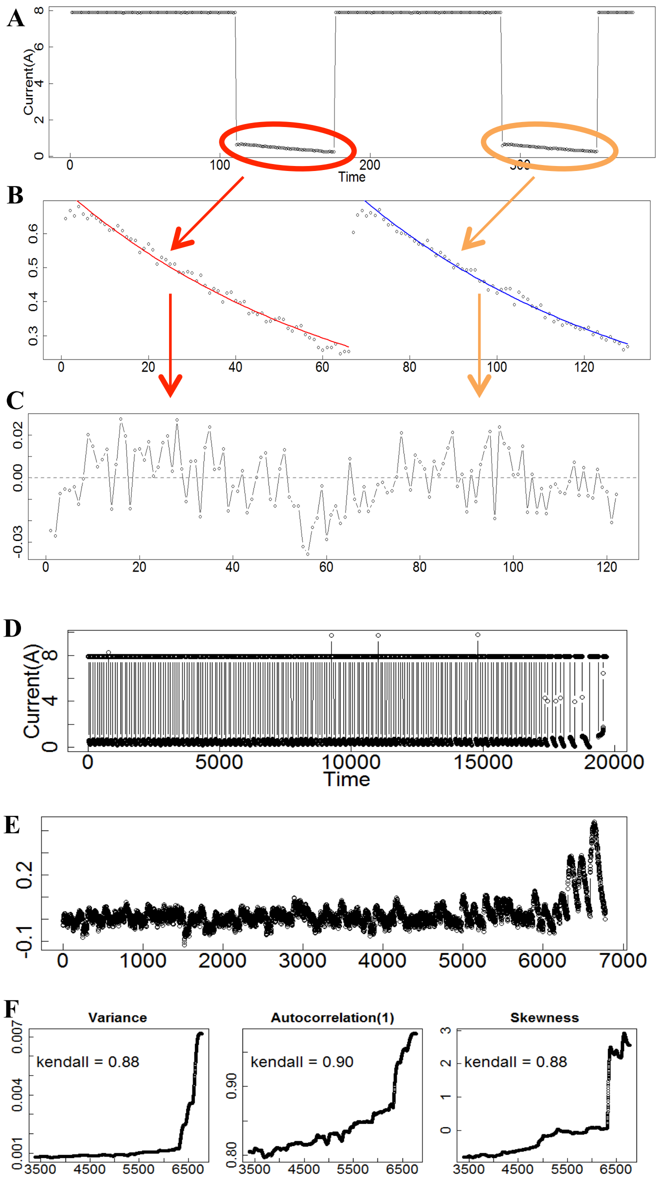

Fig. 2. The Fluctuation Mining (FM) process and the identification of intrinsic stochastic fluctuations. (A)-(C) The processing flow of FM on the collector current of the IGBT system**. (A)** A snippet of the time series of collector current collected from the IGBT system. **(B)** The failure sensitive component, i.e., the switch-off current that exponentially converges to 0, with the fitted curves being the operational trends, in the collector current. **(C)** The fluctuations derived after performing FM, i.e., removing the failure-insensitive components and performing a detrending process, on the previous snippet of the time series. **(D)** The original time series of collector current collected from the IGBT accelerated aging test**. (E)** The fluctuations derived after FM for (D). **(F)** The variance, autocorrelation and skewness indicators extracted from the fluctuation signals in (E). Analysis on the signals after the FM process shows strong evidence of CSD and deviating skewness.

autocorrelation, and skewness characteristics of the observed time series as the indicators of losing resilience. Although from considerably different domains, all the four systems unanimously exhibit the typical symptoms of CSD and deviating skewness (Fig. 1 and Supplementary Fig. S1). Such an observation offers strong evidence that early warning indicators can serve as the precursor of failures in engineered system.

The dynamic behaviors of an engineered system are generally reflected by the discrete samples of one or more observable signals organized as time series. The signal values in a time series are determined by both an operational trend (i.e. main trend) and stochastic fluctuations. In the case of the dynamic ecological system, a detrending (*12*) procedure is often necessary to extract the stochastic components. As exemplified by the rather obvious variations in the curves of variance, autocorrelation and skewness (Fig. 1), the operational trends may severely blur the resilience indicators in the engineered systems. We devise a Fluctuation Mining (FM) procedure to selectively identify the stochastic fluctuations that is not directly associated to the designed operation of engineered systems (Fig. 2A-C). The procedure consists of a data cleansing step that removes the failure-insensitive components in the observed signals and an estimation based detrending step. For instance, the application of the FM on the IGBT dataset successfully reveals a much clearer propensity of increasing variance and autocorrelation as well as deviating skewness (Fig. 2F-H and Supplementary Fig. S2).

The applicability of resilience indicators for predicting forthcoming failures provides evidence for the correspondence between the critical transition and the failures in engineered systems. We endeavored the Student t-test (*26*), the Gaussian kernel based probability density test (*26*), the Akaike Information Criterion (AIC) based ARIMA model analysis (*27*), and the phase space analysis (*28*) on the four engineered systems before and after they reach their failures (Fig. 3 and Supplementary Fig. S4). The analysis results consistently suggest that the studied systems undergo an abrupt change of state upon the happening of failure. For example, the bearing system remains stable under normal operation and diverges to an unstable state (Fig. 3B-E), the Turbofan engine witnesses a complete change of the underlying dynamical function (Fig. 3G), and in the case of the IGBT system, the normal functioning and failure stages show significantly varying limit cycles in the phase portrait (Fig. 3I&K). The analysis results suggest strong evidence on the equivalence between the critical transition and the system failure in the engineered systems.

Generally, the critical transition phenomenon in the social-ecological systems is the aftermath of a catastrophic bifurcation (*29*). In the engineered systems exemplified by the bearing system and the IGBT system, the sudden shift in the fluctuation signals also reveals the features of bifurcations (Fig. 4A&B). We thus anticipate that the catastrophic bifurcation and critical transition are common phenomena in engineered systems approaching failures (Fig. 4C). Typically, an engineered system is designed to deliver well-defined operational behaviors, but can degrade into a protection mode with only limited functionality and completely fall into out-of-control failure under internal or external perturbations. We propose that the engineered systems with dynamical behaviors can be abstracted to have three phases: a normal operation phase that is equivalent to the basin of attraction (*5*), a protected failure phase when the self- protection mechanism is triggered by certain faults, and an unstable failure phase exhibiting out-of-control performance (Fig. 4D). The system fails when it departs from the basin of attraction and loses its resilience.

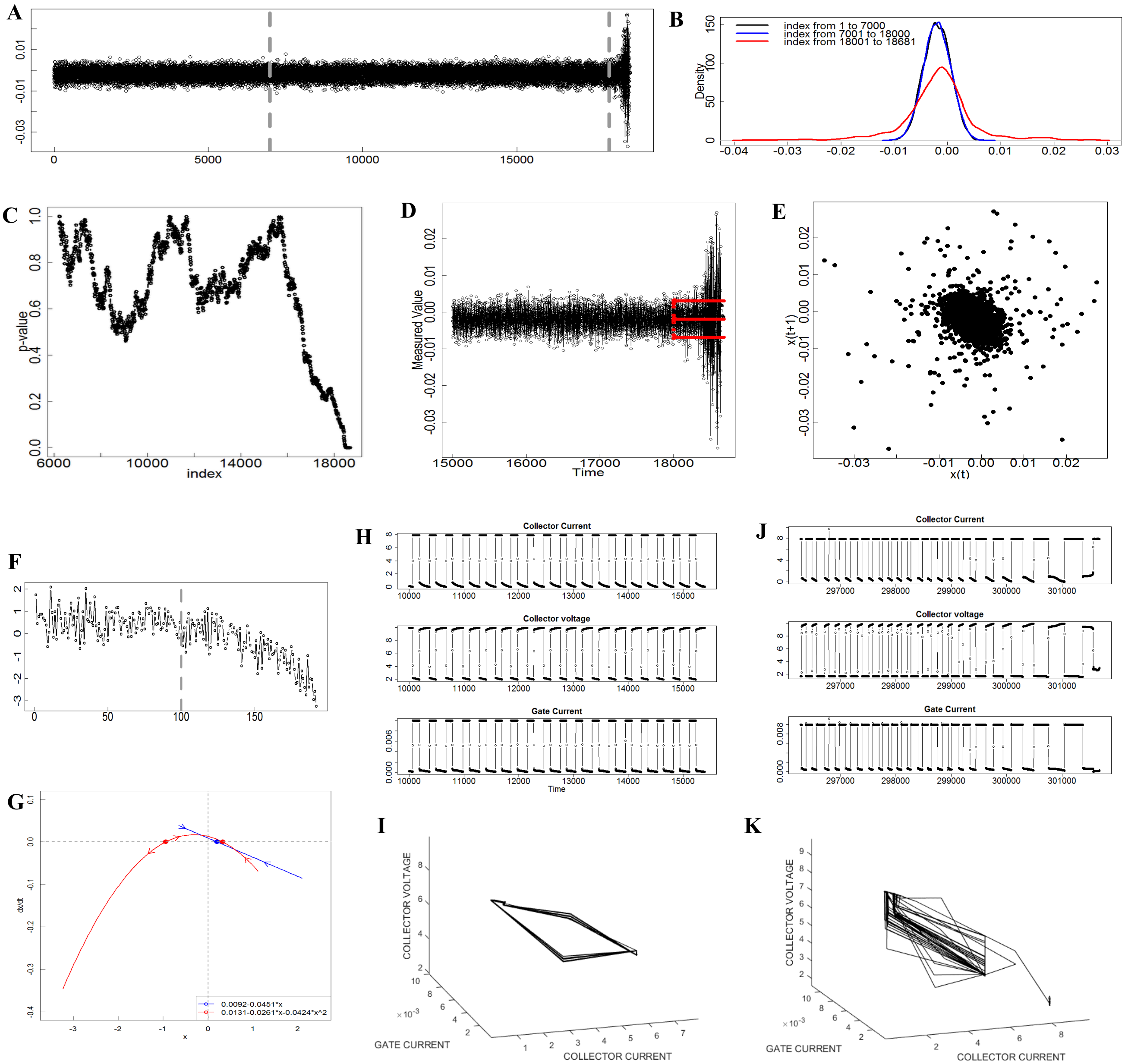

Fig. 3. Critical transition analysis of the engineered systems with various methods when running into failures. (A) The original time series of the vibration signal collected from the bearing system approaching failure, with the dashed line segment the signals into three sections for succeeding analysis. **(B)-(E)** Critical transition analysis for (A). **(B)** The Gaussian kernel based probability density estimate for the three sections of the vibration signal. The density of the third section significantly differs from the first two. **(C)** The results of Student's t-test of the vibration amplitude signal with the true value of the mean be the mean of a normally functioning section. The tested p-value show an evident decrease to below 0.01, which significantly denies the null-hypothesis, indicating that the system evolves into a different state when getting into system failure. **(D)** A forecasting with a 95% confidence interval (enclosed in the red bars) derived from the AIC based ARIMA model for the third section of the vibration signal. The badly fail in encompass the vibration signal in the section suggests a phase transient. **(E)** Logistic map for phase space analysis of the vibration signal. The first two sections are rather concentrated while the third section diverges to unstable. **(B)-(E)** indicate that there is a critical transition in the bearing system when it is arriving a system failure. **(F)** A time series of the turbofan engine system during the degradation simulation process with the dashed line separates the signals into two sections at a departure point. **(G)** The phase portrait of the two sections of the time series signal of the turbofan engine system. It shows that the left section has only one stable equilibrium point, while the right section has two, of which the one at the negative axis potentially drives the system to unstable (*i.e.*, the corresponding system failure). **(H)&(J)** Two snippets of the three selected signals of the IGBT system at the normal functioning stage and the close-to-failure stage. **(I)&(K)** The phase portraits of the signals in (H)&(G). The phase portrait of the normal functioning stage has a clear limit cycle serving as the basin of attraction, while the portrait of the close-to-failure stage reveals divergent behaviors indicating the occurring of critical transition. The above analysis of the engineered systems suggests that the systems undergo certain critical transitions when running into system failures.

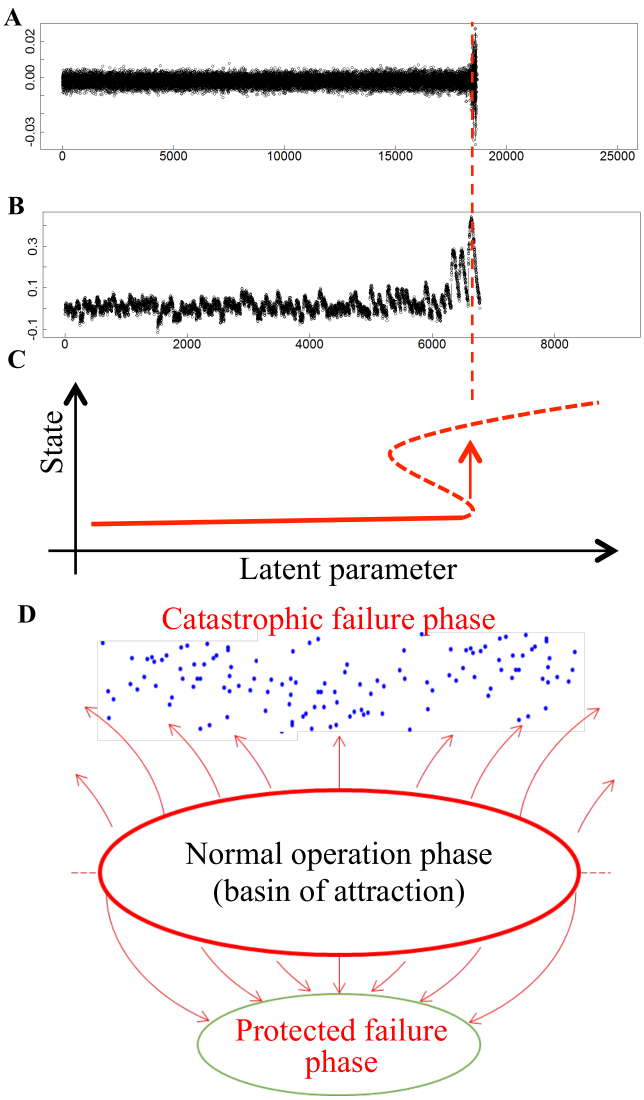

Fig. 4. The potential catastrophic bifurcation and critical transition in engineered systems. (A) The abrupt state change in the vibration signal of the bearing system while running into failure. **(B)** The abrupt state change in the fluctuation of the IGBT collector current extracted with FM. **(C)** The hypothesized catastrophic bifurcation at the system failure. The catastrophic bifurcation can be mapped to the sudden regime shifts in (A) and (B). Considering the nonlinear phenomenon like hysteresis (*30*), the above hypothesis is likely to hold. **(D)** The proposed three phases, a normal operation phase that is equivalent to the basin of attraction, a protected failure phase when the self-protection mechanism is triggered by certain faults, and a failure phase exhibiting out-of-control performances, in engineered systems with dynamical behaviors. The catastrophic bifurcation leading to critical transition occurs when the system departs from the basin of attraction and lose its resilience as the system fails.

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