



# Non-linear boiling water reactor stability with Shannon Entropy



Omar Alejandro Olvera-Guerrero, Alfonso Prieto-Guerrero, Gilberto Espinosa-Paredes\*

División de Ciencias Básicas e Ingeniería, Universidad Autónoma Metropolitana-Iztapalapa, Av. San Rafael Atlixco 186, Col. Vicentina, Cd. de México 09340, Mexico

## ARTICLE INFO

### Article history:

Received 4 February 2017

Received in revised form 19 April 2017

Accepted 20 April 2017

### Keywords:

BWR stability

Decay Ratio

Shannon Entropy

Reduced Order Model

Largest Lyapunov Exponent

## ABSTRACT

The most common indicator currently used to assess boiling water reactor (BWR) instability is the Decay Ratio (DR), which is an indicator that assumes stationarity and linearity of BWR signals. However, it is well known that BWRs are complex dynamical systems that may exhibit *chaotic* behavior when an instability event occurs, jeopardizing the DR validity and reliability when the reactor is working at a specific operating point. Thus, it is required to study new stability indicators that satisfy as much as possible this complex dynamics of BWR systems. With this latter fundamental idea in mind, in this work, the non-linear Shannon Entropy (SE) is explored to study BWR instability. The SE measures the *uncertainty* of BWR signals to appraise for system stability, a *low* SE estimation indicates a predictable BWR operation (stable behavior) whereas a *high* SE estimation indicates an unpredictable BWR operation (unstable behavior). The SE estimation was validated with artificial signals from a non-linear Reduced Order Model (ROM), that represents qualitatively the dynamic behavior of a BWR system. The result comparison proves that the SE satisfies the BWR complex dynamics whereas the DR does not during the *chaotic* behavior. The SE was also compared with the Largest Lyapunov Exponent (LLE), which represents adequately the chaotic behavior of a BWR but, from the practical point of view, it cannot be applied to an online stability monitor, while the methodology presented in this work based on the SE, is a good candidate.

© 2017 Elsevier Ltd. All rights reserved.

## 1. Introduction

The BWR stability has been so far evaluated by the Decay Ratio (DR) calculated from the impulse response function of an autoregressive (AR) model, where the autocorrelation function of the estimate AR model of the cyclical series usually acts damping cyclical evolution (Shi et al., 2001). The Decay Ratio is regarded as a convenient index for scaling a margin to the stability boundary and this property is the main output of most stability monitoring systems (Hotta and Ninokata, 2002). The use of the DR as a practical stability measure of BWRs has been widely used and accepted, however it has been observed that a reactor working at an operating point with a small DR can be close to instability (Van der Hagen et al., 2000) and such work also questions the extreme overconfidence of the BWR scientific community to believe that the dynamic features of a BWR can be grasped from one single indicator (and a linear one). Moreover, reactor operators can be misled by a small DR, not realizing that their system can be closer to instability than they might think. Thus, such authors advocate a reconsideration of the use of the DR in stability monitoring.

In addition, Konno et al. (1999) clearly showed that, due to non-linear effects, the measured DR can be strongly dependent on the frequency content of the parasitic noise that is perturbing the system. On the other hand, the DR sometimes jumps discontinuously from the well stable to the far-unstable region (Pazsit, 1995). The stability is of primary interest from the point of view BWR operation, since the stability margin may be strongly reduced during plant maneuvering and transients (Gialdi et al., 1985). Based on these facts, the DR could not be a reliable monitoring index under some operating conditions.

Regarding the popular use of AR models behind DR estimation, Manera et al. (2003) performed a benchmark to compare the performances of exponential autoregressive (ExpAR) models against linear autoregressive (AR) models with respect to BWR stability monitoring. The model of March-Leuba (1986) was used in this work to generate the time series to be studied. The ExpAR is a technique that can generate a wide spectrum of non linear dynamic behaviors, from unlimited oscillations to *chaos* (Ozaki et al., 1985). Thus, the premise is that these models are more suited than standard AR-models to model dynamics of non-linear BWR systems. However, these authors found that in all the cases treated, the ACF and AR methods gave reliable results whereas the ExpAR model is not as accurate as the previous two methods in predicting

\* Corresponding author.

E-mail address: [gepe@xanum.uam.mx](mailto:gepe@xanum.uam.mx) (G. Espinosa-Paredes).

the DR for stable cases (thus, no case was found where the ExpAR performs significantly better than conventional methods).

Additionally, the DR is dependent on the choice of the AR model order based on the AIC criterion (Shi et al., 2001). But, this choice can lead to strong underestimation of the DR. Thus, there is a window of opportunity to study alternative methods (not necessarily based on AR techniques or on further improvements of it) to address the BWR stability problem to estimate more powerful stability indicators.

Besides, in normal operation conditions, the need for stationary signals can be a drawback and, hence it is interesting to explore the use of alternative methodologies adapted for non stationary signals.

Navarro-Esbri et al. (2003) studied the time dependence of the natural frequency through a methodology based on the short time Fourier transform when the BWR signal is non-stationary. Later, the wavelet theory was applied to explore new alternatives for transient instability analysis (e.g., Espinosa-Paredes et al., 2005, 2007; Sunde and Pazsit, 2007). However, in general BWR signals are non-stationary and non-linear, thus Fourier-based or wavelet-based approaches might lead to a biased stability analysis.

The BWR instability is possible even at the normal plant operation conditions, and significant core power oscillations may threaten core fuel integrity due to the fuel cladding dryout occurrence and/or due to the strong pellet-cladding mechanical interaction (Ikeda et al., 2008). Therefore, an accurate prediction for the onset of the BWR instability with a method based on the non-stationarity and non-linearity of the signal, is the next step in the research for the operation safety in BWRs. Shi et al. (2001) explored a reliable method based on a non-linear exponential autoregressive (EAR) model to estimate the DR for detecting a BWR instability. The EAR model is useful for revealing of non-linear dynamics such as fixed point, limit cycle, and even chaos, being a real time model suitable for on-line BWR instability detection. Other methods for nonlinear analysis of instabilities in boiling water reactors (BWRs) have been applied (e.g., Castillo et al., 2004; Gavilán-Moreno and Espinosa-Paredes, 2016), which were used to analyze BWR signals containing stationary and non-stationary limit cycles.

In this work we explore the Shannon Entropy (SE) as a possible non-linear stability indicator for BWRs. The Shannon Entropy is a concept introduced by Claude E. Shannon (1948) to characterize a discrete source through the *content of the information* of this source. In other words, the SE is a statistical index that quantifies the *complexity* of a signal. In our case, the BWR stability problem is studied by quantifying the *intricacy* of BWR signals through this proposed indicator SE. A low SE estimation indicates a predictable BWR event (a stable event) whereas a *high* SE value indicates an unpredictable BWR event (an unstable event). The SE estimation was validated with artificial signals issued from a Non-Linear Reduced Order Model (ROM), which represents qualitatively the dynamic behavior of a BWR system.

In the BWR stability domain, the Kolmogorov Entropy was explored before by Zboray et al. (2004) for the study of nonlinear dynamics of natural-circulation boiling two-phase flows. The Kolmogorov Entropy (KE) is an index that characterizes the dynamics (time evolution) of a chaotic system. KE entropy measures the rate of information loss (or gain) along the attractor of the system. In the cited work, the authors estimated the KE with a maximum-likelihood KE estimator that requires a certain embedding dimension (or lag  $J$ ) to compute KE, such authors provided an empirical rule to select  $J$ , as twice the average cycle time or larger than that to reconstruct *system dynamics*. Thus, their KE estimator is largely dependent on the choosing of  $J$  (based on unknown *a priori* information regarding system dynamics that must be taken for granted). Given these observations, the SE (whose estimation does not depend on complex system dynamics reconstruction tech-

niques) is studied instead of further developments of different KE estimators.

This work is organized as follows: Non-linear behavior of BWR with Reduced Order Model (ROM) given by March-Leuba (1986) and the route to chaos are introduced in Section 2. The used Shannon Entropy estimator is discussed in Section 3. In section 4, we present the Decay Ratio estimation based on an AR modeling. In Section 5, the methodology and the obtained results based in Shannon Entropy (SE) to study the BWR stability, is presented. In Section 6 a comparison of the results obtained with DR and SE is presented. These results are also discussed considering the Largest Lyapunov Exponent. Finally, our discussions and conclusions are given in Section 7.

## 2. Non-linear behavior of a BWR

### 2.1. A Non-linear Reduced Order Model (ROM)

Reduced Order Models are used to study system stability and dynamics of a system. They are usually obtained by averaging over time and/or space, and often represent a system by a set of non-linear ordinary differential equations (ODEs). In the nuclear engineering discipline, the basic point reactor kinetics model needs to be extended to capture the effects of several feedback mechanisms that play a significant role in reactor dynamics. For instance, changes in reactor power lead to changes in core component temperature and void fraction, which in turn have an impact on the reactivity. A simple but powerful model which has been extensively used for BWR stability analysis was developed by March-Leuba (1986), such non-linear Reduced Order Model (ROM) represents qualitatively the BWR dynamics, the complex (i.e., *chaotic*) dynamics of BWR unstable behavior are also captured by this ROM. The ROM is given by the next set of differential equations:

$$\frac{dn(t)}{dt} = \frac{\rho(t) - \beta}{\Lambda} n(t) + \lambda c(t) + \frac{\rho(t)}{\Lambda} \quad (1)$$

$$\frac{dc(t)}{dt} = \frac{\beta}{\Lambda} n(t) - \lambda c(t) \quad (2)$$

$$\frac{dT(t)}{dt} = a_1 n(t) - a_2 T(t) \quad (3)$$

$$\frac{d^2 \rho_x(t)}{dt^2} + a_3 \frac{d\rho_x(t)}{dt} + a_4 \rho_x(t) = \kappa k_0 T(t) \quad (4)$$

$$\rho(t) = DT(t) + \rho_x(t) \quad (5)$$

Here the variables  $n(t)$  and  $c(t)$  are converted by the following equations as fluctuations caused from the equilibrium values  $N_0$  and  $C_0$  of the steady state:

$$n(t) = \frac{N(t) - N_0}{N_0} \quad (6)$$

$$c(t) = \frac{c(t) - C_0}{N_0} \quad (7)$$

where  $n(t)$  is the excess neutron population normalized to the steady state neutron population,  $c(t)$  is the excess delayed neutron precursors concentration also normalized to the steady state neutron population;  $T(t)$  is the excess average fuel temperature; and  $\rho_x(t)$  is the excess void reactivity feedback. For this model, the only non-linear term appears in the neutronic equation through the parametric feedback produced by the reactivity  $\rho(t)$ . Since we are interested in the non-linear region above the threshold for linear stability, the indicators for the base case were calculated from a

Download English Version:

<https://daneshyari.com/en/article/5475135>

Download Persian Version:

<https://daneshyari.com/article/5475135>

[Daneshyari.com](https://daneshyari.com)