International Journal of Heat and Fluid Flow 57 (2016) 79–90

Contents lists available at ScienceDirect

International Journal of Heat and Fluid Flow

journal homepage: www.elsevier.com/locate/ijheatfluidflow

Nonlinear time series analysis from large eddy simulation of an internal combustion engine

Jukka-Pekka Keskinen*, Ville Vuorinen, Ossi Kaario

Aalto University, School of Engineering, Department of Energy Technology, 00076 Aalto, Finland

A R T I C L E I N F O

Article history:
Received 18 June 2015
Revised 12 November 2015
Accepted 23 November 2015
Available online 17 December 2015

Keywords:
LES
Chaos
Engine
Ttime series
CCV

A B S T R A C T

Nonlinear time series analysis was applied for the first time to time series obtained from large eddy simulations (LES) of an internal combustion engine (ICE). The aim of the study was to obtain more information about the cycle-to-cycle variation (CCV) in the studied simplified ICE geometry than what is available from standard methods. Phase space reconstructions were created from the time series and then estimates for the largest Lyapunov exponent were calculated. The time delays used in the phase space reconstructions were determined using average mutual information while the proper embedding dimensions were chosen according to the method of false nearest neighbours. Quantitative information on the behaviour of the flow and the CCV was acquired from three-dimensional phase space reconstructions. Introduced modifications to the flow were clearly visible in the phase space reconstructions of energy and dissipation, indicating that these quantities are appropriate for monitoring and analysing the state of the system. The estimates for the largest Lyapunov exponents were positive for almost all time series, indicating chaotic dynamics. The permutation spectrum test was used to confirm the chaoticity of the CCV. The present results indicate that the used methods offer a promising new framework for characterising the CCV from the viewpoint of nonlinear time series analysis.

1. Introduction

In an ideal case, the cycles of an internal combustion engine (ICE) would repeat themselves in exactly the same manner. However, in reality variation between the cycles exists. Small scale variation inherent to turbulence is unavoidable and is in many cases desired. However, the low frequency variation in the mean quantities, cycle-to-cycle variation (CCV) (Heywood, 1988; Ozdor et al., 1994), is more problematic. The velocity field u in a turbulent engine flow can be divided into three main components (Heywood, 1988):

$$u = \overline{u} + \hat{u} + u'. \tag{1}$$

The ensemble average component $\overline{u}$ is the mean velocity that varies only with the crank angle degree (CAD) but not between cycles while the CCV component $\hat{u}$ is a mean quantity that varies with both the cycles and CAD. The turbulent component u' adds another layer of fluctuation to the overall velocity, also showing differences between cycles. The effects of CCV vary depending on the engine and the severity of the CCV but can include increased emissions, lowered efficiency, unstable operation, and even engine failure. Currently, experimental approaches are the main approach in the study of CCV. However, the increase in available computational resources and the importance of the in-cylinder flow field in ICE operation has made the use of computational fluid dynamics (CFD) more attractive.

Large eddy simulation (LES) is a CFD approach based on the spatial filtering of the flow field so that only the large, energy containing length scales are solved directly from the Navier–Stokes equation (Pope, 2000; Sagaut, 2006). In the commonly used Reynolds-averaged Navier–Stokes (RANS) approach the CCV is essentially filtered out. In contrast, the delicate turbulence approach of LES together with a finer spatial resolution offers a way to study the CCV. The potential of LES to resolve CCV was realised already during the early 1990's, when the first applications of LES on an ICE flow were carried out (Naitoh and Kuwahara, 1992; Naitoh et al., 1993). Although these early simulations had a rather modest spatial resolution and only few engine cycles were computed, CCV was still observed. The contemporary ICE LES is usually characterised by relatively high spatial resolution (Enaux et al., 2011b) or by a large number of simulated cycles (Baumann et al., 2013). However, as properly converged statistic require a very large number of cycles (Baumann et al., 2013), the computational requirements are still a limiting factor for the LES of the ICE.

Several approaches have been used in the analysis of CCV from LES data. The simplest is direct comparison of quantities from

* Corresponding author. Tel.: +358505979702.
E-mail address: jukka-pekka.keskinen@aalto.fi, jpkeskinen@gmail.com (J.-P. Keskinen).

http://dx.doi.org/10.1016/j.ijheatfluidflow.2015.11.009

Nomenclature

Subscripts and superscripts

i, j	Vector component (1,2,3)
max	Maximum
NN	Nearest neighbour
num/mod	Numerical and/or modelled
r	Radial component
res	Resolved
rms	Root-mean-square
tot	Total
z	Axial component

Symbols

D	Segment length
E	Kinetic energy (J/kg)
l	Section length
N	Number of points
n	Embedding dimension
P	Probability density
p	Pressure (m^2/s^2)
Re	Reynolds number
S	Average of the effective expansion rate
T	Time delay (CAD)
t, t'	Time
$\mathcal{T}$	Set of time instants
$\overline{u}$	Ensemble average velocity (m/s)
u	Instantaneous velocity (m/s)
u'	Fluctuating velocity (m/s)
$\mathcal{U}_t$	Phase space orbits close to a phase space point of time t
$x(t)$	Time series
x_i	The ith spatial coordinate
$\mathbf{y}(t)$	Reconstructed data vector
z	Axial distance to cylinder top (mm)
ϵ	Distance parameter
ε	Dissipation (J/kgs)
ν	Kinematic viscosity (m^2/s)
τ	Sampling interval (CAD)
τ_L	Time increment (CAD)

Abbreviations

AMI	Average mutual information
BDC	Bottom-dead-centre, i.e. 180 CAD
CAD	Crank angle degree
CCV	Cycle-to-cycle variation
CFD	Computational fluid dynamics
COV	Coefficient of variation
DNS	Direct numerical simulation
FNN	False nearest neighbours
ICE	Internal combustion engine
ILES	Implicit large eddy simulation
LES	Large eddy simulation
PISO	Pressure-implicit with splitting of operators
POD	Proper orthogonal decomposition
RANS	Reynolds-averaged Navier-Stokes
SGS	Subgrid scale
TDC	Top-dead-centre, i.e. 0 CAD

different simulated cycles (Bottone et al., 2012; Goryntsev et al., 2010; Haworth and Jansen, 2000; Keskinen et al., 2015; Naitoh et al., 1993). The approach has the benefit of providing intuitive and easily understandable information. However, it can be very difficult to distinguish between CCV and purely turbulent structures when instantaneous fields are used. Also, as the comparisons are done on a specific CAD, it is difficult to obtain an overall impression of the CCV or to deduce the causes behind them.

Another popular approach in the study of CCV from LES data is to use time series. An impression of the CCV can then be acquired by plotting the time series of each cycle on top of each other as a function of CAD. A wide variety of time series can be extracted from LES data and the used quantities include pressure (Thobois et al., 2007; Vermorel et al., 2009), vorticity magnitude (Banaeizadeh et al., 2013), energy (Montorfano et al., 2014), and the mode coefficients of proper orthogonal decomposition (POD) (Fogleman et al., 2004; Liu and Haworth, 2011). However, apart from identifying the range of CAD with the largest CCV, the direct plotting of time series reveals very little about the dynamics of the flow. The use of more advanced approaches in the time series analysis of ICE LES data has been very limited. The only exceptions are return maps (Enaux et al., 2011a; 2011b), where a quantity is plotted against its value at the preceding cycle.

A wider range of approaches have been used in the analysis of experimental ICE time series. Nonlinear time series analysis appears especially well suited for the purpose as chaotic processes have been identified as the source of CCV in at least in certain engines and operating conditions (Daw et al., 1996; 1998; Finney et al., 2015; Kantor, 1984; Matsumoto et al., 2007; Wendeker et al., 2003; Yang et al., 2015). Return maps have been used quite widely (Daw et al., 1996; 1998; Scholl and Russ, 1999; Wagner et al., 1998) while similar methods, such as recurrence plots and Poincaré sections, have also been applied to experimental ICE data (Sen et al., 2008b; Chew et al., 1994; Li and Yao, 2008; Litak et al., 2008; Yang et al., 2015). In several cases, the phase space portrait of the system has been reconstructed (Boguś and Merkisz, 2005; Chew et al., 1994; Li and Yao, 2008; Litak and Longwic, 2009; Matsumoto et al., 2007; Wendeker et al., 2003) and its properties have been used to analyse the nature of the CCV further. For example, the largest Lyapunov exponent of the system can be used to quantify the chaoticity of the CCV (Yang et al., 2015). Perhaps the most significant development with the nonlinear time series analysis of experimentally obtained data is the possibility for control and subsequent stabilisation of the CCV (Matsumoto et al., 2007). Indeed, using the information acquired through nonlinear time series analysis allows one, at least in principle, to transform chaotic motion into a periodic one only by introducing small changes to the system's parameters (Abarbanel, 1996). Other nonlinear approaches that have been applied to ICE time series include wavelet analysis (Sen et al., 2010; 2008a; 2008b), multifractals (Sen et al., 2010), and symbolic analysis (Daw et al., 1998; Green et al., 1999; Wagner et al., 1998). The review by Finney et al. (2015) provides an introduction to the use of deterministic approaches in the analysis of experimental ICE data while the textbook of Abarbanel (1996) gives a good overview of nonlinear time series analysis.

The aim of the present paper is to study the CCV in the present, simplified ICE flow using nonlinear time series analysis. More specifically, the objectives are to show that the CCV of the present flow is a chaotic process, to study the chaos on global and local level, and to demonstrate how nonlinear time series analysis can be applied to LES data. To the authors' best knowledge, nonlinear time series analysis has not been applied to LES data of an ICE before. We first reconstruct the phase space of the system using several different time series that have been obtained earlier using LES (Keskinen et al., 2015). The reconstruction is carried out using the time delay method, mostly as outlined by Abarbanel (1996). The used time delays are decided according to the average mutual information (AMI) of the time series while the proper embedding dimensions are decided based on false nearest neighbours (FNN). The reconstructed phase spaces of volume-averaged energy and dissipation time series appear to be better suited for the analysis of the system than point-based quantities. The estimates for the Lyapunov exponents (Kantz, 1994) and the permutation spectrum test (Kulp and Zunino, 2014) indicate that the CCV in the studied axisymmetric case is a chaotic process.