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Probabilistic analysis of a fuel cell degradation model for solid oxide fuel cell and gas turbine hybrid systems

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ABSTRACT

The performance of a solid oxide fuel cell (SOFC) is subject to inherent uncertainty in operational and geometrical parameters, which can cause performance variability and affect system reliability. Operating conditions such as current demand, cell temperature and fuel utilization play an important role on the degradation mechanisms, which affect typical SOFCs. In previous work, a deterministic empirical degradation model of a SOFC was developed as a function of such operating conditions. By the nature of experimental data and regression fitting, this model was not deterministic. The aim of this work is to evaluate the impact of the uncertainties in the degradation model through a stochastic analysis. In particular, the Response Sensitivity Analysis (RSA), an approximate stochastic method based on Taylor series expansion, is applied to a standalone SOFC model and a fuel cell hybrid system model both subjected to cell degradation. The attention is principally focused on the impact on the fuel cell lifetime. To provide an indication of degradation effect and resulting lifetime uncertainty on economic performance, a cursory economic analysis is performed.

1. Introduction

Energy systems are largely affected by aleatory and epistemic uncertainties, due to tolerances in materials, variable operating conditions, environmental uncertainty, or inaccurate estimation of parameters [1–3]. Different fields of engineering use different ways to describe this uncertainty and adopt a variety of techniques to devise designs that are at least partly insensitive or robust to uncertainty. For this reasons, design under uncertainty of energy systems has been of interest for decades [4,5]. Recently, the increasing deployment of renewable energy plants has required a special attention on the uncertainty of renewable sources and its impact on the economic performance [6].

In engineering field, models are typically treated deterministically, even though input values can have significant uncertainties that inevitably propagate through the system to the outputs; this deficiency can be overcome by treating the inputs and consequently the outputs probabilistically. The uncertainties associated with model input parameters can affect both short- and long-term performance and consequently cost. In order to reduce the error associated with the uncertainty of the input variables, methods for system design under uncertainty become essential.

The research available in the open literature related to uncertainties in energy systems is mainly focused on steady-state models [7–9]. Probabilistic methods are mostly applied for optimization purposes and design performance evaluation [2,8,10] and very few cases are related to dynamic energy system analyses. Model uncertainties, materials variability, and uncertainty in operating parameters were considered in SOFC systems and the effects on the performance were evaluated [7–9,11,12]. Response sensitivity analysis (RSA) was applied to a proton exchange membrane (PEM) fuel cell in order to count for the uncertainty in load profile and costs, evaluate the impact on fuel cell performance, and optimize the design and the operating strategy [2,13]. Model uncertainties were taken into account in a multi-objective optimization approach for a SOFC based system [10].

In analyzing fuel cell long-term performance, it is important to consider that useful operative life is currently limited by different degradation mechanisms. As such, particularly in high temperature fuel cells such as SOFCs, performance degrades over time due to various mechanisms that reduce the cell active area and consequently the generated power [14,15]. These mechanisms are influenced by operating conditions, such as current density and

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Nomenclature

ANOVA	ANalysis Of VAriance
CFN	Annual cash flow [$]
COV	Coefficient of variance [%]
EOL	End of life [yr]
FC	Fuel cell
FPI	Fast probability integration
FU	Fuel utilization
HS	Hybrid system
IRR	Internal rate of return [%]
LHS	Latin Hypercube Sample
LSM	Lanthanum strontium Manganite
MCS	Monte Carlo simulation
NBCR	Net benefit to cost ratio [%]
NETL	National Energy Technology Laboratory
NPV	Net present value [$]
PBP	Pay-back period [yr]
PC	Polynomial Chaos
PDF	Probability density function
PEM	Proton exchange membrane
RSA	Response sensitivity analysis
SOFC	Solid oxide fuel cell
TCI	Total capital investment
TPB	Triple phase boundary
YSZ	Yttria-stabilized zirconia
A	Area [m^2]
C_{el}	Electricity price [$ kWh^{-1}]
C_f	Fuel cost [$ kg^{-1}]
C_{main}	Maintenance cost [$]
c_p	specific heat [$J\ kg^{-1}\ K^{-1}$]
δ	step size
F	Faraday's constant [$C\ mol^{-1}$]
G	Gibbs free energy [kJ]
$g_{Mj}(Z)$	functional relationship between j-th output parameter and the inputs Z
h	specific enthalpy variation from 298 K condition [$kJ\ kg^{-1}$]
	Convection coefficient [$W\ m^{-2}\ K^{-1}$]
i	current density [$A\ cm^{-2}$]
i_0	exchange current density [$A\ cm^{-2}$]
K_p	Equilibrium constant
k	Conduction coefficient [$W\ m^{-1}\ K^{-1}$]
L	cell length [m]
M_j	j-th parameter of output for the system
$\dot{m}$	Mass flow rate [$kg\ s^{-1}$]
n	number of transferred electrons
P_{el}	Electricity production [kWh]
P_f	Fuel consumption [kg]
P_{GT}	Gas turbine power [kW]
p	pressure [bar]
$\dot{Q}$	Fuel cell thermal output [kW]
q_{gen}	Generated heat [$W\ m^{-1}$]
R	Area specific resistance [$\Omega\ m^2$]
R_g	Ideal gas constant [$J\ mol^{-1}\ K^{-1}$]
r_d	Degradation rate [% kh^{-1}]
T	Temperature [K]
t	time [s]
V	Voltage, overpotential [V]
x	mole fraction
Z_i	i-th parameter of input for the system
α	charge transfer coefficient
η	efficiency
μ	mean
ν	variance
ρ	density [$kg\ m^{-3}$]
σ	standard deviation

Subscripts

act	activation
an	anode
ca	cathode
dif	diffusion
ohm	ohmic

temperature [16,17]. The effect of fluctuations and inherited variability of these parameters was analyzed in open literature for SOFC and PEM [9,11,12]. Many deterministic models of degradation in SOFCs can be found in the open literature, for example on the influence of operating parameters on fuel cell long-term degradation [18,19]. The effects of uncertainties on performance degradation of a fuel cell were analyzed by different authors [20,21]. Monte Carlo approach was used by Thomas et al. to predict the life of a lithium-ion cell with a degradation model [20], while Placca et al. studied the effect of temperature uncertainty on cell voltage and degradation rate in a PEM through ANOVA [21]. At the best of the authors' knowledge, probabilistic degradation models for SOFCs are not present in the literature.

In a previous work, Zaccaria et al. developed an empirical degradation model for a SOFC as a function of three operating parameters [22]. By nature of experimental data, this model was characterized by uncertainties in the coefficients, although only deterministic analyses have been conducted so far. With the deterministic model, it was demonstrated that SOFC lifetime can be extended if cell voltage is maintained constant allowing power and fuel utilization to degrade over time [23]. However, economic benefits of this operating strategy cannot be fully assessed if results uncertainty and confidence interval are not presented. In addition, the real-time capability of the model makes it a powerful tool for control development to mitigate degradation effects; in this perspective, uncertainty analysis can be valuable for robust controllers design [24].

In general, probability theory is very effective when sufficient data is available to quantify uncertainty using probability distributions. However, when sufficient data is not available or there is lack of information on the process model, the classical probabilistic methodology may not be appropriate. Traditional probabilistic approaches include Monte Carlo Simulation (MCS), Latin Hypercube Simulation (LHS), and Analysis of Variance (ANOVA), which are sampling methods and typically require a large number of samples to obtain the probabilistic information (i.e. mean, variation, skewness, and probability distribution function). However, when a large number of degrees of freedom are used to determine the performance of the system, the MCS is so computationally intensive that, combined with complex and expensive systems, it makes the problem computationally intractable. This computational difficulty can be overcome by using approximate methods like fast probability integration (FPI), response sensitivity analysis (RSA), or polynomial chaos (PC) methods [2,25–29]. Such methods