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A nonlinear-hybrid fuzzy/probabilistic load flow for radial distribution systems

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ABSTRACT

Uncertainty analysis of future system operation is the key feature of current study. This paper shows that how subjective differences in representing fuzzy inputs can affect the final outputs. We consider a confined range of forecasted samples in terms of fuzzy membership functions as well as the range of historical forecasting errors in terms of probability density functions. On this basis, this paper proposes a combined fuzzy/probabilistic evaluation of distribution system voltages, considering hybrid fuzzy/probabilistic uncertainties for consumption and generation. The proposed method allows the sampled fuzzy inputs to incorporate in a Monte Carlo-based nonlinear fuzzy load flow including Wind Turbine Generating Units (WTGUs). As a result of hybrid uncertainty representation, the evaluation of fuzzy load flow results will be assessed in probabilistic framework. Numerical simulations are performed on the unbalanced IEEE 34-bus test distribution system equipped with WTGUs.

1. Introduction

Generally many of observations in practical systems contain considerable amount of uncertainty. This fact forms a basis for employing especial analysis tools to evaluate the power systems under such observations. Power systems sustain a wide range of uncertainties from determination of system parameters, variables, and future decisions to future estimation of the system variables. Moreover, presence and increasing growth of WTGUs in distribution systems put a great deal of uncertainty in distribution system studies; because, these units strictly depend on the wind speed. Therefore an appropriate evaluation of the system under these uncertainties requires an appropriate analysis tool. Uncertainty analysis of power systems fundamentally is carried out by two primary approaches: probabilistic load flow and fuzzy load flow. Depending on fuzzy or probabilistic points of view, the power flow analysis differs in the nature of algorithm and results. In probabilistic methods as usual, system variables have been assessed by means of Monte Carlo technique with uncertainties in terms of Probability Density Functions (PDFs). Caramina in [1] provided a qualitative exploration of the probabilistic techniques existing in the power flow study such as linear, nonlinear Monte Carlo (MC) and convolution techniques. The exact non-linear form of the load flow equations has been used in most probabilistic load flow studies [1,2]. Some studies have incorporated wind farms and their uncertainties in probabilistic load flow [2,3] and some have modeled the uncertainties in the fuzzy set [3–9]. Although some approaches in wind fuzzification is transferring the wind speed probability density function directly into possibility membership function [3], generally fuzzy load flow results in the uncertainty analysis of the state variables when there is insufficient statistic information to assign probability density function [4,9]. The key aspect of the fuzzy power flow is achieving the method through which the fuzzy inputs lead to the best befitted fuzzy outputs. In some approaches, system variables are assessed in the fuzzy set; however, evaluation of system variables is performed through the fuzzy arithmetic calculations [4,5]. Since fuzzy arithmetic roles hardly meet a feasible solution of power flows, Many of papers make an attempt to modify the fuzzy calculations even in a simple sum and subtraction operation to fit fuzzy solution [5]; Nevertheless, some fuzzy power flows do not outrage real calculation roles of power flow by attributing the fuzzy power flow as a sort of boundary power flow [6–8]. These techniques facilitate reaching the fuzzy results thanks to the system linearization. Although the linearization yields approximate results, invoking Jacobean matrix, it reasonably provides possible variations of results under the input variations.

Another approach determines the extremes of each line flow at α – level of possibility by solving a vast number of optimization problems under input bounds associated with α that $0 \leqslant \alpha \leqslant 1$ [9].

In the current study, we aim to perform a sort of short-term load flow analysis of uncertainty in the near future. Forecasting models provide necessary information about the state of future variations. One of the important aspects of this study is that in this case, fuzzy function is not indicative of that mere uncertainty but of prospective bound of the inputs. And somehow it reveals

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Nomenclature

α	alpha cut of a fuzzy number
a_i	membership i of fuzzy number
$\bar{a}_i$	mean value of fuzzy membership
σ	standard deviation of members
[BIBC]	Matrix of Bus Injection to Branch Current
[BCBV]	Matrix of Branch Current to Bus Voltage
ΔV_{abc}	voltage deviation of phases a, b and c
[DLF]	Matrix of Distribution Load Flow
e^k	real part of bus voltages at iteration k
f^k	imaginary part of bus voltages at iteration k
Δf^k	deviation of f^k
AR	real parts of DLF matrix
AX	imaginary parts of DLF matrix
V^k	bus voltages at iteration k
P_{sp}, Q_{sp}	specified active and reactive bus injected powers
$\tilde{U}$	fuzzy absolute of bus voltage
$\tilde{\varnothing}$	fuzzy phase of bus voltage
U	absolute of bus voltage
$\varnothing$	phase of bus voltage
UL_i	uncertain load number i
SL	system loss
P_{UL}, Q_{UL}	uncertain active and reactive powers
pf	power factor
σ_p	standard deviation of active power
DLF	deterministic load flow
PLF	probabilistic load flow
FLF	fuzzy load flow
F/P LF	fuzzy/probabilistic load flow
WTGU	Wind Turbine Generating Unit
PDF	Probability Distribution function
MC	Monte Carlo
Std	standard deviation
F/B	forward/backward
NLMCS	Nonlinear Monte Carlo Simulation
SUF	system unbalance factor
P_{cal}, Q_{cal}	calculated active and reactive bus injected power
[K]	nonlinear transformation matrix between power deviation and voltage deviation
$(\Delta P)^{sp}$	the specified active power deviation
$(\Delta Q)^{sp}$	the specified reactive power deviation
w^{sp}	the specified wind speed
P^{as}, Q^{as}	active and reactive powers of asynchronous WTGU
I_{as}, V_{as}	current and voltage of asynchronous WTGU
R_1	stator resistance in Equivalent circuit of WTGU
R_2	rotor resistance in Equivalent circuit of WTGU
X_{l1}	stator reactance in Equivalent circuit of WTGU
X_{l2}	rotor reactance in Equivalent circuit of WTGU
X_m	magnetizing reactance in equivalent circuit of WTGU
s	slip of asynchronous WTGU
V_{me}	extreme value of voltage number m
V_{m0}	central value of voltage number m
K_{mn}	deviation coefficient of voltage m by deviation of power n
P_{ne}	extreme value of power number m
P_{n0}	central value of power number m
f_{ai}	PDF function of membership a_i
$(\tilde{P})^{sp}$	specified fuzzy number of active power
$(\tilde{Q})^{sp}$	specified fuzzy number of reactive power
$(P)^{sp}$	specified active power in load flow study
$(Q)^{sp}$	specified reactive power in load flow study
$(P_{gen})^{sp}$	specified active power generation in load flow study
$(U_{gen})^{sp}$	specified at voltage regulated buses in load flow study
σ_q	standard deviation of reactive power
$\bar{a}_i$	mean value of the fuzzy member i
σ_w	standard deviation of wind speed
K_d	unbalance factor
V_i	positive sequence of bus voltage
V_d	negative sequence of bus voltage
ts	time span of the forecasting horizon

possibility spectrum of the future variations based on the prior knowledge that forecasting models provide. On the one hand, depending on the relationship between the impact factors and response variables, each forecasting model is expected to predict only up to a particular limited horizon; therefore, the period for which system analysis is going to be performed is the minimum horizon over which all forecasting models are quite reliable to predict. Input variables are introduced in terms of fuzzy function reflecting the state of variation of forecasted samples. On the other hand, deviation of forecasted samples from targets provoked by inherent error of forecasting models puts a new uncertainty in the variation-based forecast of fuzzy functions. In order to address this new uncertainty, we consider the historical rang of forecasting error in terms of probability density function. This consideration leads to the definition of a new hybrid fuzzy/probabilistic uncertainty under which the system demands a new methodology for uncertainty analysis.

This issue implies a new methodology that incorporates Monte-Carlo technique in the fuzzy load flow. In Monte Carlo iterations, the fuzzy load flow runs under fuzzy inputs randomly selected within the range of some predetermined probability density functions. Most fuzzy load flow methods that yields fuzzy solution based on Jacobean matrix, consider balanced line model similar to that in Newton–Raphson power flow [6,8]. Strongly asymmetric lines carrying unbalanced loads in distribution systems raise the issue of determination of Jacobean matrix which is not as straightforward as Newton–Raphson's; nevertheless, some studies in distribution systems use sensitivity matrix instead of conventional Jacobean matrix [7].

Moreover, this paper suggests a new approach to the issue of hybrid uncertainty to fulfill a successful nonlinear Monte Carlo based fuzzy load flow in distribution systems without the need for any sort of sensitivity matrix.

2. Hybrid fuzzy/probabilistic modeling of the future system variables

2.1. Fuzzy modeling of the future system variables

Probabilistic framework conventionally is used in the case of uncertain data, having a sufficient range of information to assign probability characteristics. The fuzzy set theory, on the other hand, has been recognized as a potential tool for enhancing the ability to deal with problems that are too complicated or ill-defined to be solved by conventional methods. Fuzzy membership functions establish relationship between possibility of the variables and their variations. A fuzzy model may describe both a degree of uncertainty in its exact value and a linguistic description of its nature or possible range of value based on human judgment [4,16–19].

Herein, uncertainty analysis of future state of the distribution system is accounted as the principal concern. The uncertainty is considered for consumption of some stations as well as generation of WTGUs, while the rest takes the certain values. Fig. 1 shows the