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Optimization of Spinning Reserve in Stand-alone Wind-Diesel Power Systems

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1. Introduction

Spinning reserve carried on synchronized units is the most effective resource available to the system operators for managing unforeseen power unbalances, such as demand fluctuations and the sudden loss of generation equipment. The amount of reserve and the speed that it can effectively be deployed determine the supply reliability that the generation system can achieve.

Carrying more spinning reserve reduces the probability that the generation system become unable to preserve the momentary power balance and costly remedial actions, such as involuntary load shedding, turns unavoidable to prevent a system collapse. Nevertheless, providing spinning reserve on a continuous basis is expensive. Indeed, the provision of spinning reserve entails incurring in startup costs to commit generating units in excess of the forecasted load, which consequently have to be dispatched at less efficient operating points.

The problem of keeping the power balance is still more difficult in stand-alone wind-diesel power systems, since these systems are additionally subjected to random power fluctuations originated in the uncertain and intermittent nature of the wind resource. Furthermore, autonomous power system cannot rely on power imported from interconnections for preserving the power balance. The inherent characteristics of these systems require scheduling more reserve on synchronized units for ensuring adequate security and reliability levels. The higher reserve requirements may substantially deteriorate the economy of these supply systems.

The costs of keeping spinning reserve must be compared with the benefits that it provides in terms of lower expected costs of interruptions. In essence, the optimal reserve level can be set so that the marginal cost of carrying an additional MW equals the marginal reduction of the expected load curtailment costs.

Despite the apparent simplicity of this optimality condition, determining the optimal amount of spinning reserve in a practical setting presents substantial modelling complexities and computational challenges. Given the random nature of the disturbances and contingencies that may face a generation system, assessing the benefits of carrying a certain amount of spinning reserve involves quantifying the occurrence probability, duration, extent and costs of load loss events. Such evaluation entails modelling the stochastic behaviour of system operation by considering the random failure of system components and the stochastic fluctuations of load and wind generation. The problem is

Source: Wind Power, Book edited by: S. M. Muyeen,
ISBN 978-953-7619-81-7, pp. 558, June 2010, INTECH, Croatia, downloaded from SCIYO.COM

probabilistic in its very nature and thus it may be appropriately treated by applying stochastic modelling techniques. Only with the advent of more powerful computing hardware, the problem of optimizing the spinning reserve has attracted the interest of researchers and its solution is currently deemed practicable.
This chapter proposes a novel method for determining the optimal amount of spinning reserve that should be carried in autonomous hybrid wind-diesel generation systems. The optimal spinning reserve is determined by comparing the cost of its provision with the economic benefits it delivers in terms of supply reliability. The proposed approach is still general and can be applied in straightforward manner to establish the optimal reserve level in large interconnected systems.
The presented methodology considers with accuracy the probabilistic features of the load and the wind generation, as well as the random outages of the conventional generating units. By applying high-resolution chronological simulation techniques, the stochastic features of the integrated operation of the diesel units and the wind turbine can be detailed replicated. The mathematical model appropriately considers all relevant characteristics and operational constraints of the generating units, e.g. non-linear heat rate curve, maximum and minimum output, startup and synchronization time, minimum down and uptime, ramping, etc. Massive stochastic simulation methods allow assessing the system reliability and valuing the economic costs of loss load events.
Global search methods like particle swarm optimization (PSO) are proposed for finding the optimal scheduling policy and spinning reserve requirement that minimizes the sum of the expected operation costs and the expected costs of the energy not served.
The remaining of this chapter is organized as follows. Section 2 is devoted to revisit the conventional Unit Commitment problem and presents a new stochastic formulation for coping with uncertainties affecting renewable-integrated systems. In Section 3, a number of models for simulating the chronological operation of wind-diesel systems under stochastic conditions are described. Section 4 provides some exemplary high-resolution simulations of the integrated operation of the wind generator and the diesel generating units. Additionally, results of the optimization procedure are given. Conclusions and suggestions on further research work are drawn on Section 6.

2. Mathematical formulation of the reserve optimization problem

2.1 The deterministic thermal UC problem

The single-bus Unit Commitment (UC) problem consists on scheduling available generating units and setting their respective generation outputs in order to meet a forecasted load sequence, so that all relevant unit specific and system-wide constraints are satisfied while a performance measure is optimized, e.g. minimum production costs, maximum social welfare, etc. Mathematically, solving the UC problem entails the formulation of a complex optimization problem, which is stochastic, non-linear and mixed-integer in its very nature.
Let consider a thermal-only generation system with I generating units. In discrete time, the objective function of the standard deterministic reserve-constrained UC problem for T time stages of duration Δt can be mathematically formulated as the minimization of the sum of unit start-ups and generation costs over the considered time span as follows:

$$\min_{u_i^t, P_i^t} \left[\sum_{t=1}^{T} \sum_{i=1}^{I} C_i(u_i^t, P_i^t) + S_i^t(u_i^t) \right] \tag{1}$$

where $u_i^t \in \{0,1\}$, $i = 1,2,...,I$ and $t = 1,2,...,T$ are binary decision variables indicating whether unit i is scheduled to generate on time period t (0: stand-by, 1: synchronized); P_i^t is the output generation level of generator i during period t; C_i and S_i^t are the generation and time-dependent start-up costs of unit i respectively.
Solving the UC problem involves choosing a set of decision variables so that the objective function in (1) is minimized subjected to a number of constraints:

System constraints

System demand: the total system generation must meet the forecasted power demand L^t at each time period

$$L^t - \sum_{i=1}^{I} u_i^t P_i^t = 0 \quad \forall t \in T \tag{2}$$

System reserve: the scheduled spinning reserve on the committed units must satisfy the exogenous reserve requirement R^t set by the system operator based on deterministic or probabilistic criteria

$$L^t + R^t - \sum_{i=1}^{I} u_i^t P_i^{\max} \leq 0 \quad \forall t \in T \tag{2}$$

Technical constraints on the operation of generating units

Typically, generating units impose some strict operating limits in order to ensure a secure operation and safeguard their lifetime.
Generation limits: the power generation of each scheduled unit i at any time t should be within its lower and upper rated output capabilities, $P_i^{\min}$ and $P_i^{\max}$ respectively

$$u_i^t P_i^{\min} \leq P_i^t \leq u_i^t P_i^{\max} \quad \forall i \in I,\ \forall t \in T \tag{3}$$

Ramping limits: In addition, important intertemporal constraints on the operation of the generating units must be accounted for in the problem formulation. The change in generation output between adjacent time intervals should observe units ramping capabilities

$$r_i^{\min} \Delta t \leq \left(P_i^t - P_i^{t-1}\right) \leq r_i^{\max} \Delta t \quad \forall i \in I,\ \forall t \in T \tag{4}$$

where $r_i^{\min}$ and $r_i^{\max}$ are respectively the minimum and maximum permissible change rate per unit time of the generation output, expressed for example in kW/s.
Minimum up/down time: the scheduling decisions must also comply with the minimum time in standby T_i^{off} between consecutive shut down/start-up decisions and minimum operating time T_i^{on} between consecutive start-up/shut down decisions

$$\begin{aligned} &\left(X_{i,t-1}^{on} - T_i^{on}\right)\left(u_i^{t-1} - u_i^t\right) \geq 0 \quad \forall i \in I,\ \forall t \in T \\ &\left(X_{i,t-1}^{off} - T_i^{off}\right)\left(u_i^t - u_i^{t-1}\right) \geq 0 \quad \forall i \in I,\ \forall t \in T \end{aligned} \tag{5}$$

where $X_{i,t}^{on}$ and $X_{i,t}^{off}$ are the time durations the unit i has been on and off at time stage t from the last start-up and shut down decision respectively.

2.2 The stochastic wind-diesel UC problem

The conventional deterministic UC problem formulated in Section 2.1 needs some important modifications and extensions in order to consider the costs of scheduling decisions under uncertain future operating conditions due to fluctuating wind generation and in order to accommodate particular constraints of diesel gensets.

Unlike the reserve-constrained UC problem described in the previous section, in the proposed formulation the reserve requirement is endogenously determined for each time period being itself a result of the optimization procedure. By introducing in the objective function the expected damage costs $E[C_E]$ associated to supply interruptions, the spinning reserve requirement may be optimized by trading off its economic benefits with the cost of its provision.

The objective function of the stochastic wind-diesel UC problem can be formulated in terms of the mathematical expectation of the overall system costs as follows

$$\min_{u_i^t, P_i^t} E\left[\sum_{t=1}^{T}\sum_{i=1}^{I} C_i(u_i^t, P_i^t) + S_i^t(u_i^t) + C_E(u_i^t, P_i^t)\right] \tag{6}$$

The proposed formulation does not require imposing system-wide constraints since the optimization procedure determine the optimal load demand to be met as well as the optimal spinning reserve held on committed units.

It is important to mention that in small autonomous systems the power needed for serving the unit-related auxiliary loads (e.g. fans, pumps, heaters, etc.) $u_i^t L_i^{aux}$ are often relevant in relation with the system demand, and hence, their serving costs must also taken into consideration. The amount of parasitic loads to be served mainly depends on the number of the committed units, and thereby is a result of the scheduling decisions.

In addition to the unit specific constraints stated in (3) to (5), further operational limits of diesel units have to be introduced in order to find feasible solutions.

Generation limits

It is important to distinguish the various rating limits of diesel gensets. The *continuous rating* is the maximum power that the diesel generator can delivered to a constant load for unlimited time, i.e. load factor of 100%. The *prime rating* refers to the peak power that can be delivered to a time-varying load for unlimited time. Typical load factors are 60% to 70%. The *emergency rating* is the genset overload capability for a time-constrained emergency use. Typically the overload capacity is 10% above the prime rating for a maximum duration of 1 h, maximum frequency of 1/12 and cumulated overload operating hours not exceeding 24 h/yr. The continuous, prime and emergency ratings involve the consideration of integral constraints over the optimization period, which must be appropriately handled.

Start up and synchronization time

After receiving the starting signal, diesel generators require some time before they can effectively deliver electrical power. This time is needed for cranking the diesel engine, accelerate to rated speed, warm-up and synchronize with the system. This time depends on the size of the genset and the prevailing ambient conditions. Typically, diesel generators can accept load from 10 s to few minutes after the start signal.

2.3 Solution techniques

The UC problem is probably one of the most investigated scheduling problems, for which a wide variety of approaches has been proposed along the years. Most notably, Dynamic Programming (DP), Lagrangian Relaxation (LR), Linear Programming (LP), Quadratic Programming (QP), Mixed-Integer Programming (MIP) as well as Artificial Intelligence based algorithms like Genetic Algorithm (GA), Artificial Neural Networks (ANN), Tabu Search (TS), Simulated Annealing (SA), Ant Colony Systems (ACS) have been proposed for solving the underlying optimization problem (Padhy, 2004; Yamin, 2004; Sen & Kothari, 1998; Sheble *et al.*, 1994).

Most recently, emerging techniques from Swarm Intelligence are being investigated for treating complex optimization problems (Kennedy & Eberhart, 1995; Kennedy & Eberhart, 1995). Particle Swarm Optimization (PSO) is currently considered a suitable derivative-free search method for dealing with many optimization problems present in the planning and operation of power systems, e.g. reserve scheduling, reactive power dispatching, power system control (AlRashidi & El-Hawary, 2009; del Valle *et al.*, 2008). PSO-based algorithms are also being increasingly considered suitable for treating the UC problem (Lee & Chen, 2007; Zhao *et al.*, 2006; Ting *et al.*, 2006). Moreover, the optimal scheduling of wind-integrated power systems solved with PSO-based techniques has recently been investigated (Swaroop *et al.*, 2009).

In this chapter, a hybrid variant of the conventional PSO algorithm referred as EPSO (Miranda & Fonseca, 2006, 2002a, 2002b), which incorporates elements of evolutionary programming (i.e. mutation, reproduction and selection), is applied for finding the optimal schedule of diesel units for each 5-min time interval over a 24-h planning horizon in order to minimize total expected system costs.

In the PSO terminology, a particle p is a matrix of scheduling decisions for each generating unit i and for each time stage t. For each particle p at the j-th iteration, the fitness of the proposed scheduling decisions is assessed by evaluating the objective function stated in (6). The expected costs are estimated by simulating the system operation under the proposed commitment decisions for a large number of possible realizations of the uncertain variables, i.e. random unit outages and stochastic fluctuations of the power demand and wind generation. In order to capture the influence of ramping constraints on accessing the spinning reserve for matching fast wind power fluctuations, the operation of the system is simulated with a time resolution of 10 seconds.

It is noteworthy to mention that the high time resolution required for simulating relevant operational features of these systems together with the computationally intensive nature of Monte Carlo and PSO methods impose a rather big computational challenge. However, the coarse-grained nature of the problem makes it amenable to be solved in a distributed computing environment.

3. The simulation model

3.1 The exemplary system

A real stand-alone hybrid wind-diesel system comprising 10 thermal units and a 2-MW wind turbine has been selected for illustrating the applicability of the proposed optimization framework. The total installed capacity of this exemplary generation system is 15.4 MW. The time horizon of the simulation model spans 24 h in order to account for the daily seasonality of the load demand and the wind resource. The time resolution for simulating the operation of the system and the load dispatch is 10 s, which allows capturing ramping constraints of the diesel units when managing power fluctuations. The unit commitment is set for each 5 minutes with a time horizon of 24 h. In the following sections, details of various models necessary for describing the stochastic behaviour of operating conditions of the autonomous wind-diesel system are presented. Emphasis on stochastic models describing the random nature of unit outages and wind power fluctuations is given.

3.2 Modeling the conventional diesel generation system

The considered thermal generation system encompasses ten identical diesel gensets with prime power rated capacity at site elevation of 1339 ekW. Further relevant technical specifications of diesel gensets are summarized in Table 1.

Specification	Parameter value
Caterpillar CAT3516B (4-stroke bi-turbo V16)	50 Hz/1500 rpm/6.6 kV
Fuel	LFO/Cmin
Gross engine capacity (at site elevation)	1415 bkW
Generator efficiency	0.95
Prime rating	1339 ekW
Continuous rating	972 ekW
Minimum operable output	280 ekW
Unit-related auxiliary load consumption	209 kW
Upward (downward) ramping capacity	50 (15) kW/s
Starting and synchronization time	120 s
Minimum up (down) time	300 (300) s

Table 1. Technical data of the considered diesel units

The operating cost of diesel generating units can be distinguished in start-up and variable hourly production costs.

According to experimental data shown in Fig. 1, the hourly fuel consumption c_F of a typical diesel genset within its operating limits is nearly linear with the delivered power output P

$$c_F = c_1 P + c_0 \tag{7}$$

where $c_0 = 0$ is a constant term and $c_1 = 0.225$ [l/ekWh] is the unit's average specific fuel consumption. The fuel consumption at idle is about 32 l/h. The lube oil consumption c_{oil} has been estimated in about 0.00106 [l/ekWh]. Assuming a fuel price $p_F = 0.811$ [US\$/l] and lube oil price $p_{oil} = 1.81$ [US\$/l], the total hourly generation costs C_G^T [US\$/h] can be computed in terms of the hourly fuel C_F costs and the lube oil costs C_{oil}

$$C_G^T = C_F + C_{oil} = \left(p_F c_1 + p_{oil} c_{oil}\right) P = 0.18438 P \text{ [US\$/h]} \tag{8}$$

Start-up costs are incurred mainly in the fuel and oil consumption during the phase of engine start, warm-up, acceleration to rated speed and synchronization before it delivers electrical power to the supply system. These costs are modeled as a constant value

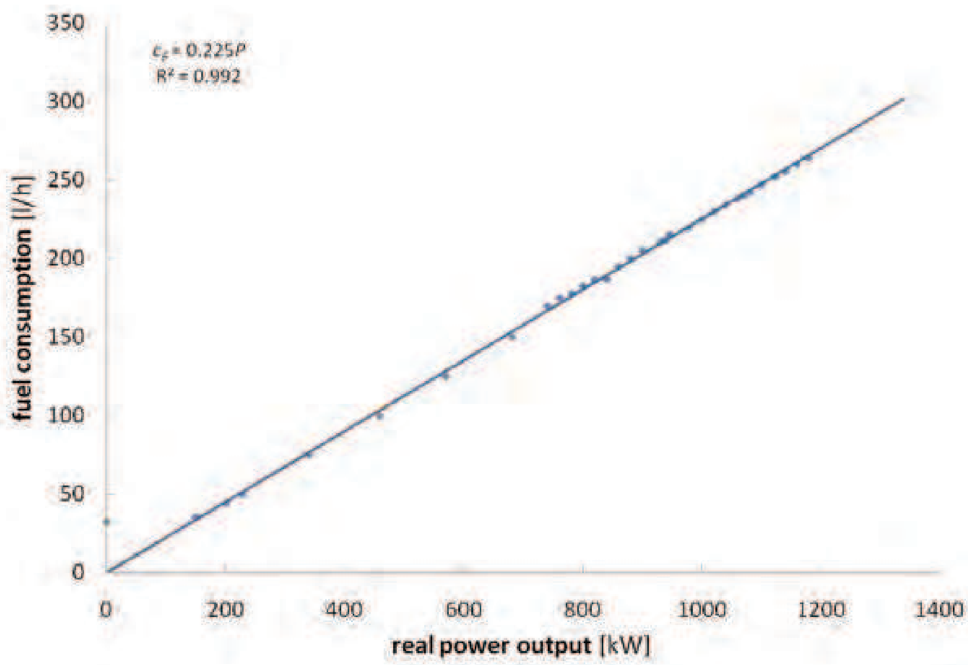

Fig. 1. Measured hourly fuel consumption of a diesel-fuelled generating unit

irrespective of the time the unit has been is standby. Considering a synchronization time of 120 s after receiving the start signal, the startup costs can be estimated in 1.07 US$. In addition, incremental parasitic loads due to startup decisions are also taken into consideration, but they are summed to the system load. Power consumption of unit-related auxiliary loads is estimated in 209 kW. The cost of supplying auxiliary loads cannot be neglected as they represent about 21.5% of the unit's continuous rate capacity[1]. Economic costs related to reduction of engine lifetime and incremental need for unit maintenance with the number of cold starts are here not considered.

The system must hold spinning reserve for managing power imbalances resulting of the sudden loss of generation equipment. Therefore, an appropriate reliability model for describing the stochastic behavior of unit failures and repair process is needed. Presently, it is well known the fact that the two-state unit model is inadequate for cycling units (IEEE Task Group, 1972). As the probability of a failure when the unit is down is typically very low compared to failure probability when the unit is operating, a simple four-state unit reliability model has been proven adequate for describing the interaction with the operating pattern of cycling units (Billinton & Jingdong, 2004). Neglecting the possibility of failure during the time the unit is unsynchronized, the simplest 4-state reliability model of a diesel unit is illustrated in Fig. 2, where transition rates λ and μ are the mean failure and repair rate respectively.

If the failure and repair rate are assumed time-invariant, the time between failures t_O and the repair time t_F are exponentially distributed and the model hold the Markov properties. This simple model does not consider failure to synchronize, postponable outages and failures leading to derate the unit capacity. Typical reliability parameters for diesel units

[1] Power consumption of plant-related auxiliary loads, i.e. loads that do not depend on UC decisions, such as lights, fuel pump and heaters, etc., must be simply added to the system demand. For the considered facilities, the fixed plant consumption is estimated in 274 kW.

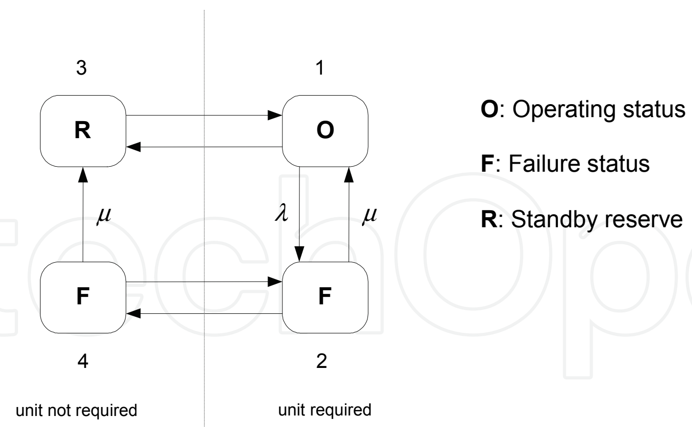

Fig. 2. Four-state Markov reliability model for a cycling diesel generating unit

FOR	λ	μ	MTTF	MTTR
0.02	0.00102041 h^{-1}	0.05 h^{-1}	980 h	50 h

FOR: Forced Outage Rate, **MTTF:** Mean Time to Failure, **MTTR:** Mean Time to Repair

Table 2. Typical reliability parameters of diesel units

have been adopted form the literature (NERC, 2006) and are summarized in Table 2. Relationships between these reliability parameters are given below

$$\begin{aligned} \mathrm{FOR} &= \Pr(\mathrm{F}) = \lambda(\lambda+\mu)^{-1} \\ \mathrm{MTTF} &= \mathrm{E}[t_{\mathrm{O}}] = \lambda^{-1} \\ \mathrm{MTTR} &= \mathrm{E}[t_{\mathrm{F}}] = \mu^{-1} \end{aligned} \tag{9}$$

where FOR is the forced outage rate representing the unit's failure probability, MTTF is the mean time to failure or the expected operating time $\overline{t}_{\mathrm{O}}$ between two consecutive failures and MTTR is the mean time to repair or expected time $\overline{t}_{\mathrm{F}}$ the unit resides in the failed state.
Under the Markov hypothesis, simulations of operation and repair times, t_{O} and t_{F} respectively, of generating units can be obtained by taking i.i.d. random samples from an exponential distribution with parameters λ and μ respectively (Billinton & Allan, 1996):

$$t_{\mathrm{O}} = -\frac{1}{\lambda} ln\left(\mathrm{U}[0,1]\right) \; ; \; t_{\mathrm{F}} = -\frac{1}{\mu} ln\left(\mathrm{U}[0,1]\right) \tag{10}$$

where U [0,1] are uniform i.i.d. samples over the interval [0,1].
It is important to mention that in addition to random failures, deterministic unit unavailability periods due to planned maintenance activities must also be taken into consideration in the scheduling algorithm.

3.2 Modeling the wind generator

Wind turbines exhibit highly non-linear generation characteristics. A typical wind speed – power curve is illustrated in Fig. 3. Four well-defined operating zones of the wind generator can be distinguished.

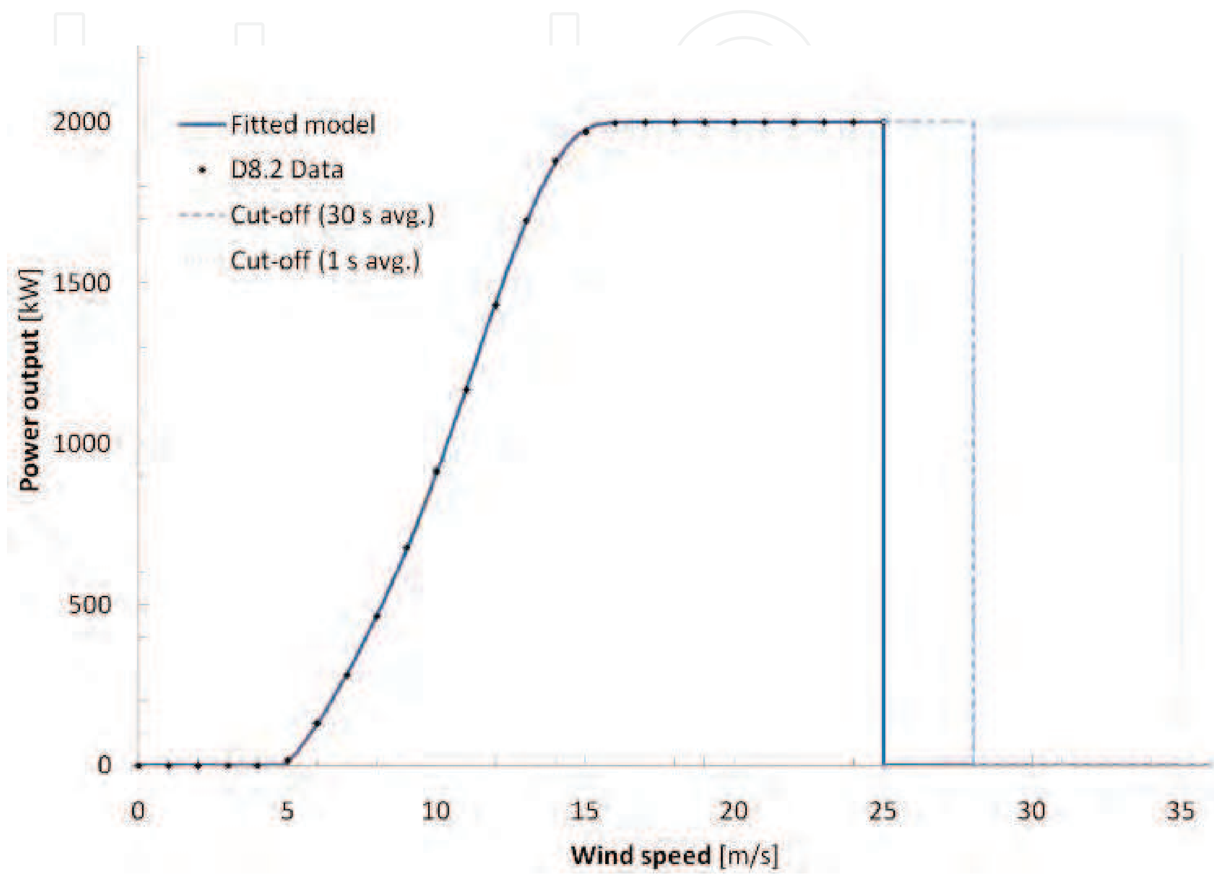

Fig. 3. Characteristic wind speed – power output of the DEWind D8.2 wind turbine

Generation is zero if prevailing wind speeds is lower than the cut-in wind velocity v_{in}. Wind power output rapidly increases from this point to the rated wind speed v_r at which the wind generator delivers its rated power capacity $P_W^{\max}$. Fluctuations of the wind speed between these operating limits leads to large power fluctuations, which have to be balanced by the available spinning reserve carried on diesel units. If wind speed exceeds the rated velocity, the pitch control keeps the power output at the rated generation capacity. In order to safeguard the equipment, the turbine is shut-down if wind speeds exceed some predefined thresholds during certain time period. The cut-off wind speeds v_{off} are typically defined in term of time moving averages for various window widths.

A piecewise non-linear function describing the wind-power characteristic curve for the 2-MW wind turbine integrated to the considered supply system is given by the following expression:

$$P_W(v) = \begin{cases} 0 & 0 \le v \le v_{in} \\ \sum_{i=0}^{6} a_i v^i & v_{in} \le v < v_r \\ P_W^{\max} & v_r \le v < v_{off} \\ 0 & v_{off} \le v < \infty \end{cases} \tag{11}$$

where

$$\begin{aligned} &P_W^{\max} = 2000 \text{ kW} \\ &v_r = 16 \text{ m/s} \\ &v_{in} = \frac{1}{T}\sum_{t=\tau}^{\tau+T} v_t = 4 \text{ m/s} \quad T = 600 \text{ s} \\ &v_{off} = \begin{cases} \frac{1}{T}\sum_{t=\tau}^{\tau+T} v_t = 35 \text{ m/s} & T = 1 \text{ s} \\ \frac{1}{T}\sum_{t=\tau}^{\tau+T} v_t = 28 \text{ m/s} & T = 30 \text{ s} \\ \frac{1}{T}\sum_{t=\tau}^{\tau+T} v_t = 25 \text{ m/s} & T = 600 \text{ s} \end{cases} \end{aligned} \tag{12}$$

It is noteworthy to mention that once some of the cut-off conditions is reached, the turbine cannot be restarted while the 10-min average wind speed do not fall below 22 m/s. The synchronization time of the wind generator is 300 s. The ramping rate from 0 kW to the power output corresponding to the prevailing wind speed conditions is 33 kW/s. The down-ramping of the wind generator after a cut-off event is 200 kW/s, what imposes a considerable burden to the response capability of the thermal generation system.
For describing the stochastic behavior of turbine outages, a 3-state reliability model is proposed and illustrated in Fig. 4.

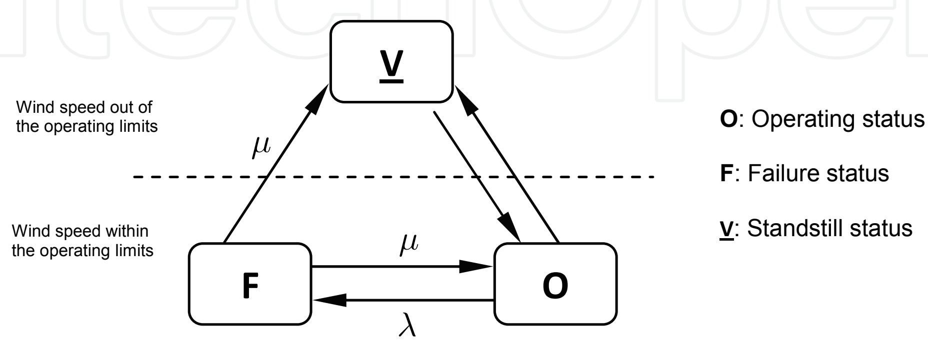

Fig. 4. Proposed Markov reliability model for the wind generator

The proposed reliability model assumes that wind turbine can fail only when it is synchronized and generating. Transitions from the operating status to idle and vice versa occur when the moving-averaged wind speeds are either lower than v_{in} or higher than v_{off}. If the turbine is repaired, depending of the prevailing wind conditions, transitions either to the operating status or standstill are possible.
Assumed reliability parameters of the wind generator for this study are given in Table 3. These values are consistent with a turbine sited in a remote location and subjected to extreme weather conditions (Castro Sayas & Allan, 1996).

FOR	λ	μ	MTTF	MTTR
0.05	0.0004 h^{-1}	0.0076 h^{-1}	2500 h	131.6 h

FOR: Forced Outage Rate, **MTTF:** Mean Time to Failure, **MTTR:** Mean Time to Repair

Table 3. Reliability parameters of a wind turbine

3.3 Modeling wind power fluctuations

The rapid fluctuations introduced by wind power generation are a major source of variability and uncertainty in the short-term operation planning of small autonomous supply systems. Because of the unpredictable nature of fast wind speed changes, additional spinning reserve must be carried to ensure that the power balance is kept at any time instant. In order to compute the spinning reserve requirement for balancing the fluctuations of the wind generation, a model accurately reproducing the severity and occurrence probability of the possible wind speed excursions is therefore needed.
By applying such a stochastic model, the system operation can sampled for a large number of possible chronological realizations of the wind speed. This allows exploring the rare occurrence of severe operating conditions, under which the system find exhausted its balancing resources and load shedding actions are needed.
In this section, results from a developed algorithm for simulating the stochastic dynamics of horizontal wind velocities are presented. The mathematical modeling details of the developed stochastic wind model are extensively treated in (Olsina & Larisson, 2008a, 2008b). High-resolution wind time series are generated in two sequential stages, i.e. 10-min average wind speeds and, based on this information, the non-stationary wind turbulence.
The proposed methodology rely on frequency-domain techniques, namely the well-known spectral representation theorem, for synthesizing random fluctuations of wind speeds over the various time scales according to the probabilistic and spectral properties observed in wind data gathered at the turbine site.
The simulation algorithm is able to accurately reproduce the remarkable non-Gaussian and non-stationary features of wind speeds. An iterative procedure and a non-linear memoryless transformation are applied to simultaneously match the observed evolutionary spectral content and the marginal non-Gaussian probability density function (PDF) of the random wind speed fluctuations. In addition, the proposed method is non-parametric, i.e there is not model parameters to be calibrated. Therefore, the proposed model does not require neither assumptions on the dataset nor the expedient postulation of a model structure or model equations to represent the wind speed variability. This is in fact an important advantage, as the very general nature of the non-parametric modeling framework allows applying the

wind stochastic model to sites with very different wind characteristics. The main parts of the developed wind speed simulation procedure are illustrated in Fig. 5.

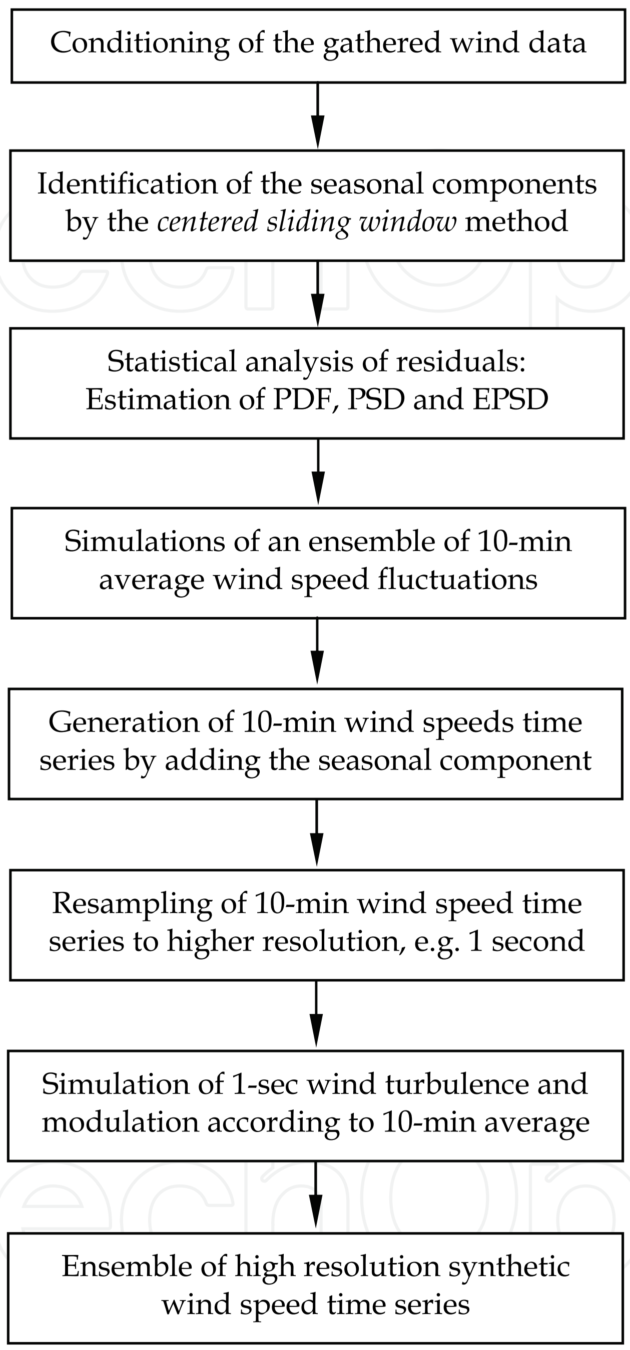

Fig. 5. Chart flow of the stochastic wind speed simulation algorithm

Before proceeding with further analysis, the gathered 10-min wind speed data, measured at 20 m, must conditioned for possible missing entries and outliers. Correction of wind data to the hub height (in this case 60 m) is typically also required at this stage. For this purpose, either the power or logarithmic law for the vertical wind speed profile can be used.

Changes in the prevailing wind conditions can be distinguished in deterministic and stochastic variability. The wind dataset v_t can be decomposed as the sum of deterministic regularities m_t, which can exactly be predicted, and random fluctuations z_t:

$$v_t = m_t + z_t \tag{10}$$

Regular deterministic patterns at daily and seasonal scales are identified by averaging wind data of the same hour over a *sliding window* centered at the time instant being estimated. A window width of 30 days has been applied to the available dataset. As an example, Fig. 6 shows the strong daily pattern identified for a week in January (summer).

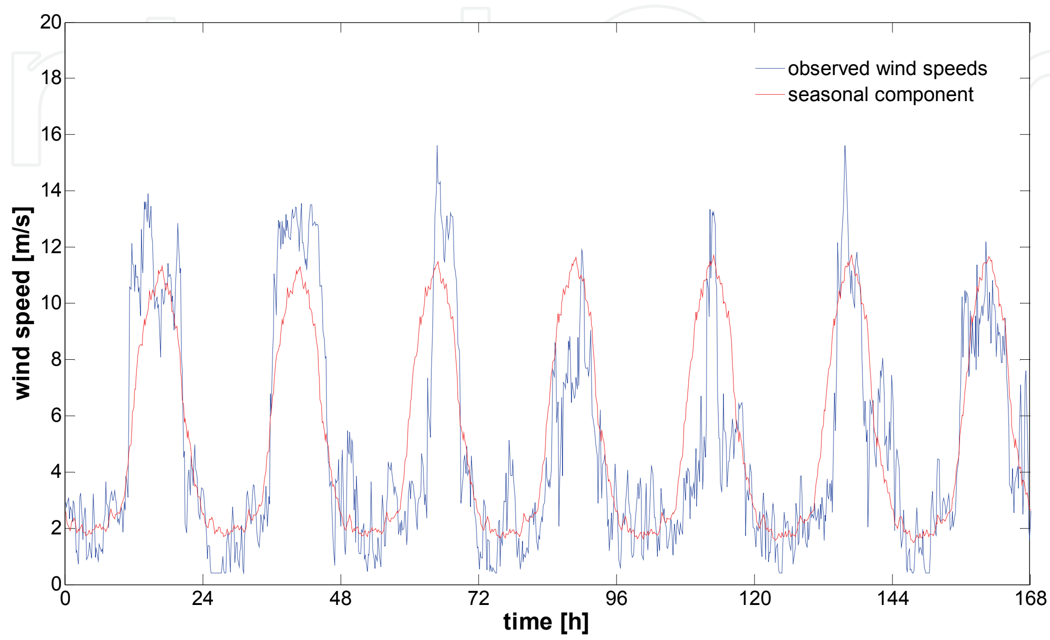

Fig. 6. Estimated deterministic component of wind speeds by using a 30-day sliding window

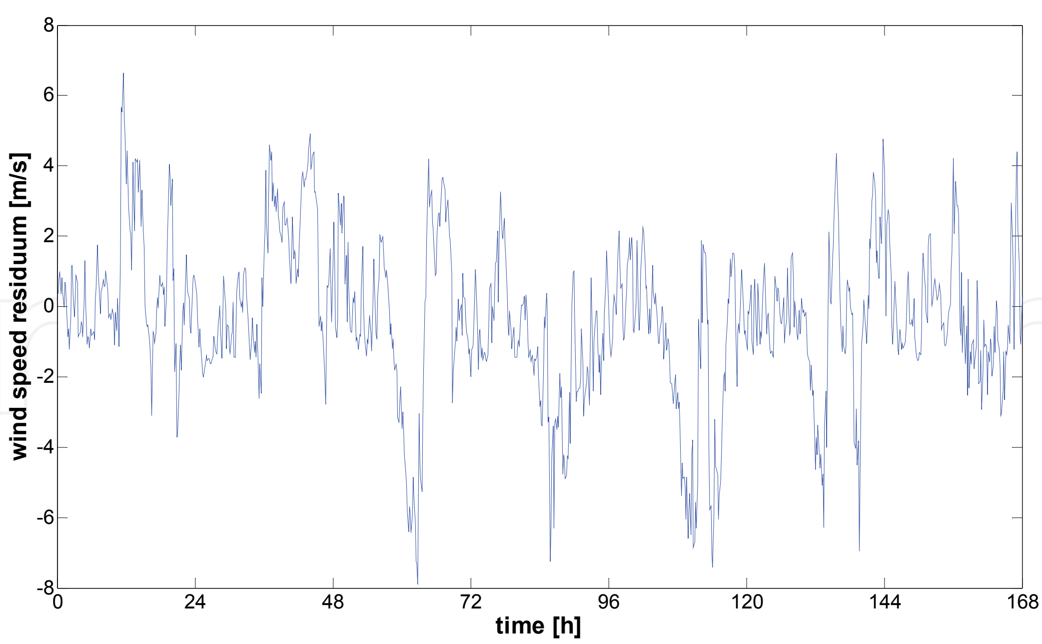

Fig. 7. Deseasonalized residuum of the 10-min average wind speed time series

After identifying the deterministic component, it can be subtracted from the dataset leaving only the stochastic part of the wind speed fluctuations. Fig. 7 shows the residuals z_t for the same January week after removing the seasonal pattern.

Fig. 7 clearly reveals the non-stationary behavior of the wind variance along the day. In fact, wind speed is much more variable an uncertain on daylight hours than on night hours. Furthermore, large deviations from the time-varying mean occurs frequently at about 10:00 AM and at 8:00 PM primarily as consequence of the uncertainty on the time the wind arrive and cease to blow.

Once the random part of the wind speed fluctuations has been isolated, a statistical analysis for characterizing the probabilistic and spectral properties of the time series is required, as simulation were generated according to this information.

The probabilistic characteristics of the wind speed time series are obtained by computing the empirical probability density function (PDF) by means of the non-parametric Kaplan-Meier method.

The stochastic dynamics of the wind fluctuations over the various time scales (seconds to months) is characterized by the (stationary) power spectral density function (PSD), which is also computed by non-parametric techniques. The Welch method provides a parameter-free, accurate and smoothed estimate of the PSD of wind residuals.

The non-stationary features of wind speeds over the year are adequately captured by computing the evolutionary power spectral density function (EPSD), which represents a complete time-frequency description of the time- varying statistical properties of the wind dataset. Here, it is assumed that non-stationary characteristic of the wind data are well represented by an intensity (uniformly) modulated stochastic process. The modulating function is therefore only function of time and depends on the local process variance. Similarly to the local mean identification, the time-varying local variance of the process is also computed with the sliding window method as referred above.

The first step in the synthesis of 10-min wind speeds is the generation of a zero-mean stationary Gaussian ensemble, i.e. a set of independently generated random processes, according to the empirical PSD by means of the spectral representation method (Shinozuka & Deodatis, 1991). Before proceeding to the next step, the generated ensemble is modulated with an envelope function in order to account for non-stationary characteristics. By means of a memoryless non-linear transformation the observed non-Gaussian PDF is satisfied. The non-stationary ensemble is iteratively corrected according tho the target PSD. The reader interested in details of the mathematical formulation of the iterative spectral correction procedures is further referred to (Deodatis & Micaletti, 2001). It is important to mention that the same spectral-based algorithm has been applied to the stochastic simulation of electricity prices, which are random processes well-known for their stochastic complexities and the challenging modeling difficulties they present (Olsina & Weber, 2008).

Fig. 8 illustrates a single sample of the generated stochastic ensemble of 10-min wind speed fluctuations. The statistical properties of the simulated samples are compared with the observed characteristics in Table 4. It can be concluded that synthetic wind fluctuations accurately replicate observed statistical features of the wind dataset.

In Fig. 9, the probability density functions for the observed wind speed residuals as well as for the simulated sample are compared by potting them together. This plot confirms that the probabilistic properties of simulated wind speed fluctuations are nearly identical to those observed at the wind turbine site. It must be noted the excellent agreement at the tails of the distribution, as the probability of large wind speed excursions largely determines the spinning reserve requirement.

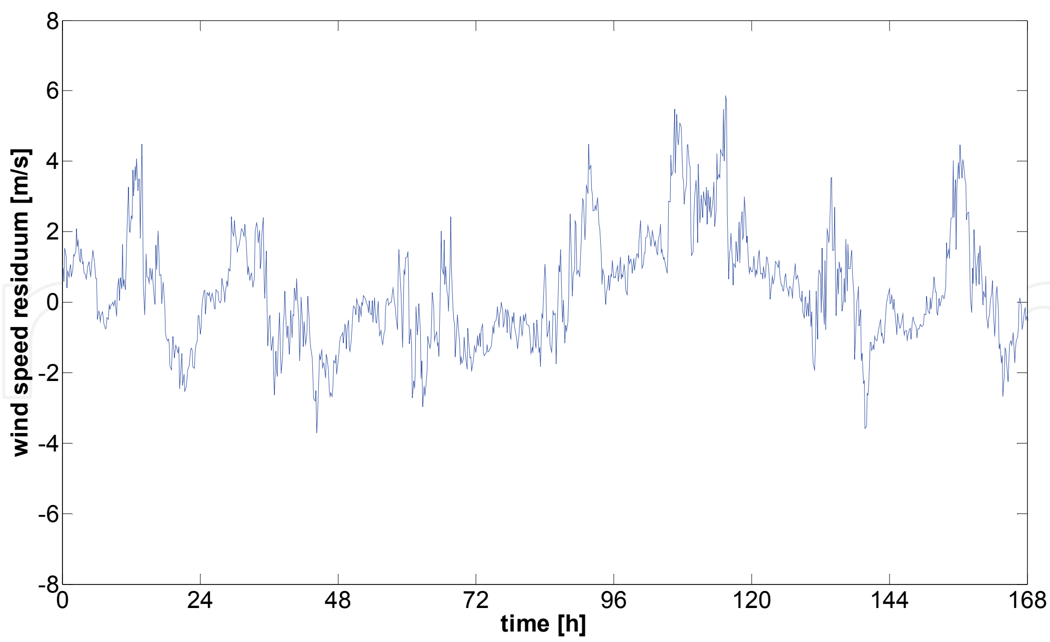

Fig. 8. Non-Gaussian non-stationary simulated sample of 10-min wind speed changes

Parameter	Observations	Simulations
Minimum [m/s]	-10.29	-10.2967
Maximum [m/s]	19.66	19.6647
Mean [m/s]	0	0.0382
Std. Dev [m/s]	3.95	3.9050
Skewness	0.5274	0.6204
Kurtosis	3.4044	3.8279

Table 4. Descriptive first-order statistics of simulated random wind speed residuals

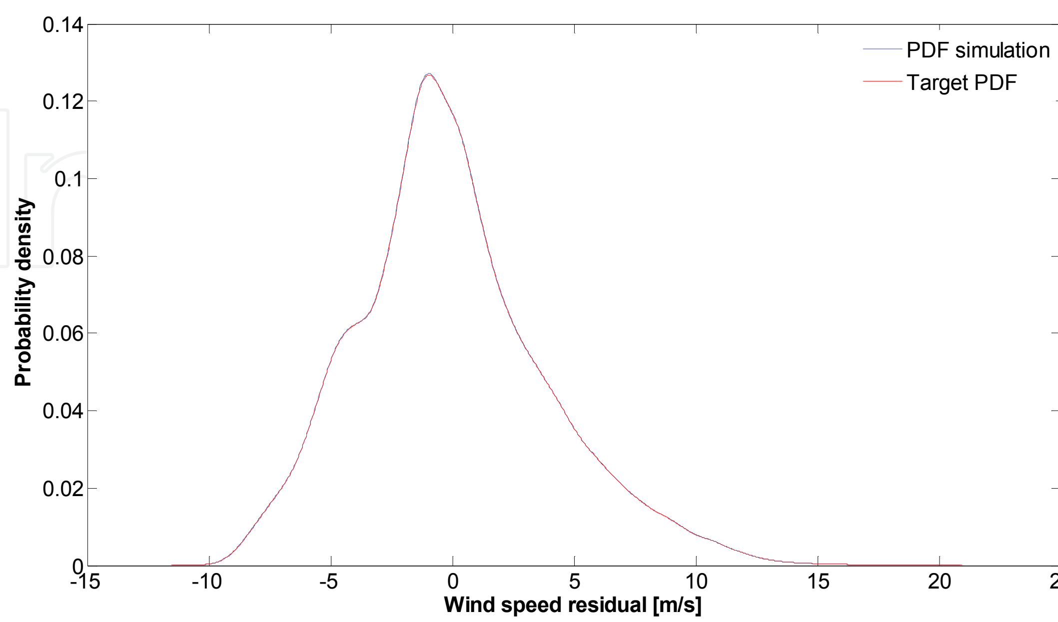

Fig. 9. PDFs of a simulated annual sample and the wind speed fluctuations over a year

In addition to the first-order statistical properties, second-order statistics are compared with the aim at checking for similarity of the stochastic dynamics of simulated samples to the observed random fluctuations. Fig. 10 depicts the frequency content of wind speed fluctuations for both the observed time series and synthetically generated ensemble. The figure shows that the ensemble-average PSD is practically identical to the observed PSD over all frequency bands.

The non-stationary behavior of the synthetically generated ensemble of wind speed residuals is tested by computing the time-varying variance. The local variance computed across the simulated ensemble matches with very high accuracy the observed local variance of the random wind fluctuations, as it can be observed in Fig 11.

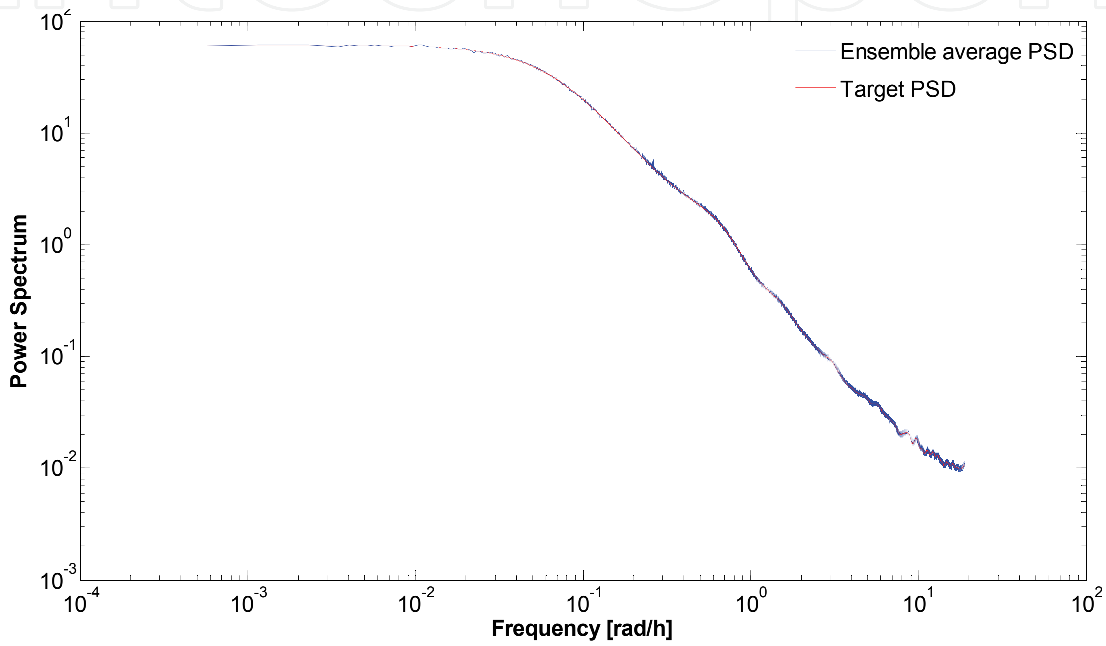

Fig. 10. Power spectra for the simulated ensemble and for observed wind speed fluctuations

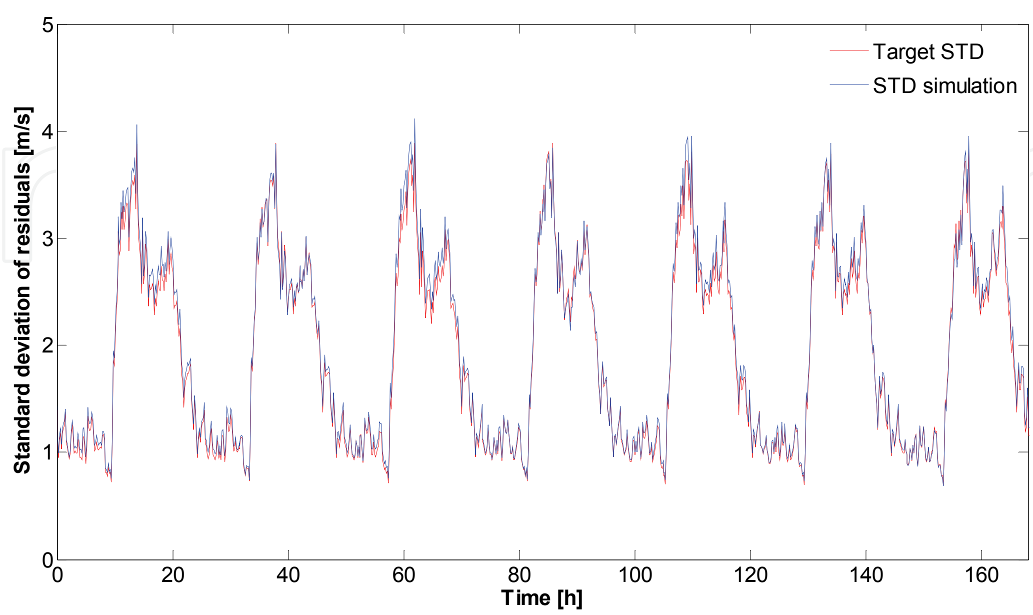

Fig. 11. Local non-stationary variance of simulated samples and observed fluctuations

By adding the deterministic component to the simulated random fluctuations, an ensemble of 10-min average wind speeds can be generated, as shown in Fig. 12. By comparing this plot with Fig. 7, we can see that the most important features of wind are captured by the proposed algorithm. This is also confirmed by comparing the spectral content of wind fluctuations in Fig. 13.
Likewise, first-order statistics provided in Table 5, as well as the probability and occurrence frequency of wind speeds exceeding the cut-off, computed from observations and the simulated ensemble are very similar.

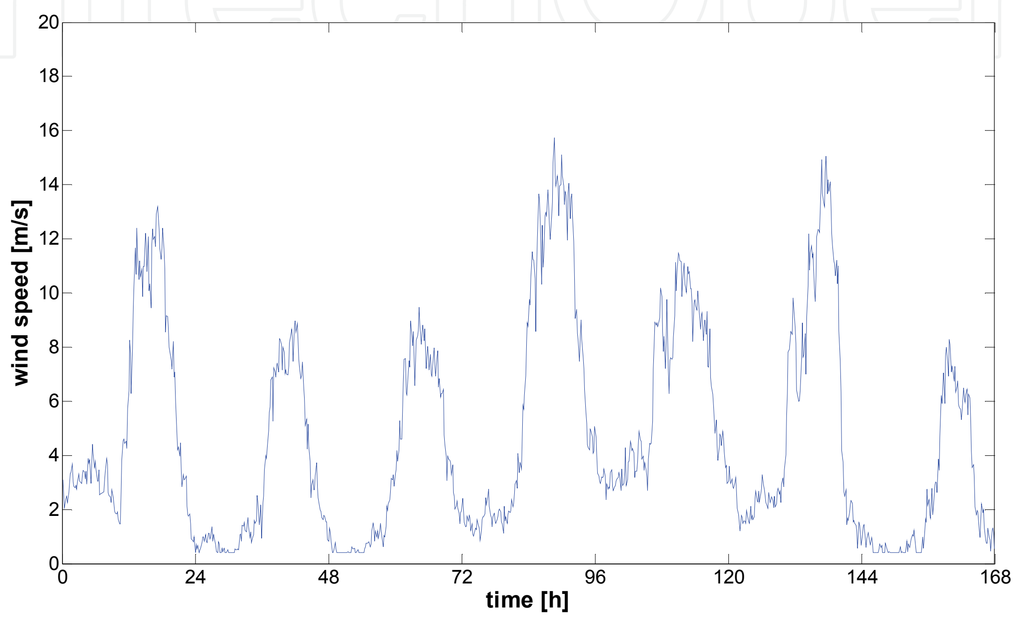

Fig. 12. Simulated sample of 10-min average wind speeds for week in January

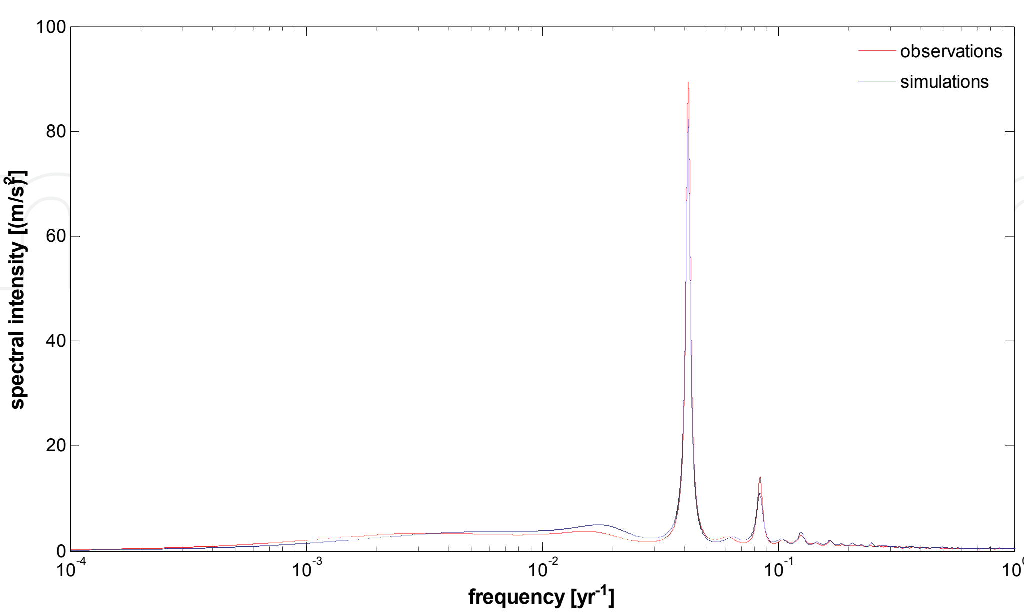

Fig. 13. Mean spectral intensity of observed and simulated 10-min wind speeds

Parameter	Observed	Simulated
Minimum [m/s]	0.4	0.4
Maximum [m/s]	26.42	32.2096
Mean [m/s]	7.0554	7.1879
Std. dev. [m/s]	5.0641	4.9590
Skewness	0.4361	1.6327
Kurtosis	2.1028	3.9796
Pr(v>25 m/s**)**	0.0003044	0.00024507
Up-crossing freq. [yr^{-1}]	4.00	6.023

Table 5. Descriptive first-order statistics of simulated 10-min average wind speeds

For simulating the fast power fluctuations introduced by the wind generator, simulations must incorporate the rapid wind speed changes due to the turbulence phenomena. Wind turbulence is typically regarded a Gaussian frequency-modulated non-stationary stochastic process. In order to apply the same simulation algorithm, we assume that the turbulence can still be modeled as an intensity-modulated process. For this purpose, an intermediate velocity (v = 10 m/s) for the Kaimal spectrum of wind turbulence has been selected (Kaimal *et al.*, 1972). The envelope function modulating the local variance of the turbulence is determined by imposing the condition that the turbulence intensity remains constant. The mean turbulence intensity of simulation and observations is 0.1558 and 0.1613 respectively. Fig. 14 illustrates the excellent agreement of the probabilistic and spectral properties of simulated turbulence samples when compared to observed data.

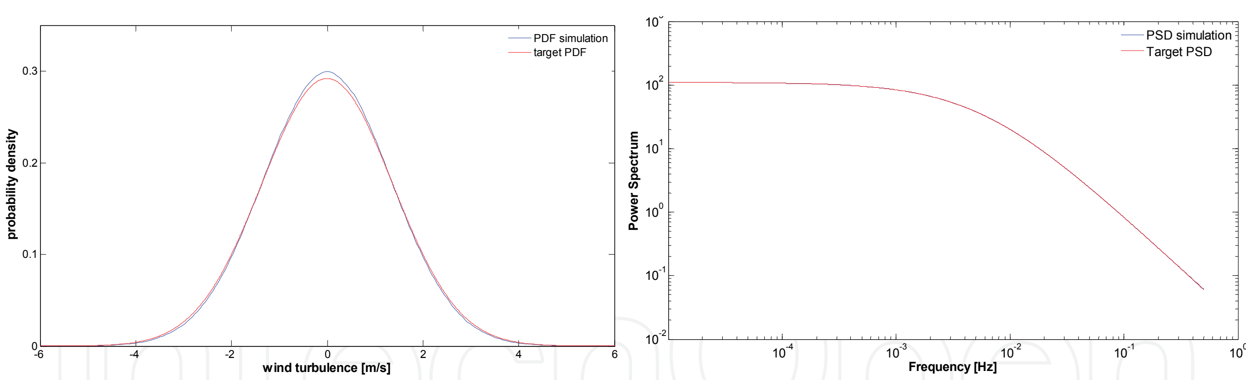

Fig. 14. PDF (left) and PSD (right) of the simulated and observed wind turbulence

The non-stationary (local-mean dependent) wind turbulence is added to the 10-min average wind speed time series in order to obtain wind speed samples at very high resolution (1 sec). For doing this, the 10-min wind speed time series are resampled at the desired temporal resolution by means of filtering techniques. A generated 24-h sample of wind speeds resulting from summing the deterministic component, the random fluctuations of 10-min wind speed averages and the wind turbulence simulated at 1 Hz is depicted in Fig. 15. The plot also shows in red the resampled 10-min average wind speed. We can observe that wind turbulence depends on the prevailing mean wind speed. The observed fast excursions of the wind speeds require scheduling significant balancing resources in order to compensate for the related wind power fluctuations.

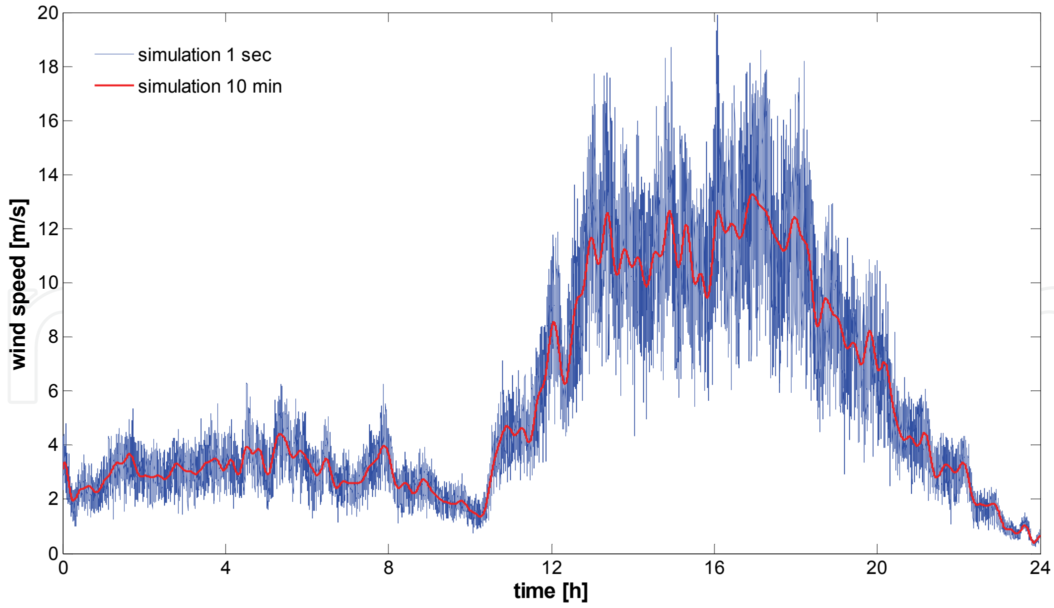

Fig. 15. Wind speed sample simulated at high resolution (1 second) for a day in January

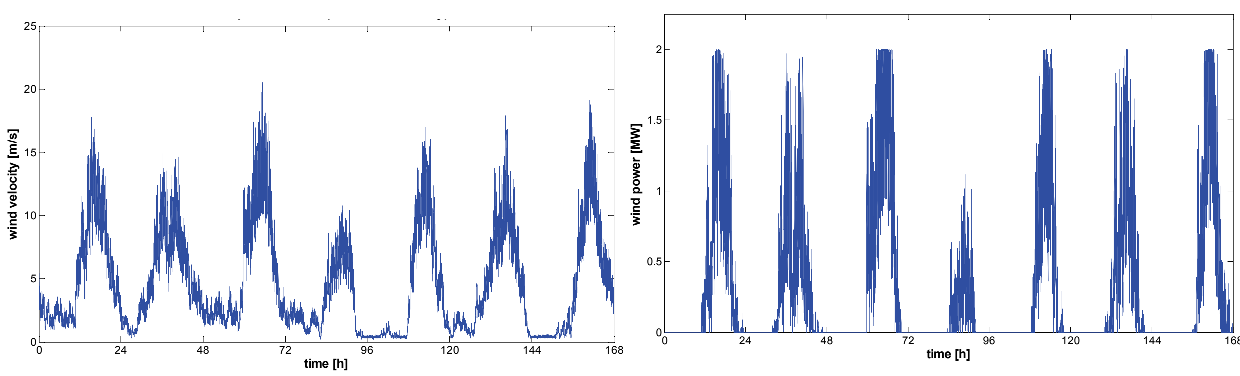

Fig. 16. Simulated 10-sec wind speeds and wind power samples for a week in January

Generated wind samples are averaged on a 10-sec-width moving window for matching the time resolution of simulations of the system operating conditions. By applying to the wind speed samples the non-linear transformation given by the wind speed - power curve of the turbine (see eqs. 11 and 12, and Fig. 3), wind power time series can be generated. Fig. 16 illustrates the resulting wind power time series from a given wind speed sample.

3.4 Modeling load demand fluctuations

The developed spectral-based simulation algorithm described in the previous section has been applied without modifications to the simulation of random fluctuations of the power demand. Load samples are simulated according to observed spectral and probabilistic properties of load measurements. Fig. 17 shows a weekly sample of the load demand simulated at very high resolution and averaged on a moving window spanning 10 s.

3.4 Prediction of the residual load demand

The residual load L_R is the power demand that must effectively supplied by the conventional generation system. As the variable costs of wind generation are considered

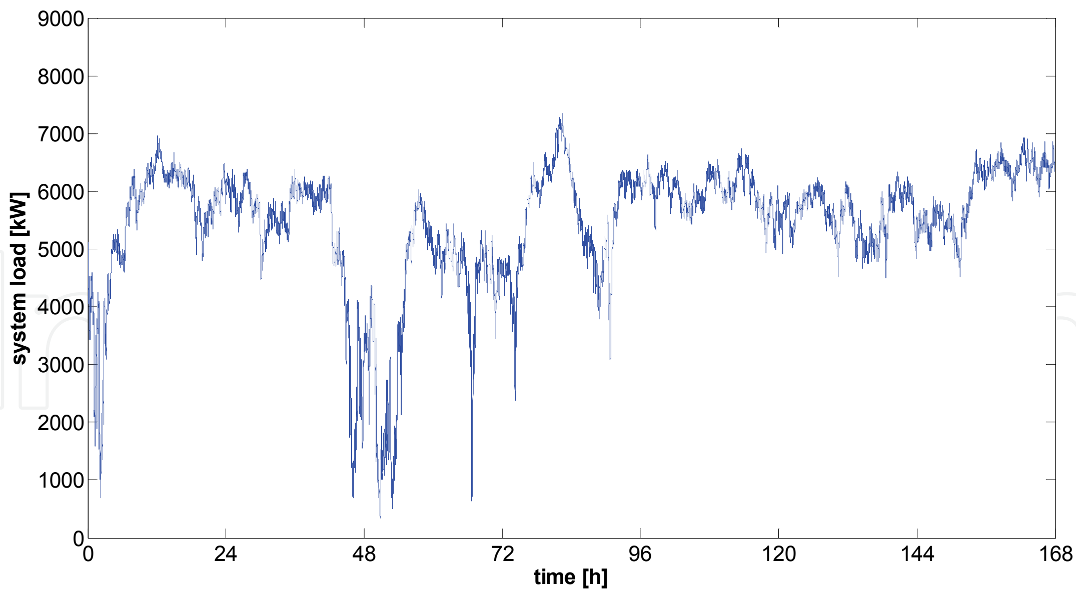

Fig. 17. Simulated 10-sec mean of the system power demand over a week

negligible, wind is dispatched first if available. Therefore, the residual load can be computed by discounting wind generation P_W from the power demand L. For optimally scheduling the diesel units, the residual load must be predicted for each time interval t of the optimization horizon. Here, we assume that the prediction of the 5-min mean of the residual demand $\overline{L}_R^t$ coincides with its expected value, i.e. the forecast is unbiased. Mathematically, the residual load prediction is given by:

$$\chi_{L_R}^t = \mathrm{E}\left[\overline{L}_R^t\right] = \mathrm{E}\left[\overline{L}^t - \overline{P}_W^t\right] = \mathrm{E}\left[\frac{1}{T}\sum_{t=kT}^{(k+1)T}\left(L^t - P_W^t\right)\right]; T = 300 \text{ s}; k = 0,1,2,\ldots,287 \quad (13)$$

The forecast of the 5-min average residual load computed for each five minutes of the considered 24 h optimization horizon is depicted in Fig. 18.

3.5 Simulating the integrated operation of the hybrid generation system

For each set (particle) of generation and reserve scheduling decisions proposed by the optimization algorithm, the expected operating and interruption costs are accurately estimated by chronologically simulating the integrated operation of the diesel units and the wind generator over a large number of possible realizations. The software package Stochastic Wind Diesel Simulator (SWDS®) has been applied for this purpose (Olsina & Larisson, 2008c). The optimal load sharing (referred also as economic dispatch, ED) among the synchronized units is run each 10 s of the 24-h optimization horizon and under 100 independent daily realizations of the uncertain variables. Therefore, the evaluation of the fitness of each particle position entails solving 864000 time-coupled ED problems.

Minimum and maximum unit power output, up and down ramping constraints, as well as synchronization times, shut-down times, minimum up and down times are strictly enforced by the simulation algorithm. The processes of starting, synchronizing and ramping a committed unit as well as downramping a decommited unit are detailed modeled. Power output of units ramping-up after synchronization or ramping-down for being decommited are considered as must-run power for purpose of solving the ED problem.

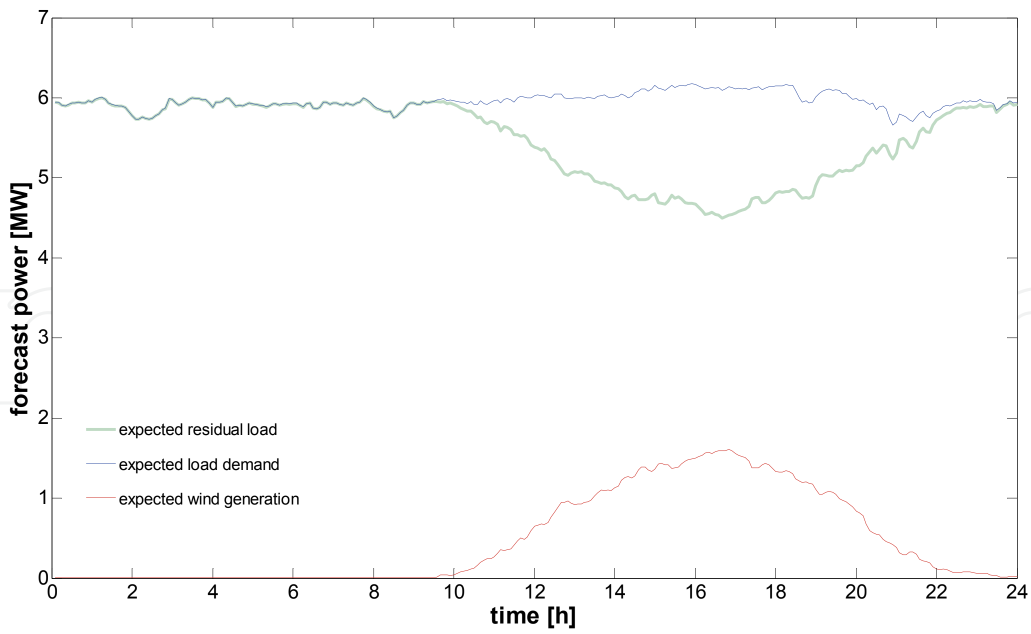

Fig. 18. Expected value of 5-min residual load average for a time horizon of 24 hours

The simulation model also takes into consideration all possible situations under which the system is unable to keep the momentary power balance. For example, a large upward excursion of the demand may lead to exhaust the spinning reserve carried on synchronized generators. Under such circumstances, load shedding is needed in order to prevent a system collapse. Likewise, rapid wind power fluctuations may exceed the aggregate ramping capacity available on synchronized units. Even though the amount of the spinning reserve may be sufficient to balance the magnitude of such fluctuations, ramping constraints impose severe limits to the speed it can effectively be deployed and again load curtailments may turn necessary.

The considered exemplary hybrid stand-alone generation system lacks of automatic load disconnection devices in order to protect the system from collapsing due to frequency instability. Therefore, if for any reason the conventional diesel system is unable to meet the instantaneous residual load a system collapse follows. The system load cannot begin to be restored before 10 minutes after collapse but the beginning of the restoration does not exceed 15 minutes. After a system collapse, the load is restored as quickly as possible by starting and synchronizing all available diesel units. The time elapsed between the generator receives the starting signal and that it delivers the prime power rating is 150 s. The wind generator does not participate during the load restoration period. The wind turbine can only be synchronized 5 minutes after the load restoration is concluded. A battery system supports all auxiliary loads while the system runs on black start until the diesel units are synchronized. The deficit power is computed as the unserved load of each time interval. The interruption costs expressed as per unserved energy unit are estimated in 9 US$/kWh.

4. Numerical results

4.1 Stochastic simulation

In this section, results from high-resolution simulations of the integrated operation of the autonomous wind-diesel generation system under a number of stochastic realizations of the exogenous variables, i.e. load demand, wind resource and random generator outages, are shown. Simulations are run on a single PC with a 2.33 GHz Intel Core 2 Quad processor and 4 GB of RAM. The CPU time required for computing a set of 100 independent daily simulations of the system operation at 10 second resolution is about 180 seconds.

The chronological simulation of the system operation for a large number of possible scenarios allows exploring and analyzing events of low probability under which the system operates near its limits or in emergency conditions. The expected operating costs (fuel costs and startup costs) as well as the expected interruption costs can be accurately assessed. Fig. 19 illustrates the chronological simulation of the operating conditions of the hybrid generation system at 10 second time resolution.

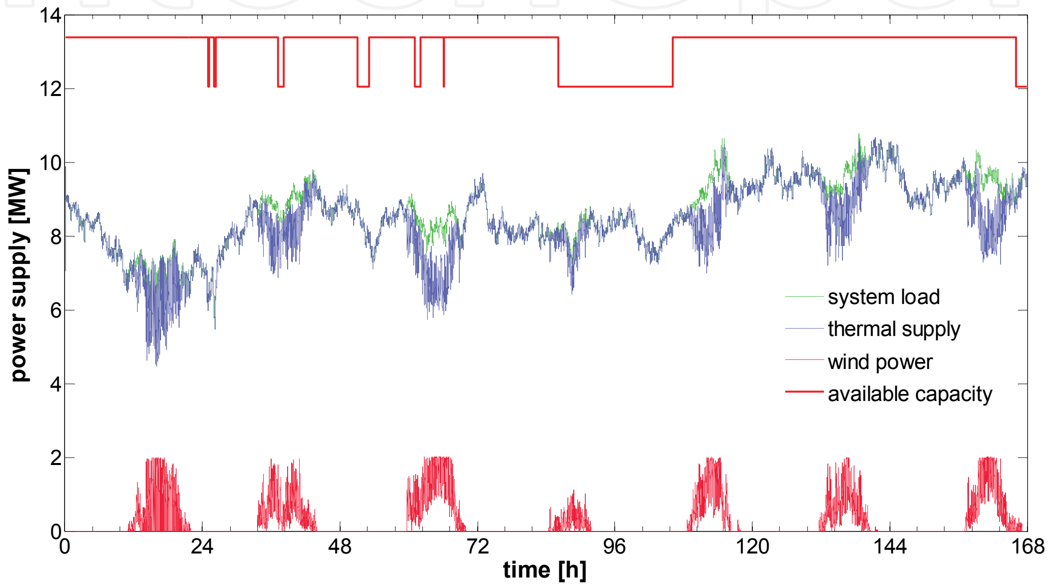

Fig. 19. Simulated chronological operation of the wind-diesel system for a week in January

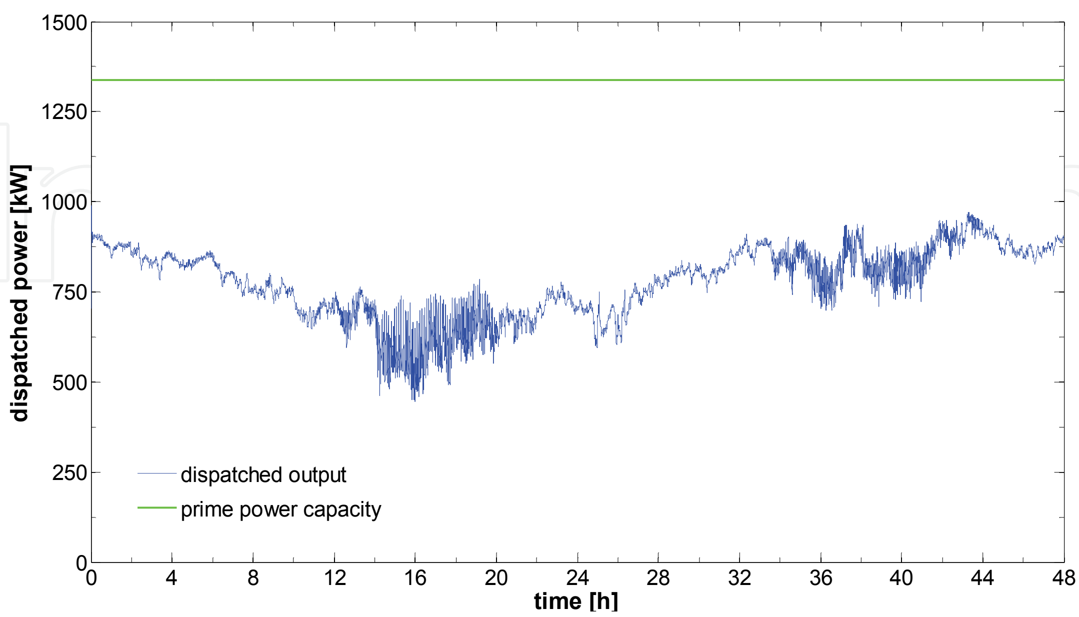

Fig. 20. 10-sec simulation of the dispatched power of a diesel generator over a 48-h period

It can be clearly observed that operating conditions are much more volatile and irregular during the time periods the wind turbine is generating. This can be better analyzed by plotting the power output of a diesel generator for two days as shown in Fig. 20.

4.2 Stochastic optimization

Solving the optimization problem involves finding the combination of scheduled units that minimizes the expected system costs over the day. Considering a system of 10 diesel gensets and 288 scheduling intervals, the total number of binary control variables is 2880. The size of the search space is given by the number of all possible permutations P_r^n of $r = 2880$ elements taken from a binary set with size $n = 2 \cdot 2880 = 5760$:

$$P_r^n = \frac{n!}{(n-r)!} = \frac{5760!}{2880!} = 4.3249 \cdot 10^{10722} \qquad (14)$$

The massive dimension of the problem turns it intractable for conventional optimization methods. Thus, the EPSO algorithm is applied for solving the combinatorial stochastic optimization problem, as stated in eq. 6.

Particles are binary coded in order to represent the schedule status of diesel generators for each five-minute time interval over the 24-h optimization horizon. For reducing wasted CPU time, all proposed generation schedules are checked for infeasibility before simulating the system operation. Specific knowledge on the scheduling problem has been exploited, in order to reduce the problem dimension to 864 binary variables. Accordingly, the search space is reduced to $1.7691 \cdot 10^{2682}$, which is still a very huge number. In addition, some known good schedules are provided as initial solutions to the algorithm for speeding up convergence.

A population of 85 particles has been selected for finding the best solution. The swarm stops evaluating the search hyperspace after 20 iterations. By applying evolutionary techniques, the EPSO self-adapts progressively the coefficients and weights of the searching algorithm. Solving these stochastic optimization problem entail running the SWDS simulation engine 420 times for evaluating the fitness of the proposed solution, which requires about 21 CPU hours on 5 desktop PC. The expected total costs of the best generation scheduling found after 20 iterations is 33241.26 US$/day. The unit scheduling that minimizes the expected generation and production costs over the optimization horizon along with the expected residual load is shown in Fig. 21. The available power capacity on the synchronized units in excess of the forecasted residual load is the scheduled spinning reserve.

It is interesting to note that despite the expected residual load is lower than at other time periods, an additional diesel unit is needed for about 50 minutes at about 8:00 PM. This occurs because of the high uncertainty and variability of wind at these moments.

A breakdown of the expected system costs evaluated at the best found scheduling policy is provided in Table 6.

The total system cost is itself a random variable as it depends on stochastic factors affecting the system operation. The probability density function of the total system costs determined at the best solution found from a sample of 100 daily realizations of the operating conditions is depicted in Fig. 22.

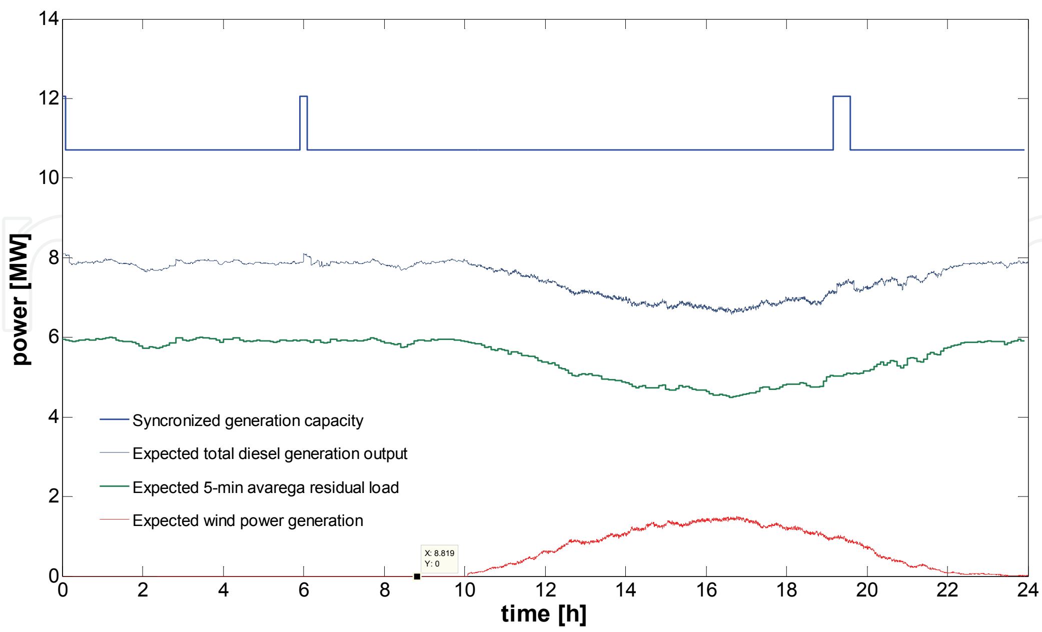

Fig. 21. Optimal scheduling of diesel units over the 24-h optimization horizon

System cost statistics	**Value** [US$/day]
Expected fuel costs	32893.31
Expected lube oil costs	335.94
Expected total generation costs	33229.25
Expected annual starts costs	1 2.01
Expected total operating costs	33241.26
Expected unserved energy costs	0.00*
Expected total system costs	**33241.26**

* The actual expected interruption costs must always be higher than zero. The relatively low sample size of 100 realizations does not allow a better estimation of the expected costs of the energy not served.

Table 6. Cost statistics at optimum

Since operating conditions are typically time-varying over the day, the expected total operating costs are not constant and vary with the time interval considered. The chronological simulation of the expected system costs for each time interval evaluated with the optimal scheduling solution found is plotted in Fig. 23. Clearly, it can be identified the fuel cost reduction during the time periods the wind turbine supply the system.

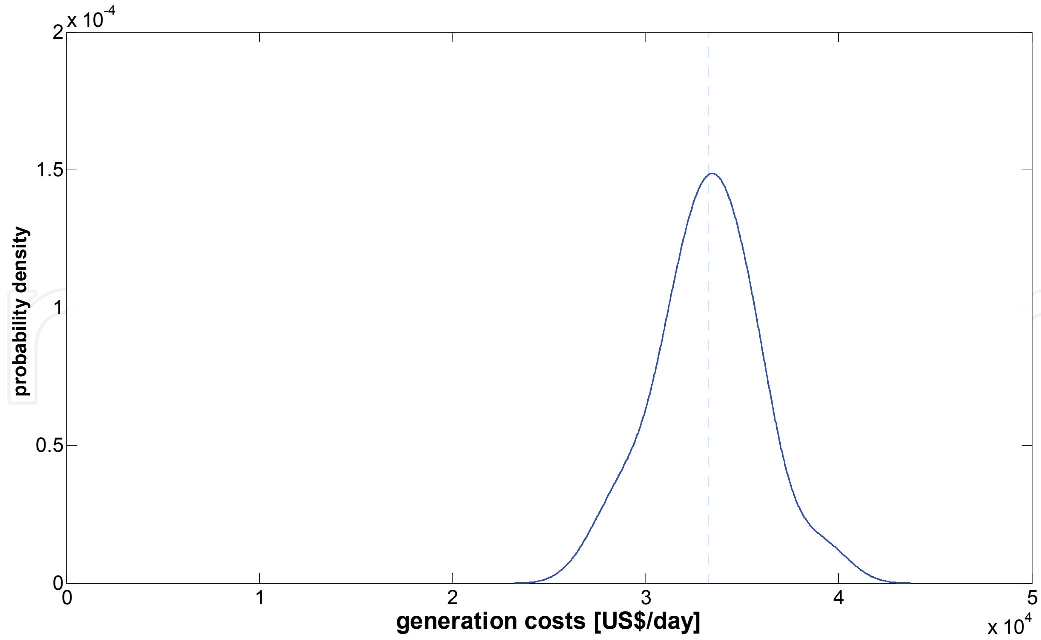

Fig. 22. Probability distribution of the daily total system costs

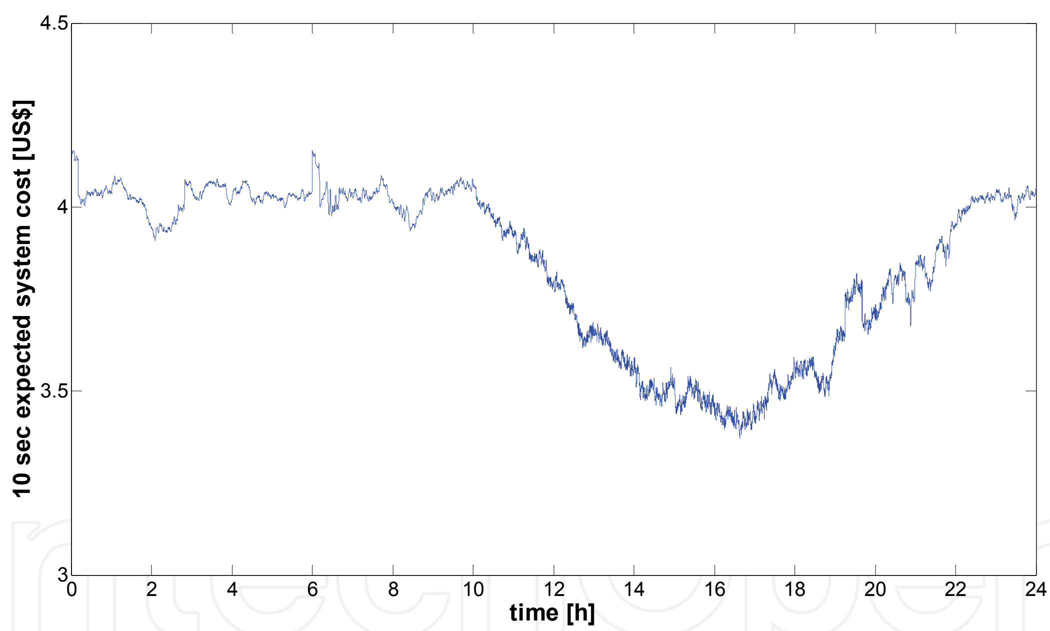

Fig. 23. Time-varying expected total system costs over the 24-h optimization horizon

5. Conclusion

The economy and the supply reliability level that an autonomous wind-diesel generation system can achieve largely depend on the UC decisions. The scheduling optimization of diesel units is a large-scale time-coupled stochastic non-linear mixed-integer problem. This chapter proposes a new methodology for solving this complex combinatorial optimization problem based on stochastic simulation and hybrid metaheuristic optimization methods.

A number of models accurately representing the several parts of the generation system, its operation as well as models for simulating the exogenous random factors affecting the operating conditions have been developed and described along this chapter. Chronological simulations of the system operation are carried out at a very high temporal resolution for capturing the effect of ramping constraints on the speed the reserve is effectively activated. A hybrid PSO algorithm for finding five-minute generation schedule that minimizes the sum of the expected operating and interruption costs over a 24-h horizon is applied. The spinning reserve is scheduled based on a cost-benefit analysis. The resulting optimal spinning reserve scheduling is uneven over the day, which reflects the changing conditions over the day and the trade-off between the costs of its provision and the benefits it provides in terms of lower interruption costs.

The proposed methodology, though very accurate, is costly in terms of computational effort. Nevertheless, PSO-based optimization techniques are naturally suited to distributed computation. Distributed-based PSO is currently an open avenue for further investigation which would enable algorithms of this kind to be implemented in real time applications, such as in closed-loop unmanned dispatch centers for stand-alone wind-diesel systems. For the purpose of further reducing the computation burden, more expert knowledge on the problem needs also to be introduced.

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Wind Power
Edited by S M Muyeen

ISBN 978-953-7619-81-7
Hard cover, 558 pages
Publisher InTech
Published online 01, June, 2010
Published in print edition June, 2010

This book is the result of inspirations and contributions from many researchers of different fields. A wide verity of research results are merged together to make this book useful for students and researchers who will take contribution for further development of the existing technology. I hope you will enjoy the book, so that my effort to bringing it together for you will be successful. In my capacity, as the Editor of this book, I would like to thanks and appreciate the chapter authors, who ensured the quality of the material as well as submitting their best works. Most of the results presented in to the book have already been published on international journals and appreciated in many international conferences.