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تعزيز و تقييم و تنفيذ طريقة التنبؤ بالحمل الكهربائي

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الملخص:

أثر عدم اليقين لتوقعات الحمل الكهربائي تكون واضحة المعالم إذا كان بعض من سعة الاحتياطي المخزون يتم الاستعانة بها لتوفير حمولة زائدة عن الكمية المتوقعة و بالتالي فان الاحتياطي المخزون يخفض. النموذج تم تطويره للحصول على الحمل المتوقع لمملكة البحرين.

طريقة الحساب تمت باستخدام طريقة مونت كارلو لنمذجة الحمل الكهربائي. النموذج المستخدم يستطيع أن يتنبأ بالحمل الكهربائي مع مرور الزمن خلال فترات سنوية بحيث تم تقسيم كل سنة الى 52 اسبوعا. النموذج المعد للتنبؤ يقوم بحساب الحد الأدنى لمتوسط الخطأ التربيعي (MMSE) لمتوسط القدرة المخزونة المشروط والانحراف المعياري المشروط في كل فترة محددة للتنبؤ بالأحمال الكهربائية المتوقعة. لعمل ذلك، وضحت النتائج المتوسط المشروط و نماذج التغاير من منظور تصفية خطيه وطبقت تكرار التوقعات المشروطة على المعادلات العودية لكل فترة تنبؤ عند كل زمن. وقد تم استنباط النتائج وتمت مناقشتها في هذه الدراسة.

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ORIGINAL ARTICLE

Enhancement, evaluation and implementation of a load forecasting method

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KEYWORDS

Monte Carlo;
Load forecast;
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Kingdom of Bahrain

Abstract The effect of load forecast uncertainty may be well-defined if some of the spinning reserve capacity is needed to supply the load in excess of the amount predicted and, thereby the spinning reserve is reduced. The model was developed for load estimation of Kingdom of Bahrain. The calculation method involves a Monte Carlo technique for the simulation of the load. The model enables the predication of the load against the time during years, where each year is divided into 52 weeks. The forecasting model, computes minimum mean square error (MMSE) forecasts of the conditional mean of reserve power and conditional standard deviation of the innovations in each period over a user-specified forecast possibility. To do this, it views the conditional mean and variance models from a linear filtering perspective, and applies iterated conditional expectations to the recursive equations, one forecast period at a time. The results are obtained and discussed.

1. Introduction

The prediction method used in the present paper is based on Monte-Carlo simulation in which it is well known that any approach using the Monte Carlo simulation method does not solve the equations describing the model. The Monte Carlo simulation uses a random number generator. And this generator is needed to bring the stochastic element in the calculations. The researcher could use a physical random-number generator such as electrical load variation through a certain period.

The Monte-Carlo simulation requires the creation of random numbers, in this paper, the generated numbers were chosen to follow the normal distribution with average value and standard deviation of the electrical load of Bahrain.

In Bordalo et al. (2006) they presented a probabilistic short-circuit approach to generate the probability distributions of the system average variation index. The methodology followed is based on the combination of the Monte-Carlo simulation and the admittance summation method.

In El-Khattam et al. (2006) they presented a novel algorithm to evaluate the performance of electric distribution systems, including distributed generation. Monte Carlo simulation is employed to solve the system operation randomness problem. The simulation is implemented to perform the analysis of all possible operations of the system under study. The system loading follows several typical load curves.

In Ionescu et al. (2006), the purpose of their study was to obtain a performable tool based on generalized stochastic Petri

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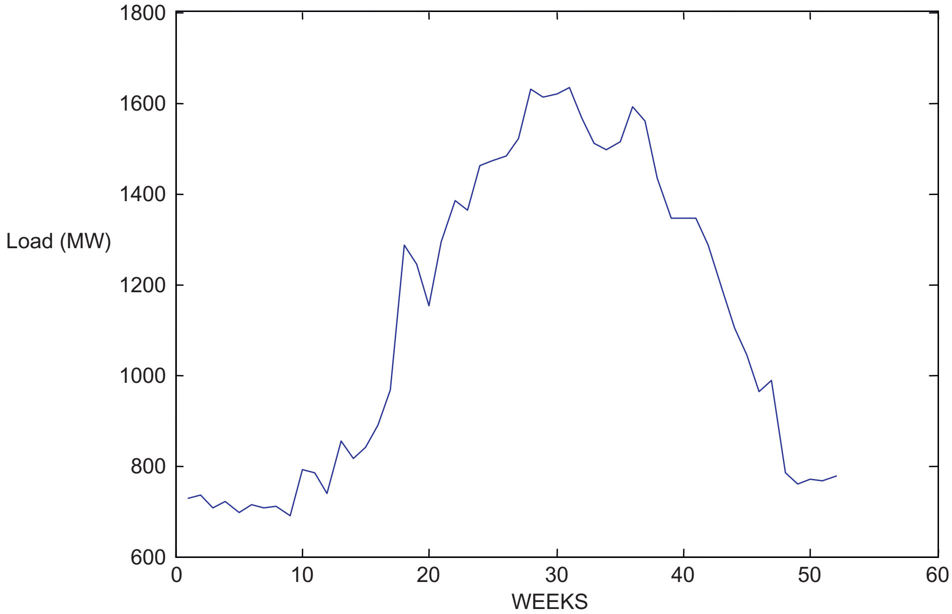

Figure 1 Load forecasts of one year in Kingdom of Bahrain (year of 2002).

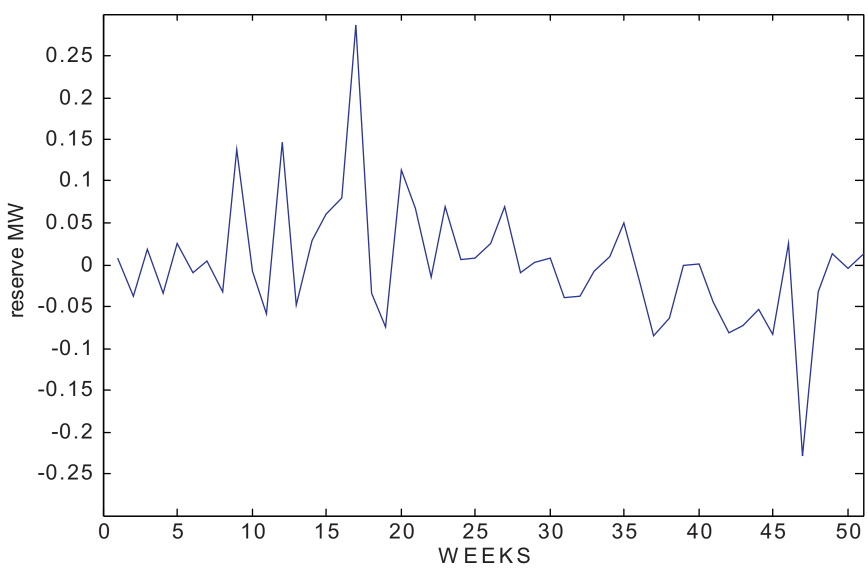

Figure 2 Translation of weekly power to weekly reserve.

Nets (GSPN). After description and implementation through GSPN, each configuration has been evaluated, in order to choose the most appropriate structure.

Batlle and Barquín (2004) in their paper (2004) present a fuel prices scenario generator in the frame of a simulation tool developed to support risk analysis in a competitive electricity environment. A multivariate Generalized Autoregressive Conditional Heteroskedastic model has been designed in order to allow the generation of future fuel prices paths. The model makes use of a decomposition method to simplify the consideration of the multidimensional conditional covariance. An example of its application with real data is also presented.

Gonos et al. (2003)present in their paper (2004), a method which estimates the lightning performance of high voltage transmission lines based on the Monte-Carlo simulation technique. On several operating Greek transmission lines, the method is applied and showing good correlation between predicted and field observation results. The proposed method can be used as a useful tool in the design of electric power systems, aiding in the right insulation dimensioning of a transmission line.

In Zhaohong and Xifan (2002) study (2002) they present a new variance reduction technique of Monte Carlo simulation – fission and roulette method. The proposed method reduces the variance of simulation and speeds up the computation dramatically.

Wehenkel et al. (1999), the authors deal with probabilistic approach to the design of power-system special stability controls. They used Monte-Carlo simulations, which take into ac-

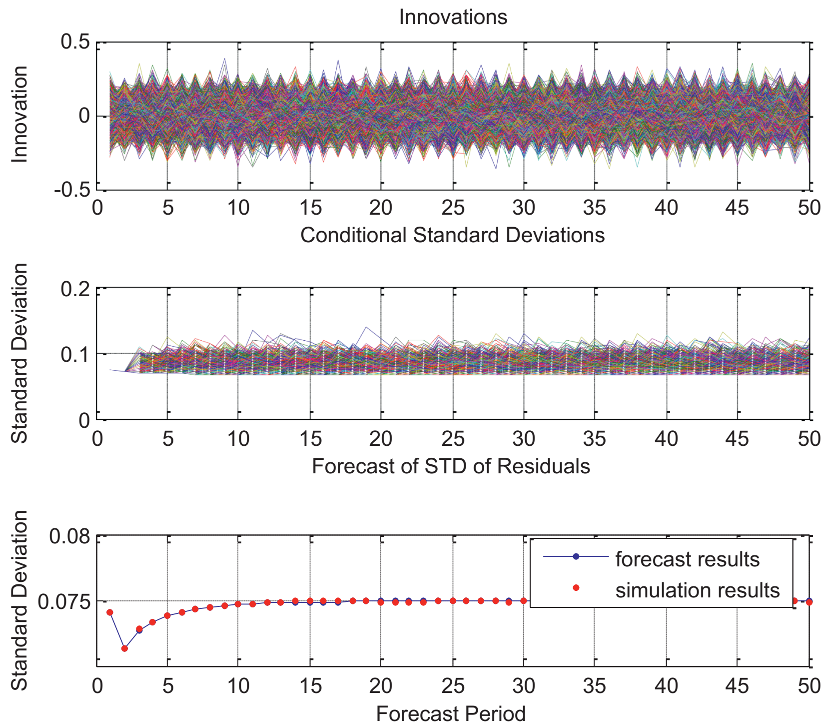

Figure 3 Application of Monte Carlo simulation.

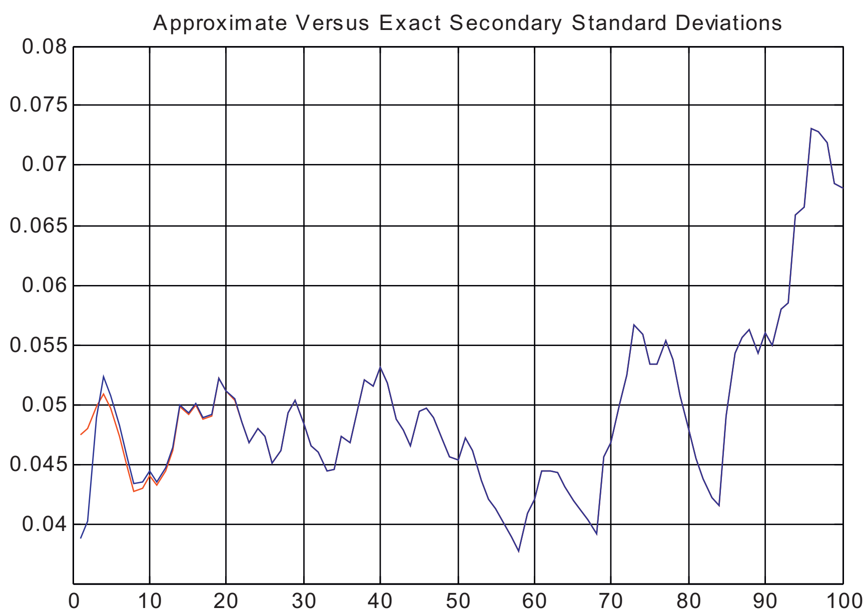

Figure 4 Graphical comparisons of the first realization of the approximate and the exact secondary conditional standard deviations.

count all the potential causes of blackouts. The approach is tested on a large-scale study on the South–Eastern part of the extra-high-voltage system of Electricité de France.

2. Methodology

A wide variety of forecasting methods are available to the management. The evaluation of soft computing techniques has increased the understanding of various aspects of the problem environment and consequently the predictability of many events. The concept of a time series, an ordered set of observations of a time-series correspond to time-tagged indices, or observations, and correspond to sample paths, independent realizations, or individual time series. In any given column, the first row contains the oldest observation and the last row contains the most recent observation. In this representation, a time-series array is said to be column-oriented.

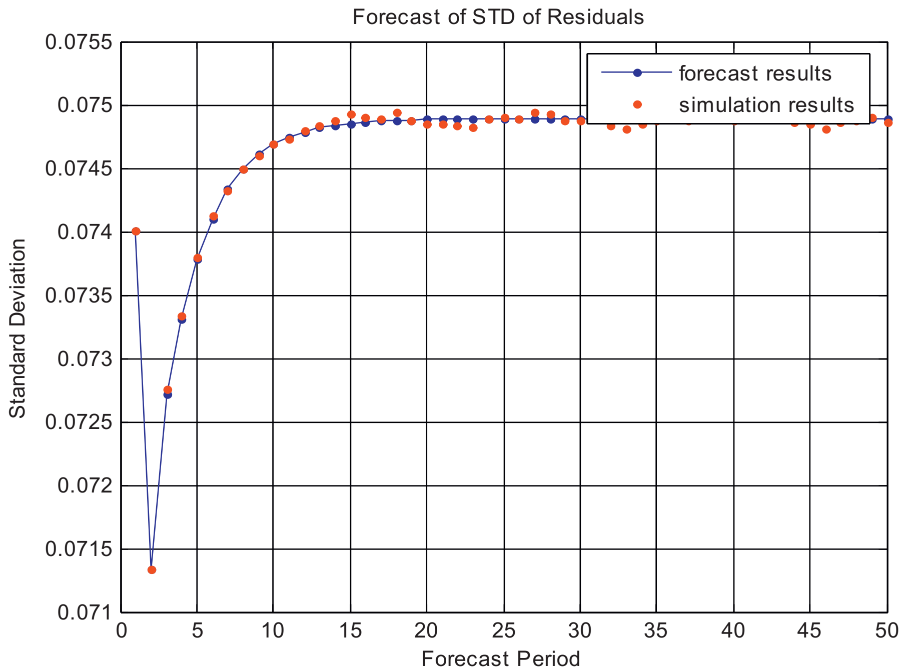

Figure 5 Compare the first forecast output, i.e., the conditional standard deviations of future innovations, with its counterpart derived from the Monte Carlo simulation.

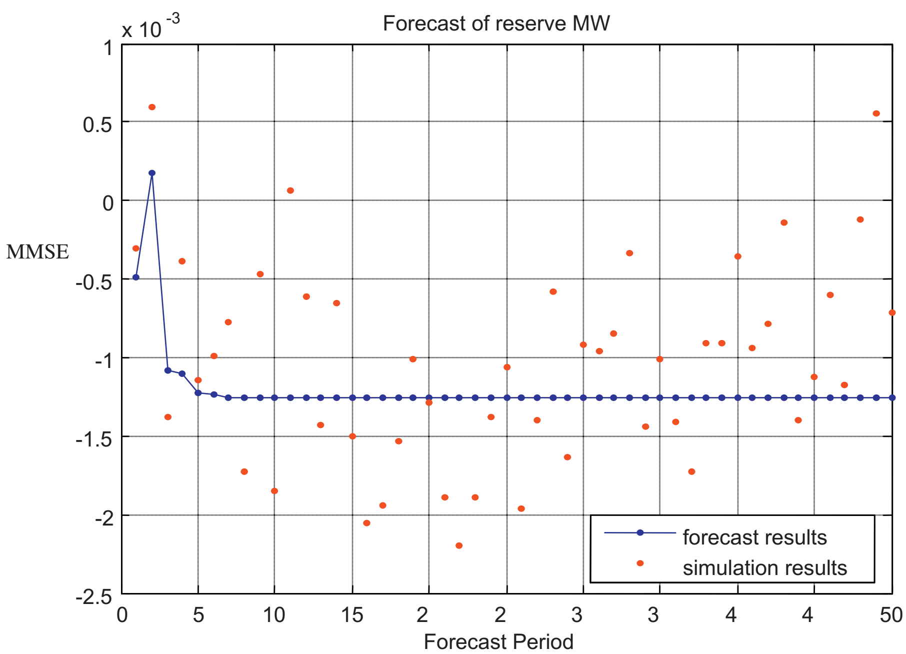

Figure 6 Compare the second forecast output, the minimum mean square error forecasts of the conditional mean of the Kingdom of Bahrain reserves power series, with its counterpart derived from the Monte Carlo simulation.

In the present model, it is assumed that time-series vectors and matrices are time-tagged series of observations. If we have a power series, the model lets you convert it to a reserve series using either continuous compounding or periodic compounding. If it denotes successive power observations made at times t and $t + 1$ as P_t and P_{t+1}, respectively, continuous compounding transforms a power series P_t into a reserve series y_t as (Bollerslev, 1987; Bollerslev, 1986; Box et al., 1994; Enders, 1995).

$$y_t = \log \frac{P_{t+1}}{P_t}$$

Periodic compounding defines the transformation as:

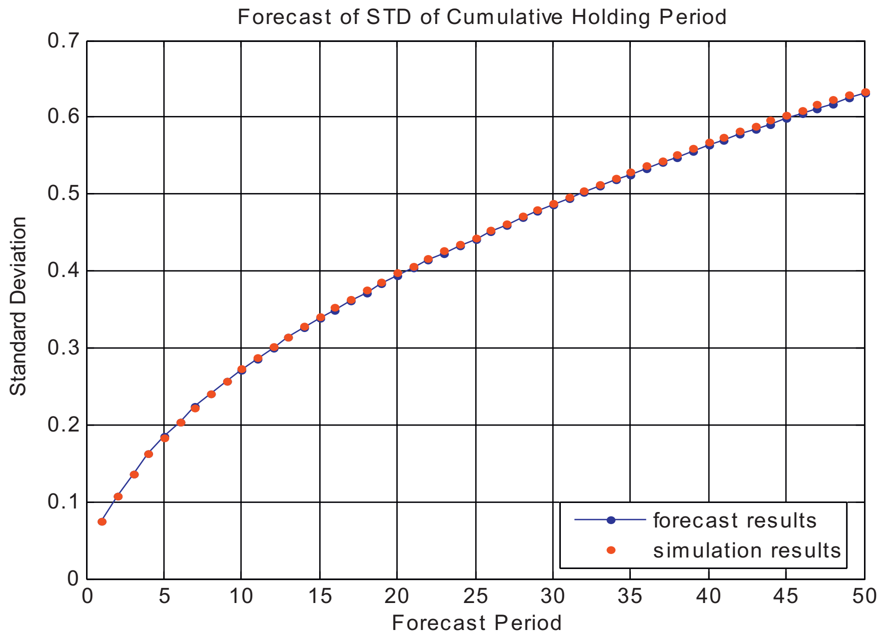

Figure 7 Compare the third forecast output, cumulative holding period power reserves, with its counterpart derived from the Monte Carlo simulation.

$$y_t = \log \frac{P_{t+1}}{P_t} - 1$$

Our modeling is typically based on relatively high frequency data (i.e. weekly observations). The models are designed to capture certain characteristics that are commonly associated with time series. Probability distributions for quality reserve often exhibit fatter tails than the standard normal, or Gaussian distribution. In addition, power time series usually exhibit a characteristic known as volatility clustering, in which large changes tend to follow large changes, and small changes tend to follow small changes. In either case, the changes from one period to the next are typically of unpredictable sign. Large disturbances, positive or negative, become part of the information set used to construct the variance forecast of the next period's disturbance. In this manner, large shocks of either sign are allowed to persist, and can influence the volatility forecasts for several periods.

3. Forecasting of power time series

If we treat a financial time series as a sequence of random observations, this random sequence, or stochastic process, may exhibit some degree of correlation from one observation to the next. This correlation structure can be used to predict future values of the process based on the past history of observations (Engle, 1982; Engle et al., 1987; Glosten et al., 1993; Hamilton, 1994). The following equation uses these components to represent a model of an observed time series y_t.

$$y_t = f(t-1, X) + \varepsilon_t$$

where

$f(t-1, X)$ represents the forecast, of the current reserve as a function of any information known at time $t + 1$, including past innovations. The variable ε_t is the random component.

The autoregressive (AR) models include past observation of the dependent variable in the forecast of future variances, and for the conditional mean apply to all variance models:

$$y_t = C + \sum_{i=1}^{R} \phi_i y_{t-1} + \varepsilon_t + \sum_{j=1}^{M} \theta_j \varepsilon_{t-j} + \sum_{k=1}^{N_x} \beta_k X(t,k)$$

With autoregressive coefficients ϕ_i, moving average coefficients θ_j, regression coefficients β_k, innovations ε_t, and reserve y_t, C represents the constant. X is an explanatory regression matrix in which each column is a time series and $X(t,k)$ denotes the t-th row and k th column. Where, R and M represent the order of the conditional mean model.

4. Probability estimation

Given models for the conditional mean and variance, and an observed reserve series, the estimation concludes the innovations (i.e., residuals) from the reserve series, and estimates, by maximum probability, the parameters needed to fit the specified models to the reserve series (Nelson, 1991).

Given the vector of current parameter values and the observed data series, the log-probability functions conclude the process innovations by inverse filtering (Engle, 1982; Engle et al., 1987; Glosten et al., 1993). This inference, or inverse filtering, operation rearranges the conditional mean equation to solve for the current innovation ε_t:

$$y_t = -C + y_t - \sum_{i=1}^{R} \phi_i y_{t-1} - \sum_{j=1}^{M} \theta_j \varepsilon_{t-j} - \sum_{k=1}^{N_x} \beta_k X(t,k)$$

This equation is a whitening filter, transforming a correlated process into an uncorrelated white noise process. The log-probability function then uses the inferred innovations ε_t to infer the corresponding conditional variances σ_t^2 via recursive

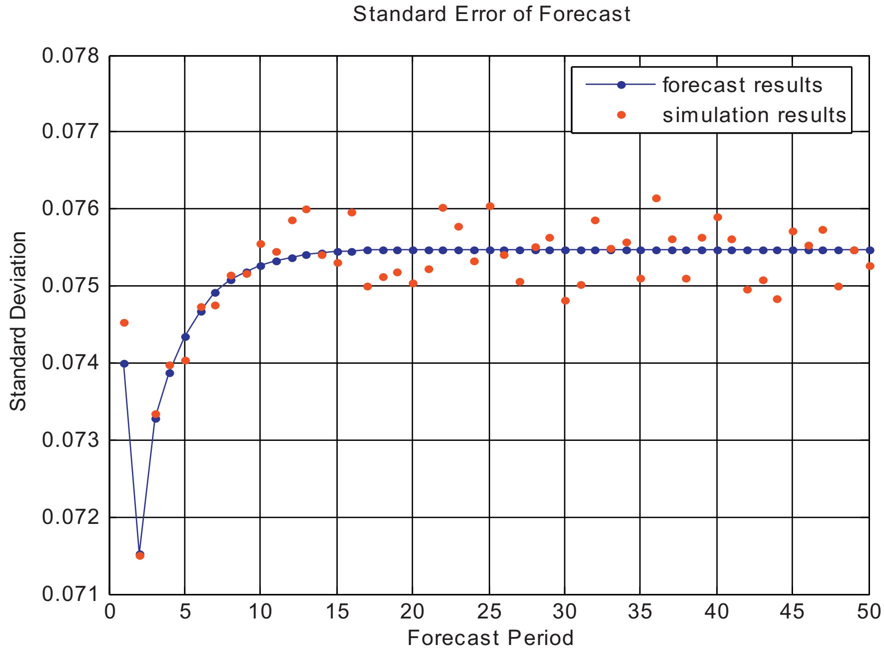

Figure 8 Compare the fourth forecast output, the root mean square errors of the forecasted power reserves, with its counterpart derived from the Monte Carlo simulation.

substitution into the model-dependent conditional variance equations. Finally, the function uses the inferred innovations and conditional variances to evaluate the appropriate log-probability objective function. If the Gaussian, the log-probability function is:

$$LLF = \frac{T}{2}\log(2\pi) - \frac{1}{2}\sum_{t=1}^{T}\log\sigma_t^2 - \frac{1}{2}\sum_{t=1}^{T}\frac{\varepsilon_t^2}{\sigma_t^2}$$

where, T is the sample size, i.e., the number of rows in the series y_t.

5. Minimum mean squire error volatility forecasts of reserve

This is designed to minimize the variance of the estimation or forecast error. The volatility forecasts of reserve over multi period holding intervals. That it contains the expected stan-

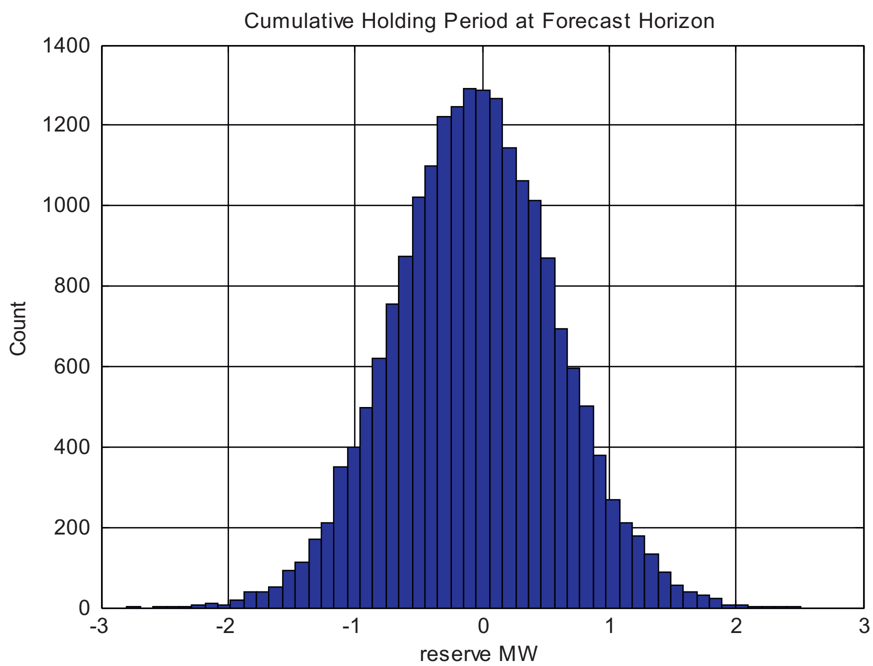

Figure 9 Histogram illustrates the distribution of the cumulative holding period reserve obtained if a quality was held for the full 52-week forecast possibility. Notice that this histogram is directly related to the final of the root mean square error.

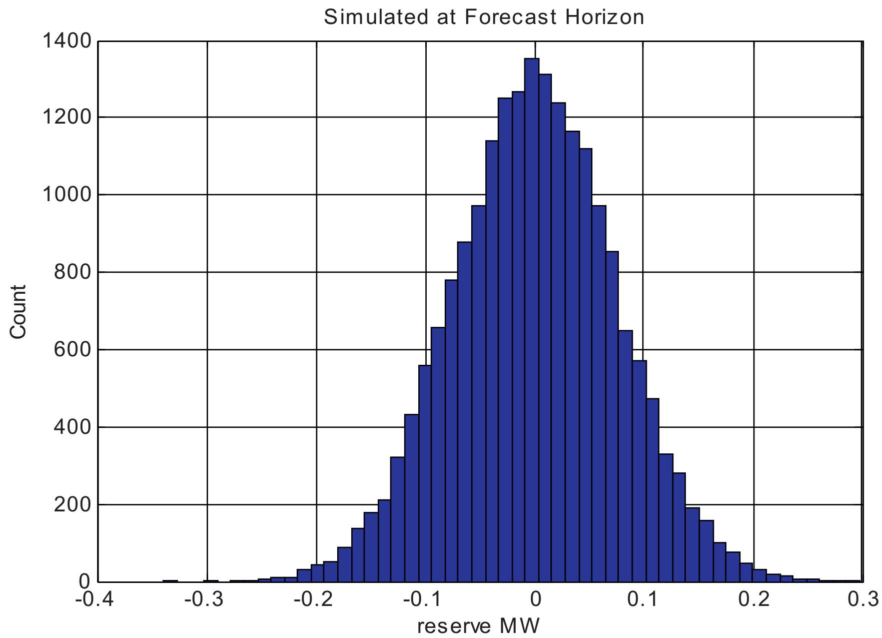

Figure 10 Histogram illustrates the distribution of the single-period power reserve at the forecast possibility. Notice that this histogram is directly related to the final of the minimum mean square error and root mean square errors.

dard deviation of reserve for assets held for one period for each realization of series. It also contains the standard deviation of reserve for assets held for two periods as shown in the results obtained during the present study. Thus, last contains the forecast of the standard deviation of the cumulative reserve obtained if an asset was held for the entire forecast horizon. Therefore it computes the elements of σ by taking the square root of:

$$\mathrm{var}_t\left[\sum_{i=1}^{s} y_{t+1}\right] = \sum_{i=1}^{s}\left[\left(1+\sum_{j=1}^{s=1}\psi_j\right)^2 E(\sigma_{t+i}^2)\right]$$

where s is the forecast horizon of interest, and ψ_j is the coefficient of the jth lag of the innovations process in an infinite-order representation of the conditional mean model.

6. Simulation results

To compute the load forecasts for the Kingdom of Bahrain reserve the power for 52 weeks for expecting the power in the future. First setting the forecast possibility to 52 weeks (i.e., one year), then the forecasting engine, with the estimated model parameters, coefficient, the Kingdom of Bahrain reserve, and the forecast possibility. Possibility = 52% which define the forecast possibility.

This will simulate reserve forecasts of conditional standard deviations of the residuals forecasts of the Bahrain reserve power. Forecasts of the standard deviations of the cumulative holding period reserve power and standard errors associated with forecasts of reserve power.

Monte Carlo simulation uses the same estimated model coefficient which is used in the forecast part of the data simulated, forecasting, to simulate 20,000 realizations for the same 52 week period. In this context, referred to as dependent-path simulation, all simulated sample paths share a common conditioning set and evolve from the same set of initial conditions, thus enabling Monte Carlo simulation of forecasts and forecast error distributions. For this application of Monte Carlo simulation, the simulation generates a relatively large number of realizations, or sample paths, so that it can aggregate across realizations. The following code simulates 20,000 paths as a result; each time-series output that reserves are an array of size possibility, 52-by-20,000.

In the present paper, we will compare data of the Kingdom of Bahrain reserve power graphically. It compares the forecasts results with their counterparts derived from the Monte Carlo trial described above. Fig. 1 shows the load forecasts of one year (year of 2002) in the Kingdom of Bahrain which clearly shows that power consumption is high between weeks 20 and 40 of high season. Fig. 2 is the translation of weekly power to weekly reserve. To segment the data in an effort to compare estimation results obtained from a relatively stable period to those from a period of relatively high instability. By examining the reserve power, it can be seen there is a distinct increase in instability starting. Fig. 3 shows application of Monte Carlo simulation, the figures show the production of a relatively large number of sample paths, so that it can aggregate across realizations. Because each understanding corresponds to a time-series output, the outputs are large. The model simulates 20,000 paths. Fig. 4 is a graphical comparison of the first realization of the approximate and the exact secondary conditional standard deviations reveal the distinction between automatically generated and user-specified pre sample data. Notice that the approximate and exact standard deviations are asymptotically identical. The only difference between the two curves is attributable to the transients induced by the default initial conditions. Although the figure highlights the first realization of conditional standard deviations, the comparison holds for any realization and for the inferred residuals as well.

7. Comparing forecasts with simulation results

Figs. 5–8 directly compare each of the forecast outputs, in turn, with the corresponding statistical result obtained from simulation. Figs. 9 and 10 illustrate histograms from which approximate probability density functions and empirical confidence bounds can be computed.

This illustration merely highlights the range of possibilities, and provides a deeper understanding of the interaction between the simulation, forecasting, and estimation model.

Fig. 5 shows the convergence of standard deviation with respect to the forecast period. For developing the forecasting models, the load demand data for 52 week period was tested from the first day of January to the last day of the year 2002 which is the end of December in the Kingdom of Bahrain.

8. Conclusion

The paper presents estimation of the load of the Kingdom of Bahrain using the Monte Carlo simulation. Satisfactory results for one year of Bahrain network was presented and verifying the accuracy of the method used. The presented method can be easily used for any electric power utilities in order to predict the electric load. The result consists of the MMSE forecasts of the conditional standard deviations and the conditional mean of the reserve power is modeled and illustrated. Note that the calculation of the standard deviation is strictly correct for continuously compounded reserve. Therefore, it is clear that the used technique is useful tool for electric power system for load estimation.

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