Scenario Generation for Price Forecasting in Restructured Wholesale Power Markets

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Abstract—In current restructured wholesale power markets, the short length of time series for prices makes it difficult to use empirical price data to test existing price forecasting tools and to develop new price forecasting tools. This study therefore proposes a two-stage approach for generating simulated price scenarios based on the available price data. The first stage consists of an Autoregressive Moving Average (ARMA) model for determining scenarios of cleared demands and scheduled generator outages (D&O), and a moment-matching method for reducing the number of D&O scenarios to a practical scale. In the second stage, polynomials are fitted between D&O and wholesale power prices in order to obtain price scenarios for a specified time frame. Time series data from the Midwest ISO (MISO) are used as a test system to validate the proposed approach. The simulation results indicate that the proposed approach is able to generate price scenarios for distinct seasons with empirically realistic characteristics.

***Index Terms*—Wholesale power prices, restructured wholesale power markets, scenario generation, ARMA model, moment-matching method**

I. INTRODUCTION

Many wholesale power markets are currently undergoing restructuring. This restructuring process refers to changes in policies and rules for market operation. Typically restructuring also involves the designation of a central market operator to manage and oversee the trading activities of market participants.

Price forecasting tools are potentially useful both for market operators and for market participants in restructured wholesale power markets. Different types of price forecasting tools have been developed that could be applied in these market contexts [1-8]. Unfortunately, the shortness of the price time series available for these markets restricts the testing of price forecasting tools and hinders the development of new price forecasting tools.

In recognition of this problem, the present study proposes a new method for amplifying empirical wholesale power price data with simulated price scenarios. Scenarios can capture typical patterns from real-world data. Moreover, scenarios also permit forecasters to amplify empirically realized data patterns with data patterns that could be realized. The availability of scenarios that reflect and amplify possible price patterns for restructured wholesale power markets could aid in the design of appropriate price forecasting tools for such markets.

Scenario generation has been widely used in other areas, such as long-range business planning [9] and interest rates [10]. Many scenario generation and reduction methods are reviewed in [11], e.g. path-based methods and time series models ([10], [12], [13], [14]) and moment-matching methods ([12], [15], [16]). However, only a few studies have applied scenario generation to power systems. Reference [17] is an example where scenario generation has been applied for forecasting of power prices in the Nordic real-time balancing market.

In this study a two-stage approach for wholesale power price scenario generation is proposed. In the first stage, the approach takes uncertainties in cleared demands and scheduled generator outages (D&O) into account by applying ARMA modeling and a moment-matching method to generate scenarios for D&O. In the second stage, in accordance with the ultimate goal of generating adequate scenarios for wholesale power prices, the D&O scenarios are connected to price scenarios using polynomial fitting.

The remaining sections of this study are organized as follows. Section II describes in detail the proposed method for generating D&O scenarios. Section III derives wholesale power price scenarios from the D&O scenarios by constructing polynomial relationships. Numerical illustrations are provided in Section IV based on data from the Midwest ISO (MISO). A discussion of possible extensions of these methods is given in Section V, and Section VI provides concluding remarks.

II. SCENARIO GENERATION FOR D&O

As stated in [1], power prices vary over time due to many uncertainties, such as weather, equipment outages, fuel prices and other price drivers. Many researchers apply statistical models in an attempt to capture the key sources of uncertainty in the determination of power prices. Sometimes the models can be very complicated since time series for power prices always display jumps as well as non-stationary characteristics (e.g., seasonalities and time-of-day effects).

The basic idea of the approach proposed in this study is to avoid the direct modeling of power prices by first

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978-1-4244-3811-2/09/$25.00 ©2009 IEEE

generating scenarios for cleared demands and scheduled generator outages (D&O) and then estimating the relationship between power price and D&O. This section focuses on the first stage, the generation of D&O scenarios through the building of time series models and the application of a moment-matching method.

A. Sources of Uncertainties for Power Price Determination

Researchers realize that there is a strong relationship between cleared demands and power prices. In this study we add another source of uncertainty—scheduled generator outages—to explore how this joint factor (cleared demands and generator outages) affects power prices. Fig. 1 gives typical plots for daily-averaged cleared demands and scheduled generator outages compared to a plot for wholesale power prices, all for MISO in 2006.

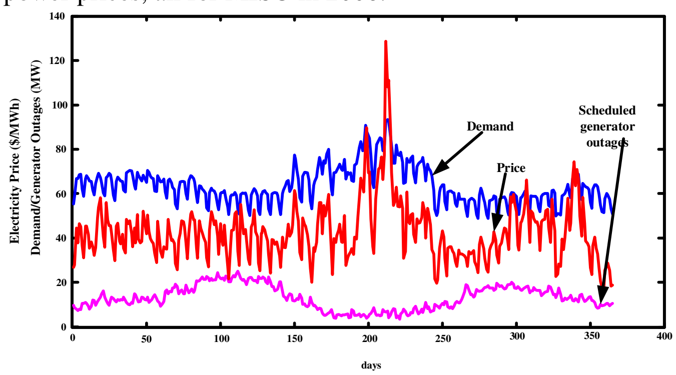

Fig. 1. MISO cleared demands, generator outages, and wholesale power prices in 2006 [18].

From Fig. 1, a positive correlation between prices and cleared demands can be observed. It is also notable that scheduled generator outages are negatively correlated with cleared demands. When cleared demands are low, large numbers of generators are scheduled for outage, and vice versa. When a generator is scheduled for outage for some amount of power, this can be modeled as an addition of the same amount of power to cleared demands [19].

Accordingly, we can sum cleared demands and scheduled generator outages to make a joint factor, D&O, which has a stronger correlation with power prices than either factor alone. Table I shows the correlation coefficient between power prices and cleared demands, and between power prices and D&O. The table indicates that D&O has the larger correlation coefficient with price. Therefore, we choose to generate scenarios for D&O rather than for cleared demands alone.

TABLE I
CORRELATION COEFFICIENTS BETWEEN WHOLESALE POWER PRICES, CLEARED DEMANDS, AND D&O

	Cleared Demands	D&O
Price	0.7725	0.8931

B. Times Series Models for D&O

Demand forecasting has been used for power system operation for a long time [20-22]. ANN and time series models are frequently used in demand forecasting. In this study we use time series methods to model the autoregressive characteristics of D&O.

More precisely, Box and Jenkins [23] were seminal contributors to the development and application of the Autoregressive Moving Average (ARMA) methodology for the analysis and modeling of time series. As will next be shown, we propose the use of an ARMA model to fit D&O data divided into parts according to different seasonal characteristics.

Let DO_t represent D&O at time t. Then an ARMA model can be formulated for DO_t in the following form:

$$\phi_p(B)DO_t = \theta_q(B)\varepsilon_t \tag{1}$$

where

$\phi_p(B) = 1 - \phi_1 B - \ldots - \phi_p B^p$, $\theta_q(B) = 1 - \theta_1 B - \ldots - \theta_q B^q$, $\phi_1 \ldots \phi_p$, $\theta_1 \ldots \theta_p$ are parameters which need to be estimated, B is a backshift operator and ε_t is a white noise error term that is assumed to be normally distributed at each time t with zero mean and constant variance σ^2.

In empirical data, a seasonal component usually exists, which means the D&O data display some periodical characteristics. In such a situation, we can attempt to eliminate the seasonality by taking a seasonal difference as formulated in (2):

$$\phi_p(B)(1 - B^s)DO_t = \theta_q(B)\varepsilon_t \tag{2}$$

where s is the seasonal period.

In order to build a reliable time series model, the following steps are proposed:

(1) Tentative identification: After plotting the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) for historical data, select the orders of p, q, and s.

(2) Estimation: Given the selected orders in (1), use a least squares or maximum likelihood method to estimate the parameters of the model.

(3) Diagnostic Checking: Test the error term to determine whether it is a white noise process. If it is, continue; if not, go back to (1).

(4) Check the Akaike Information Criterion (AIC) [24] for the model: $AIC(p,q) = N\log(\sigma^2) + 2(p+q)$, where σ^2 is the variance of the error term, N is the sample size, and p and q are the orders of the AR and MA components. Choose a model with small AIC value.

C. Generate Scenarios for D&O and Reduce Scenarios by a Moment-matching Method

When models are built using historical data, we can generate a scenario fan based on the model. As we know, in each model there is an error term $\varepsilon_t \sim N(0,\sigma^2)$, assumed to be a white noise process. When ε_t is randomly drawn from the normal distribution, and then fit into the model, there can be different scenarios for D&O. The white noise generation process is a Monte Carlo simulation [25]. Then we can use it to construct a scenario fan as depicted in Fig. 2. A large number of sample paths are produced when $\{\varepsilon_t\}$ is generated.

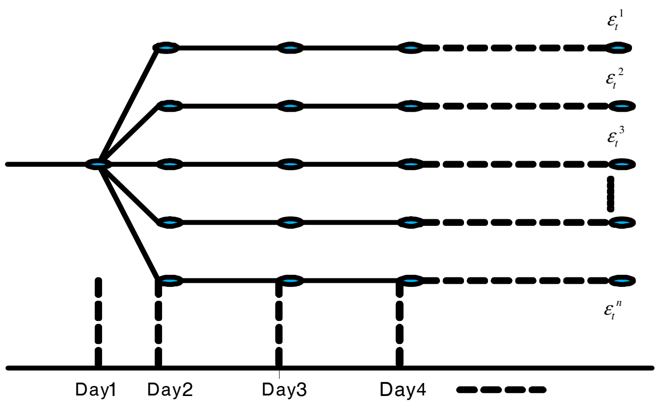

Fig. 2. Schematic depiction of the generation of a scenario fan

We can build as many scenarios for D&O as we want. However, due to the computational complexity and to the limited availability of actual D&O data, it is necessary to reduce the scenarios to an adequate but practical number.

In this study a moment matching method is proposed for scenario reduction. Four moments of historical D&O time series are determined, conditional on specified time periods. The entire time frame is divided into several time periods. It can be partitioned into seasons, weeks, etc. Let $\mathrm{T}=\{1,2,\ldots,T\}$ denote the entire time frame, let S denote any non-empty subset of T, and let $|S|$ denote the cardinality of the set S. Four moments conditioned on a given set S can then be defined as follows:

Mean:
$$E(DO\,|\,S)=\frac{1}{|S|}\sum_{t\in S}DO_t \tag{3}$$

Variance:
$$Var(DO\,|\,S)=\frac{1}{|S|}\sum_{t\in S}(DO_t-E(DO\,|\,S))^2 \tag{4}$$

In this study we use standard deviation instead of variance, which is given by:

$$std(DO\,|\,S)=\sqrt{\frac{1}{|S|}\sum_{t\in S}(DO_t-E(DO\,|\,S))^2} \tag{5}$$

Skewness:

$$skewness(DO\,|\,S)=\frac{1}{|S|}\sum_{t\in S}(DO_t-E(DO\,|\,S))^3\,/\left(\sqrt{Var(DO\,|\,S)}\right)^3 \tag{6}$$

Kurtosis:

$$kurtosis(DO\,|\,S)=\frac{1}{|S|}\sum_{t\in S}(DO_t-E(DO\,|\,S))^4\,/\left(\sqrt{Var(DO\,|\,S)}\right)^4 \tag{7}$$

These four moments are examined for each D&O scenario. If the four moments of a D&O scenario match the corresponding four moments for the historical D&O data, the scenario is accepted as a valid scenario; otherwise, it is deleted. In this way, we reduce the collection of all generated D&O scenarios to a practical manageable size.

III. PRICE SCENARIO DERIVATION FROM D&O SCENARIOS

Cleared demands and scheduled generator outages are two important factors that determine the behavior of wholesale power prices. Section II describes the process of generating scenarios for D&O. To achieve the ultimate goal of generating scenarios for wholesale power prices, we need an appropriate relationship between D&O and wholesale power prices. The requirement for price scenario generation is to capture the statistical properties of real price data, which in this study are proxied by mean, standard deviation, skewness, and kurtosis.

In restructured wholesale power markets, prices are determined by both demand and supply. A key question, then, is how supply might affect the relationship between D&O and price.

To address this question, let us first consider what happens in a simple market context. Fig. 3 indicates how a market clearing price is determined in a simple market. Suppose sellers and buyers submit supplies and demands to a market operator. The market operator obtains a supply curve (S) and a demand curve (D) by aggregating supplies and demands in ascending and descending order by price, respectively. The intersection point (Q^*, P^*) is the market clearing point; see Fig. 3.

From Fig. 3, it is obvious that both demand and supply typically play a significant role in determining the market clearing point. Movement either in the supply curve S or the demand curve D leads to a change in the market clearing price P^* as well as a change in the market clearing quantity Q^*.

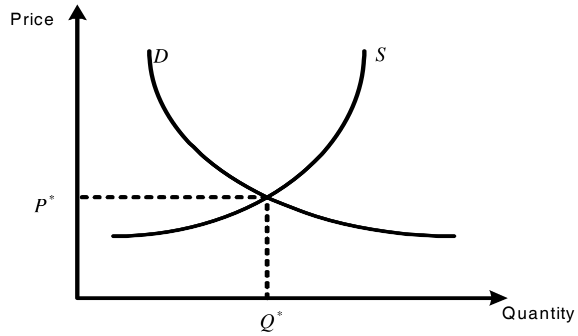

Fig. 3. Determination of market clearing point

Interestingly, the market clearing price P^* exhibits a definite correlation with the market clearing quantity Q^* in two special cases. For the first case, suppose the demand curve D varies but the supply curve S remains fixed; see Fig. 4. In this case, P^* is positively correlated with Q^*, meaning P^* increases when Q^* increases, and conversely. For the second case, suppose the supply curve S varies but the demand curve D remains fixed; see Fig. 5. In this case, P^* is negatively correlated with Q^*, meaning that P^* decreases when Q^* increases, and conversely.

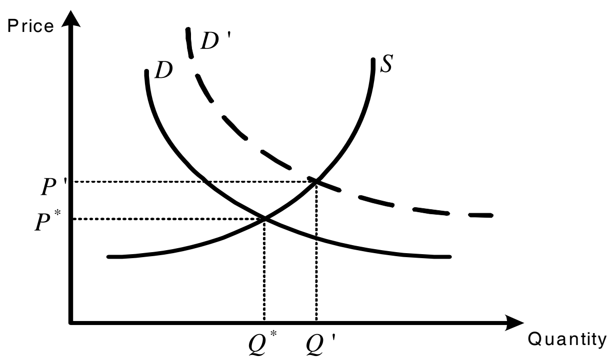

Fig. 4. The market clearing price is positively correlated with the market clearing quantity when only the demand curve shifts.

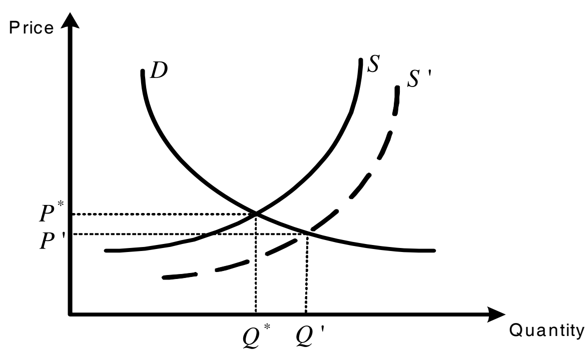

Fig. 5. The market clearing price is negatively correlated with the market clearing quantity when only the supply curve shifts.

For restructured wholesale power markets operating under Locational Marginal Prices (LMPs), the determination of market clearing prices and quantities is of course not this simple. For example, a single market clearing price is determined in a day-ahead market only in the absence of transmission grid congestion. When congestion is present, the LMPs at different busses will not all be the same. Nevertheless, the above analysis might help to shed some light on the relationship between market clearing prices and quantities in these markets.

We now investigate the relationship between market clearing price and market clearing quantity for restructured wholesale power markets. The market clearing quantity is approximated by D&O. We propose the following two polynomial relationships for modeling the connection between market clearing prices and D&O.

$$P_t = \alpha + \beta DO_t + \varepsilon_t \tag{8}$$

$$P_t = \alpha + \beta DO_t + \gamma DO_t^{\,2} + \varepsilon_t \tag{9}$$

where P_t is the wholesale power price at time t, DO_t is D&O at time t, ε_t is the error term, and α, β and γ are parameters of the model which will be estimated by least squares estimation (LSE). The objective of LSE is to minimize $\sum_{t \in S} \varepsilon_t^{\,2}$, where S the fitting time frame.

We used D&O and wholesale power price data from the MISO for March 2006 to determine which fitted polynomial (8) or (9) performed better in terms of minimizing error. Our wholesale power price data are MISO system prices, which are aggregated LMPs for the entire MISO system [18]. We found that the first-order polynomial (8) performed better than the second-order polynomial (9) for this test data. The estimated parameters for polynomial (8) are

$$\hat{\alpha} = -91.5927 \tag{10}$$

$$\hat{\beta} = 1.6509 \tag{11}$$

We then used the fitted polynomial (8) and actual D&O data for the MISO in April 2006 to predict power prices for April 2006. The predicted prices are shown in Fig. 6.

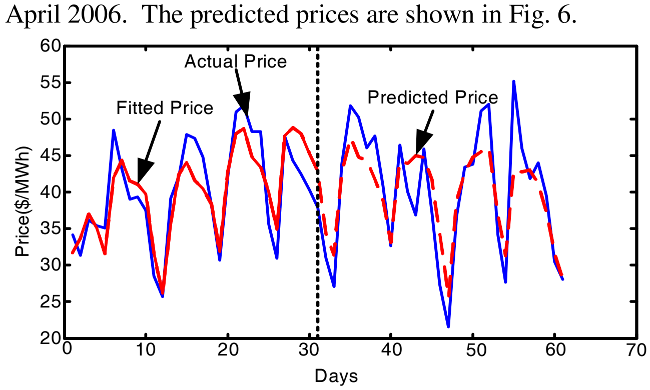

Fig. 6. Prices predicted by the fitted polynomial (8)

To evaluate the accuracy of the predicted prices $\hat{P}_t$ relative to actual prices P_t , we used root mean squared error (RMSE):

$$RMSE = \sqrt{\frac{1}{N}\sum_{t=1}^{N}(\hat{P}_t - P_t)^2} \tag{10}$$

where $N = 30$ is the number of days in April, and P_t is the daily-averaged MISO system price published by the MISO [18]. The result of this calculation was RMSE=8.4624. As indicated in Fig. 6, the fit appears to be quite reasonable. Consequently, this polynomial fitting method was adopted.

A key point to notice is the positive value for the fitted β in (11). Based on our earlier analysis, this suggests the following conjecture: For the particular test period under study, March 2006, demand exhibited greater variability than supply; see Fig. 4. A possible reason for this difference in variability between demand and supply is that the test period for fitting and predicting is only two months, which is a relatively short time period for the supply side to have any significant change.

As depicted above, the sequential formulation for the generation of wholesale power price scenarios for any specified time frame S can be summarized as follows:

a) Use historical data to build ARMA models (1) and (2) for D&O during S.

b) Generate white noise $\{\varepsilon_t\}$ for incorporation into the ARMA models to generate scenarios for D&O during S.

c) Reduce the number of resulting D&O scenarios using moment-matching for the first four moments (3)-(7).

d) Build a polynomial relationship between D&O and wholesale power prices using a polynomial such as (8) or (9) to construct wholesale power price scenarios for S.

IV. NUMERICAL RESULTS

A. Case Study

The proposed approach has been applied to day-ahead wholesale power prices for the MISO. All data resources are from the MISO website [18]. We use cleared demand data and scheduled generator data for the entire MISO system in 2006 and part of 2007. The wholesale power price data are MISO system prices, which are aggregated LMPs for the entire MISO system. According to patterns observed in MISO demand data, we partitioned 2006 into four seasons, as follows:

2006 Spring: Mar 15-May 24
2006 Summer: May 25-Sep 24
2006 Fall: Sep 25- Nov 14
2006 Winter: Nov 15, 2006- March 14, 2007

B. Scenario Generation for D&O

Due to limited space, we only show results for the Spring and Summer seasons. For other seasons in other years, the same approach can be applied to generate scenarios.

B.1. D&O scenarios for Spring

Our model identification and estimation resulted in the following model for Spring D&O:

$$\phi_p(B) = 1 - 0.8334B + 0.09178B^2 + 0.2095B^3$$

$$\theta_q(B) = 1 + 0.1863B + 0.1177B^2 + 0.1147B^3 + 0.2302B^4 + 0.2842B^5 + 0.2652B^6 - 0.684B^7$$

Our D&O scenarios for Spring are displayed in Fig. 7. It can be seen that the values for D&O follow an obvious seasonal pattern. Table II compares statistical properties (first four moments) between actual D&O data and D&O scenarios. The reported results show that, using our moment-matching method as a selection mechanism, the resulting collection of generated scenarios captures the properties of the actual D&O data.

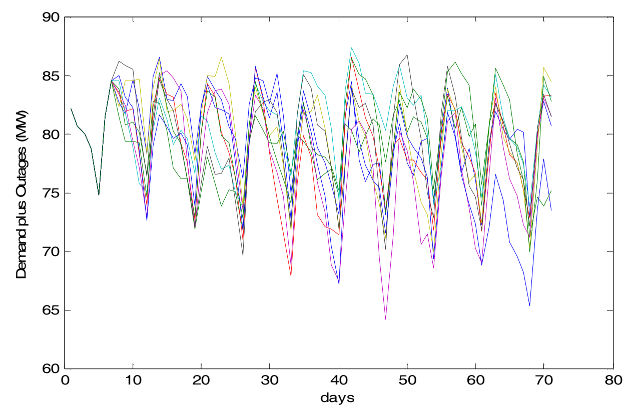

Fig. 7. D&O scenarios for Spring

TABLE II
FIRST FOUR MOMENTS FOR ACTUAL D&O DATA AND FOR GENERATED D&O SCENARIOS FOR SPRING

	mean	**Standard deviation**	**skewness**	**kurtosis**
D&O in 2006 Spring	79.4573	3.7510	-0.6020	2.3936
D&O scenarios	79.4286	3.8283	-0.4753	2.5012

B.2. D&O scenarios for Summer

Our model identification and estimation resulted in the following model for the Summer season:

$$\phi_p(B) = 1 - 1.187B + 0.4292B^2 + 0.06982B^3$$

$$\theta_q(B) = 1 + 0.1226B + 0.06924B^2 + 0.08113B^3 + 0.1172B^4 + 0.0972B^5 + 0.08054B^6 - 0.8565B^7$$

Fig.8 exhibits the scenarios we generated for D&O in Summer, which are much more volatile than those we generated for Spring. Table III reports the values for the first four moments for these generated scenarios as well as for the actual D&O data. Comparing Table III to Table II, it is seen that the standard deviation for the D&O scenarios generated for Summer is 10.3690 compared to only 3.8283 for Spring. Therefore, the approach shows its capability to generate scenarios for both volatile and non-volatile situations.

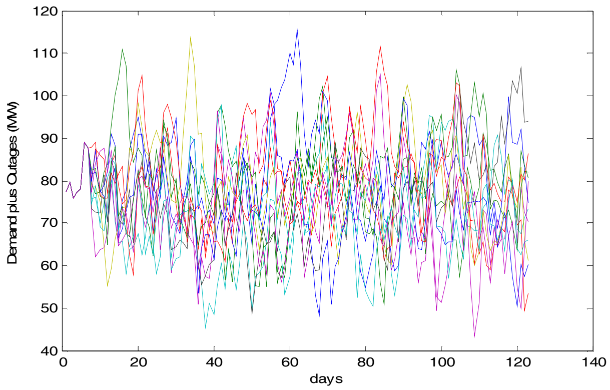

Fig. 8. D&O scenarios for Summer

TABLE III
FIRST FOUR MOMENTS FOR ACTUAL D&O DATA AND FOR GENERATED D&O SCENARIOS FOR SUMMER

	mean	**Standard deviation**	**skewness**	**kurtosis**
D&O in 2006 Summer	78.1595	7.9005	0.2988	3.0652
D&O scenarios	76.6670	10.3690	0.1847	3.1515

C. Wholesale Power Price Scenarios

The second stage is to derive wholesale power price scenarios from D&O scenarios by polynomial fitting. The ultimate objective is to generate price scenarios for which the first four moments match well against the first four moments calculated for actual power price time series data. Price scenarios for Spring and Summer are generated, and it is shown that different characteristics displayed by actual Spring and Summer power prices are well captured.

C.1. Price Scenarios for Spring

In order to generate wholesale power price scenarios from D&O scenarios, a polynomial such as (8) and (9) was fitted. Comparing the RMSE for each polynomial, we chose to use the first-order polynomial (8). Fig. 9 presents the resulting price scenarios, which indicate a regular pattern for Spring. Table IV reports the first four moments for both the generated Spring price scenarios and actual Spring price data from the MISO in 2006. These results indicate that the generated price scenarios closely match the statistical properties of actual MISO Spring price data as captured in these first four moments.

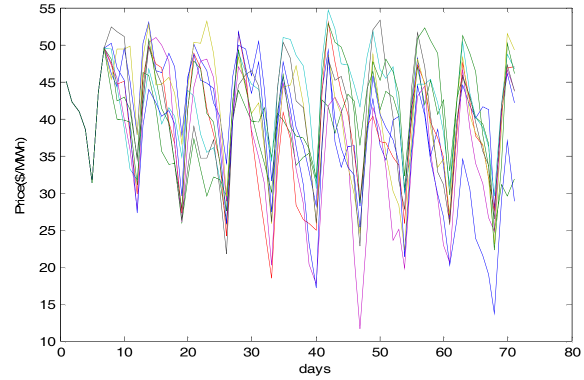

Fig. 9. Wholesale power price scenarios for Spring

TABLE IV
FIRST FOUR MOMENTS FOR ACTUAL PRICE DATA AND FOR GENERATED PRICE SCENARIOS FOR SPRING

	mean	**Standard deviation**	**skewness**	**kurtosis**
Price in 2006 Spring	40.0286	7.8655	-0.3273	2.3742
Price Scenarios	39.9753	7.1047	-0.4753	2.5012

C.2. Price Scenarios for Summer

Using similar steps, a second-order polynomial (9) was chosen to represent the fit between D&O and wholesale power prices in Summer. The resulting price scenarios are shown in Fig. 10 and Table V. Note that some extremely high prices are captured in the price scenarios depicted in Fig. 10. The large standard deviation for the actual Summer price time series data supports the appearance of these high prices in the price scenarios. Overall, the first four moments of the generated price scenarios match very well the first four moments of the actual time series price data. These results, together with the results from section C.1, demonstrate that our proposed approach can capture the different types of price patterns arising in the MISO during the Summer and Spring seasons.

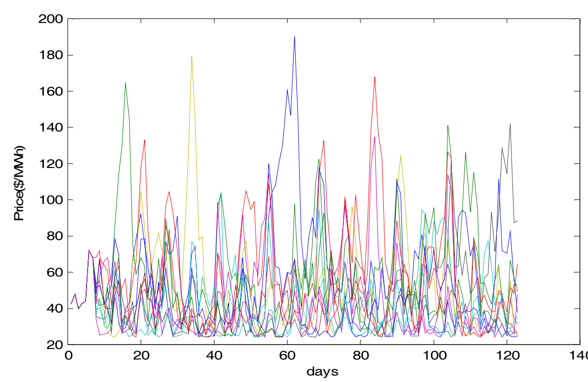

Fig. 10. Wholesale power price scenarios for Summer

TABLE V
FIRST FOUR MOMENTS FOR ACTUAL PRICE DATA AND FOR GENERATED PRICE SCENARIOS FOR SUMMER

	mean	Standard deviation	skewness	kurtosis
Price in 2006 Summer	47.2284	18.0639	1.6136	7.0294
Price scenarios	47.2468	21.9509	1.7327	6.5540

V. DISCUSSION

The motivation for this study is that the limited availability of historical time series price data for restructured wholesale power markets restricts the development and testing of price forecasting tools. A large number of price scenarios can be obtained to compensate for this scarcity of data if a scenario generation method is adopted.

This study provides a statistical approach to generate price scenarios from data for cleared demands and scheduled generator outages (D&O) without explicitly taking system structure and many other causal factors into account. Wholesale power prices also depend on supply, congestion, generation costs, and so forth, and the possible use of these factors to generate price scenarios has not yet been explored.

Bunn [26] envisions the current and future situation for load and price forecasting. He concludes that models based upon simulated artificial agents might ultimately become extremely important for price forecasting because they allow structural and supply-side determinants of prices to be considered along with demand.

In our future price forecasting work, we intend to make use of the AMES Wholesale Power Market Test Bed developed by Li, Sun, and Tesfatsion [27]. AMES is an agent-based computational laboratory designed for the systematic exploration of restructured wholesale power markets operating over ACE transmission grids with strategically interacting generation companies and load-serving entities. The D&O scenarios we generate via time series and moment-matching methods can be used as inputs into AMES in order to generate wholesale power price scenarios. In this way, structural power system aspects, supply aspects, and demand aspects will all contribute to our generation of wholesale power price scenarios.

VI. CONCLUSION

Price forecasting plays a significant role in wholesale power markets. The short length of historical time series price data for restructured wholesale power markets hinders the development and testing of forecasting tools. This paper proposes a two-stage approach to generate empirically-based scenarios for wholesale power prices. In the first stage, in order to take into account uncertainties arising from variations in demand and scheduled generator outages (D&O), ARMA models are developed and a moment-matching method is used to generate realistic D&O scenarios. In the second stage, these D&O scenarios are used to generate wholesale power price scenarios that can in turn be used to test price forecasting tools. Data from the MISO system is studied in order to validate the approach. Results indicate that the proposed approach is able to generate realistic price scenarios.

ACKNOWLEDGEMENT

This project is supported by the Electric Power Research Center (EPRC) at Iowa State University. The authors are grateful to Nanpeng Yu and Naresh Acharya for their helpful comments. This work has been undertaken as part of the EPRC forecasting project, with homepage at http://www.econ.iastate.edu/tesfatsi/EPRCForecastGroup.htm.

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