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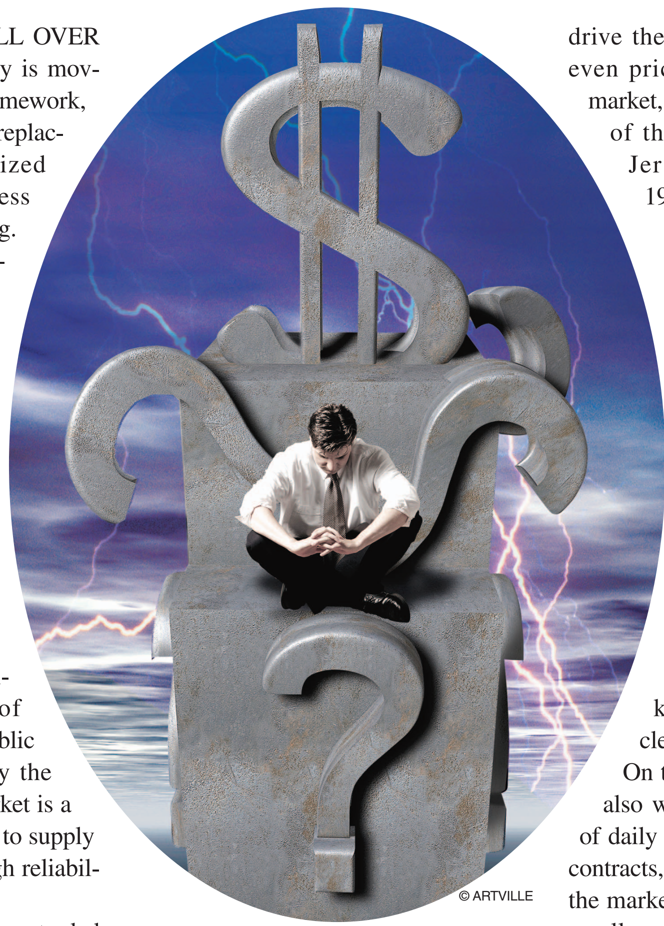
energy price forecasting

problems and proposals for such predictions

IN MANY COUNTRIES ALL OVER the world, the power industry is moving toward a competitive framework, and a market environment is replacing the traditional centralized operation approach, a process that is known as restructuring. The most fundamental characteristic of the restructuring process that is taking place in numerous countries around the world is that market mechanisms have replaced the highly regulated procedures that were used in the decision-making process under traditional regulation. The main objective of an electricity market is to decrease the cost of electricity through competition. The understanding of electric power supply as a public service is being replaced by the notion that a competitive market is a more appropriate mechanism to supply energy to consumers with high reliability and low cost.



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Most commodities have been traded for many years. Why the delay for electrical energy? For many years economists thought the electricity industry was a natural monopoly, due to the great expense of creating transmission networks. More recently it was noticed that the industry could still be restructured into a more competitive framework. Indeed, there is no reason why producers and consumers of electrical energy cannot meet in a properly designed marketplace to decide on the price of their product. However, electrical energy is different from most other commodities, and electrical market has its own complexities. The electrical energy cannot be appreciably stored, and the power system stability requires constant balance between supply and demand. Most users of electricity are, on short timescales, unaware of or indifferent to its price. These two facts drive the extreme price volatility or even price spikes of the electricity market, for instance, the price spikes of the PJM (Pennsylvania-New Jersey-Maryland) market in 1999, shown in Figure 1.

In addition to the above facts, the electricity markets are becoming more sophisticated after a few years of restructuring and market competition. They usually incorporate two instruments for trading: the pool and bilateral contracts. In the pool, the producers submit bids, consisting of a set of quantities at certain prices, and the consumers do likewise. There is an operator that clears the market and announces the set of clearing prices for the next day. On the other hand, the companies also want to hedge against the risk of daily price volatility using bilateral contracts, another instrument to trade in the market. In this setting, a buyer and a seller agree on a certain amount to be transferred through the network at a certain fixed price. Pool-type power dispatch and bilateral contract transactions invariably exist at the same time in any modern deregulated electricity supply system. The independent system operator (ISO), as transmission service provider, is responsible for the control of the whole transmission network but is independent of any market participant.

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Another essential characteristic of the electricity markets is the pricing mechanism. The choice between uniform and pay-as-bid pricing for electricity auctions has been one of the most important issues in newly deregulated electricity markets. Under the uniform pricing structure, the marginal bid block sets the market clearing price (MCP), illustrated in Figure 2. On the other hand, in the pay-as-bid (discriminatory) pricing structure, every winning block gets its bid price as its income. The pricing mechanism can affect the competition, efficiency, consumer surplus, and total revenue of the players in the electricity markets.

In the remaining parts of this article, we focus on uniform pricing and MCP prediction, although many discussions are also true for the pay-as-bid pricing.

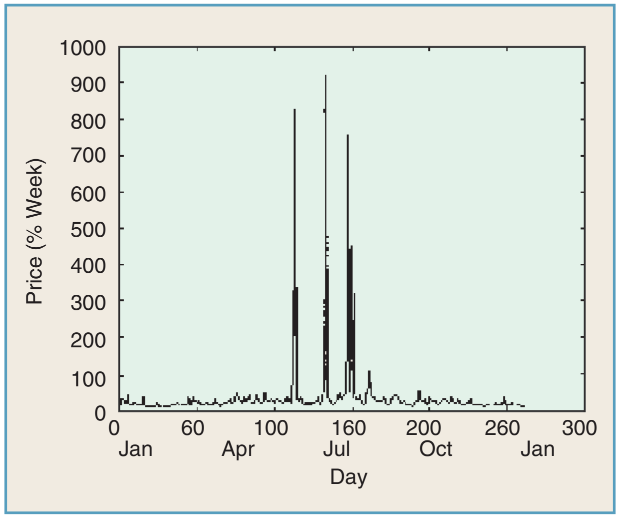

figure 1. The 1999 weekday noon PJM prices.

Why Do We Need to Forecast the Price?

The deregulated power market is an auction market, and energy MCPs are volatile. On the other hand, due to the upheaval of deregulation in electricity markets, price forecasting has become a very valuable tool. The companies that trade in electricity markets make extensive use of price prediction techniques either to bid or to hedge against volatility. When bidding in a pool system, the market participants are requested to express their bids in terms of prices and quantities. Since the bids are accepted in order of increasing price until the total demand is met, a company that is able to forecast the pool price can adjust its own price/production schedule depending on hourly pool prices and its own production costs. High-quality MCP prediction and its confidence interval estimation can help utilities and independent power producers submit effective bids with low risks. In the bilateral contracts, the price is agreed upon by both sides (buyer and seller) beforehand and it is also based on price predictions. The reason is that most of the deregulated electricity markets use a mixed bag of pool and bilateral contracts. If this is the case, companies must optimize their production schedules to hedge pool price volatility via bilateral contracts. Thus, a good knowledge of future pool prices helps to more accurately value bilateral contracts.

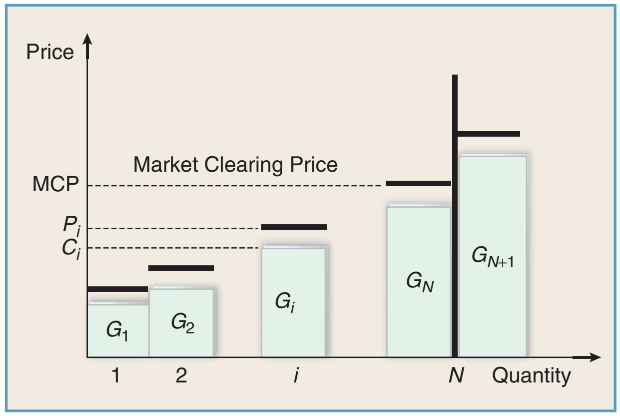

figure 2. Illustration of the uniform pricing structure and market clearing price.

In the pool, usually, MCPs are publicly available, as is the case of the day-ahead pool of mainland Spain (http://www.omel.es), the Californian pool (http://www.calpx.com), or the Australian national electricity market (http://www. nemmco.com.au). Producers and consumers rely on price forecast information to prepare their corresponding bidding strategies. If a producer has a good forecast of next-day MCPs, it can develop a strategy to maximize its own benefit and establish a pool bidding technique to achieve its maximum benefit. Similarly, once a good next-day price forecast is available, a consumer can derive a plan to maximize its own utility using the electricity purchased from the pool. If this consumer has self-production capability, it can use it to protect itself against high prices in the pool. In a medium-term horizon (six months to one year), producers must find out how much energy to sell through bilateral contracts and how much energy to sell to the pool. Consumers must make similar decisions on buying energy through bilateral contracts or from the pool. For this type of portfolio decision, it is desirable to have available forecasts of price average values over a one-year horizon.

By means of a reliable daily price forecast, producers or energy service companies are able to delineate good bilateral contracts or financial ones. Therefore, an accurate price forecast for an electricity market has a definitive impact on the bidding strategies by producers or consumers or on the price negotiation of a bilateral contract. In both pool markets and bilateral contracts, predicting the prices of electricity for tomorrow or for the next 12 months is of the foremost importance for electric companies to adjust their daily bids or monthly schedules for contracts. Energy service companies buy energy from the pool and from bilateral contracts to sell it to their clients. These companies also need good short-term and long-term price forecast information to maximize their respective benefits.

Difficulties of the Price Forecasting

One key aspect of MCPs is their volatility. Price volatility is not only important per se, but it is also crucial to calculate average annual prices and to derive from them bilateral contract prices. However, good MCP prediction and confidence interval estimation are difficult since bidding strategies used by participants are complicated, and various uncertainties interact in an intricate way. In most competitive electricity markets, the hourly price series presents the following characteristics:

- ✔ high frequency
- ✔ nonconstant mean and variance (nonstationary series)
- ✔ multiple seasonality (corresponding to a daily and weekly periodicity, respectively)
- ✔ calendar effect (such as weekends and holidays)
- ✔ high volatility
- ✔ high percentage of unusual prices (mainly in periods of high demand) due to unexpected or uncontrolled events in the electricity markets.

For instance, four examples of the price series are shown in Figures 3 and 4 (Spanish market) and Figures 5 and 6 (Californian market). The horizontal axes in all figures are in terms of hours. The price values, i.e., the vertical axes, in Figures 3 and 4 are in terms of €/kWh (€/kWh) and in Figures 5 and 6 are in terms of US$/MWh. These figures show the abovementioned characteristics, which are sufficient to produce a highly stochastic time series, creating many complexities in forecasting its future values. For instance, Conejo compared the Spanish and Californian markets and concluded that a higher proportion of outliers (unusual prices) and a lesser degree of competition results in the more volatility of the Spanish market, which in turn makes this market less predictable. Moreover, during peak hours the Spanish market shows even higher dispersion, which causes more uncertainty in periods of high demand, producing less-accurate forecasts.

Considering another viewpoint, it can be said that MCPs are inherently uncertain over time due to the uncertainty in weather, equipment outages, fuel prices, and other price drivers. This uncertainty applies to all markets; while we can see the market's closing forward price curve for crude oil in the newspaper, we can also be reasonably sure the curve will be different in tomorrow's paper. MCPs change as new information becomes available, so any forecast is doomed to be obsolete once new information comes to market. However, the fact of uncertainty (new information) does not obviate the usefulness of forecasts. It means that analysts need to complement their price forecasts with forecasts of the uncertainty as well. Representing the uncertainty "qualifies" the forecast, so the user can assess how much the prices, and their corresponding valuations, are sensitive to new information.

Addressing these forecasting challenges is a difficult job. In the next section, some of the proposed methods for this matter are discussed.

Price Forecasting Methods

A lot of methods have been developed for price forecasting of the electricity markets, especially in the last decade. Many of these methods are the load forecasting and especially short-term load forecasting (STLF) methods. However, MCPs are usually more volatile than hourly loads, and so the MCP prediction is more complex than the STLF. This is

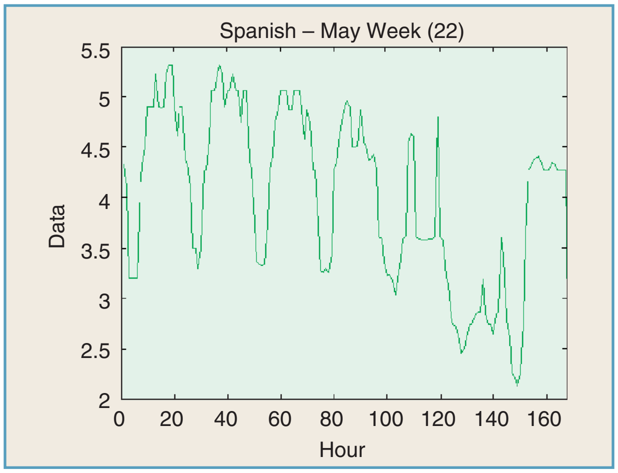

figure 3. Price series for Week 22 (May 2002) of the Spanish market.

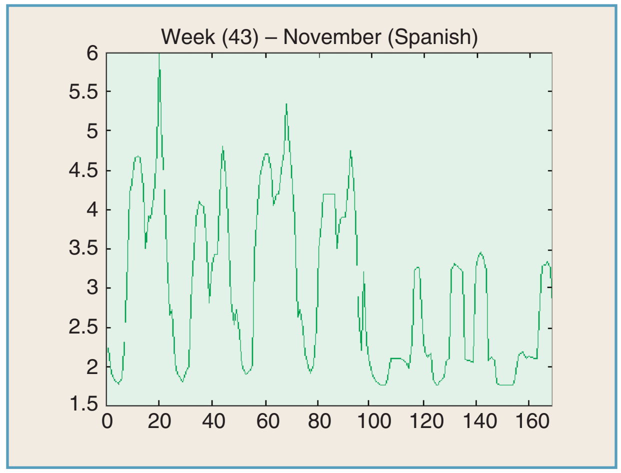

figure 4. Price series for Week 43 (November 2002) of the Spanish market.

due to the fact that MCP is dependent on the hourly loads and some other stochastic signals, such as equipment outages and fuel prices. For instance, projected surplus, Henry hub gas price, and Nymex oil price have been used in addition to hourly loads and temperatures to forecast the MCPs for the New England power market. Thus, uncertainty of hourly loads and the above stochastic signals are combined resulting in a higher level of uncertainty in the MCP. Although price curves generally keep similar change with load curves in a transaction day, the former can be affected by more uncertainty factors. This causes higher prediction error of the MCP than the hourly load in the similar conditions. For instance, daily mean error of ARIMA (autoregressive integrated moving average) time series for hourly loads can be about 1.5%, while that of MCP can be 5% or higher. In the following, a brief review of the price forecasting methods are presented.

Time series models have been already applied to forecast commodity prices such as oil and natural gas. Early applications of the time series models in the power system were related to STLF. Some commercial STLF software packages were produced based on these techniques, such as FOC (a product of ABB Company) and SAS (a product of Taipower). Currently, with the restructuring process that is taking place in many countries, autoregressive (AR) models are also being used to predict weekly prices, as in the Norwegian system. Besides, a more efficient time series model (ARIMA) has been used for price forecasting of the Spanish and Californian electricity markets. The daily mean error of the price forecasts varies from 5–8% for different weeks in the above markets and their MWE (mean week error) is about 10–11%. Two other time series techniques, i.e., dynamic regression and transfer function models, have been proposed, where daily mean errors of about 5% for the Spanish market and about 3% for the Californian market have been recorded. Another type of of time series models known as GARCH (generalized autoregressive conditional heteroskedasticity) has also been applied for price forecasting. Daily mean errors of around 4% and 7% have been recorded for the Californian and Spanish markets, respectively. All mentioned results for the Californian and Spanish markets are from 2000.

In many cases, good results have been obtained from the time series techniques for both STLF and price forecasting. However, most of these methods are linear techniques and, therefore, cannot appropriately track the hard nonlinear behavior of the target signal. For instance, the hourly load signal can have sudden changes due to rapid variations of the temperature. These nonlinear behaviors are more serious in the case of price signal as seen in Figures 3–6. Thus, large unexpected errors may be seen in the prediction of the time series techniques. Forecast errors of more than 10% in the case of STLF and of more than 20% in the case of MCP prediction have been reported. This problem can be stated in another way. The time series techniques are successful in the areas where the frequency of the data is low, such as weekly patterns. Rapid variations and high frequency changes of the target signal can be problematic for these techniques. Thus, there is a need to more efficient forecasting tools capable of tracking the hard nonlinear behaviors of hourly load and especially price signals.

In recent years, another kind of forecasting methods based on the artificial intelligence techniques, and especially neural networks, have been proposed by the researchers. A fuzzy ARMAX (multivariable ARMA) has been used for STLF. Fuzzy regression models that relate prices and demands have been applied to the Californian market by Nakashima et al. In addition, neural network techniques, which have been widely used for load forecasting, are now used for price prediction. In particular, Ramsay et al. have proposed a hybrid approach based on neural networks and fuzzy logic, with examples from the England-Wales pool market having daily mean errors at around 10%. Also, Szkuta et al. have proposed a three-layered neural network with back-propagation (BP), showing results from the Victorian electricity market with daily mean errors at around 15%. A similar neural network has been applied for the

Californian market by Gao, Nicolaisen et al. have presented Fourier and Hartley transforms as filters to the price data inputs of a neural network.

The main advantage of neural networks in forecasting problems is that they are capable of inferring hidden relationship (mapping) in data. They can approximate any continuous multivariate function to a desired degree of accuracy or predict a nonstationary process if the weights are adaptively adjusted during online updates. Radial basis function (RBF) and multilayer perceptron (MLP) neural networks in theory are universal approximators and can approximate any continuous function to any degree of accuracy given a sufficient number of hidden neurons.

However, single neural networks with traditional learning algorithms (such as BP) may encounter a high prediction error for price forecasting, which can be seen from the aforementioned error values. In view of reasons such as insufficient input-output data points or too many tunable parameters, a single network, in reality, often misrepresents part of the nonlinear input-output relationship. For example, RBF networks are effective in exploiting local data characteristics, while MLP networks are good at capturing global data trends. Moreover, traditional learning algorithms may not be effective for predicting the nonstationary processes, like the MCP time series. Use of the first-order approximations, such as the first-order steepest descent method used in the BP, may not be as efficient as required for tracking the hard nonlinear behaviors of the MCP. Replacing the BP with the ABP (adaptive BP) cannot solve this problem. The Newton learning algorithm suffers from excessive computational requirements for MCP prediction. Some other training mechanisms, such as GDR (generalized delta rule), trap in local minima or dead bands for learning the training samples of the MCP. Finally, to learn these samples, slow convergence, oscillatory behavior, and even divergence are seen in some other training mechanisms like the functional link nets.

To solve the aforementioned problems, a few methods have been represented by the researchers in recent years. The cascaded architecture of neural networks and committee machine (composed of multiple neural networks in parallel form) have been proposed to replace the single neural network. They tried to alleviate the misrepresentation of the input-output data relationship suffered by a single network. The daily mean error of the cascaded structure and committee machine reach about 9% and 10%, respectively, for the New England energy market. Besides, a kind of EKF

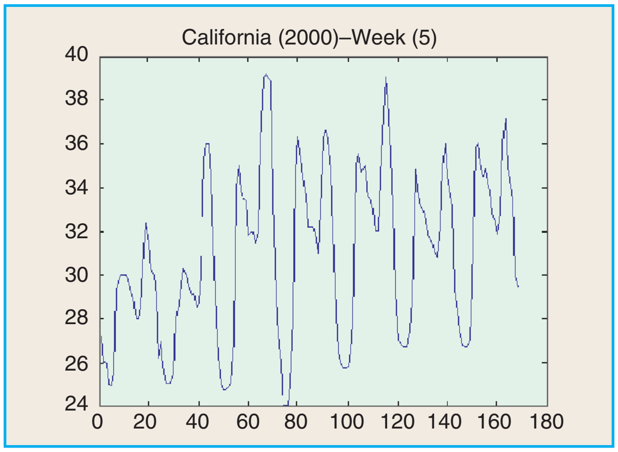

figure 5. Price series for Week 5 (February 2000) of the Californian market.

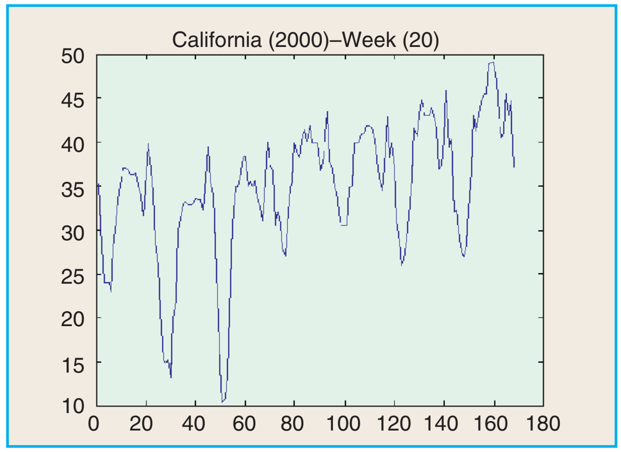

figure 6. Price series for Week 20 (May 2000) of the Californian market.

(extended Kalman filter) has been used to train the MLP neural network. The daily mean error of this approach to forecast the MCP of the New England market is about 11%. An IOHMM (input-output hidden Markov model) learning algorithm has been used to train the MLP neural networks. The MAPE (mean absolute percentage error) of this method for price forecasting in the Spanish market is 15.83%.

Other price forecasting methods, such as those based on the Fourier transform and stochastic modeling, also encountered large errors in predicting spot prices. It is seen that in spite of all performed activities, there are still large errors in the MCP prediction, confirming the need for more efficient forecast methods in this field.

Final Note

MCPs in a deregulated power market are volatile. For an independent system operator (ISO), the energy MCP is cleared by solving a unit commitment and economic dispatch problem with the bids and system conditions. High-quality MCP prediction and its confidence interval estimation would help utilities and independent power producers submit effective bids with low risks and make good bilateral transaction decisions. What is a good MCP prediction and confidence interval estimation method for a utility company who only has limited information? This is a difficult question because MCPs are heavily affected by load, which can go through rapid changes due to weather swings or seasonal changes, causing MCP to be nonstationary. Besides, other complex stochastic signals like fuel costs and equipment outages also affect the MCP time series, causing hard nonlinear behavior and sudden unpredictable changes of it.

Many researchers develop forecasting methods for this challenging task, some of which were discussed in the previous section. In spite of all the research in this field, the prediction of MCP usually involves large errors. It is seen that more efficient feature selection and forecasting methods are required. While time series techniques are efficient in tracking the stable behaviors of the MCP signal, they have difficulty predicting the hard nonlinear behaviors and rapid changes of the MCP due to the use of linear modeling. Neural networks (and especially fuzzy neural networks) are more efficient approaches to model the nonlinear behaviors of the MCP signal. However, as discussed in the previous section, a single neural network with traditional learning algorithms cannot construct all parts of the complex nonlinear mapping function of the MCP. Some researchers tried to solve this problem by cascaded or parallel architectures of the neural networks. Some others replaced the traditional training mechanisms, such as BP, with the newer learning algorithms. However, only minor improvements in the MCP prediction can be obtained. The other price forecasting methods, such as those based on stochastic modeling, also encountered large errors in the MCP prediction.

One key point in price prediction and most other forecasting processes, such as STLF, is feature selection. The selection of input features, a key issue for the success of forecasting processes, is rarely evaluated in the price prediction literature. As discussed in the previous sections, MCP is dependent on a large set of parameters, like previous MCPs, hourly loads, hourly temperatures, fuel costs (such as oil and gas costs), surplus generation (available generation minus demand), outage of important components, etc. In the previous works, usually a combination of these features are selected based on the heuristics and experience. Obviously, this selection method is not efficient due to the complex time-dependent behavior of the MCP and the large number of effective input features. Moreover, the method is not applicable for the other power systems or when the experienced operators are not available. Thus, an analytical method, which can select a minimum set of the most effective input features for the MCP prediction is so valuable. Different kinds of the sensitivity analysis and spectrum analysis can be suitable candidates for this purpose. Besides, to improve the price forecasting tools, a combination of the present techniques can produce appropriate candidates. For instance, genetic algorithms propose powerful training mechanisms for the neural networks. The insertion of fuzzy logic in the neural network, resulting in a fuzzy neural network, suggests an appropriate solution for modeling the uncertainty of the MCP. Finally, the AI-based methods and time series techniques can be combined to cover the weak points of each other.

For Further Reading

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Biographies

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