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Security Assessment and Optimization of Energy Supply (Neural Networks Approach)

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Keywords: *energy supply; security; neural networks; operating reserve*

Abstract: *The question of energy supply continuity is essential from the perspective of the functioning of society and the economy today. The study describes modern methods of forecasting emergency situations using Artificial Intelligence (AI) tools, especially neural networks. It examines the structure of a properly functioning model in the areas of input data selection, network topology and learning algorithms, analyzes the functioning of an energy market built on the basis of a reserve market, and discusses the possibilities of economic optimization of such a model, including the question of safety.*

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Introduction

A shortage in energy supply may take various forms and particular attention should be paid to: voltage non-compliance with applicable standards, i.e. excessively low voltages, temporary network overloads, power outages, and long-term supply shortages due to blackouts (Marsadek & Mohamed, 2013, p. 466). Because energy supply shortages result in economic losses, a number of measures are used to estimate them (for example Total Social Cost – TCS) and to evaluate the market's capability to satisfy demand (for example Effective Load Duration Curve – ELDC, Loss Of Load Expectation – LOLE, and Expected Energy Not Served – EENS).[1] Whichever method of evaluating the stability of the energy system is adopted, forecasting the occurrence of undesirable incidents is a key element of energy security and economic optimization. Modelling the behavior of the energy market in terms of the abovementioned shortages in energy supply is possible owing to the use of AI tools, such as Artificial Neural Networks (ANN). The forecasting of undesirable incidents should also take into account the system of reserves, whose role consists in supplying corresponding levels of production capacity in the case of unexpected operating conditions, such as damage to components of the energy system infrastructure or increase in demand. The aim of the study is to analyze the possibility of applying ANN to assess energy supply security and to analyze various reserve market models in terms of economic optimization.

Methodology of the Research

The authors conducted an energy market analysis based mainly on literature analysis. References were made to studies performed in many parts of the world and in various markets in order to ensure the applicability of the presented methods to more than a few selected energy markets. Apart from the literature analysis, the authors also used their own experiences based on empirical research conducted over many years in specific energy markets.

Principles of Artificial Neural Networks

As the name suggests, ANNs are mutually linked artificial neural cells. The definition of a neuron was developed as early as the 1940s, and figure 1

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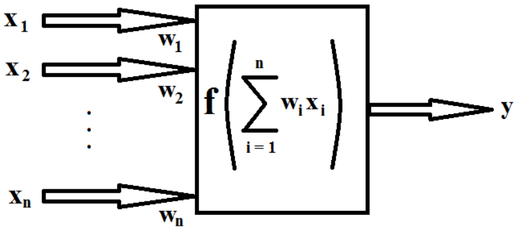
[1] More information can be found in (Jasiński, 2011).

presents the general structure of a single cell. It features a number of inputs (labelled x_1 to x_n) and corresponding 'weights', the latter being real numbers. Any signal that reaches a cell is multiplied by the corresponding weight. The products of all the inputs are then summed, and the total is transformed using an activation function. In the learning process, the weights are subject to numerous modifications, which consequently improves the responses of the ANN. We may say, therefore, that the intelligence of the network is contained within the neuron weights. The functional and learning processes of ANNs are frequently described algorithmically in the subject literature. This study focuses on the possible practical applications of ANNs rather than the IT and algorithmic details of constructing an actual network simulator.

Figure 1. Structure of a single neuron



Source: own development based on Ukil (2007, p. 80).

Selection of Input Data for the Model

The basic element that determines the quality of the forecast is the set of input data that describes the modelled phenomenon. Traditional econometric models require some indication of the type and degree of these relationships. An undeniable advantage of the use of ANNs is their ability to independently search for links between explanatory variables and explained variables. The key task is, therefore, the selection of the most appropriate input data to suit a given forecast. In terms of forecasting energy demand or pricing, the type of explanatory variables depends on the time horizon adopted. Long-term forecasts use such aggregates as GDP, while short-term forecasts focus more on weather-related data and short-term consumer behavior (i.e. related to watching popular TV programs like the Super Bowl). Jasiński (2014) and Jasiński & Ścianowska (2014) have examined information regarding the selection of input data, depending on the adopted prediction type.

Other explanatory factors are also required for analyses related to the risk of disruptions to the energy supply. The subject literature takes particular interest in the weather factor which, although often applied in most short-terms demand forecasts, in this case the volume of data required generally depends on the number of transmission lines. In other words, each transmission line usually has at least one corresponding atmospheric variable that describes the weather in which that given line operates (Marsadek & Mohamed, 2013, p. 474). A problem that can arise in the case of highly extensive transmission lines is that different atmospheric conditions may apply to its different sections. In such a situation, the input data should be complemented with a larger volume of variables, and there are no restrictions in this case regarding explanatory variables. However, the general principles of creating ANN models suggest that the quantity of input data should tend to be low in order to provide the model with only relevant data. This is confirmed in the studies by Marsadek & Mohamed (2013), in which the authors achieved an improvement of model quality by reducing the number of explanatory variables from 161 to as few as 23 for selected models, based on Principal Component Analysis (PCA).

The second type of data input is that usually derived from monitoring systems and includes information on the load on transmission lines. The actual number of variables usually depends on the number of buses (Marsadek & Mohamed, 2013, p. 474).

The third type of data comprises technical and statistical information related to the functioning of the energy distribution system, including network parameters and response times in the event of errors (Kim & Joo, 2006).

The subject literature covers both those models based on variables of the abovementioned groups and those functioning solely on the basis of a selected type of information. For example, modelling the risk of voltage drops is possible using only data for input voltage rates on the transmission lines (Chen et al., 2006). Of course, using only this type of variable at the input of the model would not forecast a network failure, as the modelled variable would require reference to the most relevant explanatory data.

Network Architecture and Learning Method

Forecasting models are characterized in this case by the variety of architecture applied. For example, Multilayer Perceptrons (MLPs) are prevalent in energy price and demand analyses, and are the most popular type of ANN. Although also constructed on the basis of MLPs (Chen *et al*., 2006, Swetha & Sudarshana, 2014), models used to estimate the risk of supply shortages are often based on other solutions as well, such as General Regression Neural Networks (GRNNs) (Marsadek & Mohamed, 2013) and Radial Basis Function Networks (RBFNs) (Rashidi & Rashidi, 2004). Both types of ANN are derived from MLPs, but with extensive modification applied to them. Jasiński (2003) gives more information on their structure.

Irrespective of the type of ANN, the goal is to optimize the remaining parameters of the model. In the case of an MLP this determines the number of hidden layers and also the number of neurons in each (the number of cells in the input and output layers depends on the number of explanatory and explained variables). Furthermore, each cell should have an appropriate activation function selected and, in most cases, its parameters as well. It is usual to construct all cells in a given layer on the basis of identical transformations. RBFNs and GRNNs do not require the determination of the optimal number of layers, as this parameter is always preset: the former have three layers whilst the latter have four.

One of the most popular MLP learning methods is backward propagation of errors (BP). However, as shown in both the literature and empirical studies conducted by the author, in many situations other gradient methods are worth applying as well. Among the ANN training algorithms, the Levenberg-Marquardt method (Swetha & Sudarshana, 2014) and conjugate gradient method appear to be particularly useful.

Prognostic models are sometimes built on the basis of several networks rather than a single one. Such an approach is justified when there is the need to model several explained variables. Theoretically, ANNs can forecast many output variables within a single network; however, experience shows that satisfactory accuracy can only be achieved when forecasting a single variable. Therefore, each of the modelled values should be forecast using a single ANN. Such an approach was applied to determine system stability where initially a short-term (one-day) forecast was made for power system load.[2] The obtained data, with concurrent knowledge of up-to-date values, were used for the next step in error estimation. Afterwards, the obtained information was used as MLP input data to predict the random component of power system load. Another network (RBFN) determined the stability margin on the basis of the expected stochastic part of the load and expected future load. The margin was added to the MLP network in order to minimize its forecast error (Ukil, 2007, pp. 146-147).

[2] Such forecasting can be successfully conducted using an ANN, although other techniques may also be used.

There are many possibilities for cooperation between ANNs sharing the same and different architectures, as well as between ANNs and other AI tools, such as the Genetic Algorithm (GA). GA support, or similar evolution strategies (ES), may be independent (without ANN) or used to assess power systems (Samaan, 2007). Another possible technique consists in using the models independently, and then verifying whether they all indicate the same conclusions.

The Role of Reserves in Providing Power System Security

The deterministic security of a network is the ability of the power system to endure unexpected circumstances without the necessity of halting operations related to satisfying demand, except in cases of voluntary waiver. There are two types of security-provision actions used for power systems: preventive and corrective.

Preventive actions include repartition of already established supply volumes under the conditions preceding the failure, whilst corrective actions include introduction of quotas for selected types of demand in specific conditions (Aghaei *et al*., 2009). This means that reserves are resources that can facilitate implementation of preventive and corrective actions to restore security.

Reserve maintenance services, called Ancillary Services (AS), can be classified as follows:

- Ten-minute spinning reserve (TMSR);
- Ten-minute non-spinning reserve (TMNSR);
- Thirty-minute operating reserve (TMOR).

The first two categories involve the capacity of units connected and units not connected to the system to provide increased energy volume for 10 minutes, whereas the third involves the capacity of units connected and units not connected to the system to provide increased energy volume for 30 minutes.

In order to utilize the supply reserve from active units, their resources must be synchronized with the network and must be able to reach the expected production level in a short time frame. The actual volume of the operating reserves is the volume of production capacity above the level resulting from demand, which ensures supply security and is available for distribution in case of system failure. Requirements concerning the volume of reserves are based on the highest possible supply volume that can be lost. The available operating reserve volume is activated to secure an energy supply in the event of system failure. Thus the supplied energy replaces the volumes that were lost as a result of the failure.

The substitute energy may be delivered in two ways:

- from active production units that operate below their maximum level of production capacity,
- from inactive production units able to begin operation and produce energy quickly (Likover, 2014).

The reserve planning strategies may take different forms (Baldick *et al.*, 2005). The most popular form utilizes a sequential approach to ordering reserves, whereby the process of scheduling reserve maintenance services proceeds after an energy supply plan for a separate market has been prepared (Liu *et al.*, 2000). Under this method, the reserve-related services are planned by quality, in descending order. This market model was adopted by independent systems operators (ISO) in California in 1998, but it proved to be vulnerable to manipulation by the market participants.

The flaw of this method, related to the functional separation of the energy market and the reserve market, is particularly visible when the original plans concerning energy supplies do not allow supply at an appropriate level of production capacity to satisfy the requirements in terms of reserves. In such a case, the market operators must inevitably apply for participation in a system to a power plant that offers energy at a higher price, which evidently leads to deterioration of social well-being and results in a loss to the entire economy.

The second method of scheduling energy reserve orders involves the simultaneous planning of different types of reserves in line with the demand level, but still on a market separated from the energy market. By this method, the reserve market, which is thus attributed with the character of substitute goods, is known as a disaggregated parallel market (Afshar et al., 2008).

The Role of the Auction Market in Providing Security and Economic Optimization of the Power System

The third method, used by such operators active on the East Coast of the United States as: PJM, New England and New York, involves system operators offering reserve provision services through planning, parallel to actual energy supplies. This facilitates optimization of each node by, for example, balancing the energy market, and satisfies the requirements for each service connected with reserve maintenance. The pricing of energy and reserves proceeds concurrently, and includes lost opportunity costs resulting from the unavailability to supply other products (Liu & Liu, 2007).

The issue of energy has been analyzed in a number of studies as it combines important aspects of power system security and efficiency. Scientific papers on energy and reserve planning by authors such as Singh and Papalexopoulos (1999) describe the auction market for ancillary services in California and their distribution, while also presenting the relationships between individual markets. While Ma *et al*. (1999) proposed a zone-based reserve model, Gan and Litvinov (2003) and Wu *et al*. (2004) analyzed the requirements for maintaining reserves throughout the system as a whole. Authors such as Afshar *et al*. (2008) presented the process of determining the level of energy reserves and described the methods of arriving at their optimum values, based on delivery costs and benefits that accrue from their availability.

The majority of studies assume that the distribution of sufficient amounts of reserves across the remaining units is a sufficient condition to return the situation to normal. However, what also needs consideration are problems connected with network security, such as transmission line overload, bus voltage limits, and reserve distribution cost estimates. It is of fundamental importance here to address the question regarding the availability of Independent System Operators (ISO) in terms of resource distribution to ensure system security (Aghaei *et al*., 2009). In their attempts to answer this question, authors such as Aganagic *et al*. (1998), Alvey *et al*., (1998), and Cheung *et al*., (2000) assessed transmission network models with constrained transfer for individual lines with pre-defined reserve levels for selected nodes or areas.

Nevertheless, ISOs have continued to struggle with the issue of determining a method of employing all possible resources to combine system safety and fair settlement policy. This issue is particularly valid for units which are considered to be the expected providers of sufficient system reserves even though they could sell their energy at higher prices on an aggregated parallel market (CAISO, 2008).

In order to overcome these problems successfully, an aggregated, parallel market framework has been developed for many products to mitigate the deficiencies of the sequential system. It also accounts for payments designed to compensate for lost opportunity costs to encourage energy providers to comply with the requirements for maintaining reserves. Adopting an additional objective function within the settlement procedures which takes into account system stability, as part of the non-linear multiple-objective constrained optimization problem, means that generation costs and safety indicators are considered competitive goals. The issue of combined energy markets and reserves has been addressed by way of Mixed Integer Non-Linear Programming (MINLP), which reconciles security concerns with commercial aspects of market settlements.

Market settlements are usually handled by the operators, who are responsible for determining the set of accepted purchase and sale proposals and the resulting market settlement prices. Therefore, the data concerning unit liabilities, production and consumption levels, as well as energy and reserve prices, are all the outcomes of the optimization procedure. These outcomes are determined by the purchase and sale proposals submitted by the market participants who are known to the market operators before the settlement procedure is initiated (Aghaei *et al*., 2009).

During the multiple-objective optimization of the settlement procedure for combined day-ahead energy markets and reserve auctions, the primary objective function is to reduce the costs of the provided energy and reserves (AGC, TMSR, TMNSR and TMOR), as well as the lost opportunity costs (LOC) for hourly delivery. In view of the above, it is assumed that generators submit price quotations on the basis of marginal costs. In the energy market these take the form of multiple blocks and on the reserve markets they take the form of a single block for all types.

Another important task of the ISO is the selection of the settlement procedure. In the most extensive form the generators are paid both on account of both lost opportunity costs and availability within the framework of reserve orders, i.e. the so-called A+L model. When system demand for different types of reserves is not satisfied, some generators have to reduce production in order to satisfy system demand as far as reserves are concerned. The lost opportunity cost due to the created reserves is defined as the cost of profit which would probably be gained by a generating unit if its generating powers were engaged in the energy market (Aghaei *et al*., 2009). This multi-criteria model also includes the category of the price of lost profits, which is the difference between the price possible on the independent energy market and the energy market shared with the reserves market.

In deliberations concerning the amount of payments for generating units based on the A+L model, in order to use LOC in the equation for costs offered by generators, prior to the optimization of function one needs to consider the issue of energy transmission. It is assumed here that an energy system should be managed so that all the levels of bus voltage are within acceptable ranges, and that none of the transmission lines in the system are overloaded.

In a market settlement procedure, the issue of system security in terms of taking into account voltage drops and transmission line overloads involves the use of indicators while formulating additional functions of purpose for the multi-criteria issue of optimization. It is assumed that one should aim to minimize those indicators defined as: the difference between the values of voltage in particular buses and the reference level to the referential and as a relation of flow of power for particular levels of lines connecting buses to their maximum flow capacity (Aghaei *et al*., 2009).

In the end, the settlement price means the highest accepted price offer as the marginal cost of a particular unit in a bus if it is selected in the energy market:

$$\rho^{MCP} \geq Z_{i,u}\, \rho^{e}_{i,u}$$

where:
ρ^{MCP} – is the highest accepted quote defined as marginal cost,
$Z_{i,u}$ – is a binary variable, which has the value of 1 if a particular unit in the bus is selected to undertake activity on the energy market, otherwise the value is 0,
$\rho^{e}_{i,u}$ – offered price of energy for unit u in bus i (Aghaei *et al*., 2009).

Conclusions

Modern solutions regarding the modelling of the energy market can be effective in the field of predicting energy supply shortage. The precision of the forecasts requires the suitable construction of a model, which in the case of an ANN means the appropriate selection of explanatory variables, network topology, learning method and other parameters. It should be expected that the quality of the forecasts can be increased through the further optimization of the model components, such as by means of applying mathematical methods to modify the input data.

Production capacity reserves are a fundamental instrument ensuring the safety of a power system. The possibility of using them within the framework of both preventive and corrective measures for security allows the system to survive undesirable events, without the necessity to cease handling demand.

However, the necessity of ensuring stability of the supply parallel to economic optimization of the activities in the system resulted in the need to seek a settlement procedure on the auction market which would allow the achieving of both these objectives at the same time.

The experiences of independent system operators in that regard show that payments received by generators should take into account the necessity of covering the lost opportunity costs, the costs of providing availability of resources within the framework of reserve orders and issues related to the security of supply of particular units.

References

Afshar, K., Ehsan, M., Fotuhi-Firuzabad, M., & Amjady, N. (2008). A method for reserve clearing in a disaggregated model considering lost opportunity cost. *Electric Power Systems Research*, 78(4), http://dx.doi.org/10.1016/j.epsr.2007.04.007.

Aganagic, M., Abdul-Rahman, K. H., & Waight, J. G. (1998). Spot pricing for generation and transmission of reserve in an extended Poolco model. *IEEE Transactions on Power Systems*, 13(3), http://dx.doi.org/10.1109/59.709110.

Aghaei, J., Shayanfar, H., & Amjady, N. (2009). Multi-objective market clearing of joint energy and reserves auctions ensuring power system security. *Energy Conversion and Management*, 50(4), http://dx.doi.org/10.1016/j.enconman.2008.12.027.

Alvey, T., Goodwin, D., Ma, X., Streiffert, D., & Sun, D. (1998). A security constrained bid clearing system for the New Zealand wholesale electricity market. *IEEE Transactions on Power Systems*, 13(2), http://dx.doi.org/10.1109/59.667349.

Baldick, R., Helman, U., Hobbs, B. F., & O'Neill, R. P. (2005). Design of efficient generation markets. *Proceedings of the IEEE*, 93(11), http://dx.doi.org/10.1109/JPROC.2005.857484.

CAISO, Scarcity Pricing Team (2008). California ISO Draft Proposal. Reserve Scarcity Pricing. February 6. Retrieved from https://www.caiso.com/Documents/DraftProposal_ReserveScarcityPricingDesign06-Feb-2008.pdf (01.12.2014).

Chen, W. H., Jiang, Q. Y., & Cao, Y. J. (2006). Low Voltage Risk Assessment in Power Systems Using Neural Network Ensemble. *Advances in Neural Networks - ISNN 2006. Lecture Notes in Computer Science*, 3972, http://dx.doi.org/10.1007/11760023_204.

Cheung, K. W., Shamsollahi, P., Sun, D., Milligan, J., & Potishnak, M. (2000). Energy and ancillary service dispatch for the interim ISO New England electricity market. *IEEE Transactions on Power Systems*, 15(3), http://dx.doi.org/10.1109/59.871720.

Gan, D., & Litvinov, E. (2003). Energy and reserve market designs with explicit consideration to lost opportunity cost. *IEEE Transactions on Power Systems*, 18(1), http://dx.doi.org/10.1109/MPER.2002.4311914.

Jasiński, T. (2014). Dane wejściowe sztucznych sieci neuronowych prognozujących krótkoterminowe zapotrzebowanie na energię. *Logistyka*, 6.

Jasiński, T. (2003). Przegląd architektur sztucznych sieci neuronowych wykorzystywanych w ekonomii do przewidywania szeregów czasowych. *Studia i Prace Kolegium Zarządzania i Finansów*, 35.

Jasiński, T. (2011). The usage of artificial neural networks on the energy market. In L. Kiełtyka (Ed.). IT Tools in Management and Education. Selected Problems. Częstochowa: Wydawnictwo Politechniki Częstochowskiej.

Jasiński, T., & Ścianowska, A. (2014). Analiza i modelowanie rynku energii w perspektywie długoterminowej. Systemy aukcji i przewidywanie popytu. *Logistyka*, 6.

Kim, M., & Joo, S. K. (2006). Feature Reduction Techniques for Power System Security Assessment. *Advances in Natural Computation. Lecture Notes in Computer Science*, 4221. http://dx.doi.org/10.1007/11881070_73.

Likover, R. (2014). Reserve Market Overview. Introduction to Wholesale Electricity Markets (WEM 101). Retrieved from http://www.iso-ne.com/support/training/courses/wem101/17_reserve_market_overview.pdf (01.12.2014).

Liu, S., & Liu, H. (2007). California ISO Issue Paper. Reserve Shortage Pricing. May 31. Retrieved from https://www.caiso.com/Documents/ReserveShortagePricingDesignIssuePaper31-May-2007.pdf (01.12.2014).

Liu, Y., Alaywan, Z., Rothleder, M., Liu, S., & Assadiam, M. (2000). A rational buyer's algorithm used for ancillary service procurement. In Proceedings of the IEEE Power Engineering Society winter meeting 2000, 2.

Ma, X., Sun, D., & Cheung, K. (1999). Energy and reserve dispatch in a multi-zone electricity market. *IEEE Transactions on Power Systems*, 14(3), http://dx.doi.org/10.1109/59.780903.

Marsadek, M., & Mohamed, A. (2013). Risk based security assessment of power systems using generalized regression neural network with feature extraction. *Journal of Central South University*, 20, http://dx.doi.org/10.1007/s11771-013-1508-9.

Rashidi, M., & Rashidi, F. (2004). Design of an Adaptive Artificial Neural Network for Online Voltage Stability Assessment. *Innovations in Applied Artificial Intelligence. Lecture Notes in Computer Science*, 3029, http://dx.doi.org/10.1007/978-3-540-24677-0_108.

Samaan, N. (2007). Reliability Assessment of Composite Power Systems Using Genetic Algorithms. In G. Levitin (Ed.), Computational Intelligence in Reliability Engineering. Evolutionary Techniques in Reliability Analysis and Optimization. Springer. http://dx.doi.org/10.1007/978-3-540-37368-1_8.

Singh, H., & Papalexopoulos, A. (1999). Competitive procurement of ancillary services by an independent system operator. *IEEE Transactions on Power Systems*, 14(2), http://dx.doi.org/10.1109/59.761872.

Swetha, G. C., & Sudarshana Reddy, H. R. (2014). Voltage Stability Assessment in Power Network Using Artificial Neural Network. *International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering*, 3(3).

Ukil, A. (2007). *Intelligent Systems and Signal Processing in Power Engineering*. Springer.

Wu, T., Rothleder, M., Alaywan, Z., & Papalexopoulos, A. D. (2004). Pricing energy and ancillary services in integrated market systems by an optimal power flow. *IEEE Transactions on Power Systems*, 19(1). http://dx.doi.org/10.1109/TPWRS.2003.820701.