

## Chapter 49

# Backpropagation Neural Network for Interval Prediction of Three-Phase Ampacity Level in Power Systems

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### ABSTRACT

*The modern way of living depends on a very high degree on electricity utilization. People take for granted that their energy needs will be satisfied 24/7 which mandates the maintaining of the power grid in stable state. To that end, the development of precise methods for monitoring and predicting events that might disturb its uninterrupted operation is immense. Moreover, the evolvement of power grids into smart grids where the end users continuously participate in the power market by forming energy prices and/or by adjusting their energy needs according to their own agenda, adds high volatility to load demand. In that sense, with regard to predictive methods, a plain single point prediction application may not be enough. The aim of this study is to develop and evaluate a method in order to further enhance this type of applications by providing Predictive Intervals (PIs) regarding ampacity overloading in smart power systems through the use of Artificial Neural Networks (ANNs).*

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## 1. INTRODUCTION

The liberalization of power systems magnified the already significant and vital issue of system stability. Except for the rapid increase of base demand that is a consequence of the development that the world experienced during the last decades, new generation power systems brought up more challenges that have to be confronted. End-users are no more price takers. They actively participate in the energy market and actually form energy prices. Furthermore, we do not anymore categorize them solely as customers. According to their own agenda can act either as customers or as sellers trying to maximize their own portfolio; a term worldwide known as prosumers (Hogan, 1998). The Renewable Energy Sources (RES) dispersed along the system and their stochastic nature put an added stress on the grid. Moreover, initiatives for a more “green” and less polluted environment force for more RES installations and as less as possible use of conventional fossil fuel energy. Further, the upcoming change of conventional cars into electric ones (Electric Vehicles - EVs) and the constant development of the emerging countries will force for higher quality power. Furthermore, the power grid cannot be continuously expanded. We cannot continue building new power generators or installing transmission and distribution lines ceaselessly. Demand-Response (DR) programs (Chrysikou et al, 2015) came to solve expansion as well as stability issues, but added high volatility to load signals. In some cases, DR programs are responsible for the so-called rebound effect where load peaks are moved to otherwise calm time periods, perhaps in more serious forms (Fainti et al., 2014; Foti & Vavalis, 2015).

It is obvious that retaining the grid stable is not an easy task. On the contrary, the System Operator (SO) who is the main responsible entity for coordinating all the vendors and engaging parties of a power system must be always aware, in time, about upcoming events that might put the grid in danger. Congestion issues, a situation where electricity flows are beyond specific limits, can have severe economic and practical impacts like lengthy blackouts and high electricity prices; especially in new generation power markets, where actually the whole coordination of the power grid is based on price signals. When congestion occurs, the SO intensively increases electricity prices to certain locations in an attempt to alleviate the consequences and avoid the degradation of the system and a possible total collapse. That is, the end-users in certain geographical areas, perhaps far away from the congested area, are facing high electricity prices.

From the above description, it is comprehended that the development of high precision tools and methods to provide information regarding the status of the system is immense and of high priority. To that end a lot of surveys have been conducted during the last years. The authors in (Li et al., 2006) developed a prediction method where the shadow prices, a product of Optimal Power Flow (OPF) calculations, and their occurrence act as an indicator of transmission congestion appearance. In (Sharma & Srivastava, 2008a) and (Sharma & Srivastava, 2008b) the issue of congestion prediction was addressed with Artificial Intelligence (AI) techniques such as cascade and hybrid neural networks. Neural Networks (NNs) were also selected by Balaraman and Kamaraj, as well as by Ivanov et al. for developing congestion prediction methods in (Balaraman & Kamaraj, 2012), (Ivanov et al., 2014) and (Ivanov & Gavrilas, 2012) with very promising results. In the first study cascade neural networks were utilized for line overloading predictions, while in the last two, multilayer perceptron neural networks were utilized for voltage limit violation predictions. The object of study in (Glazunova, 2010) was the development of a state estimator for short-term predictions regarding power system’s state variables, with the use of NNs and Kalman filter-based algorithms. The development of transmission congestion prediction methods was the concern of the studies in (Min et al., 2008) and (Zhou et al., 2011). In both works, the

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