ELM-Fuzzy Method for Automated Decision-Making in Price Directed Electricity Markets

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***Abstract*—Among many domains application of information technologies has also transformed electricity markets. Price directed markets refer to the driving the electricity consumption by controlling the electricity prices in real time. This paper frames itself in such an electricity market, where consumers receive the prices and they respond with their demand for the next hour in real time. Response is performed by a smart meter that is equipped with tailored algorithms that make decisions based on the preferences of the customer. In this paper, a responding method is proposed that is based on Extreme Learning Machine (ELM) and Fuzzy Logic Inference. The synergism of the two tools allows the automated decision making where the interference of the human customer is minimal. The proposed method, called ELM-Fuzzy, is presented and tested on a set of real-world data. Results demonstrate the efficiency of the ELM-Fuzzy method to make fast and optimal decisions aiming at reducing the electricity expenses of the customer.**

***Index Terms*—ELM, Fuzzy Logic, Decision-Making, Price-Directed Markets.**

I. Introduction

In the last decades, the vast penetration of information technologies in various domains of our everyday lives has transformed the form of services as we knew to data driven ones. One of the service domains that have been significantly impacted is the electrical power transmission and distribution services [1].

The traditional vertical power market, where the electricity from generation to transmission and distribution was controlled by a single entity has been replaced by a multiple vendors operation [2]. Therefore, a different entity is responsible for generation, different for transmission, while distribution may be controlled by one or more companies. This transformation of the power delivery system gave birth to new types of electricity markets. In practice, these new markets were simply the adaptation of existing market of other commodities to the special case of electricity. Development of the new electricity markets were based on the assumption that electricity is also a commodity [2].

Generally speaking, the driving force behind the operation of a market is the commodity price. Following a rationale behavior, market participants aim at maximizing their profit quantified as the amount of money spent or saved [3]. In particular, sellers aim at selling their whole quantity of products at the maximum possible price, while buyers aim at fully satisfying their need at the minimum possible price. Electricity marker are not an exception: producers and consumers try to maximize income and minimize expenses respectively [4].

This work place itself in the framework of price directed electricity markets where consumption is driven by prices. In particular, electricity consumers receive pricing signals at specific time points and decide the amount of electricity consumption that will be consumed for the next time interval accordingly [5]. In these electricity markets customers are connected to the distribution grid through smart meters that place electricity orders and make purchases according to customer preferences. The decisions are made automatically using price information and a set of thresholds, which denote the preferences or comfort zone of the customer. The use of price thresholds frees customers from the need to monitor energy prices 24/7. The framework of price-directed markets requires utilization of real-time decision-making based on dynamic information [6]. More particularly, pricing signals reflect the specifics of the state of the power system (i.e., distance between supply and demand, possible congestion, specific locational issues, emergent severe weather conditions, etc) while thresholds reflect electrical customer priorities and capacity for monetary cost [7].

Smart meters equipped with intelligent algorithms can automate the operation of the electricity purchase and increase its efficiency. Furthermore, an algorithm that receives the price signals from the market directly can make decisions about the electricity purchase in a way that is not only efficient but also less costly [8]. The connectivity of meters to the smart power grid promotes the adoption of intelligent algorithms that receive and process the information, adapt to system conditions and make optimal decisions for the benefit of their consumer (i.e. human consumer) [9].

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In this paper, an intelligent algorithm that implements an automated decision-making approach for electricity markets consumers is introduced. The proposed system adopts a artificial intelligence system to control the operation of a smart meter connected to the smart power system. In particular, the integration of extreme learning machines (ELM) – ELM is a two layer neural network [10] - with fuzzy logic [11] allows automated decision making by i) predicting future states (i.e., using neural network) of the market with respect to prices, and ii) fusing current and predicted information and make a decision (i.e., using a fuzzy logic based decision engine). The use of ELM in the proposed method allows the fast retraining of the neural network and subsequent prediction of market prices in very short times (<1 sec) [12].

The roadmap of the paper is as follows: section II briefly discusses ELM and fuzzy logic, while section III presents the ELM-Fuzzy method. Section IV provides the obtained results, and lastly section V concludes the paper.

II. Background

A. Elements of Fuzzy Logic

The basis of classical set theory is the binary classification of an object with respect to a given set: an object either belongs to a set or not. However, in several engineering problems, the use of classical theory fails to accurately describe and represent the problem parameters.

On the other hand, fuzzy logic extends the classical set theory by assuming that objects belong to a set with some degree [11]. Thus, an object may belong to several sets with different degrees, which is knowns degrees of membership. The degrees of membership in each set are assigned by a specific function that is called the membership function. Therefore, a fuzzy set is fully defined by its membership function, which might be discrete or continuous depending on the type of variable. It should be noted that the range of values of a variable may be spanned by one or more fuzzy sets that overlap: overlapping sets designate that some objects belong concurrently to different sets [11]. An example of fuzzy sets that span a variable X is provided in Fig. 1.

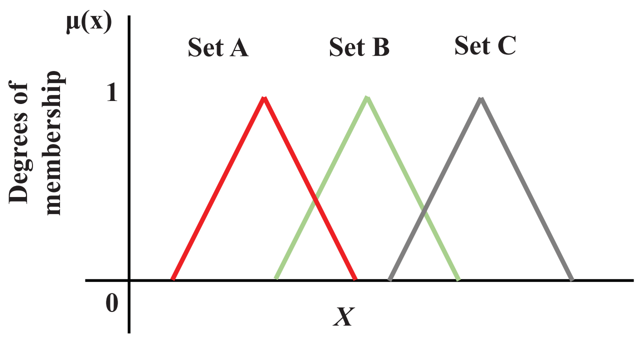

Figure 1. Example of fuzzy sets spanning the value range of variable *X*.

In Fig. 1 we observe that the membership functions of the fuzzy sets take values in the interval [0 1]. When $\mu_A(x) = 0$, then the x does not belong to the set A, while $\mu_A(x) = 1$ indicates that x fully belongs to set A [11]. Every other value between 0 and 1 indicates that x partially belongs to set A with a degree equal to $\mu_A(x)$.

Two or more fuzzy variables may be associated via the use of IF, THEN rules. These rules, which are called fuzzy rules, express the associations between the fuzzy sets of a variable with the fuzzy sets of the second variable. For instance, a fuzzy variable X spanned by sets A,B and is associated with a fuzzy variable Y spanned by sets S,T as follows:

IF X is A, THEN Y is T,

IF X is B, THEN Y is S.

Association of two variables via fuzzy rules allows the development of fuzzy inference systems that utilize a set of rules to associate a cause (the IF part), with the results (the THEN part) [11]. Notably, the strength of fuzzy sets and rules, is the quantification of the inherent uncertainty of the variables.

B. Extreme Learning Machine

One of the most common tools within the machine learning realm are artificial neural networks (ANN). ANN are utilized for both classification and regression problems by utilizing a set of parameters that are called weights [11]. There are several type of neural networks, with ELM being one of them.

ELM is a two layered feedforward neural network comprised of a single hidden layer, an input and an output layer (it should be noted that the input layer is not a computational layer and thus it is not counted in the layer architecture). The parameters of ELM are expressed as two sets of weights: the first set of weights connects the input to hidden layer, and the second set connects the hidden to output. The basic architecture of ELM is depicted in Fig. 2.

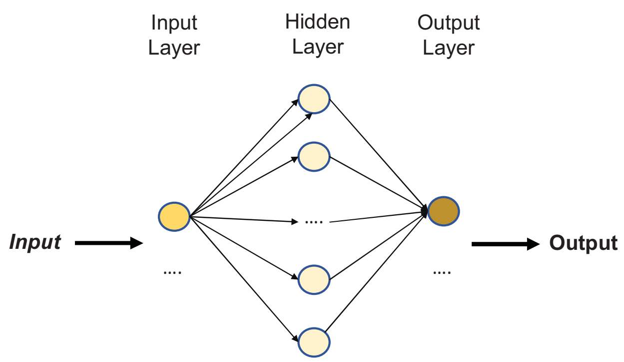

Figure 2. Basic architecture of ELM.

The main difference of ELM with the rest of the neural networks lies in the training process. In particular, the set of weights of the first layer is randomly evaluated, whereas the second set of weights is defined via a simple linear optimization problem. The optimization problem is defined via the use of the training target values and the outputs of the hidden layer. Further details on the ELM training and operation may be found in [13] and [14]. The main strength of ELM is its extremely fast training [15], which makes it suitable for real time applications as the one discussed in the current paper.

III. ELM-Fuzzy Method

A. Price Directed Electricity Markets

In this work, we consider price directed markets, where the prices are announced and the consumers respond with their demand. In the ideal case, the consumers the market operator announces the prices in very short-term intervals [16], whereas the consumers respond with their demand instantaneously. In that market, the resolution of the market is fully defined by the consumer response time, where a real time assumes that the process of price announcement and response takes some seconds.

In such time constrained time environments, the consumers must be able to monitor the prices nonstop, while making the decisions within seconds. Notably, this is impossible for human operators and inevitably they have to trust smart meters and intelligent algorithms to participate in the market on their behalf. Furthermore, the human consumer anticipates that his/her smart meter will follow the decision strategy that the human would follow if he/she could be able to follow the market prices 24/7. To that end, artificial intelligence offers the necessary tools to monitor the market, process the data and make decisions.

B. Method

In this section the newly developed method for automated decision making in price directed electricity markets. The overall goal of the method is to make optimal decisions regarding the electricity orders in real time. The driving force behind decision making is the minimization of the consumption cost. To that end, a new anticipatory method that for autonomous decision making in price directed method is proposed. In particular, the method is comprised of two components: a learning component that anticipates the future prices, and a rule-based component makes the final decision about the amount of electricity that will be purchases in the next cycle.

The block diagram of the proposed method is depicted in Fig. 3, where its individual steps are clearly shown. The first component of the method contains the ELM that is utilized for price prediction making. In particular, the current price, which was just announced by the market operator, and the 10 most recent prices are put together to form a dataset. The newly formed dataset is forwarded to the ELM where it is utilized to evaluate the network parameters, i.e. training phase. In the current work the ELM architecture is the following: 1 input, 5 hidden neurons and output neuron. The input to the ELM is the time and the output is the electricity price [17].

The training of the ELM is followed by prediction making. In particular, the trained network model is utilized for predicting the next five prices denoted in Fig. 3 as $p(t+1)$, $p(t+2)$, $p(t+3)$, $p(t+4)$ and $p(t+5)$ where t stands for the current time instance. In the next step, the current price together with the five predicted values are fed to a fuzzy inference engine. The goal of the engine is to utilize the current (known value) and the projected prices (projected values) for deciding the amount of energy to be ordered. In addition, to the price values the fuzzy inference engine has as an input the Demand Zone of the consumer that is expressed by two values: the minimum demand that must be purchased and the maximum demand that the consumer can afford. Therefore, the fuzzy engine determines the amount of electricity within the demand zone that can be purchased. To make it clearer, the output of the fuzzy inference is a single value obtained from the demand zone of the consumer.

At this point it should be noted that the fuzzy inference system implements a set of rules of the IF, THEN form. In this work, a set of 25 rules have been implemtented with some examples are given below:

IF Price(t) is *LOW*, THEN Order(t) is *HIGH*

IF Price(t+1) is *LOW*, THEN Order(t) is *HUGH*

IF Price(t+1) is *LOW* and Price(t+2) is *HIGH*, THEN Order(t) is *MEDIUM*

where the Order(t) is also a fuzzy variable that determines the percentage of the demand zone that needs to be ordered. The fuzzification of the variable Order(t) is depicted in Fig. 4. The fuzzy engine utilizes the Mamdani Min implication operator [11] to evaluate the rules and the center of area technique for defuzzification [11].

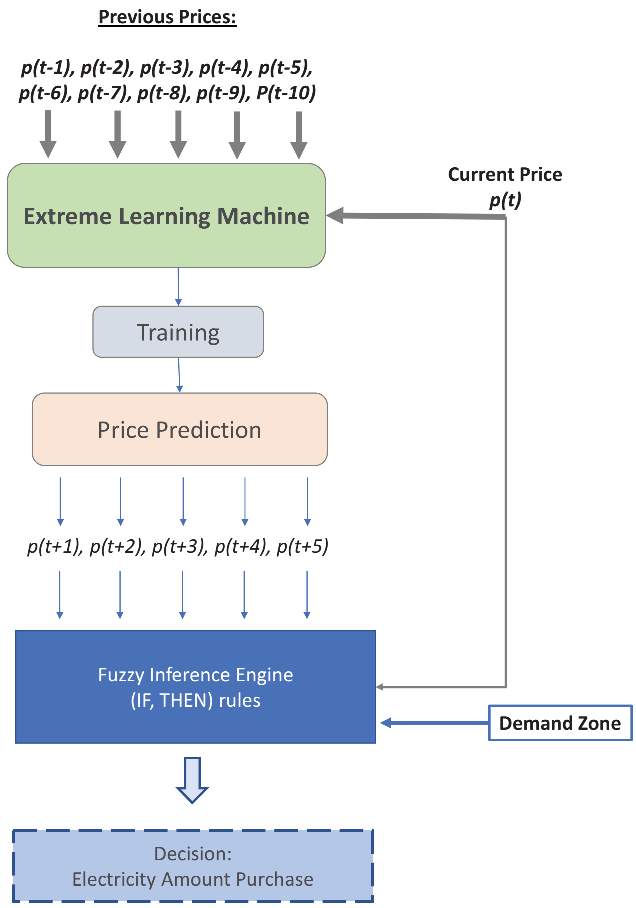

Figure 3. Block diagram of the presented ELM-Fuzzy method.

The output of the fuzzy engine determines the amount of the demand zone that may be ordered. Then, the final decision is taken as the addition of the percentage of the demand zone with the minimum demand value. The added value is forwarded as the final decision of the smart meter pertained to electricity purchase.

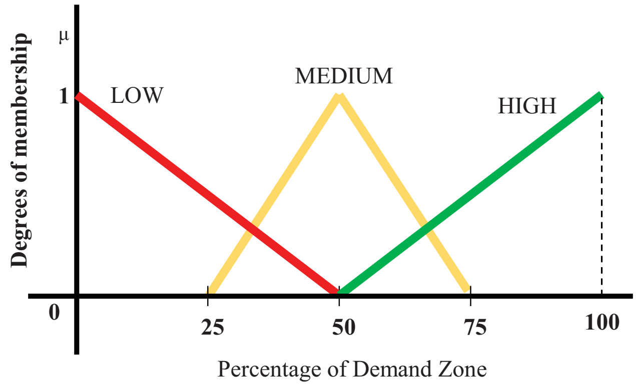

Figure 4. Fuzzy representation of consumer's demand zone.

It should be noted that the presented method allows the automated decision making in price directed methods. Notably the ELM allows fast predictions that lead to fast decision making. The ELM training is at the scale of a second, while the inference making using the 25 rules is also computational inexpensive (less than a second as well).

Lastly, it should be mentioned that the presented method requires no human intervention, while it follows the human consumer purchase strategy. The latter is implemented via the fuzzy rules: each consumer may define its own rules based on its preferences, intuition and needs.

IV. Results

In this section the presented ELM-Fuzzy method is tested on a set of real-world household data [18]. The test dataset contains the power consumption in 5-minute intervals. The presented method is tested for 10 different days. Furthermore, the price data used in this work was taken from the New England Iso [19] and in particular from the date of June 3, 2019. The price data was used for assessing the method for all the tested seven days. Furthermore, the demand zone is assumed to be +/- 30% from the real consumption power. The obtained results are recorded in terms of expenses per day (amount is recorded in US dollars), while it is compared with the expense taken if the presented approach is not applied.

The obtained results are recorded in terms of daily electricity consumption costs, and are provided in Table I. According to the obtained results, the ELM-Fuzzy method provided lower daily cost for all tested 10 days than the case that no ELM-Fuzzy is utilized. This results shows that the decrease of cost is independent of the day; this independence is explained by the fact that ELM utilizes the most recent measurements, instead of using consumption patterns from previous days for training. A more careful observation exhibits that the decrease of cost is average $2 per day, which scales up to 60$ per month. This amount is a significant amount of savings especially for a household as is the case in our testing. For visualization purposes, the load ordered by ELM-Fuzzy as compared to the original load pattern (i.e. no use of ELM-Fuzzy) for the Day 10 is presented in Fig. 5.

TABLE I. Obtained Results in terms of Expenses (US Dollars

Day	**ELM-Fuzzy**	**No use of ELM-Fuzzy**
Day 1 (5/1/07)	$ 13.44	$ 15.74
Day 2 (6/1/07)	$ 6.99	$ 8.40
Day 3 (7/1/07)	$ 14.01	$ 15.20
Day 4 (8/1/07)	$ 11.22	$13.87
Day 5 (9/1/07)	$ 9.55	$12.61
Day 6 (10/1/07)	$ 10.92	$ 14.28
Day 7 (11/1/07)	$ 13.73	$ 15.69
Day 8 (12/1/07)	$8.79	$ 9.92
Day 9 (13/1/07)	$ 15.55	$ 19.25
Day 10 (14/1/07)	$ 14.65	$ 18.16

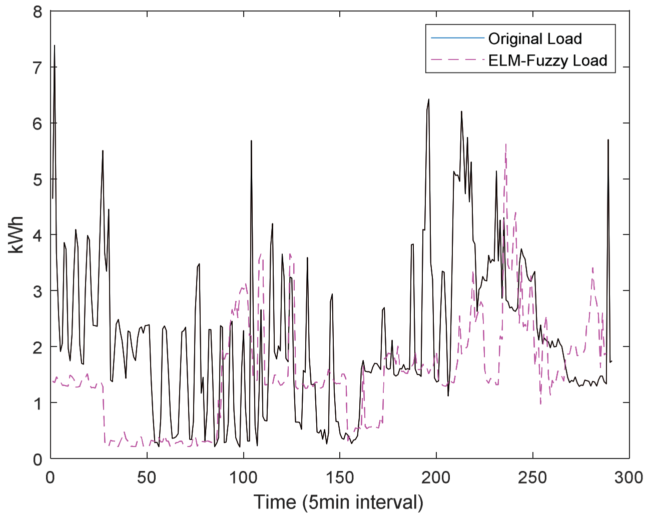

Figure 5. Load pattern taken with ELM-Fuzzy as compared to original load pattern (i.e. no use of ELM-Fuzzy) for Day 10 in Table I.

With regard to execution time, the ELM-Fuzzy method had an average execution time that was below 1 sec. This time was enough for our case that assumed that the prices were announced every 5 min.

At this point it should be noted that the results show that the proposed method has high potential to be incorporated in the smart meters of consumers to make decisions with regard to electricity ordering decisions in price directed markets. Furthermore, the presented method enables a market that may operate in very short time intervals (e.g. shorter than 1 minute) given that the ELM-Fuzzy is able to make decisions in a scale of seconds. Furthermore, the ELM-Fuzzy allows the human consumer to have minimum interference in the monitoring of the market: his/her goal is to set the rules in the fuzzy engine.

However, there were some limitations in the presented method. The main limitation is the use of the fuzzy rules. On one hand a well thought set of rules may allow the consumer to exhibit optimal behavior in the market, but on the other a shallow thought of the rules may also lead to a bad decision making pattern. Therefore, the ELM-Fuzzy performance strongly depends on the developed fuzzy rules.

V. CONCLUSION

In this paper, a new method for decision making in price directed markets is presented. the paper assumes that the consumer is connected to the power market via a smart meter and receives in predetermined intervals the electricity price. Then the consumer must respond with the amount of energy he/she wants to purchase. However, in such a market the 24/7 monitoring of prices is impossible for human consumers. Therefore, the need for automated algorithms that monitor the market and make decisions is high.

The presented ELM-Fuzzy method implements an automated decision making in two steps: in the first step, the ELM predicts the future prices, and in the second step a fuzzy inference engine utilizes the current and the predicted prices as well as the demand zone of the consumer to make a decision regarding the amount of electricity to be purchased. The use of ELM is crucial given that its fast training time allows fast decision-making time, while the fuzzy inference system implements the human consumer purchasing strategy. Resutls taken on a set of 10 days from a household load patterns exhibited that the ELM-Fuzzy attained to reduce the expenses by an average of $2 per day by morphing the household load pattern.

The limitations of the method include the definition of fuzzy rules, that require thorough thinking. Future work, will include the extensive testing of the method in a higher number of testing days, and the expansion of the fuzzy inference engine with a higher number of rules.

REFERENCES

[1] L.H. Tsoukalas and R. Gao, "From smart grids to an energy internet: Assumptions, architectures and requirements," in *Proc. 2008 IEEE Third International Conference on Electric Utility Deregulation and Restructuring and Power Technologies*, pp. 94-98.

[2] D.S. Kirschen, and G. Strbac, *Fundamentals of power system economics*, Vol. 1, New York: John Wiley & Sons, 2004.

[3] M. Alamaniotis, R. Gao, and L.H. Tsoukalas, "Towards an energy internet: a game-theoretic approach to price-directed energy utilization," in *Proc. International Conference on Energy-Efficient Computing and Networking*, pp. 3-11.

[4] Strbac, G. (2008). Demand side management: Benefits and challenges. *Energy policy*, *36*(12), 4419-4426.

[5] M. Alamaniotis, and L.H. Tsoukalas, "Integration of Price Anticipation and Self-Elasticity for Hour-Ahead Electricity Bidding and Purchasing," in *Proc. 9th Mediterranean Conference on Power Generation, Transmission, Distribution, and Energy Conversion:* (MEDPOWER 2014), November 2014, pp. 1-4.

[6] R. Fainti, A. Nasiakou, E. Tsoukalas, and M. Vavalis, "Design and early simulations of next generation intelligent energy systems," *International Journal of Monitoring and Surveillance Technologies Research (IJMSTR)*, vol. *2*(2), pp. 58-82, 2014.

[7] M. Alamaniotis, N. Gatsis, and L.H. Tsoukalas, "Virtual Budget: Integration of Electricity Load and Price Anticipation for Load Morphing in Price-Directed Energy Utilization," *Electric Power Systems Research*, Elsevier, vol. 158, May 2018, pp. 284-296.

[8] O.A. Sianaki, O. Hussain, T. Dillon, and A.R. Tabesh, (2010, September). "Intelligent decision support system for including consumers' preferences in residential energy consumption in smart grid," in *Proc. 2010 IEEE Second International Conference on Computational Intelligence, Modelling and Simulation*, pp. 154-159.

[9] J.S. Vardakas, N. Zorba, and C.V. Verikoukis, "Performance evaluation of power demand scheduling scenarios in a smart grid environment," *Applied Energy*, vol. 142, pp. 164-178, 2015.

[10] G.B. Huang, H. Zhou, X. Ding, and R. Zhang, "Extreme learning machine for regression and multiclass classification," *IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics)*, vol. 42(2), pp. 513-529, 2011.

[11] L.H. Tsoukalas, and R.E. Uhrig, *Fuzzy and neural approaches in engineering*. John Wiley & Sons, Inc., 1996.

[12] X. Chen, Z.Y. Dong, K. Meng, Y. Xu, K.P. Wong, and H.W. Ngan, "Electricity price forecasting with extreme learning machine and bootstrapping. *IEEE Transactions on Power Systems*, vol. *27*(4), pp. 2055-2062, 2012.

[13] G.B. Huang, Q.Y. Zhu, and C.K. Siew, "Extreme learning machine: theory and applications," *Neurocomputing*, vol. 70(1-3), pp. 489-501, 2006.

[14] G.B. Huang, Q.Y. Zhu, and C.K. Siew, "Extreme learning machine: a new learning scheme of feedforward neural networks," *Neural networks*, vol. *2*, pp. 985-990, 2004.

[15] G.B. Huang, and L. Chen, "Convex incremental extreme learning machine," *Neurocomputing*, vol. 70(16-18), pp. 3056-3062, 2007.

[16] M. Alamaniotis, L.H. Tsoukalas, and N. Bourbakis, "Virtual cost approach: electricity consumption scheduling for smart grids/cities in price-directed electricity markets," In Proc. *IEEE IISA 2014, The 5th International Conference on Information, Intelligence, Systems and Applications*, pp. 38-43.

[17] W. Yang, J. Wang, T. Niu, and P. Du, "A hybrid forecasting system based on a dual decomposition strategy and multi-objective optimization for electricity price forecasting," *Applied energy*, vol. 235, pp. 1205-1225, 2019.

[18] UCI Machine Learning Database [Online] Available: https://archive.ics.uci.edu/ml/datasets/individual+household+electric+power+consumption

[19] New England Iso [Online] Available: https://www.iso-ne.com/isoexpress/web/reports/pricing/-/tree/final-5min-lmp-by-node