FACTA UNIVERSITATIS
Series: **Electronics and Energetics** Vol. 27, N° 3, September 2014, pp. 411 - 424
DOI: 10.2298/FUEE1403411D

IMPLEMENTATION OF ARTIFICIAL NEURAL NETWORKS BASED AI CONCEPTS TO THE SMART GRID

Marko Dimitrijević, Miona Andrejević Stošović, Jelena Milojković, Vančo Litovski

Faculty of Electronic Engineering, University of Niš, Serbia

Abstract. *ICT and energy are two economic domains that became among the most influential to the growth of modern society. These, in the same time, due to exploitation of natural resources and producing unwanted effects to the environment, represent a kind of menace to the eco system and the human future. Implementation of measures to mitigate these unwanted effects established a new paradigm of production and distribution of electrical energy named smart grid. It relies on many novelties that improve the production, distribution and consumption of electricity among which one of the most important is the ICT. Among the ICT concepts implemented in modern smart grid one recognizes the artificial intelligence and, specifically the artificial neural network. Here, after reviewing the subject and setting the case, we are reporting some of our newest results aiming at broadening the set of tools being offered by ICT to the smart grid. We will describe our result in prediction of electricity demand and characterization of new threats to the security of the ICT that may use the grid as a carrier of the attack. We will use artificial neural networks (ANNs) as a tool in both subjects.*

Key words: *smart grid, ICT, artificial intelligence, ANN, prediction, security.*

1. INTRODUCTION

In our recent studies we addressed the problem of interaction of the ICT and energy sector including the specific interrelation through the subject of security [1, 2]. Most of the claims reported were later on confirmed in the literature as, for example, in [3, 4, 5, 6]. It is our intention here to report on some aspects of these interrelations and, via some new case studies, to demonstrate how much the modern energy distribution system may be supported by ICT. In particular, we intend to emphasize the potential role of the artificial intelligence in improving the implementation of the new emerging concepts of production, consumption and distribution of electricity.

The ICT industry plays a vital role in the global economy and is a major driver of growth and development [3]. Several of the most transformative economic trends (e.g., social media, big data, multi-channel retail, etc.) involve the use of ICT.

Received January 31, 2014; received in revised form June 5, 2014
Corresponding author: Miona Andrejević Stošović
University of Niš, Faculty of Electronic Engineering, Aleksandra Medvedeva 14, 18000 Niš,
(miona.andrejevic@elfak.ni.ac.rs)

In addition to its positive implications for economic growth, ICT's greenhouse gasses (GHG) abatement potential must also be considered [3]. The ICT industry accounted for 1.9% of total global GHG emissions in 2011, which is significantly less than its overall contribution to GDP. Nonetheless, this is a significant amount of emissions that the industry must address, especially as we expect even faster adoption of ICT in the future. However, in the last several years there have been promising strides toward decreasing the growth rate of ICT emissions.

Early on, sustainable ICT focused on green ICT initiatives that minimize the ecological impact of the development, management, use, and disposal of computing resources. That is named the first wave of sustainable ICT [7]. Green ICT tends to be product-oriented and mostly focused on reducing energy costs and carbon emissions for data centres and desktops. Several studies were reported on the energy footprint of computers and data centres [8, 9, 10]. As concerns about ICT's impact on the environment have risen, these issues have become limiting factors in determining the feasibility of deploying new ICT systems, even though processing power is widely available and affordable.

On the other side the electric power sector went through revolutionary transformations that include deregulation, use of alternative energy sources, and introduction of ICT. At the distribution level, the new requirements call for the development of:

- distribution grids accessible to distributed generation (DG) and renewable energy sources (RESs), either self-dispatched or dispatched by local distribution system operators,
- distribution grids enabling local energy demand management interacting with the users through smart metering systems, and
- distribution grids that benefit transmission dynamic control techniques and overall level of power security, quality, reliability, and availability.

The key technology supposed to fulfil these requirements today is named smart grid. Smart grids and smart power systems in the energy sector can have major impacts on improving energy distribution and optimizing energy usage [11].

Defining the smart grid in a concise way is not an easy task as the concept is relatively new and as various alternative components build up a smart grid. Some authors even argue that it is "too hard" to define the concept [12]. Looking at different definitions reveals that the smart grid has been defined in different ways by different organizations and authors. Here is one of them: "A 'smart grid' is a set of software and hardware tools that enable generators to route power more efficiently, reducing the need for excess capacity and allowing two-way, real time information exchange with their customers for real time demand side management (DSM). It improves efficiency, energy monitoring and data capture across the power generation and transmission and distribution network [13]".

The need of implementation of AI within the smart grid was recognized by the professional and scientific community [5,14]. For example, the work in [15] surveys some of the most relevant applications of ANN techniques to the field of energy systems. These applications range from a wide variety of purposes such as, modeling solar energy heat-up response [16], prediction of the global solar irradiance [17], adaptive critic design [18], or even for security issues as reviewed in [19]. The idea behind these applications is based on learning how system performances can be related to certain input values, for instance, how weather conditions (solar or wind) determine the energy output that can be expected [20].

In the past decades ANNs have emerged as a technology with a great promise for identifying and modeling data patterns that are not easily discernible by traditional

methods. A comprehensive review of ANN use in forecasting may be found in [21]. Among the many successful implementations we may mention [22, 23, 24].
Applications of ANNs for security purposes were discussed in [5, 6].

Putting all together, at this moment, one may state that the AI concepts and especially ANNs may be implemented in the following aspects of the life of modern distributed energy resources.

- Various forecasting tasks, like renewable energy forecasting, storage forecasting and demand forecasting, that need intelligent rules. We will address this issue later on.
- Protection. Being by nature fault tolerant, the ANNs are most likely a very good means for localizing the faults within a micro grid and in the same time to be capable to isolate it in case of a fault in the main grid.
- Intelligent diagnosis of equipment in micro grid. ANNs are a better option for diagnosing faults in electrical equipment for the following reasons:
  - They can interpolate from previous learning and give a more accurate response to unseen data, making them better at handling uncertainty.
  - They are fault tolerant, so they handle corrupt or missing data more effectively.
  - They are good non-linear function approximators by nature, making them better at equipment diagnostics.
  - They are more suitable for extracting the relationship between input and output in fault detection and diagnosis applications.
- Demand side management. It appears that demand-side management technologies that simply rely on reacting to control or price signals will not be enough. Rather, what is necessary are more sophisticated approaches that are truly adaptive to the state of the grid, that are able to learn the correct response given any particular situation, and that can look ahead and predict both supply and demand trends in the near future, in order to prepare for future reductions in available supply, or to make the most effective use of supply when it is available.
- Intelligent data processing including data-mining. The main challenge to be tackled in the smart grid comes from the vast amount of information involved in it. In contrast to traditional grids, in which the consumption metering information was only retrieved monthly, smart grids present a new scenario in which all the interconnected nodes are gathering information about many different matters, and not only consumption (i.e. real-time prices, peak loads, network status, power quality issues, etc.) [25]. In this sense, one of the main challenges for computational intelligence is how to intelligently manage such an amount of information so that conclusions and inferences can be drawn to support the decision making process.
- Security. Here we see the grid as a highly interconnected vulnerable communication network being exposed to all kinds of malicious cyber attacks such as eavesdropping, tempering and even jeopardizing the physical structure of the system.

The two case studies we are reporting here are interrelated by the fact that they both use artificial neural networks to improve the performance of the grid since the one (prediction) may be seen as a base for protection of the grid from overload while the second is related to profiling the loads connected to the grid and protect them of misuse. In addition, both solutions rely on the measured data generated by modern metering systems [AMI/AMR][26, 27].

The paper is organized as follows. In the second paragraph we will give a brief review on the ANNs and the structures we are using for interpolation and extrapolation. Then, in the third paragraph the implementation of ANNs in load prediction related to next day peak-load forecasting will be given. Note, the method implemented here is genera in the sense that we have application to other types of load prediction such as short, medium, and long term. The implementation of the very same ANN structures to the new eavesdropping method related to the profiling of the loads (in this case a computer) to grid, will be described in the fourth paragraph.

2. A Short Review of the Methods of ANN Implementation

We will first briefly introduce the feed-forward neural networks that will be used as a basic structure for prediction throughout this paper.

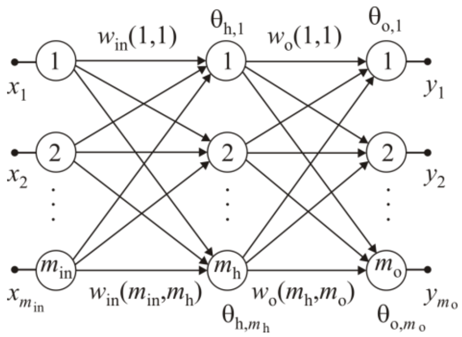

Fig. 1 A fully connected feed-forward ANN

The network is depicted in Fig. 1. It has only one hidden layer, which has been proven sufficient for this kind of problem [28]. Indices: in, h, and o, in this figure, stand for input, hidden, and output, respectively. For the set of weights, $w(k, l)$, connecting the input and the hidden layer we have: k=1,2,..., m_{in}, l=1,2,..., m_h, while for the set connecting the hidden and output layer we have: k=1,2,...m_h, l=1,2,..., m_o. The threshold is here denoted as $\theta_{x,r}$, r=1,2,..., m_h or m_o, with x standing for h or o, depending on the layer. The neurons in the input layer are simply distributing the signals, while those in the hidden layer are activated by a sigmoidal (logistic) function. Finally, the neurons in the output layer are activated by a linear function. The learning algorithm used for training is a version of the steepest-descent minimization algorithm [29]. The initialization problem was solved according to literature [30]. The number of hidden neurons, m_h, is of main concern. To get it we applied a procedure that is based on proceedings given in literature [28, 31, 32].

For prediction purposes we developed two structures [33]. The first one was named Time controlled recurrent (TCR). It is depicted in Fig. 2. The second was named Feed-forward accommodated for prediction (FFAP). Its structure is depicted in Fig. 3. Later on, these two structures were further elaborated as discussed in the succeeding paragraph. It is worth mentioning that, in our opinion, for deterministic forecasting one always needs at least two predictions being supportive to each other. Since no knowledge of the forecasting outcome is available, the second prediction is only means to corroborate the first one. Having in mind, however, that both predictions carry the same uncertainty, we decided for the best final prediction to accept the average of the two.

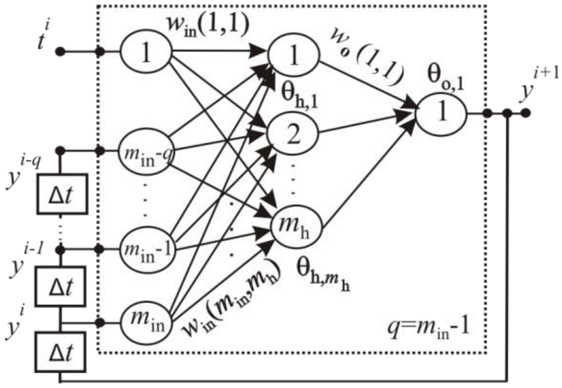

Fig. 2 Time controlled recurrent (TCR) ANN

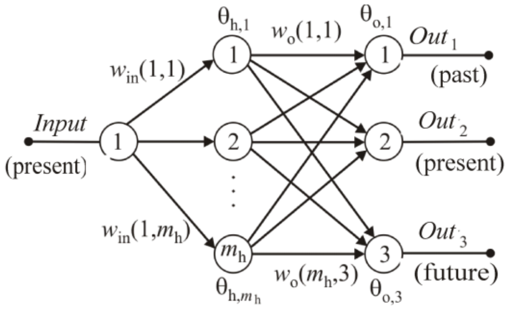

Fig. 3 The feed-forward accommodated for prediction (FFAP) structure

3. Prediction of Peak-Load at Suburban Level

Electric load prediction is essential for power generation and operation [34]. It is vital in many aspects such as providing price effective generation, system security, and planning. Among others, it enables: scheduling fuel purchases, scheduling power generation, planning of energy transactions, and assessment of system safety [35]. The load forecast errors imply high extra costs: if the load is underestimated one has extra costs caused by the damages due to lack of energy or by overloading system elements; if the load is overestimated, the network investment costs overtake the real needs, and the fuel stocks are overvalued, locking up capital investment. In a smart grid context, prediction allows for developing computationally efficient learning algorithms that can accurately predict both the prosumers' (produce/consumer) consumption and generation profiles (instead of only the usage profile for a consumer) as well as the price of electricity in real time in order to inform profitable trading decisions. Given this, a number of researchers have suggested that more sophisticated tariffs, such as real-time pricing (RTP) or spot pricing (where the price per kWh of electricity consumed is different for each half-hour and is provided to the consumer a day, or a few hours, ahead of time), in conjunction with more sophisticated 'agents' that can autonomously respond to these price signals, would avoid this [36].

Consequently, the quality of load forecasts has greatly influenced the economic planning in areas such as generation capacity, purchasing fuel, assessing system's security, maintenance scheduling, and energy transmission [37].

The power load value is determined by several environmental and social factors. Seasonal and daily profiles are the most apparent influential. Temperature and air humidity are the primary parameters determining the energy consumption generally and especially in urban residential areas. Working times, holidays, and weekends are characterized by specific load profile. Environmental disasters, sudden increase of large loads or outages, and important social events are further complicating the load-time function. All together, the load curve is a nonlinear function of many variables that map themselves into it in an unknown way.

In the next, our newest results in the application of artificial neural networks (ANNs) for prediction of daily peak loads at suburban level will be presented.

3.1. Problem formulation

We took data for the implementation of our method from the UNITE 1999 competition file [38]. The task was: given the peak values for the previous days, predict the peak-load value for the next day.

According to studies of the behaviour of the consumers, in general, one may expect the peak-value to happen at about 19.00 hours. There are some exceptions but these are not influencing the general method we implement. When speaking about the very peak-value one may recognize a regular periodicity with, unfortunately, some exceptions. Fig. 4 represents the daily peak-value for one month (April 1997) extracted from [38]. Note the difficulty to recognize the periodicity of the phenomenon.

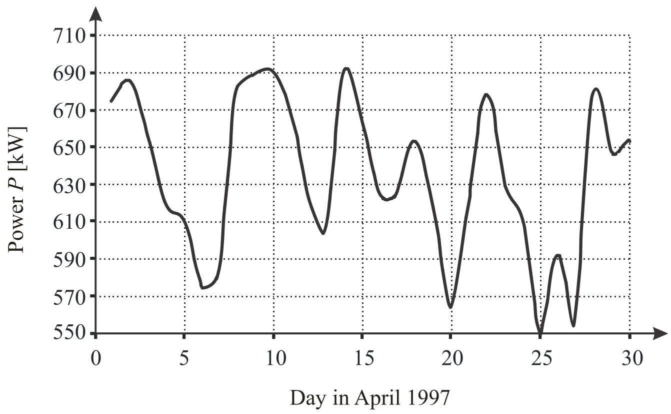

Fig. 4 The daily peak-value for one month (April 1997) extracted from [38]

The problem may be stated as follows. Given the series (t_k, $f(t_k)$), k=1,2, ...n , where t_k, is the time instant – namely day in the calendar, $f(t_k)$ the peak-value at that day, and k the counter, the last known peak-value is at the n-th day. Our task is to predict the peak-value at the (n+1)st day.

For the purpose of prediction in the subject of electricity we developed two ANN structures named ETCR and EFFAP [39] which we implement simultaneously. The idea is the following: when predicting one is making a step into the dark. If one wants to have any confidence in the prediction one has to have at least two predictions that support each other. Then, since both are of equal importance, instead of accepting one of them the average is calculated and stated as final result. We will give some rudimentary description of ETCR and EFFAP ANNs in the next.

For the verification of the method we undertook the task to predict the daily peak-values in May 1997 and to compare with the data given by the UNITE 1999 competition.

3.2. The ETCR solution

The ETCR ANN structure tailored for the application at hand is depicted in Fig. 5. The name stands for Extended Time Controlled Recurrent. It is a recurrent ANN with two feed-back loops. The first one is feeding back the peak-values of the most recent days while the second is feeding back the peak values from two previous weeks but of the same day in the week as the one to be predicted. In this way we implement two principles. First, we claim that only the most recent values have influence to the current value and there is no need for a huge amount of useless data. Second, one has to exploit the pseudo-periodic behaviour of the consumers since same days in the week have similar load profile. The ETCR is supposed to approximate the function:

$$y_i = f(i, y_{i-1}, y_{i-2}, y_{i-3}, y_{i-4}, y_{i-7}, y_{i-14}) \quad (1)$$

where the samples are the daily-peak values. When progressing in time i will raise its value by one.

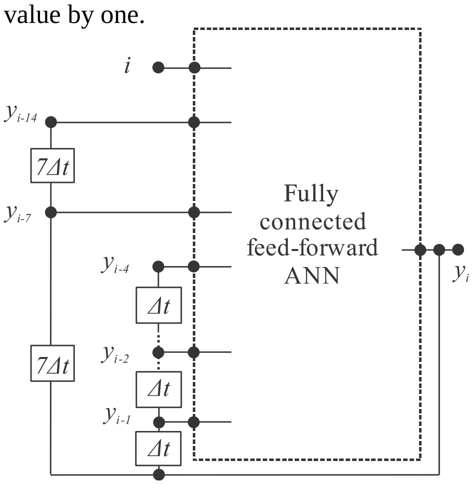

Fig. 5 ETCR: Extended time controlled recurrent according to (1)

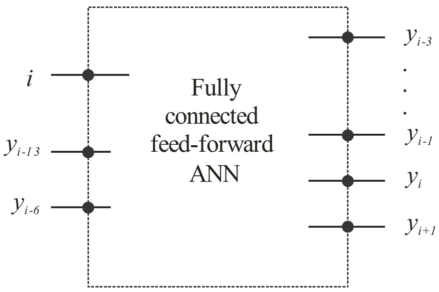

Fig. 6 The Extended feed forward accommodated for prediction (EFFAP) according to (2)

As for the first test of the method we predicted the peak-value for April 30. 1997 what according to the UNITE 1999 was 609 kW. The resulting ANN had 7 input terminals, 2 output terminals, and 5 neurons in the hidden layer. After bringing a proper excitation we got as a prediction y={625.3241}, what is depicted in Table 1.

3.3. The EFFAP solution

The EFFAP ANN tailored for the application at hand is depicted in Fig. 6. The name stands for Extended Feed Forward Accommodated for Prediction. It is a feed forward ANN with three inputs one of them being the time i, while the rest are the peak-values from the previous weeks. There are five outputs each of them supposed to learn the same function but shifted in time for one day. The following set of functions approximates the phenomenon:

$$\{y_{i+1}, y_i, y_{i-1}, y_{i-2}, y_{i-3},\} = \mathbf{f}(i, y_{i-6}, y_{i-13})\,. \tag{2}$$

Of course, this network is approximating the very same function as the ETCR does but in a different manner.

As a result for April 30th 1997, the EFFAP ANN obtained after training had 3 input neurons, 5 output neurons, and 5 neurons in the hidden layer. After proper excitation the following prediction was obtained *y*= {653.2675}. The result is again depicted in Table 1.

Table 1 Prediction of the peak-value consumption at April 30th 1997 of the UNITE data

No.	Expected value	ETCR	%	EFFAP	%	Average value of the prediction	%	Number of hidden neurons	
								ETCR	EFFAP
1	609	625.3241	2.68	653.2675	7.27	639.2958	4.975	5	5

3.4. Overall solution

As stated above, the final solution to the prediction problem in our method is obtained by averaging the ETCR and the EFFAP predictions. It is shown in Table 1, too. It is encouraging.

To get a complete picture about the capabilities of the method we made a prediction for every day in May 1997. Our first partial results were published in [40] while here we are giving complete results for the whole month as shown in Fig. 4. These allow for real evaluation of the properties of the method.

By inspection of Fig. 7 we conclude that the method proposed may be implemented for prediction of the peak-load at suburban level. The largest discrepancies between the actual and the predicted values are lower than 17% even in the worst case. In 22 out of 30 days the error was lower than 10%, while in 12 out of 30 days the error was lower than 5%.

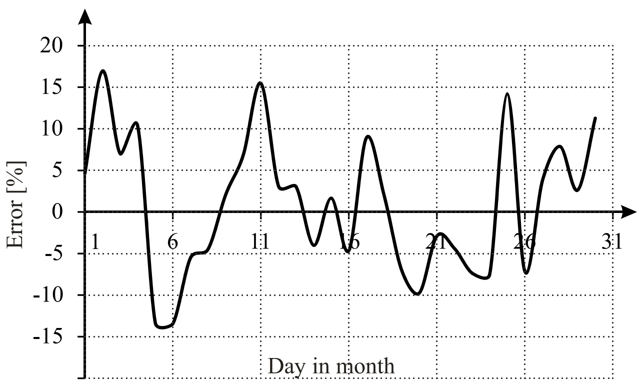

Fig. 7 Error of prediction (y-axis) as a function of the day in the month May 1997 (x-axis)

4. A VERY SPECIFIC VIEW TO THE SECURITY

Within the research of the behaviour of computers from the power consumption point of view [10], different software packages were implemented in order to create the energy profile of the computer under different "loading" conditions. We noticed, however, that not only the power consumed, but the THD was dependent on the application running within the PC. So, Table 2 contains all harmonics generated by one personal computer (DELL Optiplex 980, Intel Core i7 CPU @ 2.8GHz, 4GB RAM, 500GB HDD) under different working conditions. Approximately 50 harmonics were observed in a sample (200ms, 10000 samples) of a grid current. Since even harmonics have incomparably smaller values than the odd ones, in Table 2 only the DC, the main, and the odd harmonics are presented. Fig. 8. illustrates two columns of Table 2.

Table 2. Odd harmonics extracted from one string measurement in eight different states of the workstation

Harm. No.	Off (1)	Idle (2)	Video (3)	CPU Arithmetic (4)	GPU Rendering (5)	Multi-Media CPU (6)	Physical Disks (7)	File System Benchmark (8)
DC	-0.55	-0.84	1.3	-0.52	-0.68	-1.3	-0.23	-0.51
1	89.7	400.26	475.4	785.73	747.73	394.33	381.54	411.72
3	3.05	47.9	54.03	34.6	35.84	47.79	48.05	47.73
5	8.55	23.18	23.52	28.7	28.42	22.83	23.53	24.14
7	8.94	11.41	12.3	17.43	16.77	9.74	6.96	9.61
9	3.08	9.19	7.7	10.12	9.26	9.17	8.63	9.5
11	8.76	6.17	7.24	12.27	11.13	6.12	5.36	5.53
13	2.77	1.4	1.73	6.01	5.81	1.99	2.49	2.96
15	6.28	9.81	12.19	5.98	6.84	9.32	9.94	8.92
17	4.81	3.66	5.1	8.91	9.9	5.6	3.76	3.71
19	0.69	4.16	5.05	5.74	5.68	3.3	5.75	7.31
21	0.92	7.39	6.52	4.89	5.12	6.65	5.55	5.29
23	0.62	5.17	7.15	6.06	7.19	5.55	4.56	4.3
25	0.53	4.12	6.2	5.86	4.63	4.6	5.2	4.76
27	0.94	5.18	8.31	2.29	1.28	4.2	3.07	6.35
29	0.62	6.61	6.35	2.94	4.3	5.85	4.93	6.26
31	0.54	4.89	3.64	2.54	3.61	4.98	3.96	5.16
33	1.08	7.58	5.23	4.48	3.67	7.84	8.2	7.34
35	0.47	3.98	2.72	1.71	1.59	4.27	4.17	2.94
37	0.45	2.61	2.09	0.51	0.93	2.98	3.19	2.2
39	0.58	3.9	2.83	2.94	3.55	3.97	4.7	2.81
41	0.54	1.29	0.97	1.26	0.56	1.54	0.96	1.11
43	0.24	1.28	0.46	1.24	0.67	1.39	1.24	1.82
45	0.27	1.91	0.85	1.44	1.79	2.2	1.93	1.77
47	0.39	0.94	0.98	0.34	0.48	0.55	0.9	1.03
49	0.21	0.36	0.53	1.95	1.78	0.7	1.34	0.95

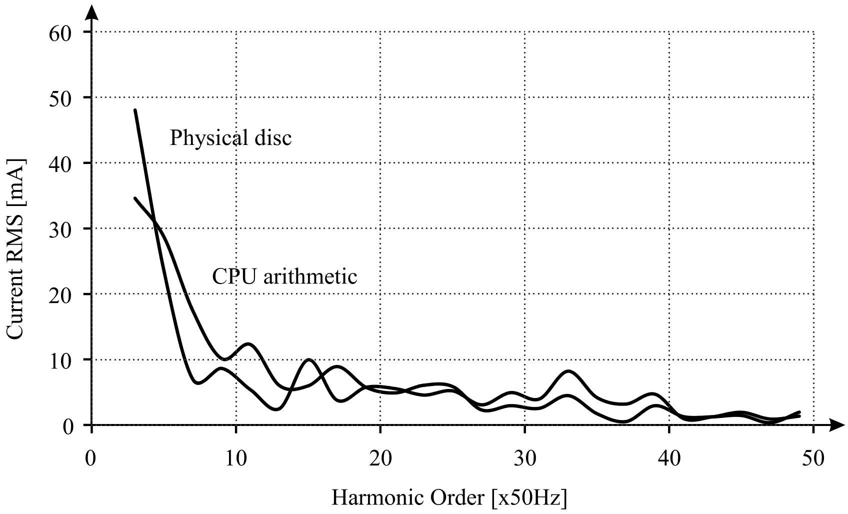

Fig. 8 Measured odd harmonics in two cases: physical disc drive active and CPU loaded by arithmetic computations. The first harmonic is omitted for convenience

Question is: What would this table have to do with security?

There are many security issues related to the grid. Among them the most vulnerable subsystem, looking from the ICT point of view, is the advanced metering infrastructure (AMI). While it could bring significant benefits, it is potentially subject to security violations such as tampering with software in the meters, eavesdropping on its communication links, or abusing the copious amount of private data the new meters are able to collect. In addition to securing market sensitive data from competitors, information systems for the power grid need to defend against to malicious attacks [41] that intend to harm the power grid as a whole. The more comprehensive an information system becomes, the greater the consequences of a successful attack and thus the need for security measures increases.

One of the ways of eavesdropping a home, an office, or a company is monitoring the power consumption and creating an energy profile of the subject [42]. Having this information a large number of malicious actions can be undertaken such as burglaries and other damaging security breaches. Here we expose an additional way of eavesdropping where the harmonic structure of the current drawn from the grid is base for information on the activities within a home or an office. The problem will be illustrated on the example depicted in Table 2.

Here the PC is taking the role of the whole which is supervised. We will show in the next how one can precisely find the state in which the computer is, based on measurements of the supply current taken by its AC/DC converter from the grid. Note, in the example depicted in Table 2, power factor correction was applied within the converter.

While there are several possibilities that allow information to be extracted from Table 2 about the state in which the computer is, here we will use ANNs.

An ANN was trained to create a response recognizing which one of the sets of harmonics of Table 2 is present at its input. Its structure is depicted in Fig. 9. To simplify, for the proper vector of harmonics, the corresponding output of the ANN was forced to unity while the rest of the outputs were kept at zero. In other words, it was trained to recognize which software was running within the computer. Full success was achieved meaning, after training, the ANN was classifying perfectly.

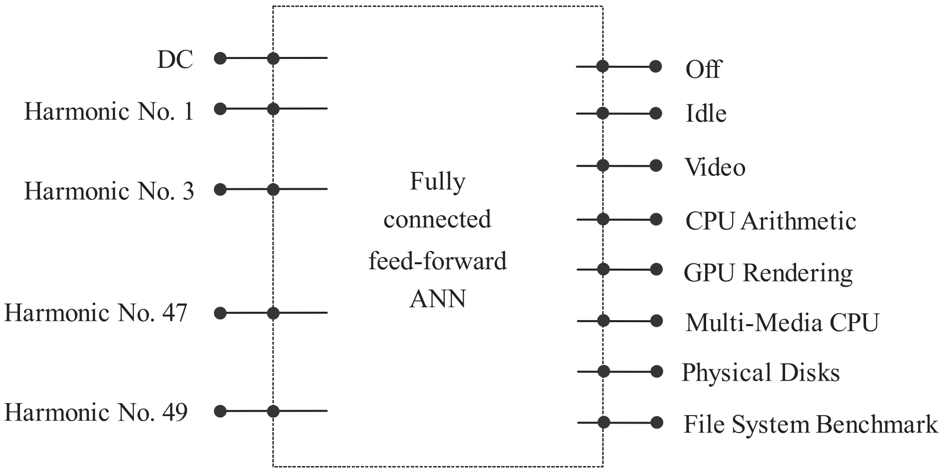

Fig. 9 Artificial neural network that eavesdrops the personal computer based on information on harmonics in its mains current

To make the problem harder, i.e. to introduce the possible variations due measurement errors, we transformed Table 2 so that every entry was recalculated by the formula

$$x_{new} = x \cdot [1 + (2 \cdot rnd - 1) \cdot 0.025]\,, \tag{3}$$

where *rnd* is a pseudo-random number with uniform distribution within the [0,1] segment. In other words a "noise" of amplitude (peak-to-peak) as large as 5% of the harmonic value was added as "measurement disturbance". Again, as can be seen from Table 3, excellent classification was obtained.

Table 3 Responses of the ANN to noisy input data

ANN's Output→ Input vector↓	Off	Idle	Video	CPU Arithmetic	GPU Rendering	Multi-Media CPU	Physical Disks	File System Benchmark
(1)	0.94189 1	-0.00826428 0	-4.98446e-05 0	0.0596502 0	0.00545632 0	-2.68923e-05 0	0.00254522 0	0.00128351 0
(2)	-0.100789 0	0.936809 1	-6.30066e-05 0	0.107029 0	-0.00390563 0	-4.56815e-05 0	0.0353001 0	0.0301201 0
(3)	0.0747284 0	-0.0347075 0	1.00742 1	-0.0946782 0	0.0368009 0	6.60139e-06 0	0.0172143 0	-0.00950488 0
(4)	0.0530374 0	-0.00513355 0	-3.01133e-05 0	0.94394 1	0.00599003 0	4.07148e-06 0	-0.00314594 0	0.0039932 0
(5)	-0.0714551 0	0.141341 0	0.000249561 0	0.347383 0	0.694706 1	2.93044e-05 0	-0.0165517 0	-0.0935344 0
(6)	-0.0390391 0	-0.068559 0	-2.64327e-05 0	0.0464038 0	-0.0182126 0	0.994595 1	0.0357881 0	0.0513166 0
(7)	0.0221675 0	-0.0245939 0	-7.75624e-06 0	-0.0287134 0	0.0235965 0	-8.00252e-07 0	1.01758 1	-0.010466 0
(8)	0.0524894 0	-0.0178626 0	-6.26366e-05 0	-0.0587603 0	0.0177179 0	1.40437e-06 0	0.00103932 0	1.00386 1

Finally, eight new sets of “harmonics” were created artificially by permutations within the rows in Table 2 and the newly created columns were used as excitation to the ANN. None succeeded to deceive the network.

To conclude, there are robust classification mechanisms whose implementation may give to a malicious attacker, having a sophisticated tool based on current monitoring, an opportunity to monitor every activity within a computer and, in general, a data centre or similar. Note, the spectrum of a current taken by a household is not much more complicated than the one of the computer since the main consumers in the household are linear loads and do not generate additional harmonics. From that point of view, we consider our method applicable to a broader list of situations then just a computer.

5. Conclusion

The modern electricity distribution system gradually evolves into a very large and very complex structure in which ICT is getting more and more important role. It is nowadays most frequently referred to as smart grid. There is almost unlimited number of possible applications of ICT subsystems within the smart grid and one is not to say that smart grid is a fixed structure whose capabilities are finally set. A special offer of the ICT to the smart grid is artificial intelligence and particularly the artificial neural networks. Here we represent our attempts to contribute to the development of the smart grid toward an advanced, reliable and secure system. The case studies reported are part of the same project since the same methodology is implemented and they are considering two important and interrelated aspects: the profiling of the load and the protection of the grid.

In particular, we discussed some of the most recent results produced within the Laboratory for Electronic Design Automation at the University of Niš, Serbia, which are related to load prediction at suburban level, and a new way of cyber-attack to the ICT connected to the grid. Both results are based on our own methodology of measurements and own concepts of implementation of ANNs.

As for the load prediction it is worth mentioning that the results reported are part of a set of implementation of our concept to short term [43], medium term [40], and long term [44] prediction of electricity loads. When appropriate, e.g. short term prediction, real-time implementation of the prediction was implemented [39]. The results related to the profiling the computer looking at it from the grid, however, are brand new and will be further elaborated and implemented to more complex computer loads such as data centres or company networks.

Acknowledgement: *This research was partly funded by The Ministry of Education, Science and Technological Development of Republic of Serbia under contract No TR32004.*

References

[1] V. Litovski, P. Petković, ”Why The Power Grid Needs Cryptography?”, Proc. of the symposium on industrial electronics - INDEL 2008, Banja Luka, 06.11.-08.11., 2008, pp. 75-81. Reprinted in: Electronics, ISSN 1450-5843, Vol. 13, No. 1, June 2009, pp. 30-36.

[2] M., Dimitrijević, J., Milojković, S., Slobodan Bojanić, O., Nieto-Taladriz, and V., Litovski, “*ICT and power: new challenges and solutions*”, Int. J. Reasoning-based Intelligent Systems, Vol. 5, No. 1, 2013, pp. 32-41. Publisher: Inderscience Enterprises, ISSN: 1755-0556, E-ISSN: 1755-0564.

[3] -,"GeSI SMARTer 2020: The Role of ICT in Driving a Sustainable Future", The Boston Consulting Group, http://gesi.org/SMARTer2020.

[4] S. Iyer, "Cyber Security for Smart Grid, Cryptography, and Privacy", Hindawi Publishing Corporation, *Int. J. of Digital Multimedia Broadcasting*, Vol. 2011, Article ID 372020, 8 pages.

[5] W. Wang, and Z. Lu, "Cyber security in the Smart Grid: Survey and challenges", *Computer Networks*, vol. 57, pp. 1344–1371, 2013.

[6] F. Aloul, A. R. Al-Ali, R. Al-Dalky, M. Al-Mardini, and W. El-Hajj, "Smart Grid Security: Threats, Vulnerabilities and Solutions", *International Journal of Smart Grid and Clean Energy*, vol. 1, no. 1, pp. 1-6, 2012.

[7] R. Harmon, H. Demirkan, "The Next Wave of Sustainable IT", *IT Professional*, vol. 13, no. 1, pp. 19-25, Jan./Feb. 2011, doi:10.1109/MITP.2010.140.

[8] -,"Electricity Consumption and Efficiency Trends in the Enlarged European Union", Institute for Environment and Sustainability, 2007, http://www.eubusiness.com/ topics/energy/electricity-jrc.bk/

[9] A. P. Bianzino, A. K. Raju, D. Rossi, "Greening the Internet: Measuring Web Power Consumption", *IT Pro*, January/February 2011, Published by the IEEE Computer Society, pp. 48-53.

[10] O. Nieto, et al., "Energy Profile of a Personal Computer", Proceedings of the LVI Conf. of ETRAN, Zlatibor, Serbia, June 2012, ISBN 978-86-80509-67-9, Proc. on a disc, Paper EL3.3-1-4.

[11] R. Adam, W. Wintersteller, *From Distribution to Contribution. Commercializing the Smart Grid*, Booz & Company, Munich, 2008.

[12] J. Miller, "The Smart Grid – How Do We Get There?", *Smart Grid News*, June 26, 2008. http://www.smartgridnews.com/

[13] -,"SMART 2020: Enabling the Low Carbon Economy in the Information Age", Climate Group, GeSI 2008, www.theclimategroup.org/assets/resources/publications/Smart2020 Report.pdf.

[14] D. Ramchurn, P. Vytelingum, A. Rogers, A., and N. R. Jennings, "Putting the 'Smarts' Into the Smart Grid: A Grand Challenge for Artificial Intelligence", *Communications of the ACM* , vol. 55, no. 4, April 2012.

[15] S. Kalogirou, K. Metaxiotis, and A. Mellit, "Artificial Intelligence Techniques for Modern Energy Applications*", Intelligent Information Systems and Knowledge Management for Energy: Applications for Decision Support, Usage, and Environmental Protection*, IGI Global, pp. 1-39, 2010.

[16] S. Kalogirou, C. Neocleous, and C. Schizas, "Artificial neural networks for modelling the starting up of a solar steam generator", *Applied Energy*, vol. 60, pp. 89– 100, 1998.

[17] P. L. Zervas, H. Sarimvies, J. A. Palyvos, N. G. C. Markatos, "Model-based optimal control of a hybrid power generation system consisting of photovoltaic arrays and fuel cells", *Journal of Power Source*, vol. 181, pp. 327–338, 2008.

[18] P. J. Werbos, "Approximate Dynamic Programming for Real Time Control and Neural Modelling". In *White DA and Sofge DA* (Eds.), Handbook of Intelligent Control, Van Nostrand Reinhold, New York, 1992, pp. 493-525.

[19] Y. Mansour, E. Vaahedi, M. A. El-Sharkawi, "Dynamic security contingency screening and ranking using neural networks", *IEEE Trans Power Syst.*, vol. 8, no. 4, pp. 942–950, July 1997.

[20] D. Riley, G. K. Venayagamoorthy, "Characterization and modeling of a grid connected photovoltaic system using a recurrent neural network", in *Proc. IEEE Int. Joint Conf. Neural Networks*, San Jose, CA, July 31–Aug. 5, 2011.

[21] B. G. Zhang, E. Patuwo, and M. Y. Hu, "Forecasting with artificial neural networks: The state of the art", *International Journal of Forecasting,* vol. 14, no. 1, pp. 35-62, March 1998.

[22] J. G. M . Zade, and R. Noori, "Prediction of municipal solid waste generation by use of artificial neural network: A case study", *Int. J. Environmental Reserch*, vol. 2, no. 1, pp. 13-22, 2008.

[23] S. Canu, Y. Grandvalet, and X . Ding, "One Step ahead forecasting using Multilayered perceptron", *Working Paper de I'universite de Technologie de Compiegne.*

[24] J. Connor, and R. Douglas Martin, "Recurrent neural networks and robust time series prediction", *IEEE Trans. On Neural Networks,* vol. 5, no. 2, pp. 240-254, March 1994.

[25] Y. Simmhan, S. Aman, B. Cao, M. Giakkoupis, A. Kumbhare, Q. Zhou, D. Paul, C. Fern, A. Sharma, V. Prasanna, "An informatics approach to demand response optimization in smart grids", Technical report, Computer Science Dept., USC, 2011.

[26] C. King, "Advanced Metering Infrastructure (AMI) Overview of System Features and Capabilities", eMeter Corporation, https://www.smartgrid.gov/sites/default/files/doc/files/Overview_AMI_System_Features_Capabilities_200405.pdf

[27] M. Dimitrijević, and V. Litovski, „Power Factor and Distortion Measuring for Small Loads Using USB Acquisition Module", *Journal of Circuits, Systems, and Computers*, vol. 20, no. 5, pp. 867-880, August 2011.

[28] T. Masters, *Practical Neural Network Recipes in C++*, Academic Press, San Diego, 1993.

[29] Z. Zografski, "A novel machine learning algorithm and its use in modeling and simulation of dynamical systems", *Proc. of S"" Annual European Computer Conference, IEEE COMPEURO'91,* Bologna, Italy, pp. 860-864, 1991.
[30] T. Denoeux and R. Lengelle, "Initializing back propagation networks with prototypes", *Neural Networks* (Pergamon Press), vol. 6, pp. 351-363, 1993.
[31] G.-B. Huang and H. A . Babri, "Upper bound on the number of hidden neurons in feedforward networks with arbitrary bounded nonlinear activation function", *IEEE Trans, on Neural Networks,* vol. 9, pp. 224-228, 1998.
[32] E. B. Baum and D. Haussler, "What size net gives valid generalization", *Neural Computing,* vol. 1, pp. 151-160, 1989.
[33] J. Milojković, and V. Litovski, "Comparison of Some ANN Based Forecasting Methods Implemented on Short Time Series", 9th Symposium on Neural Network Applications in Electrical Engineering, NEUREL-2008, pp. 179-179, Belgrade, Serbia, 2008.
[34] H. M. Al-Hamadi, S. A. Soliman, "Short-term electric load forecasting based on Kalman filtering algorithm with moving window weather and load model", *Electric Power Systems Research*, Vol. 68, No. 1, 2004, pp. 47-59.
[35] S., Tzafestas, and E., Tzafestas, "Computational Intelligence Techniques for Short-Term Electric Load Forecasting", *Journal of Intelligent and Robotic Systems*, Vol. 31, No. 1-3, 2001, pp. 7-68.
[36] F. Schweppe, B. Daryanian, and R. Tabors, "Algorithms for a spot price responding residential load controller", *Power Engineering Review* vol. 9, no. 5, pp. 49–50, 1989.
[37] F. Liu, R. D. Findlay, Q. Song, "A Neural Network Based Short Term Electric Load Forecasting in Ontario Canada", in Int. Conf. on Computational Intelligence for Modelling Control and Automation, and Int. Conf. on Intelligent Agents, Web Technologies and Internet Commerce, (CIMCA-IAWTIC'06), 2006, pp. 119 – 125.
[38] Worldwide competition within the EUNITE network. (2001). [Online] Available: http://neuron.tuke.sk/competition
[39] J. Milojković, V. Litovski, "Dynamic One Step Ahead Prediction of Electricity Loads at Suburban Level", Proc. of the First IEEE Int. Workshop on Smart grid Modeling and Simulation – at IEEE SmartGridComm 2011, SGMS2011, Brussels, October 2011, Proc. on disc, paper no. 25.
[40] J. Milojković, V. Litovski, "One Day Ahead Peak Electricity Load Prediction", IX Symposium Industrial Electronics, INDEL 2012, Banja Luka, November 2012, pp. 261-267.
[41] F. Cleveland, "IEC TC57 security standards for the power system information infrastructure beyond simple encryption", June 2007. IEC TC57 WG15 Security Standards White Paper ver. 11. http://www.xanthus-consulting.com/pages/publications.htm
[42] M. Andrejević Stošović, M. Dimitrijević, V. Litovski, "Computer Security Vulnerability Seen from the Electricity Distribution Grid Side", *Applied Artificial Intelligence*, Taylor & Francis Ltd., 2014, accepted for publication.
[43] J. Milojković, and V. Litovski, "New ANN models for short term forecasting of electricity loads", Proc. of the 7th EUROSIM Congress on Modelling and Simulation Vol.2: Full Papers (CD), Czech Technical University in Prague, Faculty of Electrical Engineering, Dept. of Computer Science and Engineering, Prague, Czech Republic ISBN 978-80-01-04589-3, September 2010.
[44] J. Milojković, V. Litovski, O. Nieto-Taladriz, and S. Bojanić, "Forecasting Based on Short Time Series Using ANNs and Grey Theory – Some Basic Comparisons"**,** in Proc. of the 11th Int. Work-Conference on Artificial Neural Networks, IWANN 2011, June 2011, Torremolinos-Málaga (Spain). J. Cabestany, I. Rojas, and G. Joya (Eds.): Part I, LNCS 6691, pp. 183–190, 2011, © Springer-Verlag Berlin Heidelberg 2011. ISSN: 0302-9743.