Proceedings of the 14th International Middle East Power Systems Conference (MEPCON'10), Cairo University, Egypt, December 19-21, 2010, Paper ID 235.

Applying Neurofuzzy Computing for Safety Improvement of Nuclear Power Reactor

Mohamed A. Metwally
Suez Canal Authority
moh_metwally@hotmail.com

Ashraf Aboshosha
Atomic Energy Authority
editor@icgst.com

Doaa khalil Ibrahim, and Essam EL-Din Abou EL-Zahab
Faculty of Engineering, Cairo University
doaakhalil73@hotmail.com, zahab0@yahoo.com

***Abstract* - Nuclear Power Reactors (NPRs) are large in scale and complex, so the information from local fields is excessive, and therefore plant operators cannot properly process it. When a plant malfunction occurs, a great data influx is occurred, so the cause of the malfunction cannot be easily or promptly identified. A typical NPR may have around 2,000 alarms in the Main Control Room (MCR) in addition to the display of analog data. During plant transients, hundreds of alarms may be activated in a short time. Hence, to increase the plant safety, this paper proposes a support system based on neurofuzzy that assists alarming and diagnosis systems. Throughout this framework the neurofuzzy fault diagnosis system is employed to fault diagnosis of nuclear reactors. To overcome weak points of both linguistic and neuro learning based approaches, integration between the neural networks and fuzzy logic has been applied by which the integrated system will inherit the strengths of both approaches.**

***Index Terms*—Nuclear Power Plant, fault diagnosis, reactor passive safety, neural network, neurofuzzy.**

I. INTRODUCTION

A fault diagnosis system is a kind of operator support system. The objective of a fault diagnosis system is to reduce human mistakes, and to ease the workload of operators by quickly suggesting likely faults based on the highest probability of their occurrence. During the first few minutes after an accident occurrence, operators in a MCR must perform highly mentally work loaded activities. The operators may be overworked and disorders may result. Information overload and stress may severely affect operators' decision making ability. In such situations, using a fault diagnosis system will be very helpful to enhance operators' decision-making ability and reduce their workload [1, 2].

Recently many advanced fault diagnosis intelligent systems have been developed using information and digital technologies. In the field of artificial intelligence, neural network is the most common used method, but with some weak features such as: the over learning, and local minima problems. To overcome those weaknesses, the nuclear power plant (NPP) is partitioned to small separate fault diagnosis systems to decrease the quantity of input/output data and make the best processing data that does not confuse neural network with all data of the NPP in same program, and then the outputs of all programs will be collected in a global fault diagnosis program [3, 4, 5].

Behaviour due to unknown input pattern signals is another weakness, adding a fuzzy logic stage prior to the neural network stage is necessary to overcome such weakness in resent used methods.

Fuzzy logic incorporates the human-like reasoning style of fuzzy systems through the use of fuzzy sets and a linguistic model consisting of a set of IF-THEN fuzzy rules [6, 7].

Neurofuzzy refers to combinations of artificial neural networks and fuzzy logic that result in a hybrid intelligent system by combining the human-like reasoning style of fuzzy systems with the learning and connectionist structure of neural networks. Neurofuzzy hybridization is widely termed in literature as Fuzzy Neural Network (FNN) or Neurofuzzy system (NFS) [8].

In this paper, the reactor passive safety for NPP and reactor's safety based on Artificial Intelligence have been introduced. The study of applying neurofuzzy diagnosis system (NFDS) on the recognition of multiple alarms in NPRs has been introduced. A proposed technique is applied on detailed fault diagnosis of a central critical node.

Throughout this framework, the alarm and fault patterns of Kori II reactor have been employed. The diagnosis of faults is approached from a pattern matching perspective in that an input pattern is constructed from multiple alarm symptoms and that symptom pattern is matched to an appropriate output pattern that corresponds to fault occurred. The first stage of the proposed technique is a fuzzy system where the rules are applied to check whether the input pattern is known, else to make two possibilities for unknown alarm pattern. The second stage is multi-layer neural network.

The results of training and testing of this proposed technique have been shown in details. Such results ensured that proposed NFDS can be used on any NPP, thus it may be used on IV generation of NPR.

II. SAFETY FACTORS OF (NPP)

NPPs are complex and large in scale; they have 17 critical points as shown in Fig. 1 [2]. Fault diagnosis can be carried out for each point of them. To increase plant safety, the operator support systems such as neurofuzzy assisted alarming and diagnosis systems become more important.

Some essential recommendations have been proposed including the passive safety of nuclear reactors. Moreover, intensive research on AI techniques for present nuclear reactors is presented.

The following attributes are essential factors for future reactor designs [9, 10]:

- The reactor should be naturally or passively safe. This means that the reactor should be "inherently" safe and not in need for external safety. In other words, the plant is placed in the most vulnerable condition; operators can withdraw all control rods and simultaneously stop all coolant flow, without any adverse impact.
- The transparency of the safety of the plant must be obvious to both the public and the regulators. The design must support risk-informed regulation (the safety must be demonstrable).
- The design should be acceptable for national and international market in terms of safety under a standard international safety authority.
- The plant should be simple to operate, upgrade and maintain for limited staff with less technical expertise.
- The plant design must support short construction time to reduce the cost with the eventual decommissioning in mind. Sizing and design of systems to facilitate rapid disassembly, ease of decontamination, and ease of disposal should be performed.
- Online capability to refuel and perform maintenance.
- The system should ensure minimal environmental impact.
- The design should use a simple fuel cycle to have high fuel burn up, and support burning mixed oxide fuels. Additionally, the fuel type used must offer ease of fuel storage, disposal and good fuel integrity.
- The reactor should be able to be site assembled and transported to the definite sites quickly.

II-A Reactor Passive Safety

The design criterion of modern reactors takes advantage of the inherent safety characteristics of specific design optimizations. Passive safety of nuclear reactors determines a safety feature of a nuclear reactor that does not require operator action or electronic feedback in order to shut down safely in the event of a particular type of emergency (usually overheating resulting from a loss of coolant or heat exchange malfunction). Such systems depend more on the engineering of components such that their predicted behaviours according to known laws of physics that would slow, rather than accelerate, the nuclear reaction in such circumstances. This is in contrast to some older reactor designs, where the natural tendency for the reaction was to accelerate rapidly from increased temperatures, such that either electronic feedback or operator triggered intervention was necessary to prevent damage to the reactor.

The current reactor generation adopted the active safety where electrical or mechanical operation on command systems are employed to achieve the safety or to shutdown the system. Some advanced reactors manage the safety entirely passively via e.g. relief valves that get the overpressure under control or high-pressure water pumps etc. This indirect passive system is still in need to redundant systems. The full passive systems rely only on physical phenomena such as pressure differentials, conversion, gravity or natural response to slow or shutdown the reactor without any instrumental intervention either mechanical or electrical.

The indirect passive safety systems are applied in some current Pressurized Water Reactors (PWR) and Boiling Water Reactors (BWR) where they have been designed with one kind of passive safety feature. In case of excessive-power conditions, as the water in the nuclear reactor core boils pockets of steam are formed. These steam voids moderate fewer neutrons, causing the power level inside the reactor to lower.

In other designs, the core of a fast breeder reactor is immersed into a pool of liquid metal. If the temperature of the reactor increases, thermal expansion of the metallic fuel and cladding causes more neutrons to escape the core, and the nuclear chain reaction can no longer be sustained. The large mass of liquid metal also acts as a heat sink capable of absorbing the decay heat from the core, even if the normal cooling systems would fail.

The migration from the old versions of nuclear reactors to the new one is a great step especially in safety and robustness. This generation incorporate passive or inherent safety features which require no active controls or (human) operational intervention to avoid accidents in the event of malfunction, and may rely on pressure differentials, gravity, natural convection, or the natural response of materials to high temperatures.

The pebble bed reactor is an example of a passively-safe reactor at overheating conditions. Doppler broadening increases the probability that neutrons are trapped by U-238 atoms. This reduces the chance that the neutrons are trapped by U-235 atoms and initiate fission. In this manner the reactor's power output is reduced and that places an inherent upper limit on the fuel temperature.

This design is considered the basic of the IV generation of nuclear reactor safety system design [10, 11].

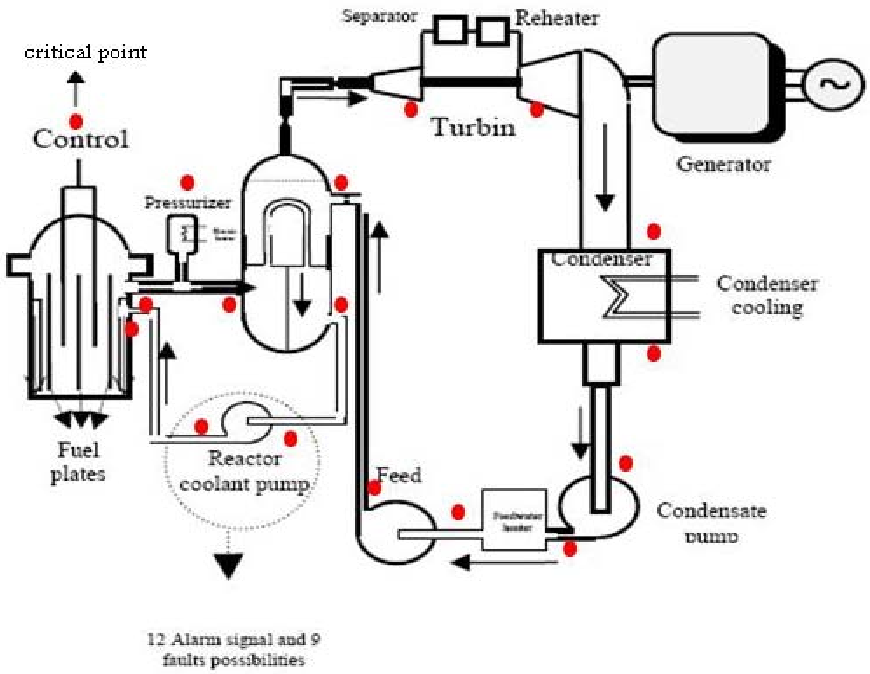

Fig. 1: A typical core and cooling cycle of pressurized water reactor with17 critical points [2]

II-B Reactor's Safety based on Artificial Intelligence AI

Fault diagnosis can be performed relying on an analytical model of the nuclear reactor under study that represents the normal behavior of the reactor in the absence of any fault. From the theoretical point of view, non-linear system diagnosis is particularly difficult. From the practical point of view, difficulties result from the model imprecision and from unknown disturbances. This leads to a trade-off between false alarm rate and missed detection rate.

Following diagnosis, recovery procedures can be implemented, resulting in what is called fault tolerant control. In complex processes, like nuclear reactor, obtaining a sufficiently precise analytical model could take years and other diagnostic methods based on new types of models must be used. Digital signal processing is another approach to fault diagnosis when an analytical model is not available. Signals may be analyzed either with time-domain methods, with frequency domain methods, or with more sophisticated methods like wavelet analysis. With these approaches, the difficulty is to ensure that a change in some quantity is characteristic of a particular fault.

AI-based diagnostic systems have been extensively studied to support nuclear reactors operators during abnormal conditions. The main tasks of a diagnostic system are alarm detection and fault diagnosis. A fault represents a deviation with respect to the expected system behaviour. Alarm signals are elaborated on real time case of study. Fault detection consists in the generation of symptoms from the fault indicators and the evaluation of the time of detection. Fault detection determines, from a set of symptoms, the kind and the location of the primary fault and relates it to a physical component whose behaviour is not consistent. Even if it is clear that diagnosis is a strategic necessity, very few real applications are yet in use.

AI based classification or pattern recognition approach is the way to deal with fault diagnosis. It is based on process data or expert knowledge about the nuclear reactor. Relevant symptoms are identified to be representative of each type of failure. The relationships between symptoms and faults are obtained by supervised learning when faults are known a priori, for instance by an expert: in this case the system decision is tuned to correspond to the right answer from a training set of known examples. The diagnostic system is a classifier that must then recognize, in real time, the actual situation represented by a new symptom vector and associate it to one of the known faults. The classifier may also have some on-line learning capacity to deal with unknown faults [4, 5].

III. PROPOSED NEUROFUZZY APPROACH

In diagnostic applications, faults are characterized by their symptoms, which can evolve with time, performing a trajectory in the observed variable space. The stages of the Neurofuzzy Fault Diagnosis System (NFDS) are shown in Fig. 2. The overall NPR has tight alarming and fault diagnosis system. This system has multi-level alarm and fault diagnosis techniques. Every part of the plant has its own diagnosis system. The overall plant has a global alarming and fault diagnosis system, which links all individual subsystems. As the control system of the plant can be tested by NFDS to define the fault if found, also all parts of the plant can be tested by a pattern recognition NFDS techniques [8].

III-A Fault Diagnosis of Kori II Cooling Pump

This subsection introduces more details on neurofuzzy fault diagnosis in a certain node, it is the cooling pump. Reactor cooling pump (RCP) is considered one of the most important parts of the NPR (1 of 17 critical points). This critical point has 12 alarming signals (a1, a2, a3, ..., a12) and the possibility of faults are 9 faults (f1, f2, f3, ... f9). The definition of the faults and their corresponding alarms are tabulated in Table 1.a, b.

Neural pattern recognition tool in MATLAB platform is used to create this neural network; it consists of 12 input nodes, 10 hidden nodes, and 9 output nodes as shown in Fig. 3. Different designs with different number of hidden nodes have been proposed but give great errors that ensured that using 10 hidden nodes give more accurate design with small accepted error. As the error back propagation training algorithm (EBPTA) is running, weights of the NFDS are changing till the allowed RMS error reaches its recommended learning value, and thus learning stops. Neural network training has been achieved using 41 known alarm patterns as shown in Table 2. Then by using these weights of the NFDS, the diagnosis of any fault caused by any other alarm patterns can be achieved.

The flow chart of the NFDS proposed is shown in Fig. 4, as it consists of two major stages: the first one is the fuzzy system and the second one is the neural network [2].

This proposed technique can be used in the global fault diagnosis system in all critical points in the NPP as shown in Fig. 1.

III-B Testing of Neural Network Training

The outputs comparison of both reference training patterns and neural network outputs showed that they are nearly typical as the percentage error is less than 1%. These results are achieved when the network has been trained using 41 known cases as given data.

Therefore, the network is well trained and it can easily detect any possible system faults.

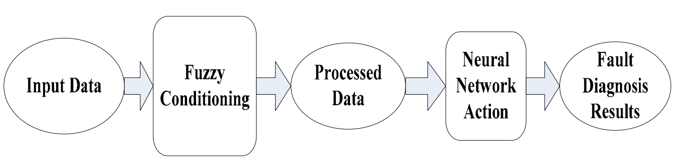

Fig. 2: Neuro-Fuzzy Diagnosis System (NFDS)

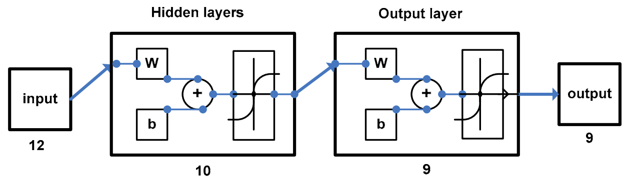

Fig. 3: Neural network using neural pattern recognition tool

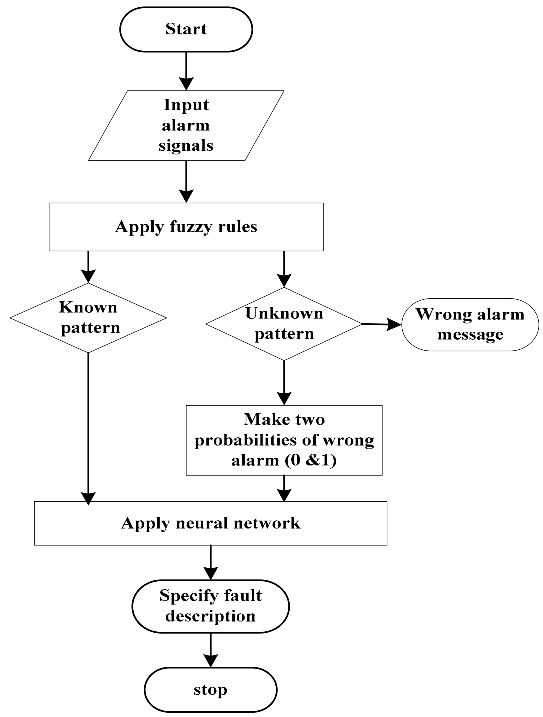

Fig. 4: flow chart of proposed NFDS

Table (1.a) Alarming signals definitions

Alarm signal	Description
a1	Seal injection filter differential pressure high
a2	Charging pump flow low
a3	Seal injection flow low
a4	No. 1 Seal differential pressure low
a5	No. 1 Seal leak off flow low
a6	Standpipe level low
a7	Standpipe level high
a8	No. 1 Seal leak off flow high
a9	Thermal barrier flow low
a10	Thermal barrier temperature high
a11	Bearing flow low
a12	Bearing temperature high

Table (1.b) Fault signals definitions

Fault signal	Description
f1	Seal injection filter blockage
f2	Charging pump failure
f3	Seal injection water high temperature
f4	Reactor coolant system pressure less than 400 psig
f5	No. 1 Seal damaged
f6	Volume control tank back pressure high
f7	No. 2 Seal failure
f8	Insufficient component cooling water flow to RCP
f9	Motor Bearing damaged

III-C Testing of NFDS

Testing NFDS is achieved with no alarm cases, some training cases, combined cases (two known cases are combined in one case) and wrong alarm cases (alarm signals lie between 0.2 and 0.8).

Because of the limited space of the paper, some of testing results are illustrated in Table 3. As obviously shown, proposed NFDS accurately detects and specifies all fault cases. It can also detect wrong alarm signal and in such case, it assumes the possibility of two alarm cases occurring and then specify either one or two faulty cases.

Table 2 : 41 alarm cases

Case no.	a1	a2	a3	a4	a5	a6	a7	a8	a9	a10	a11	a12
1	1	0	0	0	0	0	0	0	0	0	0	0
2	1	0	1	0	0	0	0	0	0	0	0	0
3	1	0	1	1	0	0	0	0	0	0	0	0
4	1	0	1	0	1	0	0	0	0	0	0	0
5	1	0	1	0	0	0	0	0	0	1	0	0
6	1	0	1	1	1	0	0	0	0	0	0	0
7	1	0	1	0	1	1	0	0	0	1	0	0
8	1	0	1	0	1	0	0	0	0	1	0	0
9	1	0	1	1	0	0	0	0	0	1	0	0
10	1	0	1	0	1	1	1	0	0	0	0	0
11	1	0	1	0	1	1	0	1	0	0	0	0
12	1	0	1	1	1	0	0	0	0	1	0	0
13	0	1	0	0	0	0	0	0	0	0	0	0
14	0	1	1	0	0	0	0	0	0	0	0	0
15	0	1	1	1	0	0	0	0	0	0	0	0
16	0	1	1	0	1	0	0	0	0	0	0	0
17	0	1	1	0	0	0	0	0	0	1	0	0
18	0	1	1	1	1	0	0	0	0	0	0	0
19	0	1	1	0	1	1	0	0	0	1	0	0
20	0	1	1	0	1	0	0	0	0	1	0	0
21	0	1	1	1	0	0	0	0	0	1	0	0
22	0	1	1	0	1	1	1	0	0	0	0	0
23	0	1	1	0	1	1	0	1	0	0	0	0
24	0	1	1	1	1	0	0	0	0	1	0	0
25	0	0	0	1	0	0	0	0	0	0	0	0
26	0	0	0	0	1	0	0	0	0	0	0	0
27	0	0	0	0	1	1	0	0	0	0	0	0
28	0	0	0	0	1	1	1	0	0	0	0	0
29	0	0	0	0	1	1	0	1	0	0	0	0
30	0	0	0	0	0	1	0	0	0	0	0	0
31	0	0	0	0	0	1	1	0	0	0	0	0
32	0	0	0	0	0	1	0	1	0	0	0	0
33	0	0	0	0	0	0	0	1	0	0	0	0
34	0	0	0	0	0	0	0	0	1	0	0	0
35	0	0	0	0	0	0	0	0	0	0	1	0
36	0	0	0	0	0	0	0	0	1	1	0	0
37	0	0	0	0	0	0	0	0	0	0	1	1
38	0	0	0	0	0	0	0	0	1	0	1	0
39	0	0	0	0	0	0	0	0	0	0	0	1
40	0	0	1	0	0	0	0	0	0	0	0	0
41	0	0	0	0	0	0	0	0	0	1	0	0

Table 3: Testing of the NFDS

Tested case	i/p Signals		o/p Results		Notes
Testing with No alarm signals	0 0 0 0 0 0 0 0 0 0 0 0		0.0001 0.0000 0.0000 0.0001 0.0001 0.0278 0.0000 0.0001 0.0000		Normal case No fault
Testing With one of the training cases	1 0 0 0 0 0 0 0 0 0 0 0		0.9997 0.0000 0.0000 0.0002 0.0003 0.0001 0.0002 0.0000 0.0005		Case no.1 The result is Fault type (f1)
Testing with two combined cases	1 1 1 1 1 0 0 0 0 1 0 0		0.9991 0.9938 0.0001 0.0001 0.0000 0.0000 0.0361 0.0000 0.0829		Case no.12 combined with case no.13 The result is Fault type (f1) &(f2)
Testing the fuzzy condition If 0.2< a <0.8	0 1 1 0.5000 0 0 0 0 0 0 0 0				One case with wrong alarm signal.
	i/p1	i/p2	op/1	op/2	
Then "a" may be either 0 or 1	0 1 1 0.00 0 0 0 0 0 0 0 0	0 1 1 1.00 0 0 0 0 0 0 0 0	0.0000 0.9996 0.0000 0.0000 0.0000 0.0008 0.0001 0.0000 0.0002	0.0000 0.9996 0.0000 0.0000 0.0000 0.0009 0.0001 0.0000 0.0002	Fault type (f2) in these two results with alarm message “alarm signal is not correct”

a: alarm signal

IV. CONLUSIONS

In this paper, the study of applying NFDS in fault diagnosis of NPRs is presented. The neurofuzzy approach has more powerful advantages (e.g., short knowledge acquisition time, low development cost, fast running time, process to noisy alarm signals, and general mapping capabilities) over the conventional alarm processing methods.

Results showed that once the neural network has been fully trained with various known alarm patterns, it can identify with accepted accuracy the faults. Moreover unknown or incomplete/sensor-failed alarm patterns are given; the network can diagnose faulty cases properly. In addition, multiple faults can be easily diagnosed using a given alarm pattern.

In conclusion, the neurofuzzy approach is almost appropriate for pattern recognition problems in environments where plant actual data are abundant and noisy. Moreover, the neurofuzzy based systems can run very fast if hardware implementations are becoming available. This makes the systems, especially well suited for real-time applications such as alarm processing and fault diagnosis in NPR.

REFERENCES

[1] B. Lu, B.R. Upadhyaya, "Monitoring and fault diagnosis of the steam generator system of a nuclear power plant using data-driven modeling and residual space analysis", Annals of Nuclear Energy, Vol. 32, pp. 897–912, 2005.

[2] A. Aboshosha, F. A. Mohamed, M. Elbardiny, N. El-Rabaie and A. Montasser, "Using Neural Networks in Fault Diagnosis of Nuclear Power Reactor", Proceedings of Fourth IEEE International conference, Electronics , Circuits, and systems ICECS 97, Cairo, Egypt, December 15-18, 1997.

[3] Keehoon Kim, Bartlett, E.B, “Nuclear power plant fault diagnosis using neural networks with error estimation by series association”, IEEE Transactions on Nuclear Science, Vol.43, Issue 4, Aug. 1996, pp. 2373 - 2388.

[4] Mustaf beylĭ, Elif Derya beylĭ, "Using recurrent neural networks for estimation of minor actinides’ transmutation in a high power density fusion reactor", Expert Systems with Applications, Vol. 37, pp. 2742–2746, 2010.

[5] Kun Mo, Seung Jun Lee, Poong Hyun Seong, "A dynamic neural network aggregation model for transient diagnosis in nuclear power plants", Progress in Nuclear Energy, Vol. 49, pp. 262-272, 2007.

[6] Enrico Zio, Piero Baraldi, Irina Crengut_a Popescu, "A fuzzy decision tree method for fault classification in the steam generator of a pressurized water reactor", Annals of Nuclear Energy 36, pp. 1159–1169, 2009.

[7] K. Zhao, B.R. Upadhyaya , "Adaptive fuzzy inference causal graph approach to fault detection and isolation of field devices in nuclear power plants", Progress in Nuclear Energy, Volume 46, Issues 3-4, Pages 226-240, 2005.

[8] E. Zio, G. Gola, "Neuro-fuzzy pattern classification for fault diagnosis in nuclear components", Annals of Nuclear Energy, 33, pp.415–426, 2006.

[9] Mario D. Carelli , L. E. Conway, L. Oriani, “The design and safety features of the IRIS reactor”, Nuclear Engineering and Design, Vol. 230 , pp. 151–167, 2004.

[10] W.E. Cummins, M.M. Corletti, T.L. Schulz, “Westinghouse AP1000 Advanced Passive Plant”, Proceedings of ICAPP ’03 Cordoba, Spain, May 4-7, 2003.

[11] C. W. Forsberg, A. M. Weinberg, “Advanced Reactors, Passive Safety, and Acceptance of Nuclear Energy”, Annual Review of Energy, November 1990.

BIOGRAPHIES

Mohamed A. Metwally was born in May 1982. He graduated with B.Sc. from Zagazige University, Faculty of Engineering Shoubra, Electrical Power and Machines Department in 2004. He was an instructor in the department of electrical power at industrial education collage in 2005. From 2006, he worked as an electrical engineer at Suez Canal Authority (S.C.A.). He joined the M.Sc. program in the field of nuclear power plant (NPP) at electrical engineering Department, Faculty of Engineering, Cairo University.

Ashraf Aboshosha graduated with a B.Sc. in industrial electronics from Menoufia University, Egypt at 1990. Since 1992 he is a researcher at the Egyptian Atomic Energy Authority (EAEA). At 1997 he received his M.Sc. in automatic control and measurement engineering. From 1997 to 1998 he was guest researcher at the central laboratory for electronics (ZEL), research centre Jülich (FZJ), Germany. From 2000 to 2004 he was a doctoral student (DAAD-scholarship) at Wilhelm Schickard Institute for Informatics (WSI), Eberhard-Karls-University, Tübingen. Ashraf Aboshosha is the Editor in Chief of the International Congress for global Science and Technology, ICGST, where he refereed thousands of academic articles from more than 50 countries. He is the organizer and co-organizer of several international conferences on computer science and engineering. At 2010 he is cited in Marquis Who's who.

Doaa khalil Ibrahim (IEEE M’06) was born in Egypt in Dec. 1973. She graduated from Cairo University, Faculty of Engineering, Electrical Power and Machines Department in 1996 and received the M.Sc. and Ph.D. in digital protection from Cairo University at 2001 and 2005, respectively. From 1996 till 2005 she was a demonstrator and research assistant in Cairo University. In September 2005, she became an assistant professor with Cairo University. From October 2005 till Dec.2008, Dr. D. Khalil was contributing in a World Bank Project in Higher Education Development in Egypt. From January 2009, she contributes in the Program of Continuous Improvement and Qualification for Accreditation in Higher Education in Egypt. Her research interests include digital protection of power system, utilization and generation of electric power and renewable energy sources

Essam EL-Din Abou EL-Zahab Received the BSc. and MSc. degrees in electrical power and machines from Cairo University, Giza, Egypt, in 1970 and 1974, respectively. He received the PhD. degree in Electrical Power from Paul Sabatier, Toulouse France, in 1979. Currently he is a Professor in the department of electrical power and machines at Cairo University. He was an instructor in the department of electrical power and machines at Cairo University from 1970 to 1974. His research areas include protection system, renewable energy, and power distribution. He is also the author or co-author of many referenced journal and conference papers.