Paper accepted for presentation at 2009 IEEE Bucharest Power Tech Conference, June 28th - July 2nd, Bucharest, Romania

Application Of Artificial Immune System For Detecting Overloaded Lines And Voltage Collapse Prone Buses In Distribution Network

J. V. Milanović, *Senior Member, IEEE* Jingwei Lu

Abstract— **Biological immune systems are highly parallel, distributed, and adaptive systems, which use learning, memory, and associative retrieval to solve recognition and classification tasks. The Artificial Immune System (AIS) are capable of constructing and maintaining a dynamical and structural identity, capable of learning to identify previously unseen invaders and remembering what it has learnt. As a part of pioneering research in application of AIS to electrical power distribution systems, an AIS based software has been developed for identification of voltage collapse and line overload prone areas in distribution network. The applicability of AIS for this particular task is demonstrated on a 295-bus generic distribution system.**

Index Terms— **artificial immune systems, voltage collapse, overloaded lines.**

I. Introduction

Power distribution systems are a vital lifeline of the modern society for maintaining adequate and reliable flows of electrical energy from transmission network to end users. Distribution reliability has a high impact on the electricity cost and customer satisfaction. A wide range of events such as equipment failures, animal contacts, and lightning strikes have been significantly affecting distributing systems over the years and some have caused power outages. It is of vital importance to diagnose the faults and restore the system operation in a timely manner in order to maintain the system availability and reliability.

Currently, when a power outage is reported to the control centre, the operators estimate the probable outage location based on available information and send their operation and maintenance crews to fix the problem [1]. The crew, typically needs to check distribution feeder section by section until they find the fault location and the cause of it. Sometimes, for safety reasons, many utilities do not restore the distribution system until they have found the cause of outage. In some cases, however, it is difficult or even impossible to find any evidence of the cause of outage, as these may have been removed from their original places [2]. The process of fault identification and network restoration may take tens of minutes to hours. Utilities around the world have been making substantial effort to expedite the network restoration procedures.

With the development of data mining techniques, historical outage data have been utilized to predict outage patterns [3] and to develop adequate network maintenance procedures to avoid outages at the first place. Many methods, mostly computational algorithms, appeared over the years based on this principle. Most of them however, share a common weak point namely, they are ineffective in dealing with data imbalance, which on the other hand is a common real-world issue in data presentation.

In last decade, the Artificial Immune Systems (AIS) have been gaining significant attention in various application areas due to its powerful adaptive learning and memory capabilities. The artificial immune recognition systems (AIRS) algorithm proposed and benchmarked by Watkins and Timmis [4] showed a very good performance as a classification algorithm. A vast array of unexplored application areas still exists for AIS, including many problem areas for which traditional artificial intelligence research techniques (neural networks, genetic algorithms, expert systems) were not appropriate. The complexity of electricity distribution networks, large number of parameters, unavailability or/and uncertainty of many parameters and phenomena involved require application of advanced non-deterministic modeling and computational tools. The AIRS algorithm has been subsequently successfully used on a few occasions in the past for fault diagnosis in power distribution system.

The principle aim of this, to a large extent pioneering project, is therefore to examine the possibility of applying AIS to distribution networks and in particular for identifying failure prone areas of distribution network. For this purpose the AIRS (algorithm and software) is developed as a first step, to identify the areas of the network where voltage collapse and line overload may occur. Developed software is tested on a 295-bus generic distribution network and proved that AIS are very promising tool for handling complex distribution network problems.

II. Brief overview of Artificial immune systems

The artificial immune system (AIS) implements a learning technique inspired by the human immune system, which is a remarkable natural defense mechanism that learns about foreign substances [5].

The immune system (IS) is a highly evolved biological system whose function is to identify and eliminate foreign

J.V.Milanovic is with the School of Electrical and Electronic Engineering, The University of Manchester, PO Box 88, Manchester, M60 1QD, UK. (e-mail: milanovic@manchester.ac.uk).

Jingwei Lu is with Mott Macdonald, Brighton, UK (e-mail: Jingwei.Lu@mottmac.com).

material to prevent development of diseases. It is a combination of cells, molecules and organs that represent an identification mechanism capable of perceiving and combating dysfunction of own cells (infectious self) and the action of exogenous infectious microorganisms (infectious non-self) [6]. The interaction among the IS and several other systems and organs allows the regulation of the body, guaranteeing its stable functioning.

The IS cells and molecules maintain constant surveillance for infecting organisms. They recognize an almost limitless variety of infectious foreign cells and substances, known as non-self elements, distinguishing them from those native noninfectious cells, known as self molecules [7]. When a pathogen (infectious foreign element) enters the body, it is detected and mobilized for elimination. The system is capable of “remembering” each infection, so that a second exposure to the same pathogen is dealt with more efficiently. There are two inter-related systems by which the body identifies foreign material the innate immune system and the adaptive immune system. [8] The innate immune system is so called because the body is born with the ability to recognize certain microbes and immediately destroy them [9], i.e., it can destroy many pathogens on first encounter. The most important aspect of innate immune recognition is the fact that it induces the expression of co-stimulatory signals in antigen presenting cells (APCs) that will lead to T cell activation, promoting the start of the adaptive immune response [10]. The adaptive immune system, as indicated by its name, is a modified, improved system in order to deal with new antigens [11].

The immune system is composed of a great variety of cells that are originated in the bone marrow, where plenty of them mature. From the bone marrow, they migrate to patrolling tissues, circulating in the blood and lymphatic vessels [12]. Some of them are responsible for the general defence, whereas others are “trained” to combat highly specific pathogens [13]. Figure 1 presents a structural division among the cells and secretions produced by the immune system. Detailed descriptions of each of the cells can be found in [5, 13, 14-18].

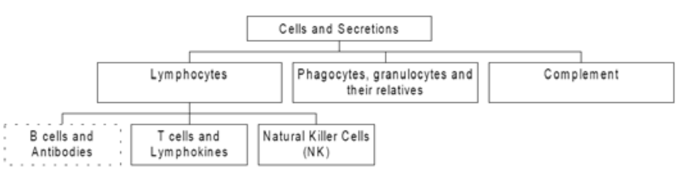

Fig 1. Division of Cells in Immune System (Adopted from [14])

This diverse “army” of cells and molecules that work in concert protects the body and the ultimate target of all immune responses is an antigen (Ag), which is usually a foreign molecule from a bacterium or other invader. Figure 2 presents a simplified version of the basic immune mechanisms of defence.

When an antigen is firstly discovered by the immune body, it is ingested and digested by antigen presenting cells (APCs) [19]. These APCs roam the body, and quickly fragment the antigen into antigenic peptides (Stage I in Figure 2). A part of these peptides are joined together to form major histocompatibility complex (MHC) molecules and are displayed on the surface of the cell [20]. T cells have receptor molecules that enable each of them to recognize a different peptide-MHC combination (Stage II in Figure 2). These T cells activated by that recognition divide and secrete lymphokines mobilize other components of the immune system (Stage III in Figure 2). Unlike the receptors of T cells, those of B cells can

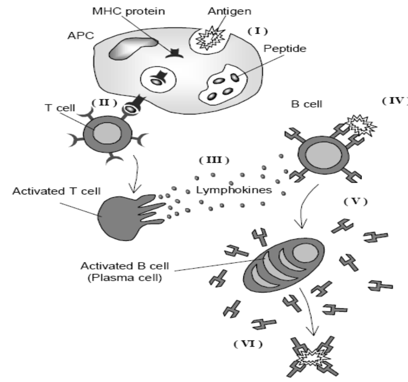

Fig 2. Defensive Mechanism of Immune System (Adopted from [14])

recognize parts of antigens free in solution, without MHC molecules (Stage IV in Figure 2) [20]. When activated, the B cells divide and secrete antibody proteins, which are soluble forms of their receptors (Stage V in Figure 2). These receptors are usually called paratopes. On the surface of each antigen, there are also receptors called epitopes which can be bound by paratopes [14]. By binding to the antigen they find, antibodies can neutralize them (Stage VI in Figure 2) or precipitate their destruction by other components of the immune system. In particular, some T and B cells become memory cells that persist in the circulation and boost the immune system’s readiness to eliminate the same antigen if it presents itself in the future [5]. Because the genes for antibodies in B cell frequently suffer mutation and editing, the antibody response improves after repeated immunizations, this phenomenon is called affinity maturation [21].

The primary advantages of the AIS are that it only requires positive examples, and the patterns it has learnt can be explicitly examined. In addition, because it is self organizing, it does not require effort to optimize any system parameters. Many models and algorithms have been developed based on immune system theories. One of its most outstanding features is that it is responsible for the production of millions (at least) of antibodies from a few hundred antibody genes, permitting animals to survive even when infected by new kinds of organisms, or foreign molecules, which are unlike any that their species has encountered before. Many classification systems are now applying this mechanism as their main learning and memorizing principle. The main characteristics of the IS include:

- It promotes diversification. It does not attempt to focus on global optima; instead it evolves antibodies which can handle different antigens (situations).
- It is a distributed system with no central controller, i.e., it is distributed throughout our bodies via its constituent cells and molecules.
- It is a naturally occurring event–response system which can quickly adapt to changing situations.

- It possesses a self-organizing memory which is dynamically maintained and which allows items of information to be forgotten. It is thus adaptive to its external environment.
- Its memory is content addressable (allowing antigens to be identified by the same antibody) and tolerant to noise in the antigens presented to it.

The areas of application of AIS include pattern recognition, function approximation and optimization, anomaly detection, computer and network security, generation of diversity and noise tolerance [22].

III. Application of AIS in Power Distribution System

There have been very few applications of AIS to power systems in the past. The total number of papers published in this area is about, or slightly over, 20. The principal areas where it has been applied include distribution network planning, fault diagnosis and classification, and online control. Therefore, the work described in this paper is largely pioneering and exploratory in nature.

To accomplish the task of identifying the areas of distribution network prone to voltage collapse and line overload the AIRS algorithm and corresponding software are developed. Load patterns (the load level on all buses in the network) are treated as antigens for the AIS. The AIRS is then trained in order to generate initial antibody pool. After a starting point is specified (a particular load pattern), the process of antibodies generation and mutation is initialized. This is implemented by generating random, diverse, load patterns. Each load pattern represents a specific antibody. The correspondence between different parameters of natural IS and AIRS applied to power system is shown in Table 1.

Table 1: Correspondence between Natural Immune System & AIRS

Natural Immune System	AIRS for Power System
Antigen	Load pattern
Antibody	Load pattern
Antibody Clone	Generating random Load patterns
Pattern Recognition	Power flow calculation
Antigen-Antibody Match	Affinity Calculation

Assuming that each load pattern corresponds to (is associated with) a particular system failure pattern, the AIS will recognise all possible failures related to newly generated antibodies. However, without prior knowledge, the software will not be able to identify any failure pattern related to any load pattern. Results of power flow calculations (voltage magnitudes and line currents) are therefore used to assist the AIS to recognize failure pattern. After all failure patterns are identified, antibodies (load pattern) together with corresponding failure patterns are stored as memory cells.

There are two steps involved in the test procedure.

The first is to train the software with training data in order to identify and store fault patterns. The training process proceeds until load levels are high enough to yield voltage collapse in the system.

The second step is independent form the first one and it generates the output of the programme for given loading scenario. The output includes prediction of voltage collapse prone areas and locations of overloaded and heavy-loaded lines. The output of this stage is compared with the power flow calculation results for the same loading scenario in order to verify the accuracy of the prediction.

After each test, a new memory cell representing the fault pattern produced is recorded and added to antibody database. This step effectively mimics the learning mechanism of natural immune system, and compensates for eventual inaccurate results obtained in previous test so that reliable database of antibodies is stored for future use.

In the training process, the two seasons (summer and winter) are treated separately. For each season, the load curve is sampled once per hour so a continuous load curve is subdivided into 24 discrete load patterns. There are 48 load patterns in total for winter and summer. The 24 load patterns for a given season are used at the training stage of the software. The program first examines each load pattern once as an ‘original load’, and then generates 10 new load patterns by randomly increasing original load at all buses.

This process represents the antibody clone and mutation process in natural immune system. Voltage collapse occurrence for a particular loading pattern can be considered as an antigen. The software randomly generates loading patterns, which represents antibodies, and matches these to different types of antigens by performing load flow calculation. The original loading pattern is a starting point for the training process.

After initial random load generation, power flow calculation is carried out for all new load patterns and the most critical one is identified, i.e., the one that results in the lowest bus voltages in the system. The locations of buses with low voltages and overloaded lines are recorded together with the corresponding loading pattern. These data are sorted added to antibody database.

When the software detects a voltage lower than 0.52 p.u. (arbitrarily chosen) the training process terminates. Loading patterns generated in this process are stored as a reference to prevent generating same or similar loading patterns in the subsequent runs in order to achieve diversity of solutions and loading patterns. Corresponding antibodies are saved in the separate file for future use.

Once these steps are accomplished, the algorithm moves to the next ‘original load’ until all 48 training load patterns have been used as starting loading patterns.

The database of antibodies generated in training stage is used for identification of voltage collapse prone areas and locations of overloaded and heavy-loaded lines for new, randomly generated loading pattern. This newly generated loading pattern is considered as an antigen in the evaluation process. Every antibody from the antibody database is compared with this antigen, and its affinity with the antigen is calculated. Simple Euclidian distance (1) between the antibody and the antigen is used as measure of affinity

$$DISTANCE = \sqrt{\sum_{i=1}^{N}(P_i - P_{i-M})^2 + \sum_{i=1}^{N}(Q_i - Q_{i-M})^2} \qquad (1)$$

where P and Q are corresponding real and reactive power of the i-th bus from the N-bus network.

Based on this affinity calculation, the algorithm identifies the best match between the antibody and the antigen.

The antibody with the largest affinity with the antigen is then chosen for identification of voltage collapse prone areas and overloaded lines.

The results produced by the AIS based algorithm are compared with the results of load flow calculation to establish the accuracy of the prediction.

In total, 131 antibodies are generated during the training stage. Based on these, six tests are conducted on the 300-bus distribution system.

IV. CASE STUDIES

Six case studies based on realistic distribution network are used to test the software in order to examine its accuracy. The study was performed using a generic distribution network (GDN). GDN comprises four 275-kV transmission in-feeds, 132-kV and 33-kV sub-transmission networks (predominantly meshed) and 11 kV distribution network (predominantly radial). There are 295 buses, 276 lines (over head lines and underground cables) and 37 transformers with various winding connections. All GDN parameters are based on realistic UK distribution networks.

The 1st, 2nd and 5th case study are random tests, which examine the overall accuracy of the software in identifying fault prone areas, e.g. voltage collapse and overloaded lines under normal loading level. The 3rd and 4th tests examine the software's performance when dealing with heavy load condition. The 6th test provides a reference for other case studies. Light loading condition is simulated in this case.

The result of each test (identified critical buses and lines) are illustrated on the single line diagram of GDN and summarised in tables together with corresponding power flow results in order compare their accuracy.

A typical daily loading curve (see Fig. 3) of a substation is used initially to produce antibodies. 48 randomly generated load patterns (24 per season) are then used for training the AIS algorithm. Two assumptions are made in the study:

1. There are no under-voltage relays in the system. This is to make sure that when the voltage drops dramatically, no bus will be disconnected from the system because of under-voltage relays.
2. A bus voltage lower than 0.52 p.u will be considered as an indication of voltage collapse. This is basically a criterion used to terminate training process before power flow solution fail to converge.

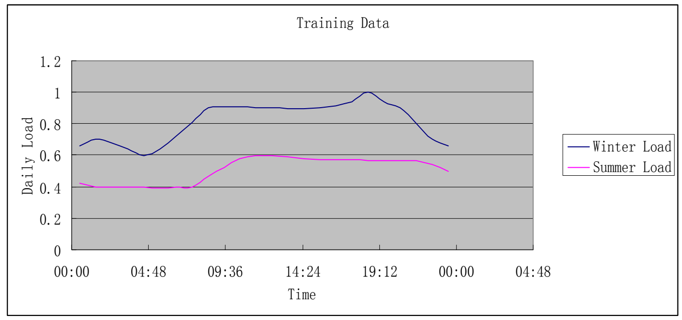

Figure 3. Typical daily loading curves for winter and summer season

The training process is repeated until one or more bus voltages drops below 0.52 p.u. The output of training process is a series of data vectors containing the location of voltage collapse and the overloaded lines and corresponding loading pattern. These data vectors represent memory cells in the natural immune system, and will be used as criteria in the test stage.

The test process is initiated separately and it is independent from training process. The output of this stage includes prediction of voltage collapse prone buses/areas and overloaded and heavily-loaded lines. The results of AIS based calculation are compared with power flow results for this case to examine the accuracy the prediction obtained with the AIS algorithm. The results of six case studies are presented in Tables 2 to 4.

Table 2 presents the lowest voltage magnitudes at GDN buses generated in all case studies. Only the first seven buses with lowest voltages are considered in each case. The ranking of buses is provided by AIS algorithm and voltage magnitudes shown to the right from corresponding bus number in Table 2 are the result of subsequent load flow calculation for that particular case study. Full agreement between the AIS generated ranking and the ranking that can be produced based on load flow results can be observed from this table. This confirms the accuracy of the applied AIS algorithm.

Table 3 presents the line currents for ten most heavily-loaded lines for the case studies 1 to 5. In case study 6, no line was identified as being overloaded or heavily-loaded.

Table 2 : Identified buses with the lowest voltages

Case 1		Case 2		Case 3		Case 4		Case 5		Case 6	
Bus No.	V(p.u)	Bus No.	V(p.u)	Bus No.	V(p.u)	Bus No.	V(p.u)	Bus No.	V(p.u)	Bus No.	V(p.u)
138	0.91	138	0.78	138	0.67	138	0.59	138	0.88	**138**	0.97
137	0.91	137	0.78	137	0.67	137	0.59	137	0.88	**137**	0.97
136	0.92	136	0.79	136	0.68	136	0.61	136	0.89	**136**	0.97
135	0.92	135	0.79	135	0.68	135	0.61	135	0.89	**135**	0.97
134	0.92	134	0.79	134	0.69	134	0.62	134	0.89	**134**	0.97
39	0.92	39	0.81	39	0.70	133	0.64	39	0.89	**133**	0.97
38	0.92	38	0.81	38	0.70	39	0.64	38	0.89	**39**	0.97

This was expected since this case illustrates a light loading condition of the system. Same as before, the ranking of lines is provided by AIS algorithm and line loadings shown to the right from corresponding line number in Table 3 are the result of subsequent load flow calculation for that particular case study. Full agreement between the two can be observed as before.

A quasi statistic calculation is conducted on the results presented in Tables 2 and 3 in order to examine how many times a particular line or bus appears among the set of critical result.

For identification oh heavily loaded lines a simple count is used to determine how many times the line appears among the set of top 20 critical lines. In case of lines which appear equal number of times (maximum is 5) among the critical set the line which is more often found to be the more loaded than the other line from the same subset (e.g., gtwo lines which both apper 5 times among 20 heavily loaded lines) is listed first. The larger
this value for a particular line is more prone the line will be to an overload.

For voltage collapse identification, the relative positions of a particular bus in each voltage vector are added together, e.g., bus 138 appeared first in all cases so its corresponding weighting is 1x6=6; bus 133 appeared 11th in case 1, 9th in case 2, 11th in case 3, 6th in case 4, 11th in case 5, and 6th in case 6, so its corresponding weighting is 11+9+11+6+11+6=54. The lower the cumulative weighting of the bus is the more likely it is that it will experience low voltages.

The results of this calculation are summarised in Table 4. They are divided into three groups. Each group contains 9 buses and 9 lines which are categorized according to their cumulative weighting. Consequently, group 1 indicates the combination of buses and lines which are most likely to fail, group 2 indicates those with the lower probability of failure, and so on. Graphical presentation of these results is shown in Figure 4. In the single line diagram of GDN in Figure 4, the contours indicate voltage collapse prone areas,

Table 3: Identified heavily loaded lines

Case 1		Case 2		Case 3		Case 4		Case 5	
Line No	I(A)	Line No	I(A)	Line No	I(A)	Line No	I(A)	Line No	I(A)
15	687.55	15	1246.51	15	2275.5	15	2585.53	15	1155.79
9	659.35	9	1229.06	9	2174.89	46	2516.51	9	1097.62
41	573.11	41	1152.45	41	2118.72	41	2493.30	130	944.32
130	572.26	130	1085.67	25	2077.78	40	2484.71	27	932.93
46	560.19	27	1075.15	27	1985.63	9	2463.27	16	716.92
27	551.07	6	1050.29	130	1896.94	25	2421.82	111	707.75
111	420.98	116	806.70	6	1882.06	26	2360.66	22	687.41
52	307.89	111	757.07	116	1378.42	27	2315.85	116	658.97
		114	662.51	111	1378.24	130	2159.68	117	582.79
		124	659.65	117	1171.35	6	2118.31	114	567.03

Table 4: General Results of Case Studies

Group 1	Bus No.	138	137	136	135	134	39	38	40	133
	Weighting	6	12	18	24	30	38	45	49	54
	Line No.	15	9	130	27	111	41	116	117	114
	Counts	5	5	5	5	5	4	4	4	4
Group 2	Bus No.	37	41	36	42	132	35	43	31	34
	Weighting	58	63	77	79	84	89	102	109	114
	Line No.	124	52	6	115	51	145	141	46	50
	Counts	4	4	3	3	3	3	3	2	2
Group 3	Bus No.	33	131	130	129	127	128	126	32	125
	Weighting	115	116	117	118	118	119	119	120	120
	Line No.	80	68	47	16	25	21	121	40	22
	Counts	2	2	2	2	1	1	1	1	1

and coloured lines the overloaded and heavy-loaded lines. The area the most prone to voltage collapse is marked by dark shaded contour while less critical areas are marked by lighter shaded contours. As far as the overloaded lines are concerned, dark colour represents overloaded transmission lines and relatively light coloured lines mark the heavily-loaded lines.

V. Conclusions

The paper presented one of the first applications of the Artificial Immune Systems in power system area. A complete AIRS algorithm was developed for identification of voltage collapse prone buses and overloaded lines in realistic size distribution network. Compared with other conventional methods used in industry to solve similar problems the AIS based solution has the following advantages:

- Real-time identification of failure prone areas in power system.

The software compares different load patterns stored in its memory (similarly to artificial neural network algorithms) so it can easily achieve close to real-time identification and failure prediction. For this realistic size network relatively small number of case studies was needed to train the algorithm and to achieve high accuracy of the solution.

- Time saving

Compared with other variables, e.g., currents and voltages at all network buses and lines, loading data required for the algorithm training purposes are relatively easy to collect. Power utilities usually store loading data for the purpose of planning network extension or load forecast and most of those are already pre-processed and corrected. There is therefore an adequate source of data for the AIS to analyse, so the relatively long time typically required for data collection and pre-processing is significantly reduced. The AIS applies a simple method to calculate affinity between antibody and antigen, which only takes few seconds of computation time before identification can be accomplished. This is much faster than, for example, calculating PV curves for every bus in the network, or sensitivity analysis using dQ/dV factor

- High overall accuracy

According to the results of case studies presented in the paper the AIS based algorithm can achieve high overall accuracy in identifying critical areas in the network. This could provide network operators with a powerful tool for network supervision, management and optimal scheduling of maintenance.

Finally, it should be pointed out though that this was one of the pioneering applications of the AIS in power system area and that there are still many avenues of potential improvements to be explored. Even though this was time limited research and very basic application of the algorithm the initial results demonstrated that the AIS based approach could be a suitable candidate for efficient identification of critical areas in the network. Its versatility and flexibility offers possibility to analyse (on its own or in combination with other data processing methodologies) seemingly uncorrelated data which are either available in existing databases in utilities, or data obtained from routine on-line monitoring of network performance. This analysis could lead to development of optimal scheduling of network maintenance and such significantly reduce network failures and ultimately black outs.

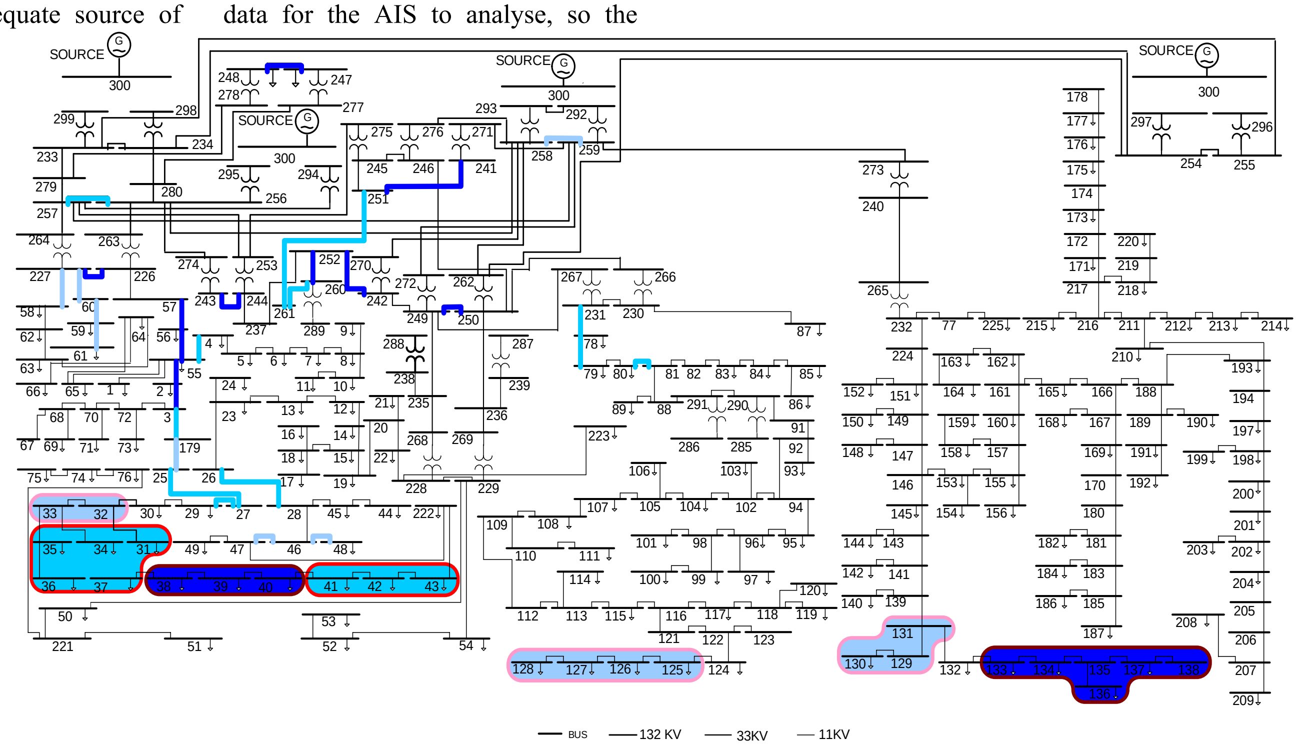

Figure 4: Combined Results of Case Studies

REFERENCES

[1] Le Xu and Mo-Yuen Chow, "Power Distribution Outage Cause Identification with Imbalanced Data Using Artificial Immune Recognition System (AIRS) Algorithm", *IEEE Transactions on Power Systems*, vol. 22, pp. 198-204, 2007.

[2] Le Xu and Mo-Yuen Chow, "A Classification Approach for Power Distribution Systems Fault Cause Identification", *IEEE Transactions on Power Systems*, 21, pp. 53-60, 2006.

[3] J.-T. Peng, C. F. Chien, and T. L. B. Tseng, "Rough Set Theory for Data Mining for Fault Diagnosis on Distribution Feeder", Proc. Inst. Elect. Eng., Gen., Transm., Distrib. 151, no. 6, pp. 689–697, 2004.

[4] A. Watkins and J. Timmis, "Artificial immune recognition system (AIRS): Revisions and refinements," in Proc. 1st Int. Conf. Artificial Immune Systems (ICARIS), pp. 173–181, 2002.

[5] John E. Hunt and Denise E. Cooke, "Learning Using an Artificial Immune System", *Journal of Network and Computer Application,* 19, pp. 189-212, 1996.

[6] Janeway Jr., C. A., "The Immune System Evolved to Discriminate Infectious Non-self from Non-infectious Self", *Imm. Today,* 13(1), pp. 11-16, 1992.

[7] Mannie, M. D., "Immunological Self/Non-self Discrimination", *Immunologic Research*, 19(1), pp. 65-87, 1999.

[8] Fearon, D. T. & Locksley, R. M., "The Instructive Role of Innate Immunity in the Acquired Immune Response", *Science*, 272, pp. 50-53, 1996.

[9] Parish, C. R. & O'Neill, E. R.,"Dependence of the Adaptive Immune Response on Innate Immunity: Some Questions Answered but New Paradoxes Emerge", *Imm. and Cell Biol.*, 75, pp. 523-527, 1997.

[10] Medzhitov, R. & Janeway Jr., C. A., "Innate Immunity: Impact on the Adaptive Immune Response", *Current Opinion in Imm.*, 9, pp. 4-9, 1997a.

[11] Medzhitov, R. & Janeway Jr., C. A.,"Innate Immunity: The Virtues of a Non-clonal System of Recognition", *Cell*, 91, pp. 295-298, 1997b.

[12] Janeway Jr, C. A., "How the Immune System recognizes Invaders", *Scientific American*, 269(3), pp. 41-47, 1993.

[13] Farmer, J. D., Packard, N. H. & Perelson, A. S., "The Immune System, Adaptation, and Machine Learning", *Physica 22D*, pp. 187-204, 1986.

[14] De Castro, L. N. & Von Zuben, F. J., "Artificial Immune Systems: Part I – Basic Theory and Applications", Technical Report – RT DCA 01/99, p. 95, 1999.

[15] Tonegawa, S., "The Molecules of the Immune System", *Scientific American*, 253(4), pp. 104-113, 1985.

[16] Tonegawa, S., "Somatic Generation of Antibody Diversity", *Nature*, 302, pp. 575-581, 1983.

[17] Perelson, A. S. & Weisbuch, G., "Immunology for Physicists", *Rev. of Modern Physics*, 69(4), pp. 1219-1267, 1997.

[18] Janeway Jr, C. A. & P. Travers, "Immunobiology The Immune System in Health and Disease", Artes Médicas (in Portuguese), 2nd Ed, 1997.

[19] Nossal, G. J. V., "Life, Death and the Immune System", *Scientific American*, 269(3), pp. 21-30, 1993.

[20] Germain, R. N.,"MHC-Associated Antigen Processing, Presentation, and Recognition Adolescence, Maturity and Beyond", *The Immunologist*, 3/5-6, pp. 185-190, 1995.

[21] Nossal, G. J. V., "The Molecular and Cellular Basis of Affinity Maturation in the Antibody Response", *Cell*, 68, pp. 1-2, 1992.

[22] Med-Help.net, "Find out How the Immune System Works", URL: http://www.med-help.net/Immune-System.html

Jovica V. Milanović (M'95, SM'98) received his Dipl.Ing. and his M.Sc. degrees from the University of Belgrade, Yugoslavia, his Ph.D. degree from the University of Newcastle, Australia, and his Higher Doctorate (D.Sc. degree) from The University of Manchester, UK, all in Electrical Engineering. Currently, he is a Professor of electrical power engineering and Deputy Head of School (Research) in the School of Electrical and Electronics Engineering at The University of Manchester, UK.

Jingwei Lu received his B.Eng. degree from North China Electric Power University, China in 2007, and his M.Sc. degree from the University of Manchester, UK in 2008. He is currently working in Mott Macdonald UK as a graduate electrical engineer.