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Power System Health Monitoring Based on Energy Losses using Genetic Algorithm

Andrei Ioaneş, Radu Tîrnovan

System health assessment becomes ever more important as consumers take for granted the apparent infallible character of power supply and the extremely high costs of prolonged down times. A system that achieves minimum operational disruptions becomes a target for all grid operators. This paper tackles the system heath issue in distribution networks by evaluating overall network losses. Using a genetic algorithm, the system health is evaluated considering key elements within the network operation.

Keywords: *Power System Health&Reliability, Power grids, Power system planning, Power system simulation*

1. Introduction.

System status, diagnosis and fault prediction are gaining more and more attention in power network as reliability becomes a given.

The instantaneous character of power system faults means the task of detecting and removing the defect relies on protection devices while in other technical environments operators might be able to observe deviation and act before trips occur. Recovering from an abnormal event is still almost exclusively a manual operation performed by human operators. This is the task of responding to abnormal events in a process. This involves the timely detection of an abnormal event, diagnosing its causal origins and then taking appropriate supervisory control decisions and actions to bring the process back to a normal, safe, operating state. This entire activity has come to be called Abnormal Event Management (AEM), a key component of supervisory control [1].

Although primary circuit elements go through the routine maintenance procedures, the technical state is assessed by element and rarely or not at all as a system. Also, the size and complexity of modern power systems can resemble to a process plant which can easily go up to 1500 process variables [2]. In turn this can lead to information overload. Furthermore, the task of fault diagnosis is made difficult by the fact that the process measurements may often be insufficient, incomplete and/or unreliable due to a variety of causes such as sensor biases or failures. Given such complexity and short intervention times, it is no wonder that human operators are prone to making the situation worst whilst trying to resolve the issue. Industrial statistics show that about 70% of the industrial accidents are caused by human errors.

2. Methods Overview

Transport and distribution of power implies, as any physical process, a loss of energy due to the irreversible thermodynamic conversions. These losses, different from the useful energy, have been referred to as technical losses [3]. Technical losses are the energy lost through conversion to heat and noise while non-technical refers to energy that has been delivered to consumers but was not billed. he EU has made considerable progress over the few last years. In 2014, its primary energy consumption was only 1.6% above its 2020 primary energy consumption target. Indeed, final energy consumption was 2.2% below the 2020 target. However, in 2015 compared with 2014, primary energy consumption increased by around 1.5%, and final energy consumption by around 2 [4].

Assessing power system health is only possible with the appearance and development of new real time measuring and communication devices. Using power losses data to assess system health by comparing actual measured values with mathematical data can allow for an observation as to how much the real system has deviated from its original design status.

Power systems faults can be categorized in two major groups:

- Cross section related
- Insulation related

In the first category, unusually high active power losses can be a sign of imperfect contacts, overloaded sections or transformer discharges which lead to overheating of network components and premature failures. For the second category, insulation degradation cause discharges that are inversely proportional to insulation/isolation health.

Operating systems with higher losses than designed means maintaining acceptable service voltages across the network by altering transformer tap settings. This combined with variable loads lead to extra strain on isolation and higher chances of a fault appearing.

Comparison between the measured signal and the estimate values generated by the mathematical model or base model directly influences the fitness function. Which in turn is used to assess the system health based on certain thresholds:

- OK
- Vigilance
- Critical

It has been observed that aged systems show low fitness function score value and have statistically higher chances of failure.

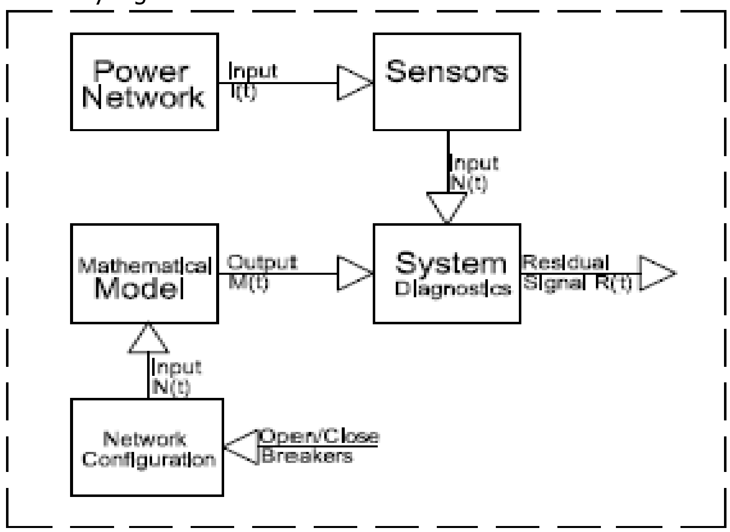

Figure 1. General Diagnostics Framework.

$$\Delta P = 3R \cdot I^2 \cdot 10^{-3} \quad ,[\mathrm{kW}] \qquad (1)$$

$$I^2 = \frac{S^2}{3 \cdot U^2} \quad [\mathrm{A}] \qquad (2)$$

The paper presented relies on real world data obtained from a functional distribution network and proposes a new minimization problem based on genetic algorithm for system health evaluation while maintaining a fully functional network.

3. Genetic Algorithm

Genetic algorithms use terms borrowed from genetics. GA actually used to compare the similarity of two things (direct analogy). It is also used to optimize the applied solution by using the biological method it is explained by Darwin. Basically, it is used in different applications its gives a exact result compare to other methods for solving specific error using GA. In this fitness function are used because to obtain the different possible solutions [5-6].

Inspired by natural systems and living populations, GA borrows search techniques and evolution mechanisms. Their basic principle is the maintenance of a population of solutions to a problem (genotypes) as encoded information individuals that evolve in time [7]. GA Program comprises three different phases of search [8]:

- phase 1: defining the initial population;
- phase 2: calculating the fitness function;
- phase 3: obtaining the new population.
- Chromosome Representation.

In each generation of the genetic algorithm, two parent chromosomes are selected based on their fitness values; these chromosomes are used by the mutation and crossover operators to produce two offspring chromosomes for the new population.

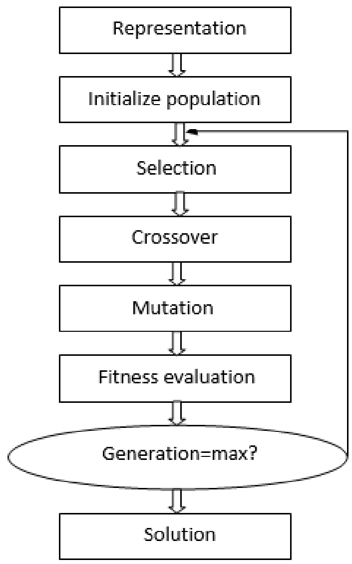

Figure 2. Genetic Algorithm flowchart

4. Problem Formulation

Monitoring system health relies on analytical redundancy or functional redundancy, meaning dissimilar signals are compared and evaluated to identify the existing faults in the system or its components. This comparison is between the measured signal and the estimated values generated by the mathematical model of the system. Residual generation is the heart of a model-based approach. However, the techniques involved in model-based diagnosis differ in the generation and definition of a residual, for instance in some cases it is the discrepancy of output (from the system) estimation and in some cases, it is the error in parameter (of the system's model) estimation itself. It is imperative that the generated residual be dependent only on the faults in the system and not on its operating state [11].

System health and reliability evaluation within a power distribution network requires an objective function or a Fitness Function if we use a Genetic Algorithm. The Fitness Function is selected to evaluate and categorize the system status. Different scenarios are used in this study to determine the effectiveness of the proposed algorithm. The fitness function will be optimized in the presence of constraints that need to be fulfilled to define the system health. Due to the number of tie switches and thus high number of possible network configuration, the genetic algorithm provides a fast and optimum evaluation of the system studied.

- Initial Population. During design stage, for each element of the network either being feeder, transformer or another part losses in normal operational conditions are estimated as stand-alone components. Overall system losses calculation is obtained for the normal operational structure. This will be used as the benchmark for comparison when operating in real life.
- Fitness Function. During normal operation network topology can suffer important alterations which can greatly influence losses. The objective function assesses each possible individual (network topology) and assigns a fitness score based on the level of losses. These are the calculated/estimated losses obtained from power flow specialized software. Further on, with the help of smart metering systems, real losses are registered through a differential system arrangement.
- Selection. From the initial population pool, individuals are selected to mate/exchange genes based on their fitness score.
- Crossover. Genes (network topology possible alterations) are swapped resulting in new network topologies.
- Mutation. A certain degree of random probability within crossover can help towards a faster solution convergence.
- Termination. The Genetic Algorithm searches for the individual (solution/network topology), while constraints are met, that can account for the level of losses registered by the metering system. If such a solution is found it means there is a network topology that can justify the level of losses.

4.1 Constraints:

a. Voltage

In order to maintain power quality, acceptable ranges must be kept in each node.

$$V_{\min} \leq V_j \leq V_{\max} \ , \forall j \in \{1, \ldots, n\} \quad (3)$$

Where Vmin and Vmax are the acceptable limits for customer service voltage at node i.

b. Active and reactive power losses constraint:

The losses after capacitor banks are installed in the distribution network should be less than or equal to losses before installing them.

PL with CB ≤ PL without CB

QL with CB ≤ QL without CB

4.2 Objective function

The Fitness Function is determined as follows:

$$\min f = a\cdot(\sum_{i=0}^{n-1} P_{Ei} / \sum_{i=0}^{n-1} P_{Li})\cdot 100 + b\cdot(\sum_{i=0}^{n-1} Q_{Ei} / \sum_{i=0}^{n-1} Q_{Li})\cdot 100 + c\cdot AVF \quad (4)$$

Where:

a,b,c,d – Fitness function weights and a+b+c=1

P_{Li} - Measured active power loss

P_{Ei} - Estimated active power loss

Q_{Ei} -Measured reactive loss

Q_{Li} -Estimated reactive loss

AVP - Average Voltage Profile

Active, reactive losses and AVP are obtained from EDSA Paladin design base load flow program. Every value is consistent to each individual scenario and obeys every constraint. After determining the base case, with the help of power-flow calculation software the system health and reliability are evaluated and the objection function is recalculated based on the new data. Computational time is greatly reduced thanks to the MATLAB environment used to run the proposed algorithm.

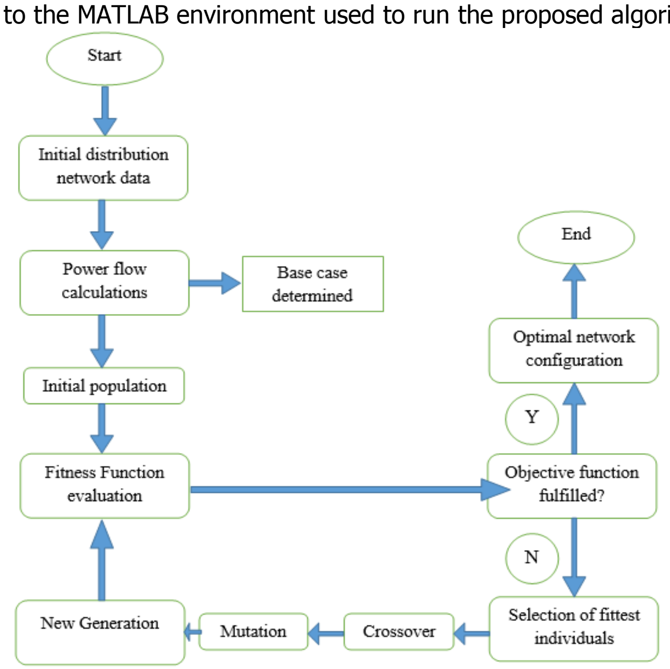

Figure 3. Proposed Genetic Algorithm

4.3 System description

The distribution network has 6 substations 20/0,4 kV that are supplying residential consumers as well as industrials ones. Their installed power varies from 630 kVA to 1000 kVA. 20kV breaker statuses, distributed generators in operation or not and reactive compensation active or not are the genes inside each chromosome that forms an individual/solution/network topology.

Health monitoring becomes even more important as systems head towards smart power grids in which the places energy is produced and consumed vary throughout the day. Of course, any changes to power network distribution systems must be economically viable. Therefore, a thorough cost-efficient analysis must be performed. However, this is not the subject of the present article.

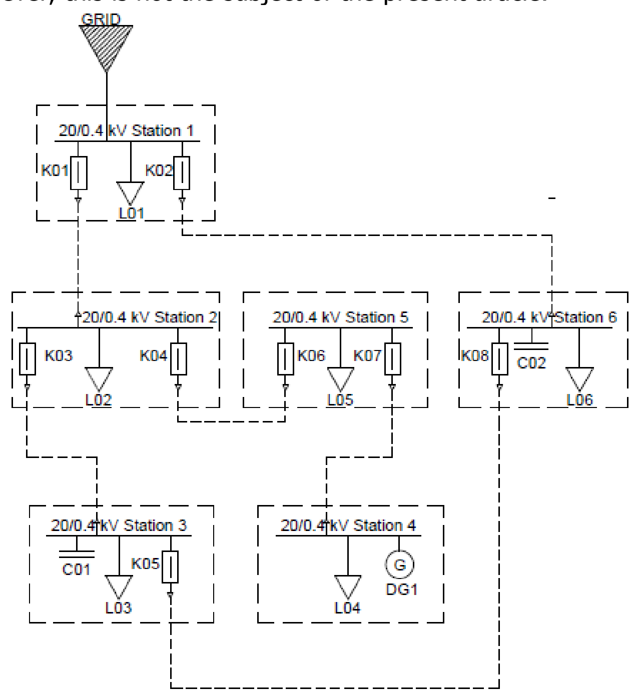

Figure 4. Proposed Genetic Algorithm

5. Genetic Algorithm

5.1 Base case scenario

Proving the efficiency of the proposed algorithm for system health monitoring is done simulating and comparing different scenarios to the base case which is the current state of the distribution network. This case describes the current state of the distribution network. Power losses and voltage profile were obtained from a load flow program for different scenarios. Power flow calculations show a 0.10 p.u. real power losses and 0.14 p.u. reactive power losses.

Table 1. Losses for base case scenario

Base Case Scenario				
P_{L1}	Q_{L1}	AVP	Fitness Score	System Health
(kW)	(kVAr)	(kV)	-	[Ok/Vigilance/Critical]
533.2	352.2	19.1	56.823	Ok

Table 1 shows the normal operational topology losses. The active losses are around 10%. A value considered acceptable for modern power systems.

Table 2. Losses for different scenarios

Scenario	P_{L1}	Q_{L1}	AVP	Fitness Score	System Health
	(kW)	(kVAr)	(p.u.)	-	[Ok/Vigilance/Critical]
1	620.4	280.1	0.901	45.621	OK
2	981.3	503.1	0.82	30.15	Vigilance

The first scenario analyses power losses on a random proposed topology while all constraints are met. The newly obtained fitness score is higher than the one obtained for the base case scenario. The Genetic Algorithm searches for a network topology that meets the constraints and can justify this level of losses. A solution is found after 10 iterations indicating the overall status of the network is healthy.

While the second case studied, proposes a topology that does not met the constraints in order to create overload on feeders and transformer and thus increase the losses. The Genetic Algorithm will search for a topology that will account for this new topology. A solution that meets the constraints whilst having this level of losses is not found.

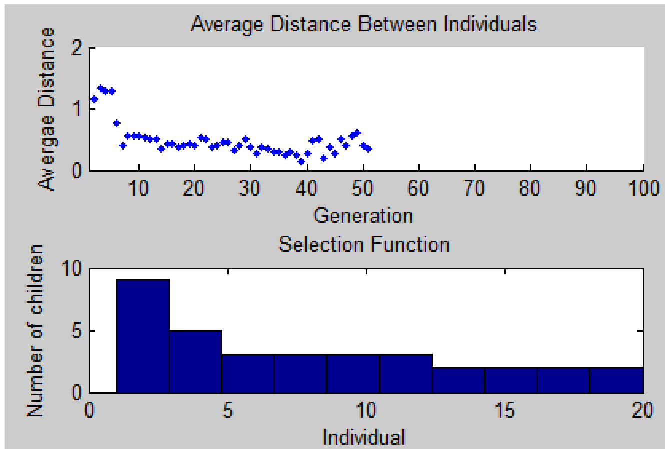

Figure 5. GA functions

6. Conclusion

In this paper, a power system health monitoring methodology is proposed based on Genetic Algorithm to evaluate network status while constraints are imposed. Only results that meet all constraints are taken into consideration. The solution searches for the network topology that can justify the level of losses while constraints are met. For the first proposed scenario, a solution that accounted for that level of losses was found. For the second scenario, in order to simulate abnormal losses, a topology is proposed that overloads feeders and transformers. The Genetic Algorithm is unable to find a topology that can justify this level of losses while constraints are met resulting in the system being included in "Vigilance". The results obtained are found to be satisfactory and the use of Rowlett wheel selection and demonstrates the effectiveness and applicability of the proposed methodology.

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Addresses:

- Andrei Ioaneş, Faculty of Electric Engineering, Technical University of Cluj-Napoca, Strada Memorandumului 28, Cluj-Napoca 400114, Romania, andrei.ioanes@gmail.com
- Prof. Dr. Eng. Radu Tîrnovan, Faculty of Electric Engineering, Technical University of Cluj-Napoca, Strada Memorandumului 28, Cluj-Napoca 400114, Romania, radu.tirnovan@enm.utcluj.ro