Fuzzy Petri Nets Efficiency in Hardware Implementation; Evidence from an Intelligent Fault Diagnostic System

Mostafa Bayati
Corresponding author email id: bayati.tech@gmail.com

I. INTRODUCTION

Nowadays, using digital processors to solve complex problems in vast range of applications are became dramatically widespread. A small chip and writing some pieces of codes can make a system smart, intelligent and more efficient. As an instance, Electrical power systems are not a mere solid connection between power generation plants and consumers anymore. In fact, several computerized devices have been added to this system to make it more efficient and resilient. However, modeling, control and implementing such a complex system in real world are some new challenges which need more research and studies. Because of the steep grows in complexity of power systems dynamics and their non-linear behaviors, it is not possible to develop a comprehensive mathematical model for each individual part of a large scale power system. For example, Akhlaghi et al. [1-2] proposed a distributed dynamic estimation approach to estimate the dynamic state of synchronous machine. Furthermore, there are a lot of devices which can fail and cause errors in power distribution network. The role of faulty section predictor and fault diagnostic systems is getting more important than before due to the growth in new power systems. Moreover, power outage time and undistributed energies are two important parameters in power distribution systems and the power system quality assessment directly takes effect by these parameters. In recent years several methods have been applied to identify faults and failures in power systems and power distribution devices based on the protection systems status. These methods mainly consist of expert systems [3-4], artificial neural networks [5-6], optimization algorithms such as GA [7-8], swarm intelligence [9-11], Tabu search [13] and also fuzzy Petri nets [14-17]. Fault/damage detection, even in mechanical structures (airplane wings, bridges, etc.), is a very hot topic among the researchers [18-19].

Having a closer look at the advantages of all recently introduced intelligent systems, it can be clearly seen that these systems are based on complex calculations and hence need powerful and expensive computers to be practical in real plants. Exploiting more powerful processors can be a viable solution for this problem in short term, but this is more rational that we find approaches to reduce the calculations, besides maintain the total efficiency, rather than allocating too much budget for research programs on how to design more powerful processors to handle more calculations. In next sections, the result of a novel approach using Fuzzy Petri Nets (FPN) concept is provided to implement complex calculations on a simple and low cost processor.

II. PETRI NET AND FUZZY PETRI NET FUNDAMENTAL RULES

Petri nets, which are being called as place-transition nets as well, developed by a German mathematician Carl Adam Petri in 1962. Petri nets have been utilized in a lot of industrial applications as well as in power systems modeling, optimized decision making and supervisory control systems [20-22].

A Petri net consists of a set of places, transitions, arcs and tokens [23-24]:

\[ N=(P,T,W,M_0) \]  \hspace{1cm} (1)
\[ P=\{p_1,p_2,p_3,...,p_n\} \]  \hspace{1cm} (2)
\[ T=\{t_1,t_2,t_3,...,t_m\} \]  \hspace{1cm} (3)
\[ M_0=\{m_1,m_2,m_3,...,m_n\} \]  \hspace{1cm} (4)

\( P \) is a finite nonempty set of Petri net places. A place demonstrates the states of a Petri net. For example whether a power circuit breaker is on or off. \( T \) is set of finite nonempty transitions. \( W \) is the Petri net incident matrix. An incident matrix shows the Petri net structure. Finally \( M_0 \) is the initial marking vector.

In a Petri net, dynamics of a system graphically is being illustrated by movement of tokens through places and transitions. The most powerful feature of a Petri net is state prediction according to state equation and its reachability.
In a discrete Petri net the state equation is:

\[ M_{n+1} = M_n + W \cdot X_n \]  
\[ X_n = [x_1, x_2, x_3, ..., x_n] \]

Where, \( M \) is the later state and \( X \) is the fired transitions vector. In continuous Petri net the state equation can be written by:

\[ M_{n+1} = M_n + W \cdot V \cdot dt \]
\[ V = [v_1, v_2, v_3, ..., v_n] \]

\( V \) is the transitions firing speed vector and \( dt \) is the time step. Nowadays, some novel and efficient features have been added to Petri nets to make it more powerful in modeling and controller design purposes.

Arithmetic modules are one of the recently added features to Petri nets [25]. Many mathematical and logical operations can be implemented by utilization of these modules in Petri net models. State equation for arithmetic can be written as follows:

\[ M_{n+1} = M_n + W \cdot W^t \cdot M_n \cdot dt + O_m \cdot W^t \cdot M_n \]
\[ O_m = [o_1, o_2, ..., o_n] \]

\( O_m \) is the operator matrix which implements mathematical as well as logical operations. \( W^t \) and \( W \) are dependent matrices to Petri net incident matrix. Fuzzy Petri nets can be developed according to the inference diagram of fuzzy systems which consist of input fuzzification, decision making and rules and finally output de-fuzzification. Such a simple fuzzy Petri nets can be used as a controller and state prediction system in many industrial applications as well as in electrical power systems. The most advantage of proposed Fuzzy Petri nets is simple matrix operation in inference procedure. As a result, developed FPN can be easily implemented on embedded systems with fast and credible response [26].

### III. FUZZY PETRI NET FAULT DIAGNOSTIC EXPERIMENT

#### A. Proposed system block diagram

Fig.1 illustrates proposed fault diagnosis system block diagram.

![Fuzzy Petri Net Inference](image1.png)

**Fig.1. Transformer fault diagnosis block diagram**

The proposed fault diagnosis system has three inputs which acquired by transformer measurement system including transformer input power, transformer vibration level in present load and transformer temperature in present load. These three inputs are normalized between 0-1 and all of the calculations are in per-unit system. The diagnosis system is based on the fact that each healthy transformer has to work in a certain vibration level and temperature value at a certain load. As an instance, when the load of transformer is high, the vibration and coil temperature must be high due to high ampere transmission, otherwise transformer is faulty.

#### B. Fuzzy Petri Net rules definition

Trapezoidal membership functions for fuzzy inputs and triangular for output have been utilized. Rules database of fault diagnosis system can be compiled according to expert person definitions such as below:

1. If \( P \) is low and \( TEMP \) is low and \( VIB \) is low then failure_p is low.
2. If \( P \) is low and \( TEMP \) is low and \( VIB \) is high then failure_p is high.
3. If \( P \) is low and \( TEMP \) is high and \( VIB \) is low then failure_p is high.
4. If \( P \) is low and \( TEMP \) is high and \( VIB \) is high then failure_p is high.
5. If \( P \) is high and \( TEMP \) is low and \( VIB \) is low then failure_p is medium.
6. If \( P \) is high and \( TEMP \) is low and \( VIB \) is high then failure_p is medium.
7. If \( P \) is high and \( TEMP \) is high and \( VIB \) is low then failure_p is medium.
8. If \( P \) is high and \( TEMP \) is high and \( VIB \) is high then failure_p is low.

#### C. Proposed FPN for transformer fault diagnostic

Fig.2 illustrates the proposed FPN for transformer fault diagnosing according to three inputs and one output parameters and one output as well as compiled rules in the previous section.
There are other methods that investigate the fault diagnostic due to physical phenomenon [27]. These methods are based on system’s practical responses.

### IV. FPN HARDWARE IMPLEMENTATION

Fig.3 illustrates utilized embedded system based on an ARM7 core, using ATMEL AT91SAM7X256 microcontroller to implement proposed fault diagnosis FPN [30]. Also Fig.4 shows a snapshot of dedicated LCD to show the resultant calculation of system.

![Utilized embedded system for FPN implementation](image1)

![LCD screenshot after an example FPN inference](image2)

### V. SIMULATION RESULTS

Fig.5, Fig.6 and Fig.7 illustrate the possibility of transformer failure according to different measured parameters including temperature, vibration level and current load level. Indeed, the regions with yellow colour are the amber lights for the malfunctionality of the transformer. For example as can be seen in figure 5, when transformer is working with no load and the temperature is high, the transformer is possibility faulty and should be repaired as soon as possible.

![corresponding failure probability to temp and pw](image3)

![corresponding failure probability to vib and pw](image4)

![corresponding transformer failure probability to vib and temp](image5)

### VI. CONCLUSIONS

Because of taking the advantage of matrix and vector operators in Fuzzy Petri Nets (FPN) inference procedure, it can be implemented on embedded systems with fast and credible response. To validate the performance of proposed approach, an ARM microcontroller was used to implement the designed FPN model for a power transformer intelligent fault diagnosis system and the results of calculations were shown on a graphical LCD for simple and convenient interaction with operators. Furthermore, proposed method can be utilized in many smart equipment as well as for optimized decision makings in complex and large scale systems.

### REFERENCES


