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Fuzzy Implementation for Predicting and Monitoring the Conditions of Transducers for Gas Turbine Cycle

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Abstract

This paper presents a fuzzy logic methodology for predicting the most important parameters that influence the efficiency cycle of the gas turbine and estimates the transducer's condition "health" and its measuring accuracy during the fault. The fuzzy method is implemented here to monitor and predict the working conditions for different sensors and transducers in the gas turbine and to ensure that it is operated at a safe level to prevent equipment deterioration by the correct evaluation of its effective parameters, and save operational costs assuming that there is a single fault occurs at a given time. The fuzzy implementation consisted of two parts, the first one predicts the actual operating parameters based on gas turbine cycle performance calculations, and second part shows the sensor's condition estimates the transducers' accuracy in a percentage scale after any alarm to assure their competence. Fuzzy logic in such applications aids us to condense a large amount of data into smaller set of fuzzy variable rules, to minimize prolonged exposure to downtimes.

Keywords: *Fuzzy sets methodology; Turbine fault, Control technology, Sensor's condition, Gas turbine*

1. Introduction

Due to the daily increasing in power demand in Jordan, power system is operated closer to their maximum limits. Therefore, this study tends to investigate the monitoring procedure of the operating conditions continuously by different sensors and instruments fixed in the gas turbine during any alarm to ensure that they are operated at a safe level, assuming that there is a single fault occurs at a given time, it also minimizes the prolonged exposure to downtimes and breakdowns by detecting the type of the malfunction whether it is transducer fault or component fault at an earlier time. Moreover, it estimates the transducers' accuracy in a percentage scale after any alarm to assure their competence.

For example, temperature transducers (thermocouples) have a direct influence on the best amount of fuel that is consumed by the turbine, therefore it is very important to keep tracking the conditions of combustion process by the transducers to avoid the malfunction and degradation in the fuel consumption as well the temperature of inlet air to combustion chamber and its pressure value [1]. Transducers play an important role in predicting for controlling the operational actuators of the power systems. Therefore their efficient working conditions have to be evaluated for any alarming situation [2].

Usually redundant sensor measurements can give more reliable measurements and possibly a correct estimation of the true system status. However, using several types of sensors necessitates for decisions regarding which sensor to choose can make erroneous predictions, because different types of sensors variations the level of granularity, on the other hand, all redundant sensors can measure the same parameters. Therefore they are exposed to the same conditions and uncertainties, due to this they could equalized in transferring wrong signals because they are facing the same conditions.

Many attempts have been made to keep gas turbines running at their peak performance, to improve operating safety and to avoid unwarranted shutdowns. Goebel and Agogino [3] presented fusion methodology to determine whether sensor failure or system malfunction has occurred. Also they set a methodology to recover the sensor's distorted signals that caused by surrounding conditions.

Ogaji et al [4, 5] used genetic algorithm to diagnose gas-path faults in gas turbines by comparing between the observed and simulated data for the turbine behavior, their approach lead to a considerable reduction in the overall taken time for turbine repair. Also they used a thermodynamic model of the behavior of a 2-shaft gas turbine to predict the required instrumentation set and to show that redundancy in the sensor set is considered

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to be unnecessary. Aretakis et al [6] used pattern recognition technique to identify faults in the sensors readings.

Zedda and Singh [7] presented a diagnostic system to analyze the performance of a gas turbine components and sensors. They used only two statistical assumption concerns the measurement, which are noise and the maximum allowed number of faulty sensors and turbine components.

Simani et al [8,9] presented an approach based on analytical classical redundancy which uses dynamic observers to detect sensor faults and isolate problems for a single-shaft industrial gas turbine. They also evaluated the best measurement/parameter combination, in terms of accuracy in gas turbine health determination; and the submission of measurements to sensor fault detection and isolation analyses, before they are used as input by the health.

However, fuzzy sets implementation lately used for tremendous evaluation applications. For example, Mamlook and Badran [10] implemented the factors that affect solar distillation productivity using fuzzy sets. Mamlook [11] has used fuzzy logic to compare between different productions options of power systems in Jordan. He compared the results to those obtained with neuro-fuzzy, which is considered to be slower learning technique than the fuzzy sets methodology.

A new approach was presented by Jaber et al [12] for evaluating energy conservation and awareness programs within residential consumers. Their method based on expert computer knowledge-based systems and fuzzy set analyses.

This paper presented method uses fuzzy implementation to evaluate the sensors' and transducers' conditions in percentage scale for the gas turbine efficiency cycle and distinguish between the real component fault and the transducer malfunction during the fault alarm.

2. Problem Statement

Usually the software that is provided by the gas turbine manufacturer can detect a wide range of different components failures, like the human machine interface (HMI) software that was made by General Electric (GE) for simple-cycle [1], single-shaft heavy-duty gas turbine, model series 9001E installed in Rehab power station in Jordan. It was noticed during the visiting trips to the power station that they lack the ability of detecting the sensors and transducers conditions and their measuring accuracy after any fault and they cannot distinguish between the real component fault and the transducer malfunction during the fault alarm, therefore, our method uses fuzzy implementation to evaluate the sensors and transducers conditions for improving the gas turbine efficiency cycle, which saves operational costs and avoids long time breakdowns due to unknown fault detection at its earlier stages.

3. Proposed Methodology

Over the past two decades, there has been a tremendous growth in the use of fuzzy logic controllers in power systems applications. A recent series of tutorials in the IEE Power Engineering focused entirely on the applications of fuzzy logic in power systems is an evidence of its growing significance in the power field [13].

The fuzzy implementation is consisted of two parts, the first one predicts the actual parameters based on gas turbine cycle performance calculations and second part shows the sensor condition scale after any alarm to assure their competence.

The following parameters, which measured by different transducers, were considered to be the inputs that needed continuous evaluation in the efficiency cycle:

Inlet compressor temperature (T_1).

Outlet compressor temperature (T_2).

Inlet turbine temperature (T_3).

Outlet turbine temperature (T_4).

Compressor discharge pressure (P_2).

Fuzzy implementation steps

Mainly, the fuzzy implementation is consisted of four steps [14]:

1- Determining the linguistic variables and the fuzzy sets.
2- Constructing fuzzy rules.
3- Performing fuzzy inference into the system.
4- Evaluation and tuning the system.

The explanations of the above steps will be as following:

Determining the linguistic variables and the fuzzy sets

The inputs for the two fuzzy parts, shown in Fig. 1 and Fig. 2, are considered to be fuzzy variables, each of which can vary over a fixed range, defined by the transducers inputs and the gas turbine performance. This range has been divided into three membership functions (MFs) for each input as shown in Fig. 3 and Fig. 4. The outputs for the two fuzzy combinations have been spanned into three or five triangular MFs as shown in Fig. 5 and Fig. 6.

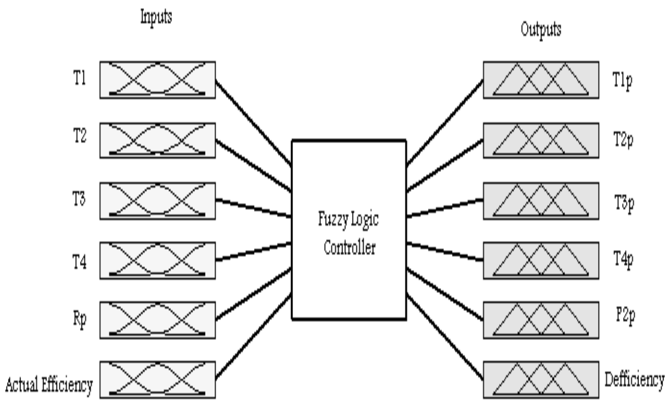

Figure 1. Fuzzy input/output combination for actual parameters prediction (part 1)

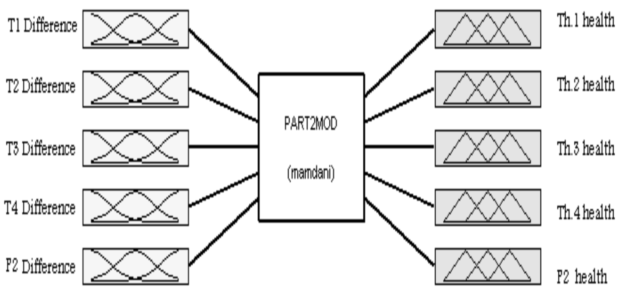

Figure 2. Fuzzy input/output combination for transducer condition detection (part 2)

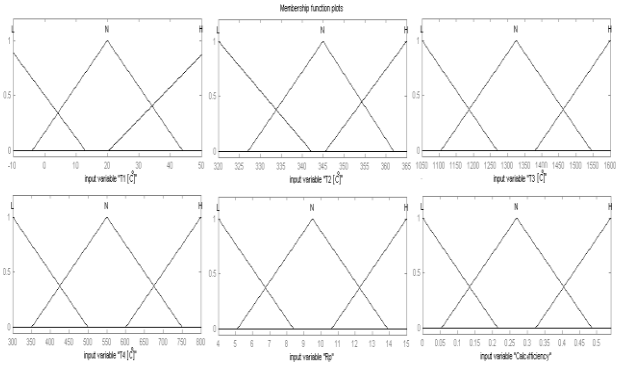

Figure 3. Membership functions for inputs

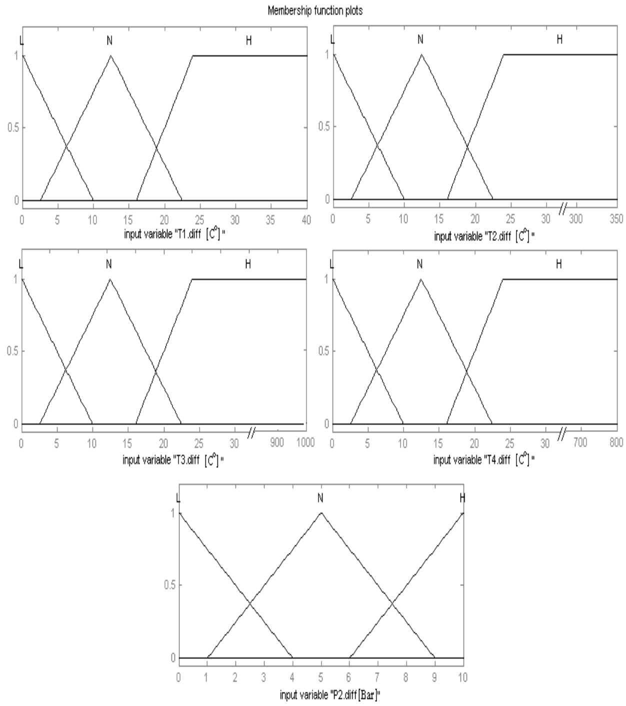

Figure 4. Membership functions of input for parameters prediction

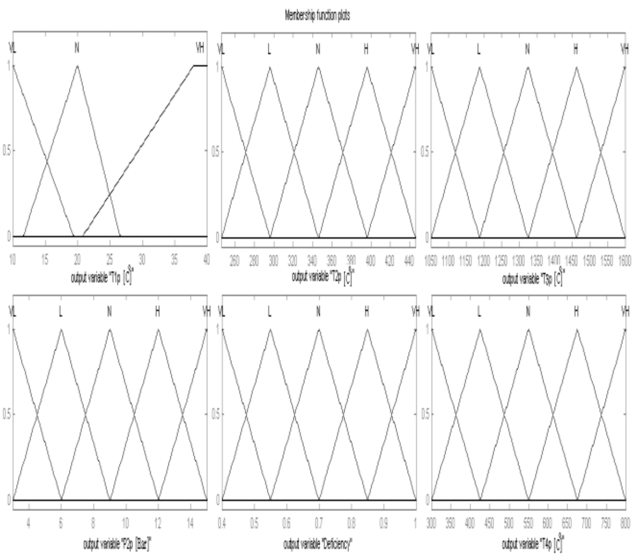

Figure 5. Membership functions of output for parameter prediction

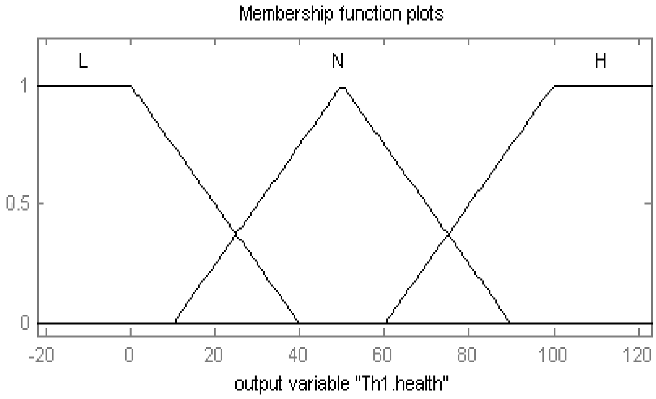

Figure 6. Membership functions of output for transducer condition

The fuzzy input/output parameters for the first part of the implementation are shown in Fig. 1.The inputs shown in Fig. 1 are $T_1[C^o]$, $T_2[C^o]$, $T_3[C^o]$, $T_4[C^o]$ (temperatures), pressure ratio R_p, and the actual efficiency, are used in the gas turbine cycle performance calculations to predict the real values for the above mentioned parameters.

The inputs are divided into three fuzzy sets as shown in the Fig. 3.

- Low value (L).
- Normal value (N).
- High value (H).
- The outputs' sets that shown in Fig. 3 are tagged with the following linguistic variable:
- Very low value (VL).
- Low value (L).
- Normal value (N).
- High value (H).
- Very high value (VH).

The "Calculated Efficiency" input represents the gas turbine efficiency that is related to the total power generation at the base mode. The "Deficiency" output shows the overall system degradation based on the parameters conditions.

The fuzzy combination that shown in Fig. 1 predicts the parameters values based on that provided by transducers that fixed in different places in the gas turbine as shown in Fig. 7.

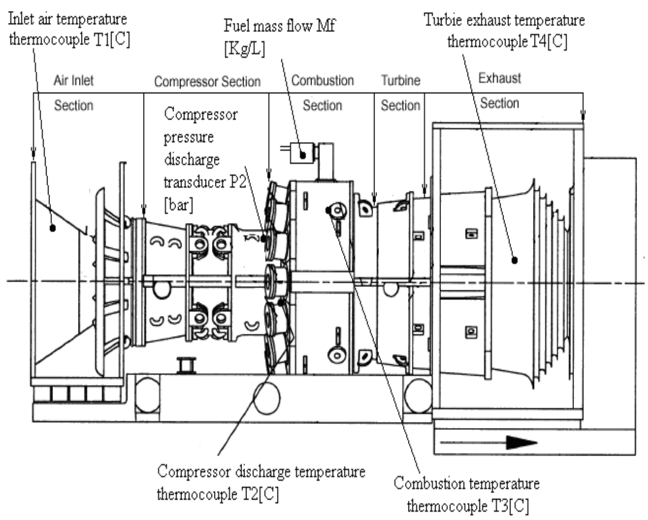

Figure 7. Simple cycle gas turbine with different input sensors

The output from the fuzzy combination shown in Fig.1 has been applied to the fuzzy process shown in Fig. 2. "T_1 Difference" input represents the difference between the values that provided by the transducers and the predicted ones that considered as outputs for the combinations shown in Fig. 1, the fuzzy inputs for the second combination are:

T_1 difference [C^o].
T_2 difference [C^o].
T_3 difference [C^o].
T_4 difference [C^o].
P_2 difference [Bar].

The inputs are divided into three fuzzy sets as follows:
Low value (L).
Normal value (N).
High value (H).

The outputs for the fuzzy combinations are shown in Fig. 6 are:
Thermocouple, that measures T_1, condition (Th1.health).
Thermocouple, that measures T_2, condition (Th2.health).
Thermocouple, that measures T_3, condition (Th3.health).
Thermocouple, that measures T_4, condition (Th4.health).
Pressure transducer, that measures P_2, condition (P_2.health).

The outputs are divided into three fuzzy sets for each output as shown in Fig. 6
Low value (L).
Normal value (N).
High value (H).

Constructing fuzzy rules

The sets that have been used in the fuzzy implementation are activated in terms of the fuzzy rules which take the general form: IF condition1 and condition2 . . . THEN decision(s). The "and" operator uses the "min" (minimum) function, while "or" operator uses "max" (maximum) function.

For example, 42 fuzzy rules have been used in MATLAB fuzzy toolbox to predict the efficiency cycle parameters based on gas turbine cycle performance calculations in statements forms as shown in Fig. 8.

The condition "health" for the transducer operation condition is based on 15 fuzzy rules as shown in Fig. 9.

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4. If (T1 is L) and (Rp is N) and (Calc_efficiency is N) then (T2p is L) (1)
5. If (T1 is N) and (Rp is N) and (Calc_efficiency is N) then (T2p is N) (1)
6. If (T1 is H) and (Rp is N) and (Calc_efficiency is N) then (T2p is H) (1)
7. If (T1 is L) and (Rp is H) and (Calc_efficiency is H) then (T2p is N) (1)
8. If (T1 is N) and (Rp is H) and (Calc_efficiency is H) then (T2p is H) (1)
9. If (T1 is H) and (Rp is H) and (Calc_efficiency is H) then (T2p is VH) (1)
10. If (T4 is L) and (Rp is L) and (Calc_efficiency is L) then (T3p is VL) (1)
11. If (T4 is N) and (Rp is L) and (Calc_efficiency is L) then (T3p is L) (1)
12. If (T4 is H) and (Rp is L) and (Calc_efficiency is L) then (T3p is H) (1)
13. If (T4 is L) and (Rp is N) and (Calc_efficiency is N) then (T3p is VL) (1)
14. If (T4 is N) and (Rp is N) and (Calc_efficiency is N) then (T3p is N) (1)
15. If (T4 is H) and (Rp is N) and (Calc_efficiency is N) then (T3p is VH) (1)
16. If (T4 is L) and (Rp is H) and (Calc_efficiency is H) then (T3p is VL) (1)
17. If (T4 is N) and (Rp is H) and (Calc_efficiency is H) then (T3p is H) (1)
18. If (T4 is H) and (Rp is H) and (Calc_efficiency is H) then (T3p is VH) (1)
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Figure 8. Fuzzy rules prediction part

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1. If (T1.diff is L) then (Th1.health is H) (1)
2. If (T1.diff is N) then (Th1.health is N) (1)
3. If (T1.diff is H) then (Th1.health is L) (1)
4. If (T2.diff is L) then (Th2.health is H) (1)
5. If (T2.diff is N) then (Th2.health is N) (1)
6. If (T2.diff is H) then (Th2.health is L) (1)
7. If (T3.diff is L) then (Th3.health is H) (1)
8. If (T3.diff is N) then (Th3.health is N) (1)
9. If (T3.diff is H) then (Th3.health is L) (1)
10. If (T4.diff is L) then (Th4.health is H) (1)
11. If (T4.diff is N) then (Th4.health is N) (1)
12. If (T4.diff is H) then (Th4.health is L) (1)
13. If (P2.diff is L) then (P2.health is H) (1)
14. If (P2.diff is N) then (P2.health is N) (1)
15. If (P2.diff is H) then (P2.health is L) (1)
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Figure 9. Fuzzy rules for health detection

The rules are evaluated using MATLAB toolbox rule viewer shown in Fig. 10 and Fig. 11.

The fuzzy system shown in Fig. 10 receives different input signals from different sensors fixed in different places in the gas turbine unit as shown in Fig. 7. The fuzzy inference system analyzes these inputs and predicts the parameters' values based on gas turbine cycle performance calculations. After the prediction process, the difference between the predicted parameters, output of part 1, and the actual values, input of part 1, will be applied to the fuzzy combination that shown in Fig. 11.

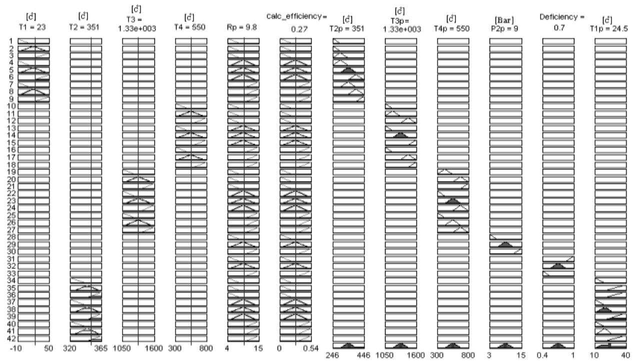

Figure 10. Parameters prediction using fuzzy implementation (part 1)

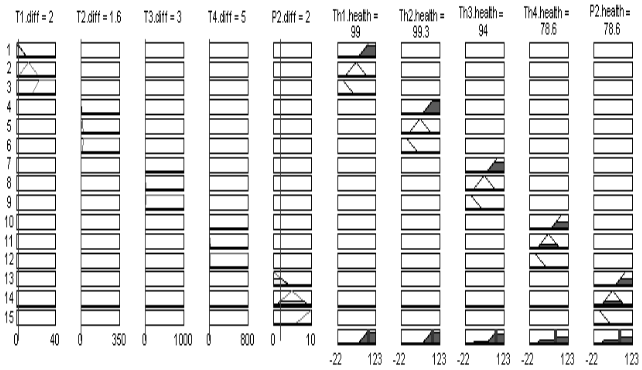

Figure 11.Transducers health detection using fuzzy implementation (part 2)

Performing fuzzy inference into the system

Systems fuzzy inference is the process of formulating the mapping from a given input to an output using fuzzy logic method. The mapping then provides a basis from which decisions can be made, or patterns discerned. The process of fuzzy inference involves: membership functions, fuzzy logic operators, and if-then rules [13-23]. This procedure is used to compute the mapping from the input values to the output values, and it consists of three sub-processes, fuzzification, aggregation and defuzzification as shown in Fig. 12.

Fuzzification turns crisp numeric values into linguistic descriptions (N, L, and H). This process is accomplished by evaluating the membership functions (MFs) with respect to the input value in order to establish the degree of activation of each output membership function. At the end of this process, list of activations are obtained and can be carried forward to the next stage (aggregation sub-process). In the aggregation sub-process, the effects of each rule on the possible output conditions are accumulated. Defuzzification carries out the estimation of the crisp outcomes of the inference process. Each output variable is analyzed separately as shown in Fig. 12.

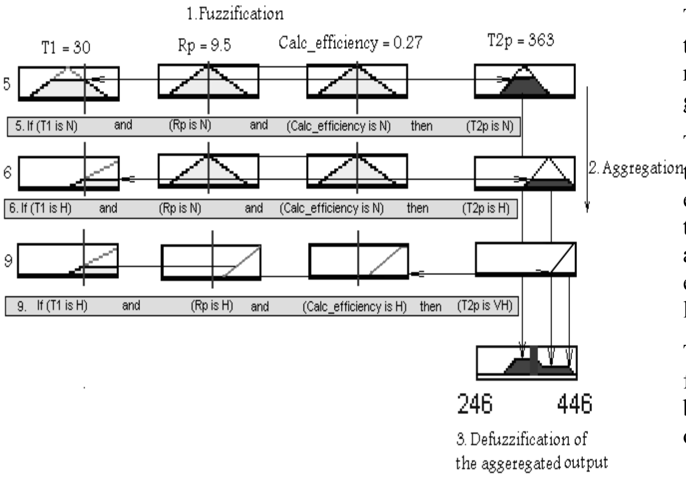

Figure 12. Fuzzy implementation sequence

As shown in Fig. 12, T_1 and R_p are 30°C and 9.5 respectively, while the Calculated efficiency is 0.27, the degree of activation for the output set at rule 5 carries the same minimum input set (T_1) degree, because the operator was (and). The activated sets due to fuzzification sub-process will be aggregated in the next step to form the combined shape, after that it will be defuzzified to get a crisp number (T_{2p}=363°C).

4. Case study

Case study has been established for simple-cycle, single-shaft heavy-duty gas turbine unit, (model series 9001E) in Rehab power station at the city of Irbid in the northern part of Jordan (Fig. 13). The fuzzy rules were set based on the parameters of the data sheets for the mentioned gas turbine.

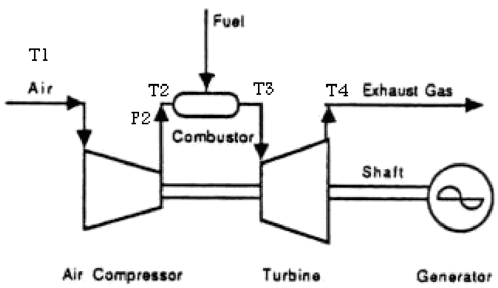

Figure 13. Simple cycle gas turbine

The software that provided by the gas turbine (HMI) [1] detects the faulty conditions, then these conditions are used for further investigations by fuzzy implementation to check if there is a fault component or transducer malfunction. And the software is used to determine the working condition 'health' of the transducers that measures the temperatures or pressures at each turbine stage, as a parametric input data of the turbine cycle, to check its defective condition after the occurrence of the alarm. Random values were applied to the fuzzy systems to show the sensor's condition and to detect the fault type, whether it is component malfunction or sensor fault as shown in Table 1. For example, T_1 is the real temperature that is provided by thermocouple no.1 shown in Fig. 7, T_{2p} is the predicted value by the fuzzy combination shown in Fig.1, $T_{2\ actual}$ is temperature that is provided by thermocouple no.2, Rp is the pressure ratio, the calculated efficiency was around 27%.

The sensor's faulty reading (as in the first case, Table 1) is due to the sensor degradation and other uncertainties that are represented with the signal distortion, transducers aging and general malfunctions.

The implementation sequence starts with alarm that imply for two possible errors; the component error or the transducer error, then the fault will be subjected to further investigation by the first fuzzy implementation (Fig.1) . The final step is accomplished by the second fuzzy implementation (Fig. 2) by estimating the sensor's condition (health) and verifying if the last alarm had caused any defection into it.

The software that is provided by the gas turbine is responsible for detecting primer faults when any measured value goes beyond its limited boundaries that set by manufacturer or the operator.

5. Conclusions and Discussion

One of the advantages of using fuzzy logic method is for the prediction and monitoring of the faulty components, and measuring sensors working conditions of gas turbine used in the thermal power plants.

The method presented uses fuzzy implementation to detect the fault type (whether it is component's fault or transducer's fault) and to estimate the transducers' accuracy in a percentage scale after any alarm to assure their competence, which in turn increases the power production by adjusting the proper operating parameter which can save operational cost, avoids long time breakdowns, and detects the component's faults at its earlier stages. The sensor's faulty reading (as in the first case, Table 1) is due to the sensor degradation and other uncertainties that are represented with the signal distortion, transducers aging and any general malfunctions that could happen to the sensor.

The method presented is considered as a complementary process to the software that provided by common gas turbines manufacturers to investigate the faulty component, and detects the transducers' working conditions (health).

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