Intelligent Techniques for Control and Fault Diagnosis in Pressurized Water Reactor: A Review

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Abstract: Nuclear reactors serve approximately 10% of the world's energy usage, and over 430 Nuclear Power Plants (NPP) are currently built globally. They are safety-critical systems as neutron flux density in the nuclear reactor core has to be critically controlled within limits. The parameters of a reactor core should be monitored and optimally regulated to increase the performance of the system. Also, any fault in an NPP system may potentially compromise plant safety. Thus, implementing early Fault Detection and Diagnosis (FDD) techniques becomes crucial. With considerable advancements in computational speed and electronics becoming cost-effective, Artificial Intelligence (AI) has grown implausible in recent times. This review article discusses on few AI techniques to optimally control the neutron flux density and design an effective fault diagnosis algorithm to detect sensor faults in the nuclear reactor core.

Keywords: Fault diagnosis; Neural Networks; Artificial Intelligence; Optimization Techniques; Nuclear reactor, Swarm Inteligeence

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1. Introduction

Power regulation and early fault detection are crucial in a safety-critical process like a nuclear reactor. Whether nuclear energy is produced independently or in a combined cycle with other renewables, artificial intelligence may play a critical role in proceeding with innovation regardless of the future guidelines enacted to satiate the world's energy demand. Computational intelligence has long been considered to have a variety of uses in the nuclear sector. Artificial intelligence has progressed tremendously in recent years due to computing power and cheaper hardware developments. Approximately 10% of the world's electricity is at present produced by nuclear reactors, and more nuclear power stations are enthusiastically being built across the globe. However, the nuclear sector was under pressure to innovate following a few nuclear accidents like Fukushima, Three-mile Island and Chernobyl, particularly in affluent nations.

The paper by Suman [1] briefly overviews the AI techniques reported in the literature for application in the nuclear power sector. The author highlights AI algorithms like Neural Networks [2,3], Genetic Algorithms [4,5,6], Particle Swarm Optimization [7,8], Ant Colony Optimization [9,10], Artificial Bee Colony Optimization [11,12], Simulated annealing [13] and Support vector machine [14,15] which are applied to the nuclear energy sector. The author also mentions the following AI application areas:

- Load following operation
- Fuel management
- Fault diagnosis in nuclear power plant
- Identification of nuclear power plant transients
- Identification of accident scenario

The nuclear energy industry is driven to innovate, and new reactor designs are marketed as inherently safe, reliable, cost-effective, and versatile. Current nuclear reactors aim to increase safety, maintain availability, and lower operating and maintenance costs. The studies focusing on integrating the capabilities of artificial intelligence in the nuclear industry have come a long way and the time has come to teach this in upcoming advanced nuclear power plants [90]f

. The objective of this paper is to investigate two such areas in NPP where AI techniques can be implemented. They are as follows:

- Utilization of Swarm Intelligence algorithms for the design of optimal PID controller that regulates neutron density.

- Utilization of Neural Networks for state estimation and fault detection in Pressurized Water Reactor core.

An extensive literature survey is carried out to gain insights into the above two technologies. Abbreviations used in this article are listed in Table 1.

Table 1: Abbreviations

AI	Artificial Intelligence
ACO	Ant Colony Optimization
AGR	Advanced gas-cooled reactor
ART1	binary Adaptive Resonance Network
AVR	Automatic Voltage Regulator
BRNN	Bayesian Recurrent Neural Network
BWR	Boiling water reactor
CAN	Controller Area Network
EKF	Extended Kalman filter
FDD	Fault Detection and Diagnosis
FDI	Fault Detection and Isolation
FEM	Finite Element Method
FNR	Fast neutron reactor
GM	Gain Margin
HTGR	High temperature gas-cooled reactor
IAE	Integral Absolute Error
IAEA	International Atomic Energy Agency
IMC	Internal Model Control
ISE	Integral Square Error
ITAE	Integral Time Absolute Error
KNN	K-Nearest Neighbors
LRNN	Locally Recurrent Neural Network
LWGR	Light water graphite reactor
MSE	Mean Square Error
NARX	Nonlinear Autoregressive Network with Exogenous Inputs
NPP	Nuclear Power Plant
PCA	Principal Component Analysis
PID	Proportional-Integral-Derivative
PHWR	Pressurized heavy water reactor
PM	Phase Margin
PSO	Particle Swarm Optimization
PWR	Pressurized Water Reactor
RBF-NN	Radial Basis Function Neural Network
RNN	Recurrent Neural Networks
SISO	Single Input Single Output
SVM	Support Vector Machine
TEP	Tennessee Eastman Process
UKF	Unscented Kalman Filter

2. System Description

2.1 Nuclear reactor

In a nuclear reactor, energy is released by splitting atoms of radioactive elements. This energy is captured as heat in either a gas or water and is utilised to generate steam. It is released from the regular fission of the fuel's atoms. The steam powers the electricity-generating turbines (as in most fossil fuel plants). Among the several nuclear reactor types, Pressurized Water Reactors (PWR) are the most prevalent, as depicted in Table 1.1 (Source: www.iaea.org). According to the International Atomic Energy Agency's (IAEA) nuclear power status report [16] approximately 308 PWR-type nuclear reactors are providing 294.8 GW of power worldwide.

Table 2 Operable Nuclear Power Plants

Reactor Type	Number	Power (GWe)	Fuel	Coolant	Moderator
Pressurized water reactor (PWR)	308	294.8	Enriched UO2	Water	Water
Boiling water reactor (BWR)	61	61.9	Enriched UO2	Water	Water
Pressurized heavy water reactor (PHWR)	47	24.3	Natural UO2	Heavy water	Heavy water
Light water graphite reactor (LWGR)	11	7.4	Enriched UO2	Water	Graphite

Advanced gas-cooled reactor (AGR)	8	4.7	Natural U, Enriched UO2	CO2	Graphite
Fast neutron reactor (FNR)	2	1.4	PuO2 and UO2	Liquid sodium	None
High temperature gas-cooled reactor (HTGR)	1	0.2	Enriched UO2	Helium	Graphite

Pressurized Water Reactors utilizes water as both moderator and coolant. The design is eminent by a primary cooling unit which flows water via the core of the reactor with very high pressure, and a secondary unit which produces steam to drive the turbine [17]. This PWR is also known as water-water energetic reactors (VVER) in Russia. A PWR has vertically arranged fuel assemblies with 200-300 enriched uranium filled fuel rods.

Since the water in the reactor core attains a temperature of around 325°C, it must be reserved under a pressure of nearly 150 times that of the atmosphere to avoid boiling. In a pressurizer as seen in Figure 1.5 [18], steam preserves the pressure. Water serves as a moderator in the primary cooling circuit. If any of it went to steam, the fission reaction would be slowed. This is the negative feedback effect. The fission reaction can be controlled or shut down by the use of control rods. Control rods are the chief control element of the reactor core. Water boils in the heat exchangers, which acts as steam generators, in the secondary unit due there is less pressure there. The steam condenses and returns to the heat exchangers in contact with the primary circuit after powering the turbine to generate electricity [88].

2.2 Pressurized water reactor model

The reactor power model is built on point kinetic equations with three groups of delayed neutrons $c_{ri}, i = 1,2,3$; and reactivity feedback is affected by changes in fuel and coolant temperatures [19, 89]. There are seven state variables in this SISO model. The following are the equations for a Pressurized water nuclear reactor core:

The three groups' delayed neutrons-based point kinetic equations are

$$\frac{dn_r}{dt} = \frac{\rho_t - \beta}{\Lambda} n_r + \sum_{i=1}^{3} \frac{\beta_i}{\Lambda} c_{ri} \quad (1)$$

$$\frac{dc_{ri}}{dt} = \lambda_i n_r - \lambda_i c_{ri}, i = 1,2,3 \quad (2)$$

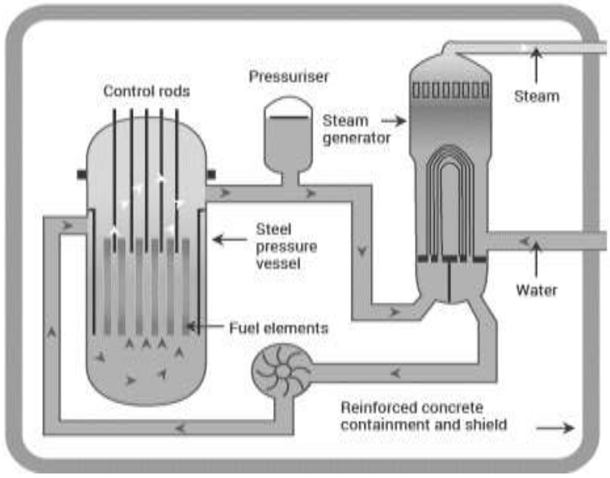

Figure 1 Layout of Pressurized Water Reactors [18]

Where n_r is normalized neutron density, c_{ri} is ith group normalized delayed neutron precursor density. Delayed neutrons are neutrons produced during the radioactive decay of certain neutron-rich fission fragments. They are produced within a few milliseconds to seconds after the fission reaction. These delayed neutrons are grouped into three or six groups.

The reactor's thermal-hydraulic model is given by,

$$\frac{dT_f}{dt} = \frac{f_f P_0}{\mu_f} n_r - \frac{\Omega}{\mu_f} T_f + \frac{\Omega}{2\mu_f} T_{in} + \frac{\Omega}{2\mu_f} T_{\text{out}} \quad (3)$$

$$\frac{dT_c}{dt} = \frac{(1-f_f)P_0}{\mu_c} n_r - \frac{(2M+\Omega)}{2\mu_c} T_{\text{out}} + \frac{(2M-\Omega)}{2\mu_c} T_{\text{in}} \quad (4)$$

Where T_f is Fuel average temperature and T_c is Coolant average temperature. T_{in}, T_{out} are coolant inlet and outlet temperatures respectively.

Nuclear reactors use the essential term "reactivity" to describe when a reactor system deviates from criticality. A shift toward supercriticality is indicated by addition of small positive value. A shift toward subcriticality is indicated by addition of small negative value. This reactivity changes as the speed of the control rod variations, as does the total reactivity is

$$\frac{d\rho_{rod}}{dt} = G_r Z_r \quad (5)$$

$$\rho_t = \rho_{rod} + \alpha_f (T_f - T_{f0}) + \alpha_c (T_c - T_{c0}) \quad (6)$$

ρ_{rod} is the reactivity induced due to control rods and ρ_T is the reactivity induced due to fuel and coolant temperatures. ρ_t is total reactivity. Also $\mu_c, M, \Omega, \alpha_f$,and $\alpha_c$are related to initial equilibrium neutron density (n_{r0}). The following equations demonstrate the dependency.

$$\mu_c = \left(\frac{160}{9}\right) n_{r0} + 5 \quad (7)$$

$$\Omega = \left(\frac{5}{3}\right) n_{r0} + 4.9333 \quad (8)$$

$$\alpha_f = (n_{r0} - 4.24) \times 10^{-5} \quad (9)$$

$$\alpha_c = (-4n_{r0} - 17.3) \times 10^{-5} \quad (10)$$

The reactor power is expressed as,

$$p_t = p_0 n_r(t) \quad (11)$$

The reactor model's parameters and values are listed in Table 2 and Table 3.

Table 2. Parameters in PWR model

P_0	Full core power, MW
n_r	Normalized neutron density (relative to neutron density at rated power P^0)
cr_i	ith Group normalized precursor density (relative to density at rated power)
T_f	Fuel average temperature, ºC
T_{f0}	Fuel average temperature at the initial condition, ºC
T_c	Coolant average temperature, ºC
T_{c0}	Coolant average temperature at the initial condition, ºC
T_{in}	Coolant inlet temperature, ºC
T_{out}	Coolant outlet temperature, ºC
ρ_t	Total reactivity, δK/K
ρ_{rod}	Reactivity due to control rod movement, δK/K
ρ_T	Temperature reactivity feedback, δK/K
Zr	Control rod speed, fraction of core, length/s
Gr	Control rod total reactivity, δK/K
β	Effective delayed neutron fraction
β_i	ith group effective delayed neutron fraction
α_c	Coolant temperature coefficient, (δK/K) / ºC
α_f	Fuel temperature coefficient, (δK/K) / ºC
Λ	Neutron generation time, s
λ_i	ith Delayed neutron group decay constant, s^{-1}
Σ_f	Macroscopic thermal neutron fission cross-section, cm^{-1}
v	Average number of neutrons produced per fission of 235U
G	Useful thermal energy liberated per fission of 235U, MW-s
V	Core volume, cm^3
f_f	Fraction of reactor power deposited in the fuel
μ_f	Fuel total heat capacity, MW.s/ ºC
μ_c	Coolant total heat capacity, MW.s/ ºC
M	Mass flow rate time heat capacity of water, MW/ ºC
Ω	Coefficient of heat transfer between fuel and coolant, MW/ ºC”

Table 3 Values of parameters used in reactor model

Parameters	Values
Thermal power	3000 MW
Core height	400 cm
Core radius	200 cm
Σ_f	0.3358 cm-1
G	3.2×10^{-11} MW · s
G_r	14.5×10^{-3} δK/K

T_{in}	290°C
μ_f	26.3 $MW\ s/$°C
f_f	0.92
Λ	10^{-4} s
β	0.0065
β_1	0.00021
β_2	0.00225
β_3	0.00404
λ_1	0.0124 s^{-1}
λ_2	0.0369 s^{-1}
λ_3	0.632 s-1

3. Review of swarm intelligence algorithms for control

Swarm Intelligence is one of the progressive research areas in the domain of Artificial Intelligence, which has become prevalent in solving various optimization problems and thus has a wide range of applications. Specifically in the control domain, it has become one of the useful methods for optimally tuning the controller parameters to achieve efficient control [12]. Swarm Intelligence is driven by the cohesive nature of the social insect territories or other animal communities [104].

Optimization is the procedure of finding the best inputs u* in obtaining the optimal output y* with minimum cost J*. Optimization problem is solved by choosing the design parameter, then formulating the constraints and defining a cost function. The aim of the cost function is to determine a value for chosen design parameter satisfying the given constraint that delivers the optimum response. With respect to controller tuning, optimization algorithms will provide optimal controller tuning parameters that minimize the error and control effort [23].

Around 90% of control loops in the process industries use the PID control algorithm. This wide application is because of its simple structure that could be effortlessly understood by process operators. A typical structure for a regular PID controller comprises three components namely: proportional gain k_p, integral gain k_i and derivative gain k_d. The derivative gain develops the control action according to the rate of change of error, the integral gain develops the control action in response to the sum of all past errors, and the proportional gain produces the control action for present error. PID controller tuning is done either by trial and error using the operator's process knowledge or by conventional tuning methods.

The frequently used traditional PID tuning techniques, like Cohen-Coon and Ziegler-Nichols, may not provide effective tuning parameters due to changing process dynamics and inaccurate process models [82]. The optimal controller gains for good performance can be attained via swarm intelligence which is measured in terms of fitness functions such as integral square error, absolute error, mean square error, etc. These optimization algorithms are simple, flexible to search randomly and also avoid local optima [24].

3.1 Framework

Essentially, swarm intelligence algorithms are iterative stochastic search procedures, where heuristic data is shared to perform the search. Figure 2 shows a general framework for swarm intelligence algorithms. It is compulsory to define the parameter values prior to the initialization process. Initialization and the ensuing strategies set off the evolutionary process. A termination condition is set to stop the iteration process which may be a single condition or a combination of two criteria. The fitness function, which can be either one basic metric or a combination, is responsible for evaluating the search agents. Agents are updated by the algorithm until the preceding termination condition is met. The best search result is then obtained. The execution of each step may occur in a varied order for a given swarm intelligence algorithm, and some processes may be repeated multiple times inside a single iteration.

3.1.1 Classification

Swarm Intelligence algorithms mimic the collective behaviour of birds or fish or insects that are prevalent throughout the ecosystem. As these algorithms are widely applied in various engineering domains, classifications by various collective behaviour were proposed by researchers [25]. The rough classification of such algorithms is illustrated in Figure 3. A detailed literature study is carried out for PSO and ACO algorithms in this article.

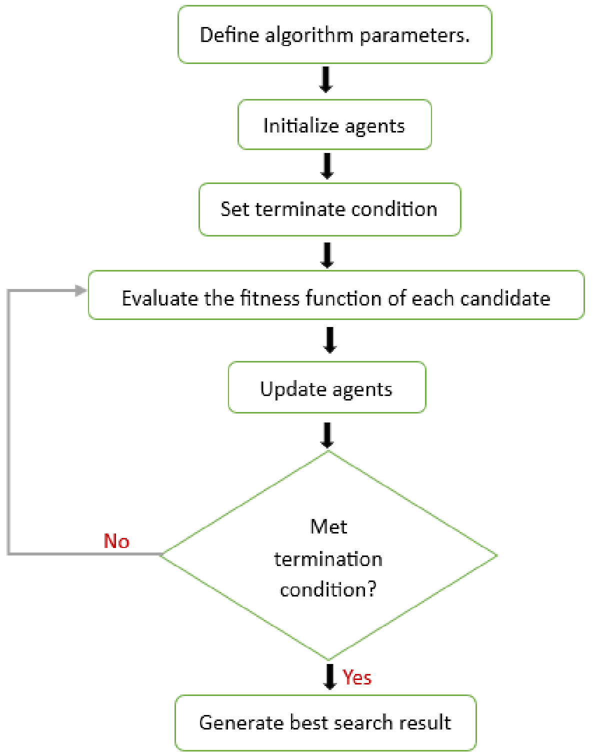

Figure 2 General Framework of Swarm Intelligence Algorithm

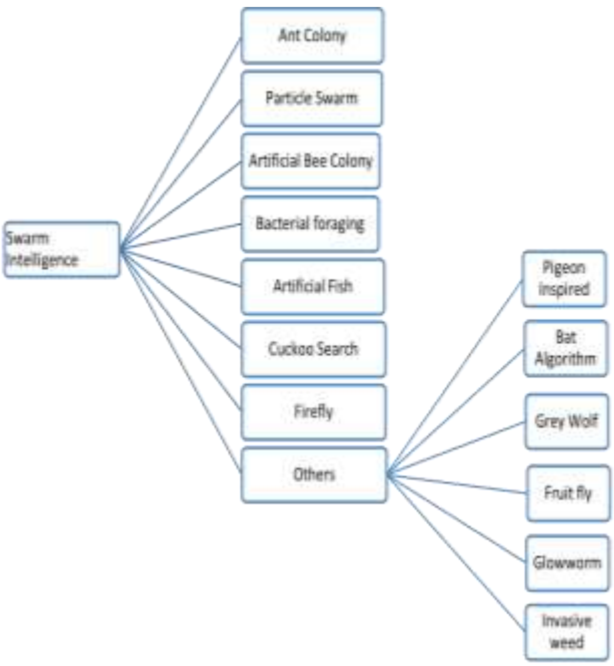

Figure 3 Classification of Swarm Intelligence Algorithms

3.1.2 Particle Swarm Optimization

Particle Swarm Optimization (PSO) is a popular metaheuristic optimization technique inspired by the social behaviour of bird flocking or fish schooling [92]. Introduced by Dr. James Kennedy and Dr. Russell Eberhart, PSO is widely used for solving various optimization problems in diverse domains, including engineering, economics, medicine, and machine learning (Kennedy 2006). PSO has been used in various applications of automatic control systems that heavily rely on PID controllers.

Particle swarm optimization simulates the behavioural patterns of swarming birds or schooling fish. The flowchart of PSO is as shown in Figure 4 [26]. Each particle/bird has its own position and velocity. These particles adjust their velocities to alter their position in order to seek meal, avoid danger, or identify best possible environmental parameters. Furthermore, each particle remembers the best location that it has identified. Each particle conveys this information about the best location to the other particles. The velocity of such particles is then updated based on the particle's or the group's flying experience.

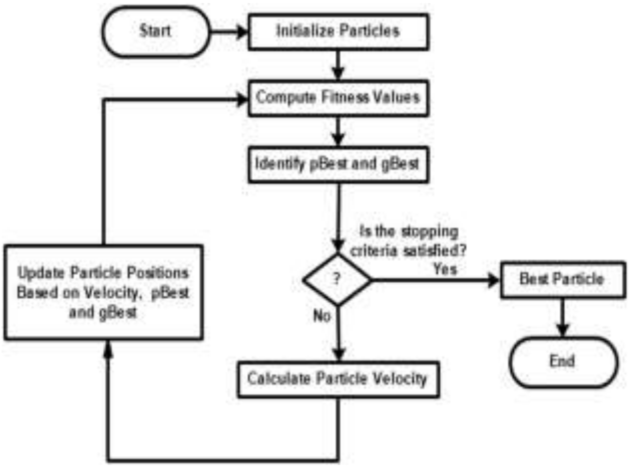

Figure 4 Flow diagram for Particle Swarm Optimization

Gaing provided a thorough explanation of how to use the PSO method to quickly find the ideal PID controller parameters for an Automatic Voltage Regulator (AVR) system [27]. The suggested method exhibited excellent characteristics, such as simple implementation, consistent convergence behaviour, and good computational efficiency. The proposed method proved effective and reliable in increasing the step response of an AVR system when compared to the Genetic Algorithm (GA). Moreover, the PSO algorithm is also employed to design a fractional order PID controller for an AVR system [29]. In this work, a novel cost which is a function of Overshoot, rising time, settling time, steady state error, Gain Margin (GM) and Phase Margin (PM) is used.

To execute the optimisation of the controller gains and enhance the performance of a single-shaft Combined Cycle Power Plant, a fractional order fuzzy-PID (fuzzy-FoPID) controller based on the PSO algorithm is presented [23]. In order to increase the response during frequency drops or changes in loading, the proposed controller is employed in speed control loops. The simulation results demonstrate the performance and efficacy of the suggested strategy for frequency decrease or loading modification.

Using PSO, Zeng *et al* optimized an IMC PID controller to stabilise the core power of the Molten Salt Breeder Reactor [29]. A control technique based on a process mathematical model for controller design is known as Internal Model Control (IMC). IMC's principle of design is to add the inverse of the minimum phase component of the model for a single variable system to the system, approximate the dynamic inversion of the model by the controller, and parallelize the object model with the actual object.

The tuning problem of digital Proportional-Integral-Derivative (PID) variables for a dc motor controlled via the Controller Area Network (CAN) was examined by (Qi *et al.* 2020) [30]. PSO technique was introduced to optimally tune the PID controller's parameters for systems susceptible to stochastic delays. To deal with the stochastic characteristics, the optimisation method includes a stability requirement for time-delayed systems and proposes an objective function with an average value for the PSO algorithm. Similarly, much research in PSO for tuning controller gains is reported in the literature [7,31,32,33]

3.1.3 Ant Colony Optimization

An algorithm known as Ant Colony Optimisation (ACO) was inspired by how ants forage. It was initially proposed by Marco Dorigo to address the Travelling Salesman Problem and other combinatorial optimisation problems. Ants in nature interact with one another and build pathways between their nests and food sources via pheromones. The pheromone trail gets stronger the more ants move along a particular path. The quickest routes between the nest and the food supply are formed by ants generally following the routes with higher pheromone levels. This idea is used by the ACO algorithm to locate efficient solutions to optimisation issues [34, 83]. This principle can be used to tune PID controllers.

Ant colony optimization is a probability – based technique in which the optimal route in a plot is sought observing the behaviour of ants looking to find a path between their colony and a food source. The ants find the best route to any distanced food source. Refer to Figure 5 to understand the mechanisms behind this [26]. First, an ant leaves the hives in looking for food and finds it in a particular location; the leftover ants will follow the pheromones left by the first ant. If there are different routes to the same source, the pheromones on the quickest route will last longer than the pheromones from the other paths, causing the quickest route more rewarding for new ants emerging from the nest, The pheromone intensity on that path will rise, while the pheromone intensity on the longest path will drop.

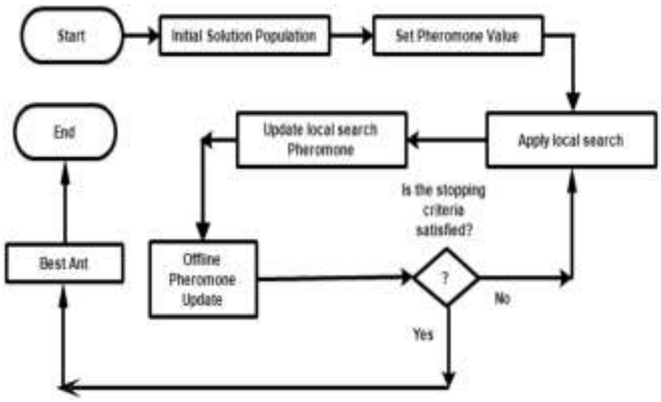

Figure 5 Flow diagram for Ant Colony Optimization

Hsiao et al. (2004) obtained good load disturbance response by minimizing the integral absolute control error [35]. At the same time, a good transient response is guaranteed by minimizing the time domain specifications. This study proposes a solution algorithm based on the ant colony optimization technique to determine the parameters of the PID controller for getting good performance for a given plant. The proposed method was implemented and tested on several plants with promising results that compare with known methods.

Multiobjective ant colony optimisation was utilised by Chiha et al. to fine-tune PID controllers [36]. To find the Pareto-optimal solution, multiobjective ant algorithms are required. Results from simulations show that the new tuning method employing multiobjective ant colony optimisation outperforms both the traditional "Ziegler-Nichols" approach and genetic algorithms in terms of control system performance. Youssef Dhieb et al. employed an ACO-tuned PID to eliminate the induction motor's harmonics and speed ripple [37]. Using the finite element method (FEM), the parameters of this motor were determined. Two distinct tuning methods based on manual and ACO tuning of PID-controller parameters have been presented.

The control of a levitating object in a magnetic levitation plant using a fractional order PID (FoPID) controller is presented in [9]. The parameters of this FoPID controller have been updated using the Ziegler Nichols method and the Ant Colony Optimisation (ACO) algorithm. For comparison study, the output results of the FoPID controller are compared to those of the conventional PID controller. In comparison to the conventional PID controller, the FoPID controller has demonstrated incredibly effective outcomes due to its additional parameters.

Arun & Manigandan constructed an Ant colony Optimization-based PID controller for a zeta converter [38]. The higher-order zeta converter system is reduced to second order using three distinct reduction techniques. Then, the ACO-based PID controller is designed for a reduced-order process and is matched with the full-order zeta converter. The results show that the designed controller for the zeta converter gives a good response for both models, the controller gives good performance indices based on ISE, IAE, and ITAE. Similarly, Karami used ACO-tuned PID to Micro-Robot Equipped with a Vibratory Actuator [39] and Rahman used it for vibration control of a wind turbine tower [40]

4. Fault Detection and Diagnosis Techniques

Faults are unpermitted deviations from the typical behaviour of the process or its instrumentation. It is classified as process faults, sensor faults and actuator faults conditional on the site it arises. Identifying the location of the fault and determining its magnitude is called fault diagnosis. With the huge demand for complex processes and automation, innumerable procedures were proposed to detect and locate the fault [41, 82]. An unobserved fault in the process may have catastrophic effects such as environmental hazards or safety risks. The primary stage in treating a failure is determining its location, which is vital for conserving the plant's ideal conditions [80].

The fault detection and isolation (FDI) methods are broadly classified into Model-free and Model-based approaches [85]. The subcategories are shown in Figure 6.

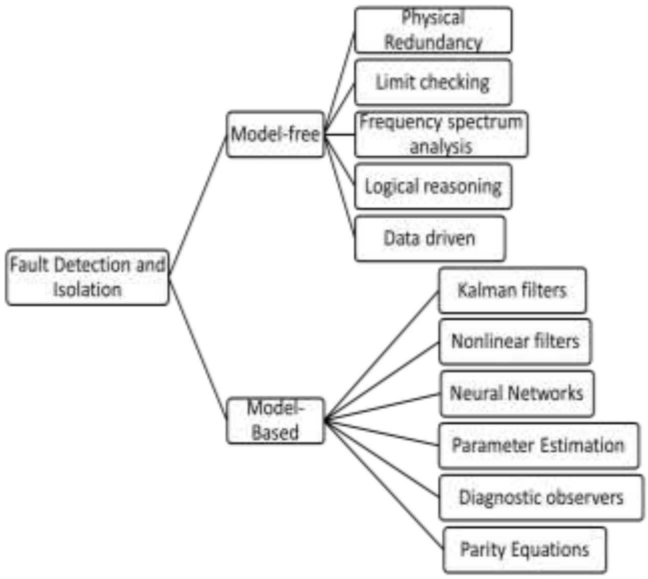

Figure 6 Methods in Fault Detection and Isolation

4.1 Model-free Approaches

Model-free approaches are FDD techniques that do not depend on explicit mathematical models of the problem under consideration. Few such model-free approaches are discussed here [42].

- In physical redundancy, many measuring devices are mounted to read the same physical entity. Any inconsistencies amongst the sensor readings will show a sensor fault. At least three sensors are needed to detect a fault in the sensor using this method.

- The limit-checking technique compares process measurements with a threshold value. Surpassing this threshold specifies a fault. Thresholds must be clearly defined as measurements will fluctuate even during normal load variations.
- Under ordinary operating circumstances, the majority of process measurements display a conventional frequency spectrum. Every departure from this is a sign of abnormality.
- In the logical reasoning technique, process information is analyzed qualitatively using tools such as if-then rules. These qualitative approaches can process inaccurate and inadequate information to reach a fault decision. Two prevalent techniques are expert systems and fuzzy logic.
- Data-driven approaches practice multivariate statistical techniques and machine learning algorithms to find a fault. They also count on associations amongst correlated measurements in a process but utilize them subtly by examining fault-free training data attained during standard operations. Thus, these methods are also denoted as process history-based approaches. Principal Component Analysis, Artificial neural networks are extensively utilized for Fault diagnosis [93, 96, 97].

4.2 Model-based Approaches

Analytical redundancy is the main idea behind model-based fault diagnosis methods. In model-based FDD, the standard behaviour of a process is characterized by a mathematical model which can be an input-output model or a state space model. Sensor outputs are predicted analytically by means of the model that defines their associations. The concept can be extended to predict new quantities analytically, such as model parameters and system states. Residuals are the variations between the analytically predicted values and the true measurements. Faults lead to violations of the normal relationships represented by the model, which causes the residuals to fluctuate abnormally. Therefore, faults can be found by statistically examining these residuals. The processes of model-based FDD can be separated into the succeeding subsystems: residual generation, residual evaluation and decision making. The model-based FDD scheme is shown in Figure 7.

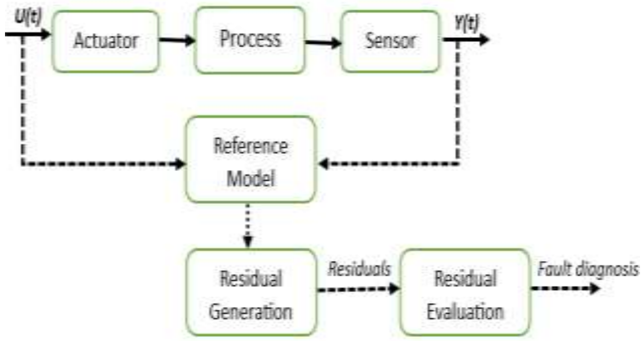

Figure 7 Model-based FDD scheme

An approximate mathematical model of the monitored process is obtained by first principle modelling or state and parameter estimation methods. Residuals produced are then evaluated to provide fault isolation decisions. Even when there is no fault, residuals are not zero because of the noise and modelling mistakes. Threshold margins are set in no-fault circumstances [42]. A structural framework's residual analysis can be utilized to regulate the fault's nature and position. The methods of residue generation are as follows:

- Kalman Filter: This filter's prediction error can be applied as a residual for fault detection. If there is any fault, the residuals violate the threshold value. This technique is useful for finding additive errors. It can handle stochastic disturbances in the system. The filter equations are as follows:

  $$\hat{x}(t+1 \mid t) = A\hat{x}(t \mid t) + Bu(t) \quad (12)$$
  $$\hat{x}(t \mid t) = \hat{x}(t \mid t-1) + K'(t)e(t) \quad (13)$$
  $$e(t) = y(t) - Cx^{(t|t-1)} \quad (14)$$

  where $K'(t)$ is Kalman gain

- Nonlinear Filters: Filters like Extended Kalman filter, Unscented Kalman filter, Particle filter can be used to generate residues for a highly nonlinear process [91,98,102].
- Neural Networks: Neural network models can be built using input-output data of the process. These models are then utilized for state

estimation. Different architectures of neural networks are available and they can be chosen based on the process data [86, 95]. A multilayer Feedforward NN includes one input layer, one or more hidden layers, and one output layer. Each component of the input vector $I = [i_1, i_2, \dots, i_k]$ is weighted by its weight matrix W. The neuron bias b is summated to give the net input

$$n = \sum_{j=1}^{k} w_j i_j + b \quad (15)$$

Then, an activation function f is utilized to produce the neuron output o. Similarly, many topologies of neural networks are available.

- Parameter Estimation: It is used to detect and isolate multiplicative faults that arise due to the plant's underlying parameters. Physical coefficients shall be estimated for diagnosis. It requires significant online computations and high input excitation. The least-square parameter estimator equation is
$$\theta = [\Psi^T \Psi]^{-1} \Psi^T Y \quad (16)$$
where θ is an estimation of θ, Ψ is a matrix consisting of $\psi^T(t)$. Y is a vector consisting of $y(t)$.
- Diagnostic Observers: Similar to state and parameter estimators, the observer innovations can also be utilized for fault detection. Observer equation is
$$\hat{x}(t+1) = A\hat{x}(t) + Bu(t) + L(y(t) - C\hat{x}(t)) \quad (17)$$
$$e(t) = y(t) - \hat{x}(t) \quad (18)$$
where $\hat{x}$ is an estimate of x, and L is is the observer feedback matrix.
- Parity Equations: They are reorganized direct input-output model equivalences subjected to linear dynamic transformation. The residuals from the transformed model aid for fault detection.
$$e(t) = G(z)u(t) - H(z)y(t) \quad (19)$$
where $e(t)$ is residual.

4.3 Review of FDD Techniques

Hardware or analytical redundancies are used to monitor and isolate the fault. The magnitude of the fault can also be found. Though hardware redundancy is reliable, it increases cost, space and weight of the process. Analytical redundancy is a model-based fault detection method wherein states are estimated analytically from other correlated measurements using the model or plant data [43]. The residuals are the differences between the analytically estimated quantities and the actual measurements. When the residual signal crosses the threshold, a fault is indicated. Upon assessing the residual trend, faults can be classified as additive or multiplicative. Instant fault isolation can be achieved via structured or directional residuals.

The survey papers [44, 45] on model-based, signal-based and knowledge-based fault diagnosis give a complete overview of the fault diagnosis methods and their applications. The merits and limitations of each technique were discussed. Model-based FDD techniques are reviewed for deterministic, stochastic systems. Signal-based FDD techniques are classified based on time and frequency domain. Knowledge-based FDD methods are on extracted quantitative or qualitative data. The books by Janos Gertler in 1998 [42] and Rolf Isermann in 2006 [43] features the model-based approach to fault detection and diagnosis in process industries and systems.

Safarinejadian & Kowsari used an Extended Kalman Filter (EKF) and Unscented Kalman Filter (UKF) with Gaussian processes to detect faults in highly non-linear dynamical aviation tracking systems [47]. For 2-D systems defined by the Fornasini & Marchesini (F-M) model, a 2-D Kalman filter based fault detection was proposed by (Wang & Shan [48]. A residual is produced using a recursive 2-D Kalman filter. The residual is explicitly tied to faults inside the evaluation window based on the residual model across a 2-D evaluation window. An intelligent particle filter for real-time fault detection on a three-tank system was proposed by Yin & Zhu [49]. A genetic operators-based approach is used to overcome particle impoverishment problems in general PF. Kumar et al tries to estimate and identify the types of faults in centrifugal pumps using a system identification approach [50]. These papers are examples of where model-based FDD techniques are used.

Based on the acoustic measurement of current amplitude, [51] presented a new Fault Detection and Diagnostics (FDD) control approach for current sensors of permanent magnet synchronous machine drives in field-oriented control mode. The suggested scheme does not require an exact system model with specific parameters, unlike the traditional observer-/model-based fault detection methods for current sensors. Instead, it simply needs data on three-phase currents and the location of the motor rotor. The goal of [52] is to detect faults in belt conveyor idlers using an acoustic signal-based approach. Mel Frequency Cepstrum Coefficients and Gradient Boost Decision Tree are used to extract and classify features in a novel manner. These two publications serve as illustrations of the application of signal-based FDD approaches.

A fault detection method based on the calculation of sets of parameters for a photovoltaic module under various operating conditions, using a neuro-fuzzy methodology, was proposed by [53]. The evaluation and comparison of norms based on the aforementioned criteria, along with threshold values, determine the condition of the PV system. The Support Vector Machines (SVMs) classification approach described by [54, 87] is used for fault detection in wireless sensor networks, which are vulnerable to a variety of problems, including hardware, software, and communication faults. [55] use supervised algorithms like support vector machines and the K-Nearest Neighbour method to anticipate boiler problems in power plants. These papers serve as illustrations of the application of knowledge-based FDD methodologies.

FDD methods are also demanded in nuclear power sectors to improve their safety and reliability. Ma & Jiang presented the various FDD that can be utilized for the following applications in NPPs: Monitoring of device calibration, dynamic performance, equipment, reactor core, loose parts and transient recognition [56]. Neural networks can be applied to all the above-mentioned applications [57, 3, 58]. This article focuses on the review of Neural networks for nonlinear state estimation.

4.3.1 Neural Networks for Nonlinear State Estimation

Robotics, control systems, and signal processing are just a few of the areas where neural networks have been successfully used to solve state estimation challenges. The neural network architecture and training method must be specifically designed for state estimation purposes. Additionally, gathering enough pertinent training data is essential for neural network applications in state estimation tasks.

Rumelhart et al. (1986) presented the backpropagation algorithm for training neural networks [59]. While not directly focused on state estimation, it laid the basis for applying neural networks to various nonlinear tasks, including state estimation. Nielsen in 1996 explored the use of neural networks for modelling and predicting nonlinear dynamic systems [60]. It delivers insights into how neural networks can be used for state estimation in such systems. The Radial Basis Function Neural Network (RBF-NN) is applied to match an Extended Kalman filter (EKF) in a data assimilation scenario.

By constraining the state estimator to adopt the topology of a multilayer feedforward network, Parisini & Zoppoli developed a novel method for solving the optimal state estimation problem using neural networks [61, 84]. It is possible to convert the original functional problem into a nonlinear programming problem by using non-recursive and recursive estimating strategies, which are both taken into consideration. Quantitative findings on the accuracy of such approximations are presented.

The use of artificial neural networks to estimate and predict bioprocess variables was examined by Karim & Rivera [62]. Two case studies were carried out on ethanol generation by Zymomonas mobilis. Results for various training sets and training strategies are shown. It is demonstrated that the neural network estimator offers accurate online estimations of the bioprocess state. The design of an artificial neural network-based model for centrifugal pumping system fault detection was described by Rajakarunakaran et al [63]. The binary Adaptive Resonance Network (ART1) and feed-forward network with a backpropagation algorithm are the two artificial neural network approaches used for developing the fault detection model. Seven different categories of centrifugal pumping system anomalies were examined to determine the effectiveness of the designed backpropagation and ART1 models.

Using 1-D convolutional neural networks with an inherent adaptive design, Turker Ince proposed a quick and precise motor condition monitoring and early fault-detection system to combine the feature extraction and classification phases of motor fault detection into a single learning body [64]. The suggested method instantly applies to the raw data (signal), which eliminates the need for a separate feature extraction algorithm and leads to faster and more hardware-efficient systems. The usefulness of the suggested strategy for real-time motor condition monitoring has been demonstrated by experimental findings acquired utilising actual motor data.

Sun et al suggested a unique deep learning methodology that uses Bayesian Recurrent Neural Networks (BRNNs) with variational dropout to discover and identify probabilistic faults [2]. Complex nonlinear dynamics can be modelled using the BRNN. In addition to producing uncertainty estimates, the suggested BRNN-based technology enables simultaneous fault detection of chemical processes, direct fault diagnosis, and fault propagation analysis. With reference to the industry standard Tennessee Eastman Process (TEP) and an actual dataset from the chemical production sector, the method's performance is shown and compared to that of (dynamic) principal component analysis.

4.3.2 State Estimation for Fault Diagnosis in PWR

One of the most popular analytical redundant methods for fault detection is state estimation. To estimate the state of a nonlinear Pressurized water reactor, several conventional nonlinear state estimators, namely the Ensemble Kalman filter, Unscented Kalman filter, and Particle filter, have been proposed in the literature. They do, however, require prior knowledge of the system's nonlinearities. Neural network estimators, on the other hand, are data-driven and rely solely on the input-output measurement of the process. The capabilities of neural networks for nonlinear state estimation have been investigated in various literatures [65] both in offline and online environments.

A pressurized water reactor is a safety-critical system that requires early fault detection, which can be accomplished via the use of analytical redundancy components. In analytical redundancy, the states are estimated analytically from other correlated measurements using the model or plant data [41] . The residuals are the differences between the analytically estimated quantities and the actual measurements. When the residual signal crosses the threshold, a fault is indicated. Upon assessing the residual trend, faults can be classified as additive or multiplicative. Instant fault isolation can be achieved via structured or directional residuals.

The dynamics of the PWR are stated in [66]. Among the state variables, Neutron flux, Fuel average temperature, Coolant average temperature are measurable via sensors. These sensor measurements can be compared with the analytical redundant component output value to identify faults. Due to the lack of suitable sensors, variables like reactivity and delayed neutron precursor concentrations can only be measured inferentially. Thus, state estimation becomes critical for control and fault detection in NPPs.

Racz recommended the Kalman filtering method to estimate reactivity for minor changes in reactivity [67]. Dong presented a Robust Kalman filter to estimate various state variables of a reactor, with the performance of the designed robust Kalman filter outperforming the Ensemble Kalman filter [68]. Shimazu & van Rooijen compared the qualitative performance of IPK and EKF techniques [69]. Zahedi & Ansarifar speculated using the EKF technique to estimate poison concentrations in PWR nuclear reactors based on reactor power measurements [70]. Mishra et al explored Adaptive Unscented Kalman Filtering for NPP Reactivity Estimation [71]. EKF and Kullback–Leibler divergence were observed by Gautam et al for sensor incipient fault detection and isolation of NPP [72]. The main limitation of the methods described above is the requirement for a precise mathematical model whose underlying parameters do not vary significantly and whose initial states are known. This cannot be guaranteed for a large reactor core.

The use of neural networks for nonlinear state estimation is impressive in this AI era [1]. Mehrdad Boroushaki et al. proposed a multi-NARX structure for estimating the core of a nuclear reactor [73]. Hatice Akkurt described a neural network estimator for predicting pressurized water reactor system parameters during transients [74]. Cadini et al. suggested a Locally Recurrent Neural Network (LRNN) for approximating a simplified nuclear reactor's nonlinear dynamic system model [75].

Aside from that, several artificial intelligence techniques such as SVM, PCA [76], and neural networks [77,2] are used in NPP fault detection and condition monitoring.

Kumar et al. compared different AI techniques for system identification and state estimation which outworths the promising nature of NN for dynamic estimation [78]. Though the neural network is claimed as a good nonlinear state estimator that works on input-output data [79], the comparative study on different topologies of NN to analyze the suitable network for state estimation in water reactors is not presented in the literature.

5. Conclusion

The prime motive of this review article is to investigate the uses of intelligent techniques to enhance safety in Pressurized water reactor core. The major contributions of this article are twofold: Utilization of Swarm Intelligence algorithms for the design of optimal PID controller that regulates neutron density and Utilization of Neural Networks for state estimation and fault detection in PWR core. Moreover, Intelligent techniques can also be applied to Fuel management, accident scenario, digital twin, fault tolerant schemes and nuclear power plant transients.

DECLARATION OF COMPETING INTEREST
The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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