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POSSIBILITIES OF UTILIZING ARTIFICIAL INTELLIGENCE FOR CONTROLLING TECHNICAL PARAMETERS OF PRIMARY AND SECONDARY COOLING CIRCUITS OF VVER-1000(1200) NUCLEAR REACTORS

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Abstract

In the following article, the possibility of using intelligent control systems (more specifically fuzzy logic controllers) to regulate the technological parameters of the 1st and 2nd loops of VVER-1000 (1200) type reactors has been analyzed. To get a comparative analysis of the regulation of fuzzy-logic-based controllers, as compared to usual PI-controllers, the comparison of the pressure regulation in the purge-recharge system (TK) of the 1st loop of the VVER-1000 reactor, by the control systems mentioned earlier was simulated using the “MatLab-Simulink” software. The ability of both types of controllers to support and maintain the required pressure level of 180 kgf/cm^2 (about 17.6 MPa) was analyzed and conclusions were drawn regarding the advantages and disadvantages of a fuzzy logic-based control system controlling the mentioned reactor parameter as compared to the usual PI-controller.

Keywords: Intelligent control systems; Reactor; regulator; Machine learning; fuzzy logic

1. Introduction

Instrumentation and control systems in a nuclear power station (NPP) can be considered as the nervous system of the plant. Through its various constituent elements (e.g. equipment, modules, subsystems, redundancies, systems, etc.), the plant I&C system senses basic parameters, monitors performance, integrates information, and makes automatic adjustments to plant operations as necessary [1]. However, at present, the majority of components utilized in the I&C systems in NPPs around the world are based on old technologies of the 1960s-70s. Since those years, there have been significant developments in instrumentation and control technologies due to the rapid advancements in digital electronics and software engineering.

These developments have led to more modern instrumentation and more automated instrumentation and control systems being adopted across different industries. One such modern control system is the "Intelligent control systems" which control the parameters of the object of control, relying on the principles of artificial intelligence (AI) [2].

In this article, the possibilities of adopting such intelligent control systems for the I&C systems of NPPs will be investigated. The architecture of the I&C system, its instruments, and personnel together serve as the central nervous system of the NPP. Utilizing its various components, the I&C system determines all the important parameters, and the performance of the station and performs corrective action on the parameters, when necessary, automatically. The system also reacts to abnormalities during the operation of the plant and takes action to ensure safety. The primary goal of the I&C system of the NPP is to provide energy production at the highest possible efficiency while ensuring the safety of the plant personnel as well as the surroundings.

To serve the purpose of the I&C system mentioned above, hundreds of technical, physical, and chemical parameters such as pressure, temperature, neutron flux, etc. of the NPP must be continuously kept within their design limits. For this purpose, in different parts of the station, various instruments of the I&C system such as valves, motors, etc. The control systems of the nuclear power plants have three primary functions.

- Regulate parameters of the station and enable the plant personnel, to take appropriate actions in time.
- Provide automatic regulation of various systems and subsystems of the NPP.
- Protect the station in the event of parameters reaching levels beyond the margins of safety due to errors made by either man or machine.

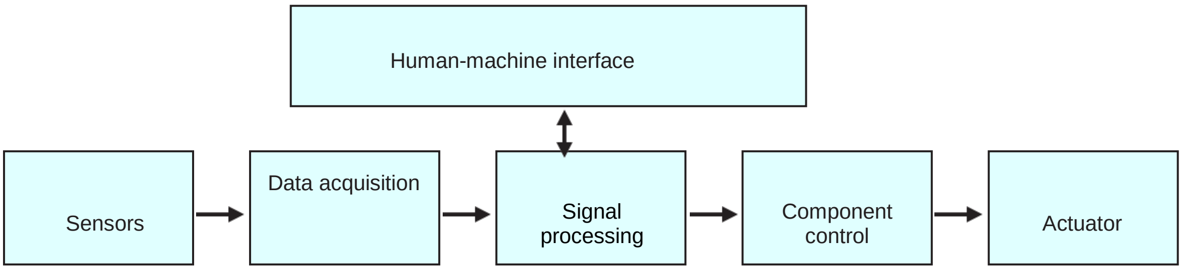

Fig. 1. Block diagram of functionality of a typical control system

In the diagram above, the overview of the functionality of the I&C system of the NPP is shown. The I&C systems rely on several sensors installed in various parts of the station to monitor different plant parameters such as temperature, pressure, neutron flux, etc. in real-time to help keep them within design limits. The type of sensor depends on the parameter it monitors. The measured value is then compared with the set-point value and depending on the difference, the system undertakes corrective action.

Depending upon their functionalities, the various components of the I&C system of NPP can be classified into the following groups [1].

- Sensors;
- Operative control, regulation, and monitoring systems;
- Safety systems;
- Human-machine interfaces;
- Actuators.

The I&C system utilizes different types of sensors such as pressure, temperature, and flow rate sensors, sensors of neutron flux, radiation, and chemical parameters such as concentration of boric acid, etc. Overall, the sensors make up the first layer of interfaces of the I&C systems. The next layer consists of transmitters, electronic devices, and signal processing systems. The third part is made up of actuation devices that can manipulate the various parameters of the NPP and are used to carry out the corrective actions commanded by the automated control system.

The next important aspect of the I&C system is field communication. This layer connects the surface interface devices such as sensors and actuators with the centralized control systems. Field communication in NPPs is carried out in accordance with different communication protocols, depending upon the modernity of the station as well as the type of data collected and the environment in which the sensor is placed. The following protocols are used to different degrees for field communication in NPPs.

- Analog communication (4-20mA DC): The majority of field communication in NPPs around the world is still carried out through analogue communication channels, using 4-20mA DC signals.
- HART (Highway Addressable Remote Transducer protocol): This is a protocol that enables digital signals to be transmitted over already existing 4-20mA DC analogue communication lines by using frequency shift keying (FSK) to superimpose digital signals on top of an analogue DC signal. This protocol is extremely popular in today's process industries.

- Digital communication (wired): Several digital communication protocols that enable the transmission of information over wires, such as SPI, RS-232, I2C, etc. Using such communication protocols information can be transmitted between transmitters and electronic signal processing devices.
- Digital communication (wireless): Such protocols and corresponding devices are rarely ever used for field communication inside a nuclear power plant, except for in some cases, transmission of information about diagnosis of station equipment. However, wireless digital communication is more suitable for devices used in radiation monitoring outside the premises of the NPP.

Cables, penetration, and junction boxes are used for the exchange of data as well as commands between the field communication devices and data transmission devices. Another important aspect of the I&C system in the NPP is the “process monitoring and control system”, it consists of the data acquisition systems and the control systems that regulate the various processes.

- Data Acquisition Systems (DAQs): These systems are utilized for the acquisition, archiving, and processing of signals in control, monitoring, and safety systems.
- Control systems: Typical single-loop regulators with a set-point value, such as the proportional-integral-differential (PID) controller are almost universally used as closed-loop control systems. Such regulators are very widely used in NPPs across the world. The PID controller tries to rectify the error value between the measured output and the desired set-point value by calculating the difference between the two values and then commanding the appropriate corrective action which would rapidly minimize the error.
- Relay-based centralized control systems: These are control systems of older standards that use relay circuits to build logic.
- Centralized electronic control systems: Electronic systems are usually a set of discrete functional blocks that are put together in an architecture to satisfy the requirements of the control systems. These blocks could be analogue input and output cards, binary input/output cards, cards used to carry out specific logical functions or special purpose cards.
- Distributed control systems: Distributed control systems are digital systems that perform the same functionality as centralized systems but, in this case, they use decentralized elements or subsystems to control distributed processes or plant systems. Hence the processing capabilities are shared between distributed processors, and the system database is also distributed amongst the various processing units.

Overall, the I&C systems of NPPs across the world rely on traditional PID controllers to carry out their functions and maintain the different parameters of the station within their design limits.

2. Overview of intelligent control systems

Advancements in the field of automation and developments of control systems have always been aimed at creating more intelligent and automated systems so that the human participation aspect in their functionality would move into more specialized positions.

With the arrival of artificial intelligence (AI), steps were taken to utilize its principles to develop more advanced and automated control systems.

Traditionally control systems are developed using the linear modelling theory, however, there exist systems that could be non-linear in their characteristics. Modelling traditional control systems for such inherently non-linear systems is a difficult task to carry out. Even though there exist methods to construct appropriate models for inherently non-linear systems using the linear modelling theory, they come with certain limitations such as the construction of regulators varying from each system to another. A universal model can be created for linear systems of any order ‘n’, however doing so for non-linear systems is impossible. Again, due to the dynamics of the construction, the stability of such systems can’t be guaranteed.

The term "intellectual control system" refers to any combination of hardware and software, which is joined by general information process, operating autonomously or in man-machine mode, and capable to synthesize the control goal and to find rational ways to achieve the control goal [3]. Intelligent control systems can be classified into the following groups based on their principle of regulation;

- Neural network-based control systems;
- Machine learning-based control systems;
- Fuzzy control;
- Bayesian control;
- Reinforcement learning-based control systems;
- Neuro-fuzzy control;
- Expert systems;
- Genetic control.

3. Researching the possibilities of utilizing intelligent control systems (fuzzy control) for components of VVER-1000 (1200) type reactors

Fuzzy control is one of the types of intelligent control that regulates and controls the control object using the principles of fuzzy logic. In recent years, this regulation method has received particular attention among various methods of parameter regulation [4]. In this case this paper, the possibility of using fuzzy control for pressure regulation in the 1st cooling circuit of the VVER-1000 nuclear reactor was investigated.

The first cooling circuit contains the purge-recharge system (TK), which is used to provide boric acid, which acts as a neutron absorber in the moderator as well as pump the water of the first cooling circuit into the water purifying systems. This system must operate at the working pressure of the first cooling circuit, which in the case of a VVER-1000, is 16.5 MPa. The automatic regulator TKC-02 is responsible for maintaining the working pressure of the first cooling circuit in the purge-recharge system. The regulator carries out its task using the PI (proportional-integral) principle of regulation. The regulatory valve "TK81S02" acts as the actuator for the pressure control system [5].

To understand and investigate the possibilities of using fuzzy control as the working principle of regulator TKC-02 instead of PI, we first need to put forward mathematical modelling of the process of pressure regulation using a regulatory valve. In the picture above (fig2.) a simplified diagram of the actuator and the water supply tube in which the pressure is to be regulated is given. As shown in the diagram, the valve, TK81S02 acts as the actuator for the pressure regulator TKC02. In this article, a 15m segment of the water supply tube that goes through the purge-discharge system of the VVER-1000 nuclear reactor is considered for simulating pressure control within [6].

In this case, the pressure in the tube shown in fig2 is the control object and the actuator is the valve, TK81S02. The process of pressure control using a valve can be mathematically represented using the following differential equation [7];

$$\left(\frac{\boldsymbol{a_{nn}}}{\boldsymbol{a_l}+\boldsymbol{a_{rv}}}\right)\Delta \boldsymbol{P}' + \Delta \boldsymbol{P} = \boldsymbol{b_{rv}}\left(\frac{\boldsymbol{a_l}}{\boldsymbol{a_l}+\boldsymbol{a_{rv}}}\right)\Delta \boldsymbol{S_{rv}} \tag{1}$$

Here, constants $a_{nn}, a_l, a_{rv}, b_{rv}$ are obtained from the constructional parameters of the regulatory valve TK81S02 and the feedwater tube through which the water flows into the purge-recharge system.

Parameter	**Value**
Working pressure	17,65 MPa
Working temperature	350^0C
Internal diameter of the feedwater tube	0.120м
Sum of local hydraulic resistance coefficients ($\Sigma\xi$	93,69
Hydraulic resistance coefficient of the valve ($\xi_{рк}$)	15,7
Water flow rate $(\overline{\text{M}})$	6,94 кг/с = 42,71 м3/час
Water density (ρ)	585,26 кг/м3
Length of the feedwater tube (L)	15м
Internal diameter of the valve	109мм
S_t(Area of the cross-section of the tube)	0,011 м2
S_{rv}(Cross-section of the regulatory valve)	9,331x10^{-3} м2

Table 1. Parameters of the water (moderator), regulatory valve and the feedwater tube

The constants in (1) can be obtained in the following way;

$$\text{a}_{\boldsymbol{nn}} = \frac{\boldsymbol{L}}{\boldsymbol{S_t}} = \mathbf{363.636} \tag{2}$$

$$\text{a}_{\boldsymbol{l}} = \mathbf{2}\text{К}_{\boldsymbol{l}}\text{M} = \mathbf{2}\,\frac{\boldsymbol{\Sigma\xi}}{\mathbf{2}\boldsymbol{\rho}\boldsymbol{S_{tp}^2}}\,\text{M} \approx \mathbf{9181,1} \tag{3}$$

$$\text{К}_{\boldsymbol{rv}} = \frac{\boldsymbol{\xi_{rv}}}{\mathbf{2}\boldsymbol{\rho}} = \mathbf{0.0134} \tag{4}$$

$$\text{a}_{\boldsymbol{rv}} = \frac{\mathbf{2}\text{К}_{\boldsymbol{rv}}\overline{\text{M}}}{\boldsymbol{S_{rv}}^{\mathbf{2}}} = \mathbf{2136.18} \tag{5}$$

$$\mathrm{B}_{rv} = \frac{2\mathrm{K}_{rv}\overline{\mathrm{M}}^{2}}{S_{rv}{}^{3}} = \mathbf{1.58}\mathrm{x}\mathbf{10^{6}} \tag{6}$$

Using Laplace transform on (1) and considering the change in pressure as output and change in cross-section of the valve as input, the following transfer function can represent the pressure control process using a regulatory valve;

$$\boldsymbol{W}(\boldsymbol{S}) = \mathrm{K}\frac{\mathbf{1}}{\mathbf{1+}\boldsymbol{TS}} \tag{7}$$

In this case, the time constant, T will be

$$\boldsymbol{T} = \left(\frac{a_{nn}}{a_l + a_{rv}}\right) \approx \mathbf{0.12} \tag{8}$$

$$\boldsymbol{K} = \boldsymbol{b}_{rv}\left(\frac{a_l}{a_l + a_{rv}}\right) \approx \mathbf{1.288}\mathrm{x}\mathbf{10^{6}} \tag{9}$$

Now the transfer function can be written as;

$$\boldsymbol{W}(\boldsymbol{S}) = \mathrm{K}\frac{\mathbf{1}}{\mathbf{1+}\boldsymbol{TS}} = \frac{\mathbf{1.288}\mathrm{x}\mathbf{10^{6}}}{\mathbf{1+0.12}\boldsymbol{S}} \tag{10}$$

4. Investigation using MATLAB

To simulate the pressure regulation process using a PI-controller as well as that using a fuzzy controller, a model of the pressure controller TKC-02 was created in the “MatLab-Simulink” environment.

In that environment, the responses of the pressure control system “TKC-02” with the usual PI controller and with a fuzzy logic controller were obtained and compared. In the given case, the actuator is considered non-inertial, i.e. as a proportional component.

$$\boldsymbol{W}_{ac}(\boldsymbol{S}) = \boldsymbol{K}_{ac} \tag{11}$$

Here, $K_{ac} = 0.4271\ m^3/hr$ (converting % opening of the valve into the water flow rate through it.)
At first pressure control using a PI-regulator was analysed and the response was obtained. Here, the proportional and integral amplification factors were taken as $K_p = 0.18$ and $K_I = 4.7$.

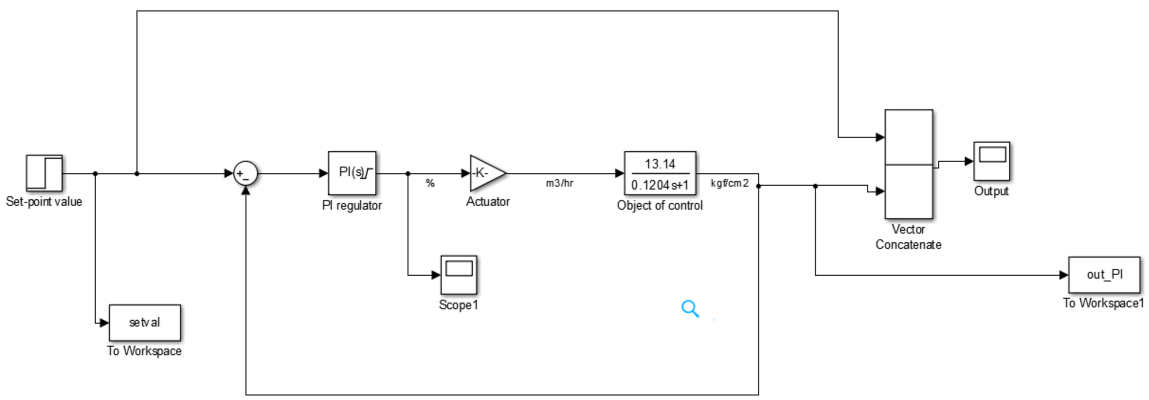

Fig. 2. Block diagram of pressure regulator TKC-02 with PI-controller

In the figure above, the schematic diagram of pressure regulation by the pressure control system TKC-02, utilizing a PI-controller is shown. For this simulation, the set-point value is taken as 180 kgf/cm^2 (≈17.65 MPa, a value above the normal working pressure of the first cooling circuit of VVER-1000). The diagram above contains the control object and actuator blocks, created using the tools available in the MatLab-Simulink library, in accordance with the transfer functions obtained from (11) and (12) respectively.

The input signal in this case is provided as a step signal of magnitude of 180kgf/cm^2. The water flow in the tube and thereby the pressure on the water can be regulated by the degree of opening of the valve (which can be expressed in %). The PI-regulator controls the % of opening of the valve and thereby the rate of flow of water through it.

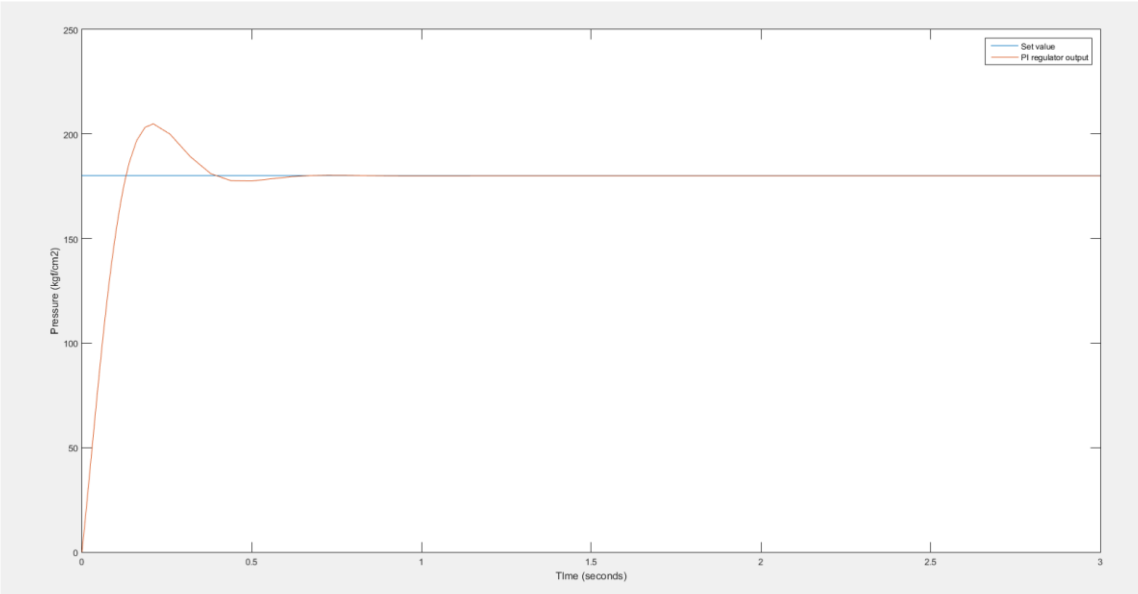

Fig. 3. System response with PI-controller

The above figure shows the response of the control system incorporating the PI-controller to the input of the set-point value of 180 kgf/cm^2. From the MatLab simulated output, it is clear that the control system can maintain the set-point value without any significant steady-state error. The output rises to the set-point value within *1.2 seconds.* It should also be noted that the output from the PI controller also included ‘overshoot’ (i.e. output exceeding the set-point value).

Next, we consider the case of a fuzzy controller to carry out the same task of maintaining the set-point value of pressure. To simulate the fuzzy controller, a set of fuzzy rules must be established for the fuzzy controller to carry out its task.

Deviation (e) (kgf/cm2)	**Level of valve opening (IN_AC) (%)**
Large deviation (225<e <325)	80% <IN_AC <100%
Medium deviation (150 <e <250)	60% <IN_AC <85%
Low deviation (75 <e <175)	40% < IN_AC <65%
Very low or no deviation (0 <e <100)	40% < IN_AC <65%
Overshoot (-137.5 <e <37.5)	0 < IN_AC<25%

Table 2. Fuzzy rules for pressure regulation

With the rules in place, the model of the fuzzy-control-based pressure regulator was constructed.

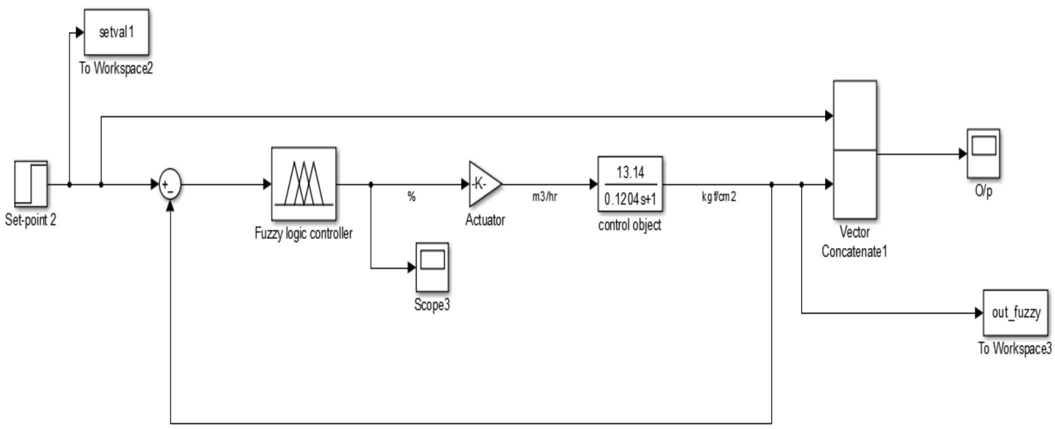

Fig. 4. Pressure controller TKC-02 with fuzzy controller

In the figure above, the block diagram of the pressure regulator based on a fuzzy controller is shown. The actuator and control object blocks are the same as those in fig4 and the set-point value of 180 kgf/cm^2 is also the same. The fuzzy controller, in this case, regulates the % of opening of the regulatory valve, which can manipulate the rate of water flow through the tube as well as pressure. With the fuzzy rules of table 2, the % of opening of the regulatory valve was controlled and thereby pressure was regulated, with the following response.

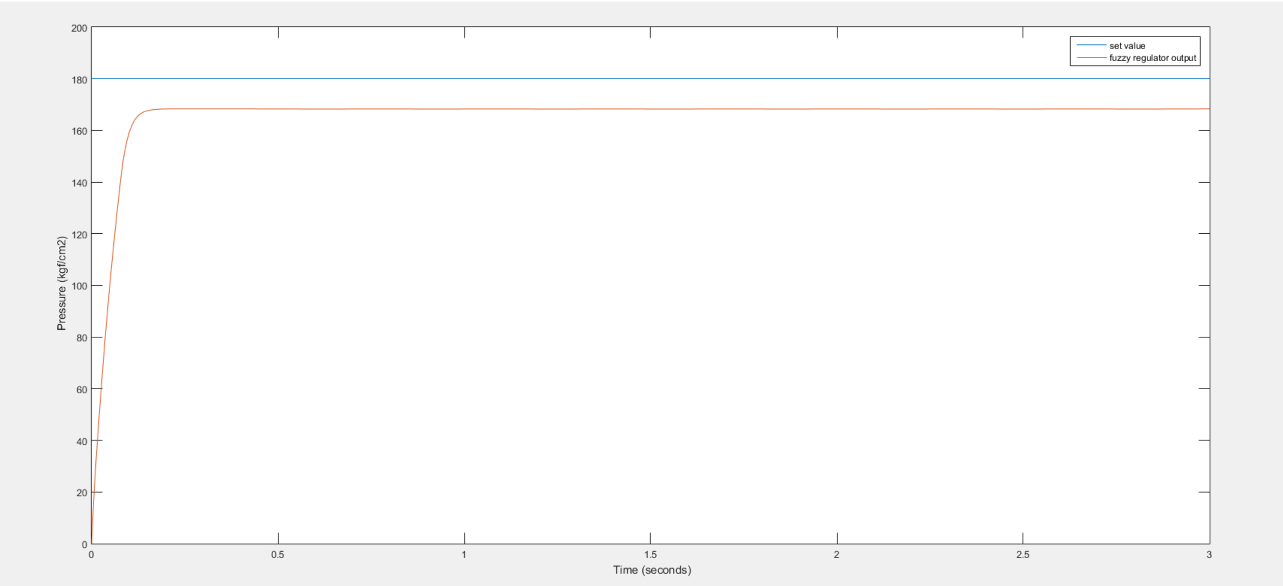

Fig. 5. System response with fuzzy controller

In fig6, the response of the fuzzy-logic-based pressure control system to the set point value is shown. In this case, it can be seen that there exists a certain value of steady-state error. For a set-point value of 180 kgf/cm^2, the fuzzy-control-based system maintains the pressure level at around 170 kgf/cm^{2,} and therefore a steady-state error of about *5%* exists in the case of the fuzzy-control-based system. In this case, the output value rises to the steady state within *0.4 seconds.*

5. Possibilities of using deep learning

Deep learning (DL) is an advanced subset of artificial intelligence that may be used to regulate and optimize the technical parameters of both main and secondary cooling circuits in VVER-1000/1200 nuclear reactors. Deep neural networks (DNNs) can represent very complicated, nonlinear interactions between input and output variables, which is critical for dealing with the intricate dynamics of nuclear cooling systems.
Deep learning algorithms must be extremely resilient, trustworthy, and interpretable to maintain safety in nuclear reactor cooling circuits. The architectures listed below are recommended for the task:

5.1. Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM):

Cooling systems work in dynamic, time-dependent settings in which past temperature, flow rate, and pressure values have a direct influence on present and future states. RNNs and LSTMs are ideal for this since they are built to handle time series data and sequential dependencies.
RNNs are intended for time-series data, where each input depends on the prior ones. They do this by including loops into their design, which allows information to persist through a concealed state vector throughout time steps. Mathematically, the hidden state $h(t)$ at time step t is computed as follows:

$$\boldsymbol{h(t) = \sigma(W_{hh}h_{t-1} + W_{xh}x_t + b_h)} \tag{12}$$

Where $x(t)$ is the input at the time step t, h_{t-1} is the hidden state from the previous time step, W_{xh} and W_{hh} are weight matrices for input-to-hidden and hidden-to-hidden connections, b_h is a bias term, and σ is an activation function (usually a tanh or ReLU).

The output y_t at time step t is then calculated by:

$$\boldsymbol{y_t = W_{hy}h_t + b_y} \tag{13}$$

Although RNNs are capable of representing sequential data, they often suffer from the vanishing gradient problem, which makes it challenging to comprehend relationships over large distances. This is where LSTMs are useful. [8]

5.2. Long Short-Term Memory (LSTM)

LSTMs perform better than regular RNNs because they have gates that control the information flow, which enables them to retain data for longer periods. The forget gate, input gate, cell state, and output gate are the four main parts of an LSTM. [9] The LSTM cell is updated as follows:

$$\boldsymbol{f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right)} \tag{14}$$

$$\boldsymbol{i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)} \tag{15}$$

$$\boldsymbol{\tilde{C}_t = tanh(W_C \cdot [h_{t-1}, x_t] + b_C)} \tag{16}$$

$$\boldsymbol{C_t = f_t * C_{t-1} + i_t * \tilde{C}_t} \tag{17}$$

$$\boldsymbol{o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o)} \tag{18}$$

$$\boldsymbol{h_t = o_t * tanh(C_t)} \tag{19}$$

Where f_t, i_t, and o_t are the forget, input, and output gates, respectively, $\tilde{C}_t$ is the candidate cell state, C_t is the updated cell state, h_t is the hidden state. LSTMs well capture long-range temporal dependencies, and their ability to retain memory across lengthy sequences makes them useful for managing nuclear cooling systems, where the system's behaviour is strongly influenced by its past states. [10]

Time-varying elements of a nuclear reactor's cooling system, such as temperature, pressure, and coolant flow rate, show temporal relationships. To support preventative maintenance or optimize control operations, LSTMs may learn these relationships and forecast future states based on previous data. We should structure the deep learning algorithms using the same input-output mapping: Deviation (e) (kgf/cm³) as the input and Valve Opening Level (IN_AC) (%) as the output to give a meaningful comparison between fuzzy logic and deep learning techniques. In this context, let's go over the algorithms in depth, highlighting how each may regulate the valve depending on variations in pressure.

RNNs and LSTMs are particularly useful for time-dependent data. Here, the deviation in pressure $e(t)$ at time t is used as input to predict the necessary valve opening level (IN_AC). Given the deviation data $e(t)$ over time, the RNN/LSTM can predict the next valve opening adjustment $_{AC}(t+1)$, ensuring the system compensates for deviation efficiently. [12]

$$\boldsymbol{h_t = \sigma(W_{hh}h_{t-1} + W_{xh}e_t + b_h)} \tag{20}$$

$$\boldsymbol{_{AC}(t+1) = W_{hy}h_t + b_y} \tag{21}$$

Where $e(t)$ represents the deviation in pressure at the time t, the hidden state h_t stores the cumulative effect of past deviations, the output $_{AC}(t+1)$ represents the predicted valve opening level based on both current and past deviations. LSTMs can handle scenarios where the pressure deviation may fluctuate or vary slowly since they take into account the history of deviations (e.g., how rapidly or slowly deviations build). However, fuzzy logic offers more transparent and understandable principles for in-the-moment decision-making, and they are less computationally intensive and sophisticated than fuzzy logic.

5.3. Summary of Comparison

Method	Input	Output	Key Strengths	Key Limitations
Fuzzy Logic	Deviation (e) (kgf/cm²)	Valve opening (IN_AC) (%)	Transparent, easy to understand and implement	Limited ability to handle complex temporal relationships
RNN/LSTM	Deviation (e) over time	Valve opening prediction	Captures time dependencies effectively	Computationally complex, harder to interpret

Table 3. Comparison of key advantages and disadvantages of fuzzy logic and deep learning-based control systems

6. Conclusion

- Here it must be noted that the response of the system in the case of fuzzy-control-based regulation was significantly faster.
- The fuzzy logic-based control system's output reached its steady state 3 times faster than that in the case of the PI-controller-based control system.
- However, in the case of the PI-controller-based system, it was possible to obtain an output without any steady-state error.
- In the case of fuzzy-logic-based regulation, a steady state error of ~5% was present.
- There are possibilities and certain advantages of using recurring neural networks and LSTM-based controllers which provide advantages such as the ability to predict the position of the valve.

From the above conclusions, we can see that the fuzzy-logic-based controller can give faster responses as compared to a traditional PI-controller-based system. As far as control systems are concerned, a faster output with less steady-state error is always a desired outcome. In this case, however, there was indeed a steady-state error involved in the case of the fuzzy logic-based controller. However, fuzzy control is just one aspect of intelligent control, there are other methods such as neural-network-based control systems, that can also be applied for such applications.

Also, the fuzzy rules used as the basis of the fuzzy controller could be made more accurate, which can reduce the steady-state error. The preliminary investigation regarding the usage of recurring neural networks and LSTM-based controllers also highlights certain possible advantages as well as complexities that require further research and investigation.

As mentioned before, the nuclear industry suffers from the usage of older automation standards and therefore further research on possible applications of modern automation technologies like intelligent control in nuclear power plants must be continued. Faster and more effective control systems can reduce the chances of irregularities and hazards occurring in nuclear infrastructures. Also, NPPs and their related infrastructure require effective automation much more than any other industry due to the nuclear radiation and reactions occurring in its core parts making them inaccessible to humans, even with protective equipment. However, the newer automation technologies must also satisfy various safety requirements and standards set by nuclear regulators such as the IAEA (International Atomic Energy Agency) to be approved for installation in NPPs. And since rudimentary research in this direction, as in the case of the given article provide encouraging results, research must continue in this direction to find more concrete data, using real-time simulation techniques and programs.

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