

# Study of a multi-strategy controller on a helium liquefier

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**Abstract.** Helium liquefier is widely used in the fields of superconducting, nuclear fusion energy and high-energy physics. However, the present PID controlling system of the liquefier is not able to keep the compressor suction pressure, outlet pressure and turbine inlet pressure all in the expected range at the same time. Thus, a multi-strategy controller for a helium liquefier is proposed in this paper. A dynamic simulation model of this liquefier is also developed and shown. To study the control effect, an operation process including cool-down, steady-state and pulse of heat is described. The simulation result of this process is presented and compared with the result of the present PID controlling system.

## 1. Introduction

Helium liquefier are widely used for cooling large scale scientific facilities such as neutron sources system, electron positron collider and Tokamark device[1]. These systems generate heat load which is pulsed, and helium refrigerators have to handle such heat loads[2,3]. For example, modern neutron sources systems can generate a high-level pulsed neutron flux in a small volume, and this pulsed neutron flux will lead to a pulsed heat load for the refrigerator. Several dynamic simulators of helium Refrigerator have been proposed by [2,4,5]. In [2], a control strategy is also developed to handle pulsed heat loads. In this paper, a multi-strategy control method intends to optimize the control loops of the GMP and turbine inlet valve base on fuzzy neural network.

This helium liquefier is based on modified Claude cycle. This refrigeration cycle consists of an oil lubricated screw compressor, a GMP, a buffer tank, three counter-flow heat exchangers, two turbine expanders and a helium tank as shown in Fig.1. In the commercial helium refrigerator control system, the usual PID controller is used. The control strategy for the existing plant is that the suction pressure (LP) is controlled by the bypass valve V1 and the outlet pressure (HP) for compressor is controlled by using V2, V3 as shown in GMP part of Fig.1. According to this control strategy, the control loops for HP and LP are independent, which can't satisfy the control purpose to the object sometimes. This paper will introduce a way to improve the PID control for the compression station of this helium



liquefier.

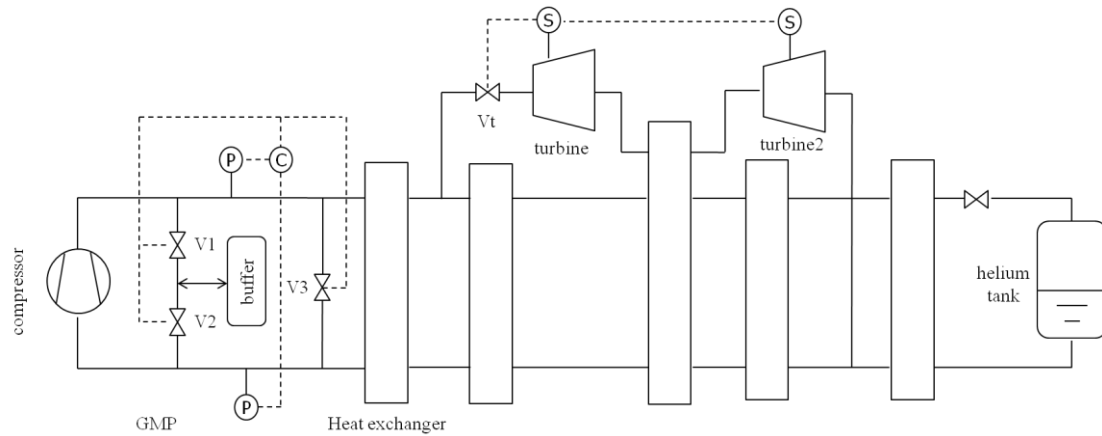


Fig.1. Flow scheme of the modified Claude helium liquefier.

## 2. Control methods

The multivariable PID fuzzy neural network controller structure has been shown in Fig.2. The controller contains three modules: fuzzy module, neural network and normal PID controller. Fuzzy control has strong robustness, and the neural network control is good at self-tuning. They were combined for their advantages, and fuzzification can avoid that the output is not sensitive with the input when the input of NN control is too big. The function of V2 and V3 is charge valve and discharge valve, respectively. For the traditional control strategy, V2 and V3 can be opened at the same time, which is not rational in principle. In the new multivariable PID neural network (NN) control, the V2 and V3 will be considered as one regulator. When the system need more helium the V2 will be open and V3 will be closed. Conversely, when there is too much helium in the system the V3 will be open and V2 will be closed. As shown in GMP part of Fig.1, LP and HP signals are sent to the controller as two input values. Then controller outputs two control values  $u_1$  (for V1) and  $u_2$  (for V2 and V3).

The error1 is denoted by  $e_1(t) = r_1(t) - y_1(t)$  where  $r_1(t)$  is the desired signal of low pressure LP and  $y_1(t)$  is the actual LP; while the error2 is denoted by  $e_2(t) = r_2(t) - y_2(t)$  where  $r_2(t)$  is the desired signal of high pressure HP and  $y_2(t)$  is the actual HP. In the discrete-time control system, the PID algorithm can be given as Eq.1[12]:

$$u(t) = u(t-1) + K_p(e(t) - e(t-1)) + K_i e(t) + K_d(e(t) - 2e(t-1) + e(t-2)) \quad (1)$$

where  $K_p$ ,  $K_i$ , and  $K_d$  are respectively, the proportional, integral and derivative gains of PID controller which should be adjusted.

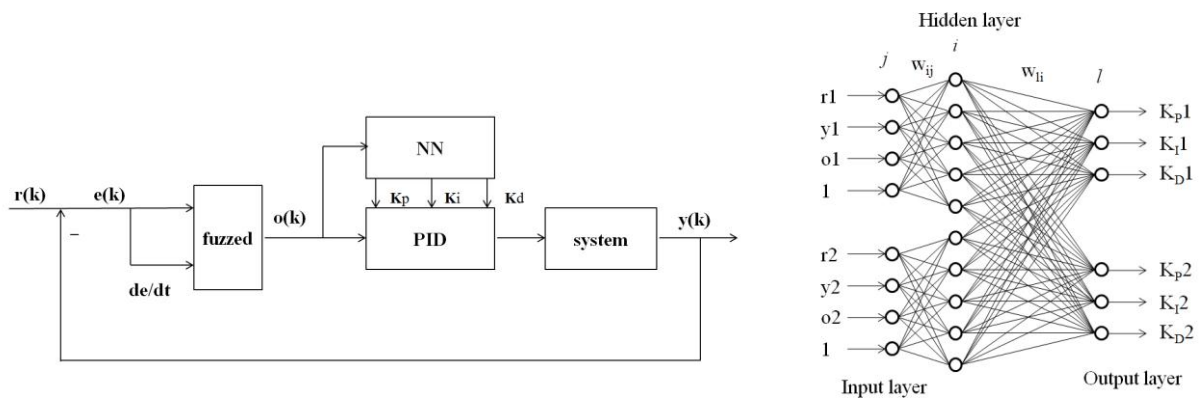


Fig.2. Multivariable PID fuzzy neural network controller structure (left). Configuration of BP neural network (right).

The change rate of error is denoted by  $de(t)/dt=e(t)-e(t-1)$ . The error and the change rate of error were fuzzed to 13 linguistic variables. The membership function has two trapezoidal members and eleven triangular members. By using the Eq.2, we can change the accurate variables to linguistic variables, where  $y$  is linguistic variable,  $x$  is accurate variable,  $[a,b]$  is the range of  $x$  and  $[-n,n]$  is the range of  $y$ .

$$y = \frac{2n}{b-a} \left( x - \frac{a+b}{2} \right) \quad (2)$$

Then the fuzzed error  $E(k)$  and change rate  $EC(k)$  were achieved, and the output  $O(k)$  can be calculated by Table 1.

Table 1. Fuzzy output

| O(k) |    | EC (k) |   |   |    |    |    |    |    |    |    |    |    |    |
|------|----|--------|---|---|----|----|----|----|----|----|----|----|----|----|
|      |    | 6      | 5 | 4 | 3  | 2  | 1  | 0  | -1 | -2 | -3 | -4 | -5 | -6 |
| E(k) | 6  | 6      | 6 | 6 | 6  | 6  | 5  | 5  | 4  | 3  | 2  | 1  | 0  | 0  |
|      | 5  | 6      | 6 | 6 | 6  | 5  | 5  | 5  | 4  | 3  | 2  | 1  | 0  | 0  |
|      | 4  | 6      | 6 | 6 | 5  | 5  | 5  | 5  | 4  | 3  | 2  | 1  | 0  | 0  |
|      | 3  | 5      | 5 | 5 | 5  | 4  | 4  | 4  | 3  | 2  | 1  | 0  | -1 | -1 |
|      | 2  | 4      | 4 | 4 | 4  | 4  | 4  | 4  | 2  | 1  | 0  | 0  | -2 | -2 |
|      | 1  | 4      | 4 | 4 | 3  | 3  | 3  | 3  | 1  | -2 | -2 | -3 | -3 | -3 |
|      | 0  | 4      | 4 | 4 | 3  | 3  | 1  | 0  | -1 | -3 | -3 | -4 | -4 | -4 |
|      | -1 | 3      | 3 | 3 | 2  | 2  | -1 | -3 | -3 | -3 | -3 | -4 | -4 | -4 |
|      | -2 | 2      | 2 | 2 | 0  | -1 | -2 | -4 | -4 | -4 | -4 | -4 | -4 | -4 |
|      | -3 | 1      | 1 | 1 | -1 | -2 | -3 | -4 | -4 | -4 | -5 | -5 | -5 | -5 |
|      | -4 | 0      | 0 | 0 | -2 | -3 | -3 | -5 | -5 | -5 | -5 | -6 | -6 | -6 |
|      | -5 | 0      | 0 | 0 | -2 | -3 | -4 | -5 | -5 | -5 | -6 | -6 | -6 | -6 |
|      | -6 | 0      | 0 | 0 | -2 | -3 | -4 | -5 | -5 | -6 | -6 | -6 | -6 | -6 |

The part of a NN block is built in order to adjust the gains of PID controllers adaptively by using the back propagation (BP) method with measurement data of  $u(t)$ ,  $y(t)$  and  $r(t)$ .

The BP is a multilayered network which consists of an input layer, an output layer and several hidden layers of nonlinear processing elements. For the new NN controller, the controller has three layers and the number of output layer neurons is  $K_p$ ,  $K_i$  and  $K_D$  and the configuration of BP neural network is shown as Fig. 2.

The input-output neurons relationship of BP NN can be expressed as follows[9,10,11]:

$$net_p^{(m)} = \sum w_{pq}^{(m)} O_q^{(m-1)} \quad (3)$$

$$O_q^{(m)} = f\left(net_q^{(m)}\right) \quad (pq = ij, li), (m = 2, 3) \quad (4)$$

where  $w_{pq}^{(m)}$  is the weights of hidden layer, the upper number  $m = 1, 2, 3$  denotes input layer, hidden layer, output layer,  $net_p^{(m)}$  is the input of neuron  $p$  in the layer  $m$ ,  $O_q^{(m)}$  is the output of a neuron  $q$ ,  $f(\dots)$  is the neuron activation function, for hidden layer  $f_1(x) = \tanh(x)$ , for output layer  $f_2(x) = \frac{1}{2}(1 + \tanh(x))$ . The learning goal of PID neural network is to minimize the average value of system output square error  $J$  which can be expressed as Eq. 5.

$$J = \frac{1}{2} \left( e_1(t)^2 + e_2(t)^2 \right) \quad (5)$$

where  $J$  is to modify the weights by the fastest descend mean, which is searched and tuned toward the negative gradient and added on a inertia coefficient to make faster constringency.

### 3. Simulation model

By the help of the simulation software ECOSIMPRO, a dynamic simulation model of this helium liquefier has been carried out, which provide a way to study and optimize control strategies of the helium liquefier. The numerical model comprises the typical components of the refrigerator: compressor, valves, heat exchangers, expanders and tank. This simulator is based on the oriented-object approach and each component is represented by a set of differential and algebraic equations. The control logic of the refrigerator is also embedded in the simulator.

As turbine is one of the most important components in this system, the simulation result is greatly affected by simulation model of turbine. For a whole cooling process, a series of isentropic efficiencies and velocity ratios of the real turbine have been calculated. A characteristic curve was achieved as shown in Fig. 3. It can be fitted to a quadratic function as shown below.

$$\eta / \eta_d = -(\nu / \nu_d)^2 + 1.9(\nu / \nu_d) + 0.1 \quad (6)$$

Where  $\eta$  is isentropic efficiency,  $\nu$  is velocity ratio and  $d$  presents design value. All isentropic efficiencies and velocity ratios were normalized to design value in Fig.3.

Base on the conservation of energy and rotational kinetic energy expression, Eq.7&8 are achieved.

$$\frac{dE}{dt} = E_{jet} - E_{brake} = \dot{m}(h_{in} - h_{out}) - E_{brake} \quad (7)$$

$$I \cdot N \cdot \frac{dN}{dt} = \dot{m}(h_{in} - h_{out}) - E_{brake} \quad (8)$$

According to these functions and design parameters, a turbine simulation model is developed.

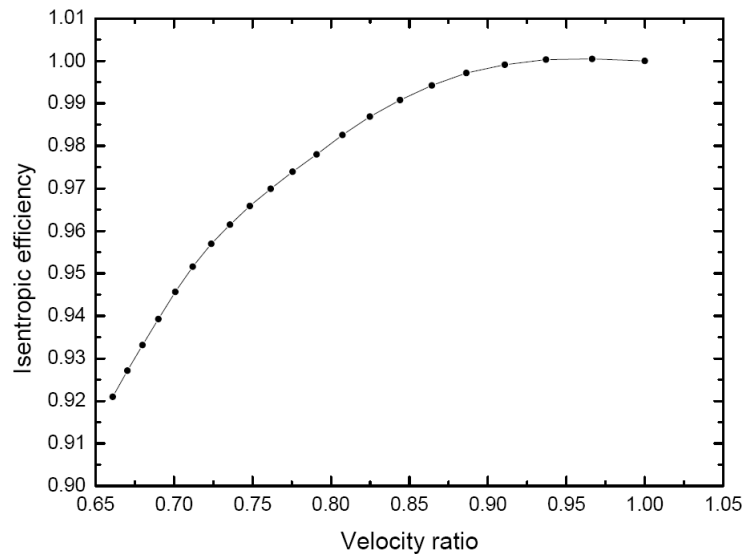


Fig.3. Relation between normalized isentropic efficiencies and velocity ratios.

#### 4. Simulation and experiment results

The simulation was base on a simulation model of a 40L helium liquefier shown in Fig.1. The experiment was on a real reverse Brayton refrigerator. The setting pressure of compressor outlet pressure is 0.8 MPa and that of compressor suction pressure is 0.105 MPa both in simulation and experiment. A 300K to 15K cool-down process was simulated to compare with a real helium liquefier. Simulation and experiment result of cool-down process is shown in Fig.4. The simulation and experiment results indicate that the simulation model has acceptable validity and accuracy.

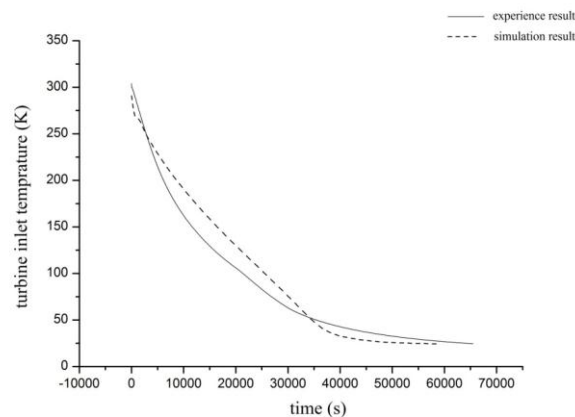


Fig.4. Simulation and experiment result of cool-down process

The simulation result of heat pulse is shown in Fig.5. When the system was cooled down and stable, a 50W heat pulse was loaded at 1000s. Then heat pulse changed to -50W at 2000s and 0W at 3000s. This multi-strategy controller shows a better control effect than PID method. Control effects  $E$  of two methods were calculated by Eq.9 [8], where  $r$  is present value and  $y$  is set value.  $E$  of FNN method is 0.0165 bar and result of PID method is 0.0269 bar.

$$E = \frac{\int e dt}{t} \quad e = r(t) - y(t) \quad (9)$$

The experiment data shows the same result in Fig.5. Two control methods were applied on a real reverse Brayton refrigerator. When compressor outlet pressure was stable at 8bar, control set value was changed to 7bar at 300s and 9bar at 600s.

The evolutions of PID parameters during the experiment are shown in Fig.6 and Fig.7. The PID gains were changed with the input variables of FNN controller. The self-learning and self-adapting abilities of FNN controller are performed.

The simulation and experiment results show that the overshooting of the FNN PID control is smaller than traditional PID control. And the governing time of FNN PID control is much shorter than traditional PID control. The simulation results indicate that the FNN PID control can increase the performances and stability of the compressor station and the expander.

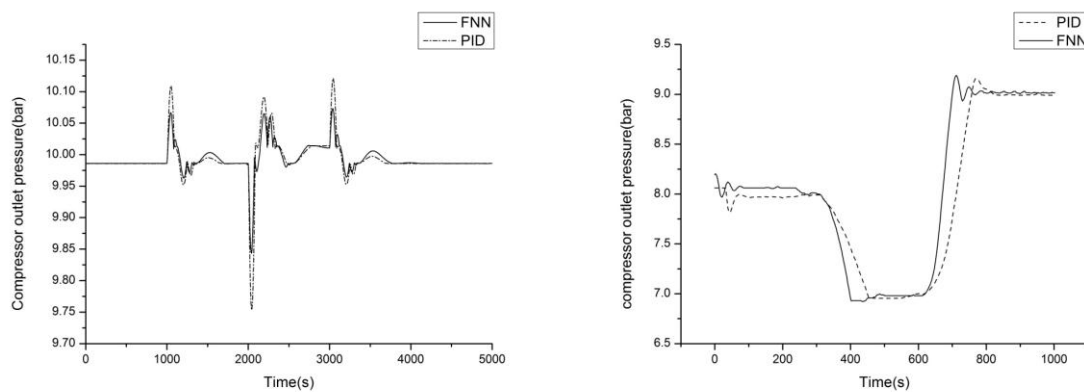


Fig.5. Simulation result of heat pulse (left) Experiment result of changing set value of compressor outlet pressure (right)

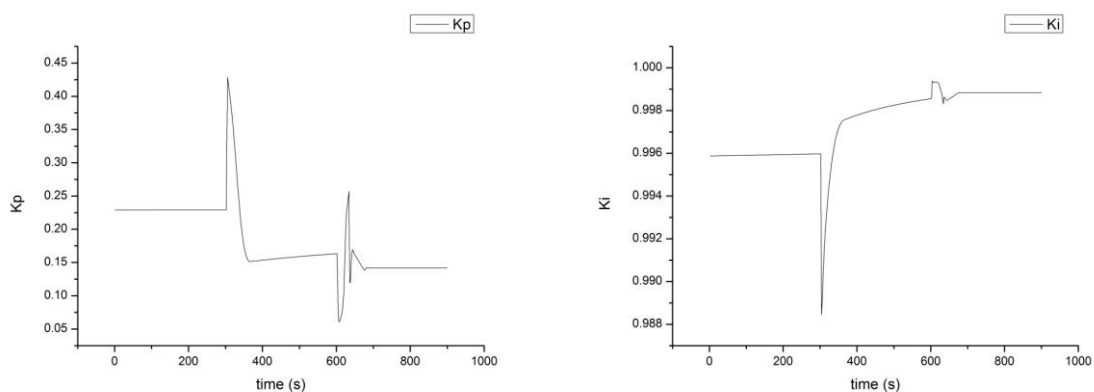


Fig.6. Evolution of Kp in the experiment (left) Evolution of Ki in the experiment (right)

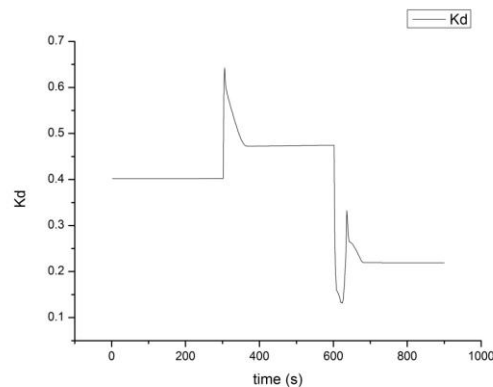


Fig.7. Evolution of Kd in the experiment

## 5. Conclusion

A fuzzy neural network PID controller, which is a method based on adaptively adjusting PID gains using BP neural network, are introduced to GMP of the helium liquefier. The neural network PID control has self-learning and self-adapting abilities and fuzzy control has strong robustness. The fuzzy neural network PID control and traditional PID control are both applied to a simulation model of a 40L helium liquefier and a real reverse Brayton refrigerator. The simulation and experiment results indicate that the simulation model has acceptable validity and accuracy, and the fuzzy neural network control system has better robustness and higher precise than traditional PID control. For future work, the fuzzy neural network PID controller will be compared with the other control methods on simulation model and the real helium liquefier.

## Acknowledgements

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