Stability of Water Flow in Tanks Using Particle Swarm Optimization (PSO) Method

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Abstract. The stability of the speed and pressure of the water flow is determined by the height and volume of the water. The speed of water flow in the actuator is determined by the use of this flow sensor system. A good tank-based water flow control model must be developed. At a certain point, the actuator stabilizes the water production rate per minute. Therefore, it is necessary to develop automatic and precise control techniques. Many Artificial Intelligence (AI) methods are used in system optimization. Among them are the Firefly Algorithm (FA) and Particle Swarm Optimization (PSO). In this research, conventional methods, Auto tuning methods, and PSO methods are used. The PSO method produces better optimization compared to the previous method. The water flow stability indicator in this simulation is shown by the size of the overshot and undershot values for each method. The best water level control simulation results are the PSO method with the smallest overshot value of 0.0333 pu, the smallest undershot value of 0.0347 pu, and the output flow results have the smallest overshot value of 0.0013 pu, the smallest undershot value of 0.0011 pu.

1 Introduction

1.1 background

A linear model estimation approach was used to study the physical workings of the Water Level System (WLS). The purpose of WLS is to depict dynamic qualities near the equilibrium point [1]. An identification method with measured input and output data is utilized to identify the dynamic nature of WLS. Technically, nonlinear time process control systems are frequently used in the development of water tank level instruments. WLS can be modeled as a global water system or partially as one[2]. Fluid flow control systems in tanks are required for industrial processes and system improvement. The production system must provide a complete list of all procedures. To improve system performance, the water flow in the water tank volume is adjusted.

This system is used to control the water flowing into the tank by using a valve as a controller. The outflow rate depends on the diameter of the outlet pipe, which is constant, and the pressure in the tank, which varies with the water level. Therefore, the system has nonlinear characteristics.

For overall control system design, several models can produce various control strategies. A number of high-level water control techniques and control of micro-hydropower plants have been investigated and developed, using artificial intelligence methods, including using the Firefly Algorithm and Flower Pollination Algorithm methods. [3][4]. This research tries to compare the performance of each method in terms of water flow stability. The PSO system is often used for system optimization[5]. PSO succeeded in showing its performance in finding optimization and stability of several systems, including optimization in designing micro-hydro control systems, wind turbine controls, solar panel tracking, vehicle driver controls, and other controls[6][7].

This research compares the performance of the PSO method with other methods in optimizing the control and stability of water flow in tanks. As a comparison, the optimization methods are the conventional method, the auto-tuning method by Matlab program, the Firefly Algorithm (FA) method[8], and the Particle Swarm Optimization (PSO) method. A comparison of optimization methods is used to obtain the best optimization results so that they can be applied in real systems[9][7][10]

2 Desigh Research

In this research there are 2 subsystem blocks in the water tank system, namely the water tank system and the valve system. The two systems act as joint interactions. Both systems act as a fluid flow to complete the entire interaction of the sorting section. The input system is technically influenced by a constant water flow rate, signal generator, and the maximum inflow of the tank[11][4]. The water flow is channeled using a pump from the storage tank. The water flow rate is regulated using an actuator. Figure 1 shows a schematic of a wave tank system with 2 inflow tunnel systems

Mathematical modeling is a model created using mathematical concepts such as functions and equations. This mathematical modeling was created based on the input and output processes of the water level of the plant tank and the dimensional specifications of the tank. This system modeling is used as a real plant tank approach for simulation needs in order to determine plant responses. Flow in and flow out values are as follows:

$$Q = V/t \quad (1)$$

Q is the air flow, V is the tank volume, and T is the time required. Stream search can get the height value using the formula:

$$H = 1/A(Q_{in}-Q_{out})1/s \quad (2)$$

H is the water height (cm), A is the cross-sectional area of the tank (cm^2), Q_{in} is the flow entering the tank (cm^2/s), Q_{out} is the flow leaving (cm^2/s), and s is the initial level (cm). The system optimization design consists of 4 sub-system blocks which are the result of transfer functions from each system. Sub-system 1 is a water flow system without control, sub-system 2 is a water flow system with conventional PID control, sub-system 3 is a water flow system with PID control which is tuned using the Matlab program, sub-system 4 is a water flow system with PID control that is detuned using PSO artificial intelligence. Each sub-system is given the same input from the signal generator and tank max inflow. Each sub-system provides 3 outputs, namely water level, flow out, and signal output.

The uncontrolled diagram of the Simulink Block may be seen in Figure 2[12];

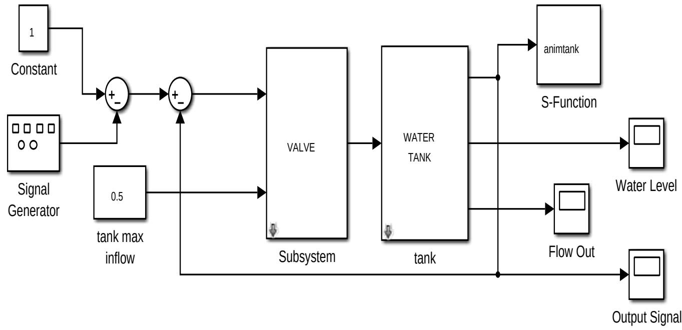

Fig 1. Simulink design without a controller model

As a reference, various output forms are given with an amplitude of 0.5 and a frequency of 0.1 in rad/sec. In the main constant value the tank max inflow is 0.5 and the constant is 1 pu. Figure 2 depicts a water block system that has been well designed using the Matlab Simulink water-level program. The Simulink Matlab water-level block diagram is built using two integrated subsystems. The unregulated Simulink water-level block interacts with the main components, especially the valve and tank unit. Figure 3 displays the Simulink water level block of the Water Tank Sub System Matlab program

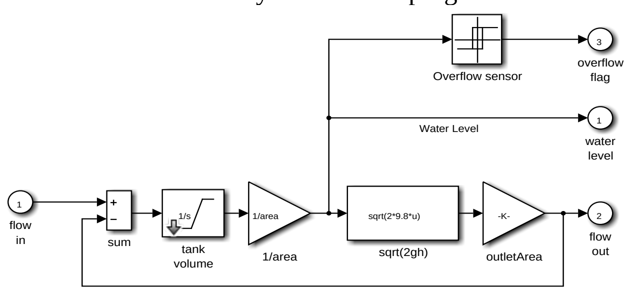

Fig 2. Design of Sub system Water Tank Model

From flow in, it enters the tank volume limiter with 3 outputs, namely overflow sensor, water level and flow out. Figure 4 illustrates the Matlab program water level subsystem block diagram in the valve system. Figure Block diagram of the sub-system on the valve system can be seen in Figure 4.

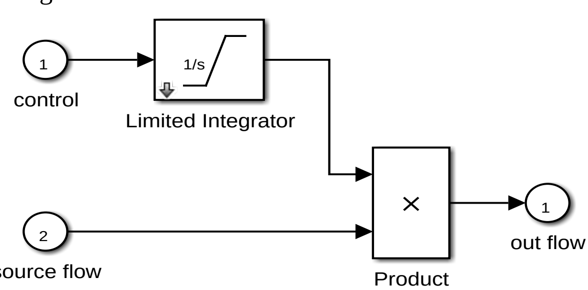

Fig 3. Design of The Valve Subsystem model

In the design of the subsystem valve, the model is given a limited integrator barrier which will produce an out flow. Figure 3 depicts the Simulink block diagram for the water tank subsystem of the water tank system, and Figure 4 depicts the valve subsystem. The water entering and leaving these systems is controlled while it is flowing through a tunnel or pipe system.

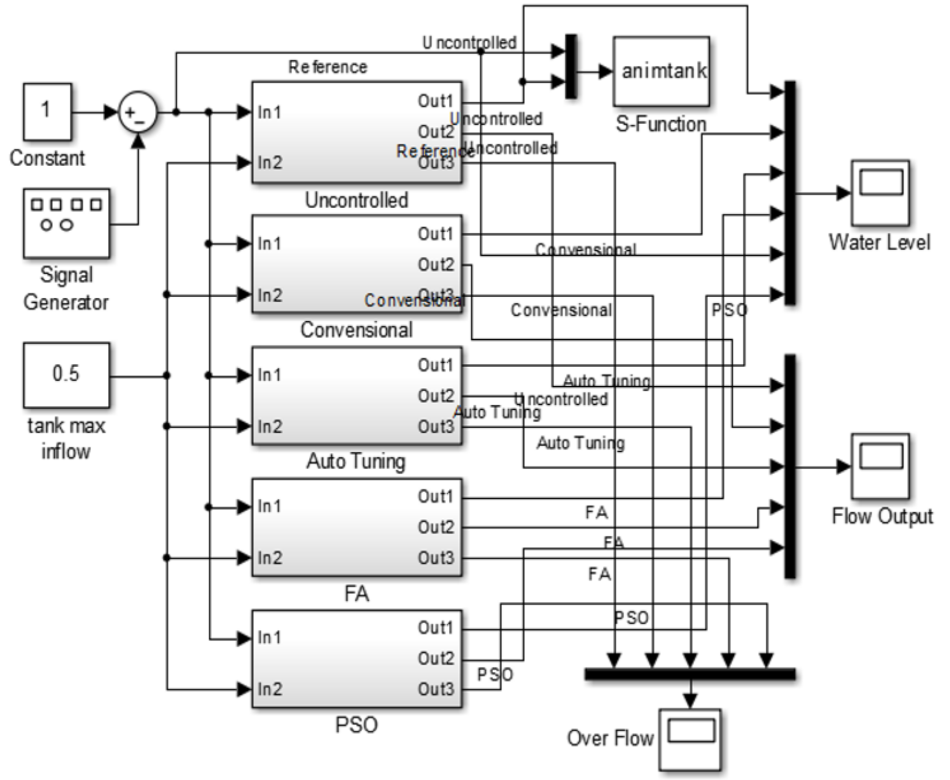

Fig 4. Surge tank system with 2 inflow tunnel systems

3 RESEARCH METHOD

Uncontrolled Model: One of the comparison models uses a model without controls. As input, constant = 1 is given by the input profile modeled by the signal generator, with maximum tank inflow = 0.5. Conventional Model: This method sets the parameters Kp = 1, Ki =1, and Kd =1. So obtained after the system output is reached in a steady state[12]. Auto Tuning Matlab Model: This method is used to find the constant parameter values of the PID controller (kp, Ki, and Kd) automatically using the Matlab program.

3.1 Firefly Algorithm (FA) Model

The Firefly Algorithm method in the optimization problem process describes the brightness of the firefly light proportional to the value of the objective function. The level of light intensity (I) on fireflies (x) is proportional to the solution of the objective function to be searched f(x). The results of the assessment will differ depending on the distance between one firefly and another. The level of light brightness can be formulated;

$$I(x) = f(x) \qquad (3)$$

The firefly attraction function can be formulated as:

$$\beta(r) = \beta_0 * e\,(-\gamma r^m), (m \geq 1) \qquad (4)$$

The distance between fireflies i and j at locations x, xi and xj can be formulated;

$$r_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \quad (5)$$

The movement of a firefly that moves towards the brightness of the light can be formulated:

$$x_i = x_i + \beta_0 . \exp(-yr^2 ij) * (x_j - x_i) + a(\text{rand} - \tfrac{1}{2}) \quad (6)$$

3.2 Particle Swarm Optimization (PSO) Model

The PSO Model is an artificial intelligence method by creates an algorithm that imitates the collective behaviour of birds in searching for food. This bird behaviour was created by an algorithm to obtain an optimization target. [6][13]. In this paper, water level system optimization is carried out to find the best PID parameter values, so the PID-PSO can produce the best optimization values with the smallest overshot and undershot indicators. [14][15]. PSO modifies each dimension of the xid position in a particle by adding a vid velocity and moving the particle towards p_bestid and g_bestd using (7) and (8).

vid(k+1)=w·vid(k)+c1 rand1(pid-xid)+c2 rand2 (pgd-xid) (7)

xid(k+1)=xid(k)+vid(k+1) (8)

FA and PSO Parameter can be seen in table 1.

Table 1. FA and PSO Parameters

FA Parameters	Value	PSO_Parameters	Value
β	0.5	Numberiof_Particles	30
α	0.5	Maximumi_iteration	50
γ	0.5	Number of Variables	3
Dimension	3	C2 (Social_Constant)	2
Number of fireflies	50	C1 (Cognitive_Constant)	2
Maximum iteration	50	W (Momentum_Inertia)	0.9
Kp_fa	0 – 100	Kp_pso;	0 – 100
Ki_fa	0 – 50	Ki_pso;	0 – 50
Kd_fa	0 – 10	Kd_pso;	0 – 10

3.2.1. Parameter selection

Performance landscape showing how a simple PSO variant performs in aggregate on several benchmark problems when varying two PSO parameters. The choice of PSO parameters can have a large impact on optimization performance. Selecting PSO parameters that yield good performance has therefore been the subject of much research.

To prevent divergence the inertia weight must be smaller than 1. The two other parameters can be then derived thanks to the constriction approach, or freely selected, but the analyses suggest convergence domains to constrain them. Typical values are in

The PSO parameters can also be tuned by using another overlaying optimizer, a concept known as meta-optimization, or even fine-tuned during the optimization, e.g., by means of fuzzy logic. Parameters have also been tuned for various optimization scenarios.[

There are three important components in PSO, namely Particles, cognitive components, and social components. There are two determinants of learning from particles, namely experience (cognitive learning) and combination learning (social learning). PSO algorithm development factor; swarm (number of particles in the population), Particles (individuals who have position and velocity), Personal best (is the current best position compared to the best solution proposed previously), Global Best (overall best position), velocity (speed) determines the direction of movement the position carried out in each iteration, inertial weights are used to control the impact of speed changes, acceleration coefficients (controlling the movement of one iteration can be determined independently[6]. The best iteration results will be stored in the constant values of Kp_pso, Ki_pso, and Kd_pso then stored in the data workspace.

3.3 RESULTS AND DISCUSSION

The simulation design is carried out with various controller models, namely Convensional controller, Auto Tuning controller,, and PSO controller. In this study, all outputs from the design results of various Water Level Control Systems can be simulated using a Simulink diagram as shown Figure 10.

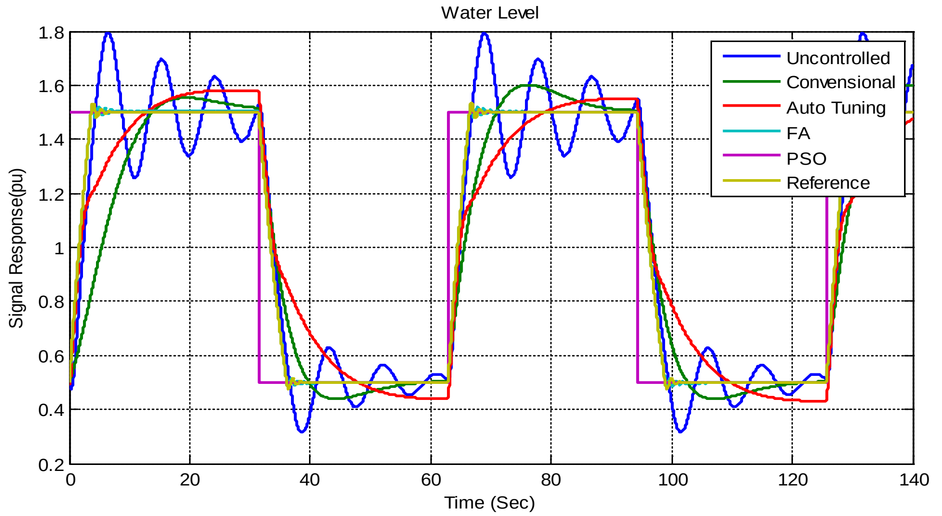

Fig 5. Water level Output Results

Figure 10 demonstrates that the PSO model provided the smallest overshot and smallest undershot on the water level. This demonstrates that PSO is the ideal model for this study of water level.

Output Flow Results were simulated using a diagram as shown in Figure 11.

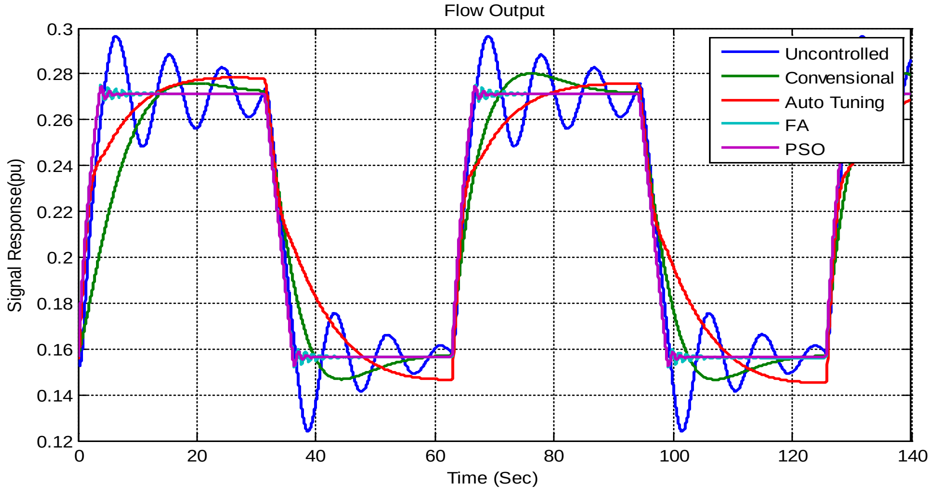

Fig 6. Output Flow Results

The PSO model provided the output flow's least overshot and undershot, as shown in Figure 11. This demonstrates that PSO is the ideal model for this study of water level.

The simulation results in Figures 10 display the overshot and undershot values from the results of controlling water levels using a variety of control strategies. The values of overshot and undershot from the results of the Output Flow are displayed in Figures 11. Table 2 displays the overall outcomes.

Table 2. Overshot and Undershot of Water Level and Output Flow

	Uncon troller	Conven sional	Auto Tuning	FA	PSO
Overshot of Water level	0.2948	0.0733	0.0876	0.0357	0.0333
Undershot of Water level	0.2834	0.0174	0.0943	0.0365	0.0347
Overshot of Output Flow	0.2103	0.0843	0.0776	0.0074	0.0013
Undershot of Output Flow	0.0742	0.0542	0.0352	0.0022	0.0011

The largest overshot of water level is uncontrolled with a value of 0.2948 pu, the smallest is PSO with a value of 0.0333 pu. The largest undershot of water level is in uncontrolled with a value of 0.2834 pu, the smallest is in PSO with a value of 0.0347 pu. The largest overshot of output flow is uncontrolled with a value of 0.2103 pu, the smallest is PSO with a value of 0.0013 pu. The largest undershot of output flow is uncontrolled with a value of 0.0742 pu, the smallest is PSO with a value of 0.0011 pu..

4 Conclusion

The water flow stability indicator in this simulation is shown by the size of the overshot and undershot values for each method. From the simulation results of water level control, the PSO model has the smallest overshot value of 0.0333 pu, the smallest undershot value is 0.0347 pu, and the output flow results have the smallest overshot value of 0.0013 pu, the smallest undershot value is 0.0011 pu. Thus, it can be concluded that the PSO method is the best controller design method.

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