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Antlion Optimization based Deep Neural Network Internal Model Controller for Shell and Tube Heat Exchanger

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Abstract

This paper proposes a novel approach using Antlion Optimization (ALO) in combination with a Deep Neural Network (DNN) Internal Model Controller for controlling the hot water outlet temperature of a shell and tube heat exchanger. This work aims to enhance controlling the outlet temperature of the hot fluid, while ensuring system stability under varying operating conditions. The Antlion Optimization algorithm, inspired by the hunting behavior of antlions in nature, is employed to fine-tune the parameters of the DNN controller. The DNN serves as the feedback controller for the heat exchanger system, offering adaptive and non-linear control capabilities. Experimental tests are conducted on a shell and tube heat exchanger under different flow rates and temperature differentials to evaluate the performance of the proposed ALO-based DNN controller. Comparative studies are performed against traditional control methods, such as PID and ANN-based controllers. The results demonstrate that the Antlion Optimization based Deep Neural Network Internal Model Controller outperforms other conventional control methods, achieving superior hot water outlet temperature control.

Key words: Antlion, Neural Network, Heat Exchanger, Controller and Optimization

1. Introduction

A shell and tube heat exchanger is a widely used device for transferring heat between two fluids without allowing them to mix. It consists of a shell, which is a cylindrical vessel, and a bundle of smaller cylindrical tubes placed inside the shell. The hot fluid flows through these tubes, while the cold fluid flows inside the shell, around the tubes. Heat is exchanged from the hot fluid to the tube walls and then to the cold fluid, achieving efficient heat transfer due to the large surface area provided by the tube arrangement [1]. To ensure effective temperature regulation and efficient operation, a controller is commonly incorporated into the heat exchanger system. The most commonly used controller in this setup is a temperature controller [2]. The temperature controller plays a crucial role in achieving precise temperature control, improving energy efficiency, and ensuring the heat exchanger operates within the desired temperature range. However, real-world heat exchanger systems may involve more sophisticated control strategies and safety measures beyond this basic representation [3].

D. Srinivasan and P. Chandramohan [4] proposes a control strategy using a proportional-integral-derivative (PID) controller to maintain the desired outlet temperature of a shell and tube heat exchanger. The PID controller is tuned using the Ziegler-Nichols method, and the performance of the proposed control strategy is evaluated through simulations and experimental results. A. Senthil Kumar et.al., [5] introduces a mathematical model of a shell and tube heat exchanger and develops a control strategy based on adaptive neuro-fuzzy inference systems (ANFIS). The ANFIS controller is used to maintain the hot water outlet temperature by adjusting the cooling water flow rate, achieving efficient heat transfer and energy savings.

Benaissa Bellachia [6] discussed a comprehensive overview of various control strategies used for shell and tube heat exchangers. It covers traditional control methods, such as proportional-integral-derivative (PID) control, as well as advanced techniques like model predictive control (MPC), adaptive control, and fuzzy logic control. The paper discusses the advantages, limitations, and application areas of each control strategy, emphasizing their potential for improving heat exchanger performance and temperature regulation. Mustapha Ouassaid [7] proposes a Model-based Predictive Control (MPC) strategy for shell and tube heat exchangers using a grey-box modeling approach. The authors develop a dynamic model of the heat exchanger and implement the MPC controller to regulate the outlet temperature. Simulation and experimental results demonstrate the superiority of the MPC strategy in achieving precise temperature control and robust performance under varying operating conditions.

Hong Ling and Douglas J. Cooper [8] designed a model predictive control (MPC) strategy with integral action is proposed for shell and tube heat exchangers. The MPC controller is augmented with integral action to eliminate steady-state errors and improve temperature tracking performance. Simulation results show that the MPC with integral action outperforms traditional PID control and provides a more robust control solution.

In recent years, there has been growing interest in employing Deep Neural Network (DNN) controllers for their ability to handle complex and non-linear relationships in heat exchanger systems. This literature review examines the research and developments related to DNN controllers specifically applied to shell and tube heat exchangers. A study by Ugli Malikov et al., [9] proposed a DNN-based adaptive control approach for a shell and tube heat exchanger. The DNN controller was trained using historical process data and demonstrated superior performance in maintaining temperature setpoints under varying load conditions. In a different approach, Li, N et al. (2018) [10] implemented Model Predictive Control (MPC) using a DNN model for shell and tube heat exchangers. The MPC-DNN control strategy demonstrated improved dynamic response and disturbance rejection capabilities. Xu et al. (2022) [11] proposed a RL-based DNN controller that autonomously adapted to changing operating conditions, resulting in optimized heat transfer performance.

The literature demonstrates a growing interest in using Deep Neural Network (DNN) controllers for shell and tube heat exchangers. In this paper, a novel control approach utilizing the Antlion Optimization (ALO) algorithm in conjunction with a Deep Neural Network (DNN) controller for optimizing the control of the hot water outlet temperture in a shell and tube heat exchanger.

2. Process Description

The two fluids involved in the heat exchange process are referred to as the "hot fluid" and the "cold fluid." The hot fluid is the fluid that needs to release heat, while the cold fluid is the one that needs to absorb heat. The hot fluid enters the heat exchanger through its designated inlet, and the cold fluid enters through its respective inlet. The hot fluid flows through the tubes while the cold fluid flows around the outside of the tubes in the shell. The heat transfer occurs through the tube walls, which act as the interface between the two fluids. As the hot fluid flows through the tubes, it transfers its heat to the colder fluid surrounding the tubes in the shell. This heat transfer can occur due to the temperature difference between the two fluids, leading to thermal energy transfer.

There are two common flow arrangements in shell and tube heat exchangers: counterflow and parallel flow. In a counterflow arrangement, the hot fluid and cold fluid flow in opposite directions, which usually provides the most efficient heat transfer. In a parallel flow arrangement, both fluids flow in the same direction, which may not be as efficient but can be useful in certain scenarios. After releasing heat to the colder fluid, the hot fluid exits the heat exchanger through its designated outlet. Meanwhile, the cold fluid absorbs the heat from the hot fluid and exits the heat exchanger through its designated outlet. Throughout the process, temperature sensors and controllers monitor and adjust the temperatures of the fluids to achieve the desired hot water outlet temperature. A schematic diagram of one pass shell and tube heat exchanger is shown in Fig.1

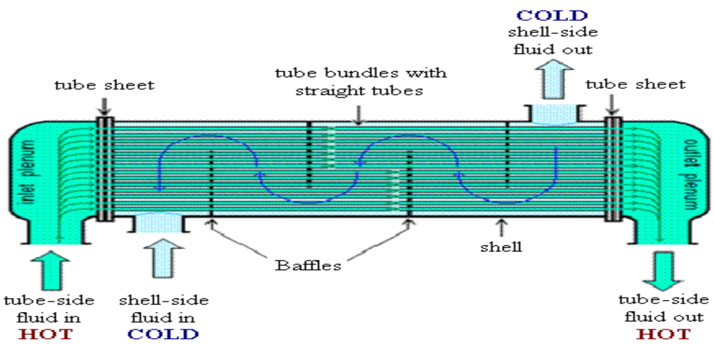

Fig.1. Schematic diagram of a one-pass shell and tube heat exchanger.

The convection term in heat exchanger is divided into a number of sections called the control volume. The final equation for the energy balance on the shell control volume given in eqn. (1) is equal to the energy gained due to change in temperature plus energy gained by convection.

$$\frac{\rho_s c_s v_s}{N} * \frac{dT_{co}}{dt} = \overset{o}{m}s\ c_s(T_{ci} - T_{co}) + \frac{h_s A_s}{N}(T_{ho} - T_{co}) \quad (1)$$

The energy balance on the tube control volume is analogous to the energy balance on the shell control volume. The energy balance equation is developed in the same manner as the equation developed for the shell control volume. The final differential equation for the rate of energy stored in the tube control volume is given by

$$\frac{\rho_t c_t v_t}{N} * \frac{dT_{ho}}{dt} = \overset{o}{m}t\ c_t(T_{hi} - T_{ho}) + \frac{h_t A_t}{N}(T_{co} - T_{ho}) \quad (2)$$

The eqns. (1) and (2) are referred as mathematical model of shell and tube heat exchanger and they are solved to get hot water outlet temperature (T_{ho}) by applying cold water inflow rate $\overset{o}{m}s(C_{in})$. C_{in} is the volumetric flow rate in LPS. The parameter specifications at nominal operating point are tabulated in Table 1.

Table 1. Parameter specifications of the Shell and Tube Heat Exchanger at nominal operating point.

Inputs		Value	Units
Density of water	(ρ_s, ρ_t)	1000	Kg/m^3
Specific Heat Capacity of water	(c_s, c_t)	4230	J/kg ^oC
Shell Heat Transfer Area	(A_s)	0.281	m^2
Tube Heat Transfer Area	(A_t)	0.253	m^2
Shell side volume	(v_s)	2.62 X 10-4	m^3
Tube side volume	(v_t)	1.43 X 10-4	m^3
Heat transfer coefficient of Shell	(h_s)	2162	$W/m^{2\,o}C$
Heat transfer coefficient of Tube	(h_t)	2162	$W/m^{2\,o}C$
Mass flow rate of cold water	$(\overset{o}{m}_s)$	0 – 0.1222	Kg/s
Mass flow rate of hot water	$(\overset{o}{m}_t)$	0.0282	Kg/s
Cold water inlet temp	(T_{ci})	33	^oC
Hot water inlet temp	(T_{hi})	60	^oC
Number of control volume	(N)	10	NA

The process parameters of shell and tube heat exchanger are observed using process reaction curve method. The obtained parameters are presented in Table 2. The PID controller is designed using Z-N open-loop tuning method. The obtained controller parameters are tabulated in Table 3.

Table 2. Process parameters of STHE.

Region	Process Gain (Kp)	Time constant (Tau)	Time delay (td)
1	-42.066	0.4388	0.22
2	-130.86	0.73045	0.1342
3	-223.45	0.9155	0.1313
4	-342.72	1.1036	0.1461

Table 3. PID controller settings of STHE.

Region	Proportional Gain (Kc)	Integral Time (Ti)	Derivative Time (Td)
1	-0.05685	0.4403	0.11
2	-0.0499	0.2684	0.0671
3	-0.0374	0.2626	0.06565
4	-0.02644	0.2922	0.7305

3. Antlion Optimization based Deep Neural Network Internal Controller

The weight updation in a Deep Neural Network (DNN) using the Antlion Optimization (ALO) algorithm is a process where the ALO algorithm optimizes the DNN's weights during the training phase. ALO is an optimization algorithm inspired by the hunting behavior of antlions, and it can be used to enhance the performance of the DNN by fine-tuning its weights and biases. Overview of how the ALO algorithm can be used for DNN weight updation is summarized below

Step(1)

The architecture of the DNN is designed with three input layers, two hidden layers and one output layer. Activation functions used in DNN is softmax.

Step(2)

Initial weights and biases of the DNN are selected with random values.

Step(3)

Datasets are constructed and trained using ALO based DNN.

Step(4)

ALO parameters such as the population size, maximum iterations, and control parameters are selected

Step(5)

Fitness function that evaluates the performance of the DNN.

Step(6)

ALO algorithm is utilized to optimize the DNN's weights. During each iteration of the ALO algorithm, the fitness function is evaluated for each antlion, and the best antlion is selected.

Step(7)

DNN's weights are updated using the information obtained from the ALO algorithm. The best antlion's position (weights) is used to update the DNN, improving its performance.

Step(8)

ALO-based weight updation process for multiple iterations are repeated until convergence, where the DNN's performance reaches a satisfactory level.
Step(9)

After training, DNN is verified on a separate validation dataset to assess its generalization performance.
Step(10)

Finally, trained DNN is tested on a test dataset to evaluate its performance in real-world scenarios.

The combination of ALO and DNN allows for efficient optimization of the DNN's weights, helping the DNN achieve better convergence and performance compared to traditional optimization methods. This approach can lead to more accurate and robust DNN models, especially when dealing with complex datasets and challenging problems.

4 Results and discussion

The ALO-DNN IMC demonstrated precise temperature control of the hot water outlet temperature in all four regions. The predictive capabilities of the DNN enabled the control system to anticipate temperature changes and adjust the heat exchanger's operation.

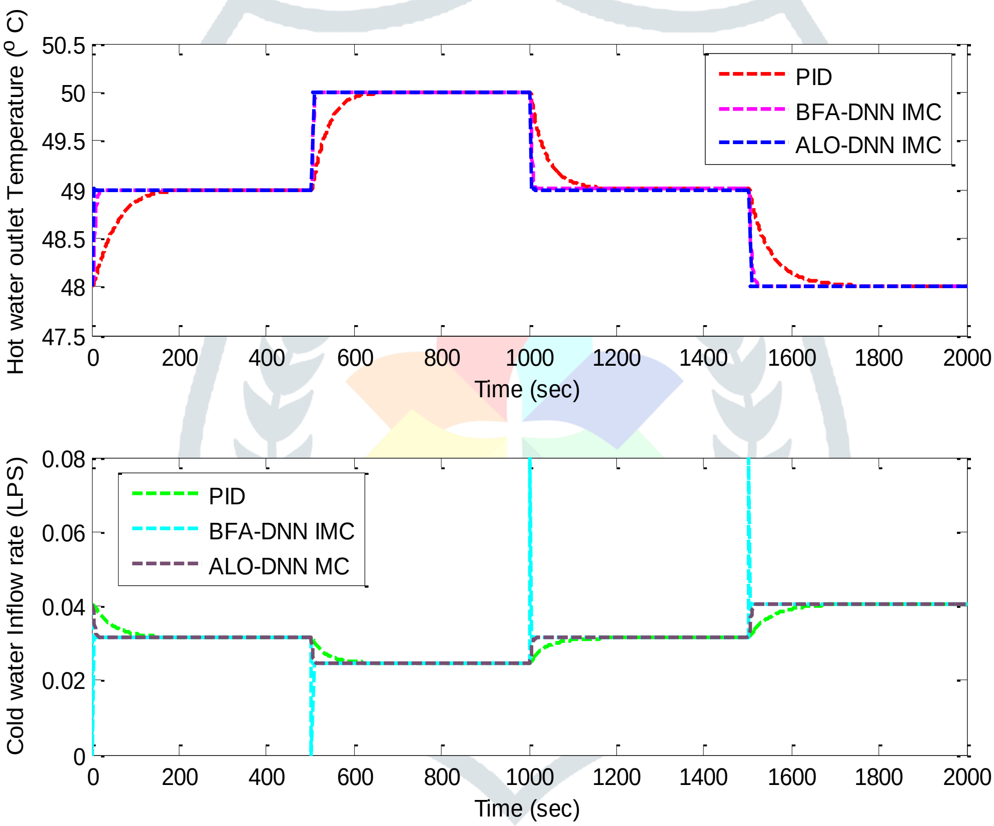

Fig.2. Servo response of shell and tube heat exchanger at region 1 with PID, BFA-DNN IMC and ALO-DNN IMC.

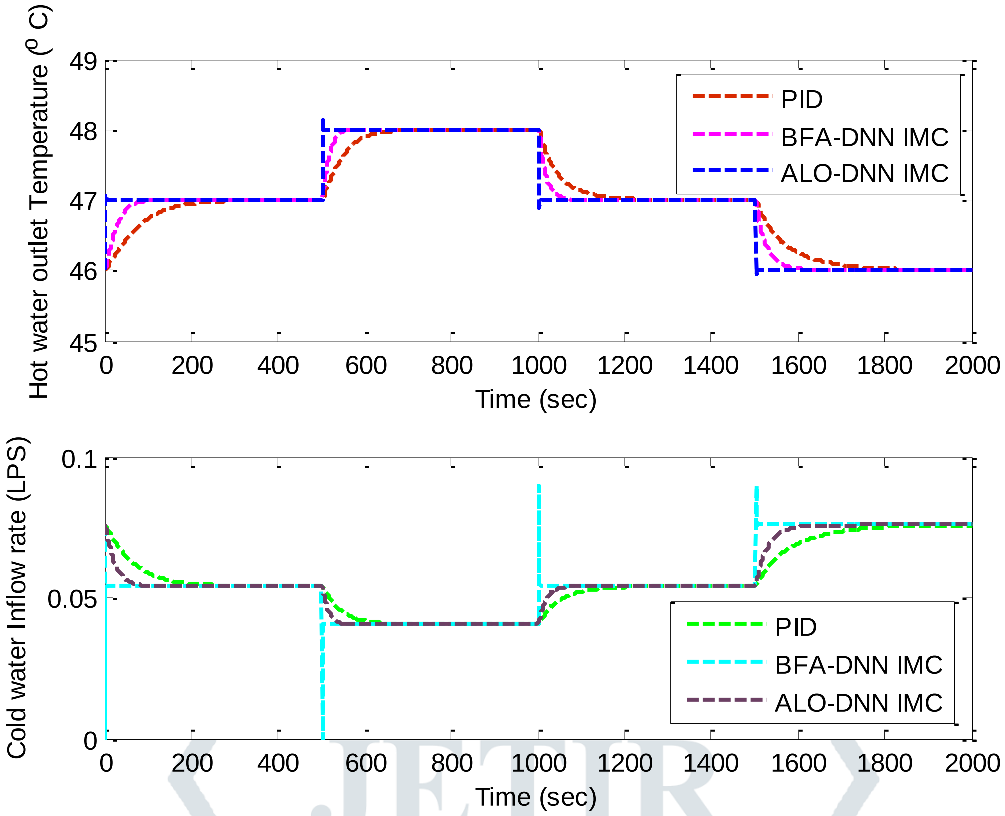

Fig.3. Servo response of shell and tube heat exchanger at region 2 with PID, BFA-DNN IMC and ALO-DNN IMC.

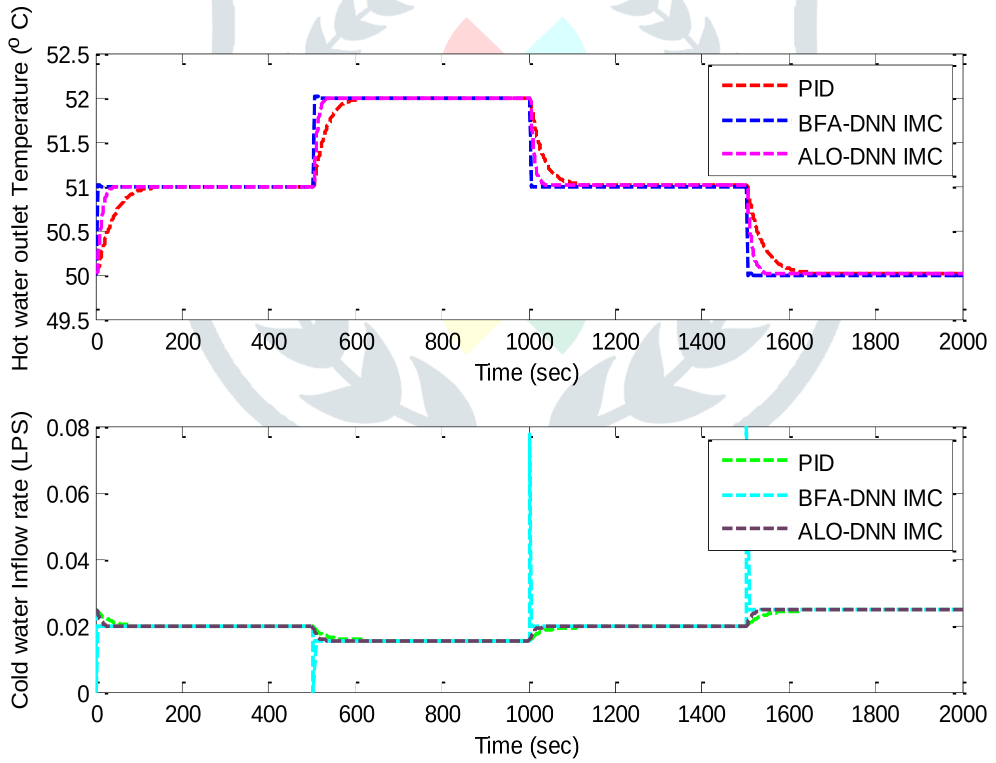

Fig.4. Servo response of shell and tube heat exchanger at region 3 with PID, BFA-DNN IMC and ALO-DNN IMC.

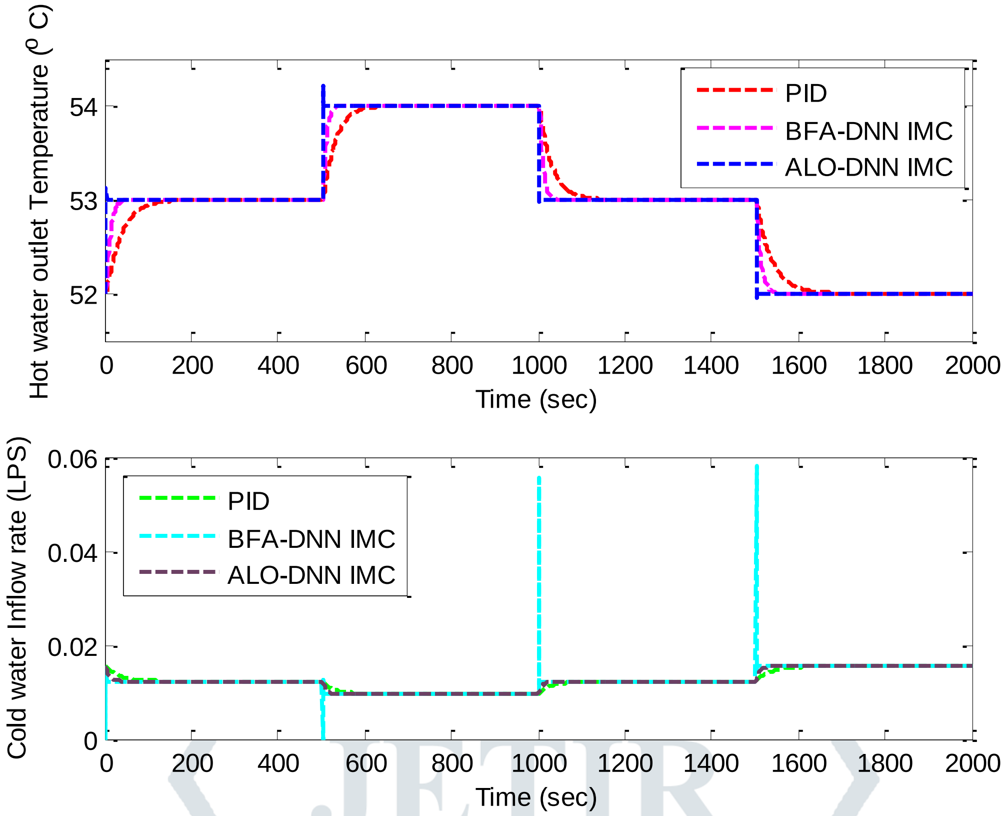

Fig.5. Servo response of shell and tube heat exchanger at region 4 with PID, BFA-DNN IMC and ALO-DNN IMC.

The ALO-DNN IMC exhibited robustness against disturbances and uncertainties in the system. The ALO algorithm's exploration-exploitation balance and the DNN's adaptability allowed the control system to handle changes in fluid flow rates, temperature differentials, and other operating parameters effectively. Comparative studies were conducted against traditional PID control and standalone DNN control approaches.

Table 4. Comparison of performance measures of ALO-DNN IMC with BFA-DNN IMC and PID controller for set-point tracking of STHE

Set point change in hot water outlet temperature	Integral square error			Settling time (seconds)		
	PID	BFA-DNN IMC	ALO -DNN IMC	PID	BFA-DNN IMC	ALO -DNN IMC
46-47 ºC	56	6.5	5.8	120	16	4
47-48 ºC	99	4.8	3.7	82	12	4
48-49 ºC	27	4.7	3.67	246	14	5
49-50 ºC	19	6.8	4.78	198	13	6
50-51 ºC	19	6.7	4.56	172	15	5
51-52 ºC	15	4.5	3.76	178	14	4
52-53 ºC	19	6.7	4.87	184	17	4
53-54 ºC	16	6.8	4.72	136	15	4

From Table 4, it is clear that ALO-DNN IMC consistently outperformed these methods, demonstrating precise temperature control, and robustness.

5 Conclusion

The combination of the Antlion Optimization algorithm with a Deep Neural Network Internal Model Controller has proven to be effective in optimizing the performance of a shell and tube heat exchanger. The results demonstrate the potential of this intelligent control system in enhancing heat transfer efficiency, temperature control, and robustness. The findings contribute to advancements in intelligent control strategies for heat exchanger systems and pave the way for more efficient and reliable industrial processes.

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