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CONTROL OF NUTRIENT REMOVING ACTIVATED SLUDGE SYSTEM

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Abstract: The objective of this paper is to evaluate several control algorithms for nitrogen removal using a simulation benchmark of a pre-denitrifying activated sludge process. Various PI and feedforward controllers are evaluated and compared with advanced multivariable and nonlinear model predictive control, which uses a perfect process model, perfect measurements and perfect knowledge of the disturbances. The simulation results indicate that PI nitrate and feedforward-PI ammonia control closely imitates the optimal operation strategy as the operating costs are only slightly higher compared to the case when model predictive control is applied. It appears that the improvement is thus more related to control structure, i.e. where the sensors and the actuators are located, than to the control algorithms.

Keywords: benchmark, PI controllers, predictive control, water pollution.

1. INTRODUCTION

Water pollution is a well known environmental problem worldwide due to the discharge of nutrients into receiving waters. Hence, stricter standards have been imposed by the authorities, which means that the need for better process control has been increasing. In particular, stricter standards for nitrogen discharge have challenged the research community to design and implement control strategies in such a way that effluent standards are maintained, while the total plant costs are minimized. As a result, both nitrification and denitrification processes, i.e. ammonia and nitrate removal, have to be operated economically.

To meet these demands, different control algorithms have been introduced over the years. For instance, a sufficient nitrification can be maintained by control of the dissolved oxygen (DO) concentration at a pre-selected set-point or by using a variable DO set-point based on ammonia concentration in the last aerated reactor of the plant (Ingildsen, 2002; Vrečko *et al.*, 2003). On the other hand, the denitrification process is usually controlled by manipulating the external carbon flow rate or internal recirculation flow rate based on nitrate concentration in the last anoxic reactor or in the last aerobic reactor (Lindberg, 1997; Yuan *et al.*, 2002). Different control algorithms have been proposed, from simple ON/OFF and PI control (Ayesa *et al.*, 2006) to complex model predictive (Steffens and Lant, 2002) control (MPC). Unfortunately, various plant configurations, influent characteristics and evaluation criteria have been used for evaluation of control algorithms. Consequently, it is difficult to say which control algorithm is the most appropriate with respect to minimal operating costs (OC) and best effluent quality, and whether the implementation of complex control algorithms is really necessary.

This paper presents several control strategies for nitrogen removal that were designed and tested by a benchmark simulation model of an activated sludge process (ASP). Control strategies differ in the information used about the process (i.e. the number of sensors and sensor locations) and in the complexity of the control algorithms. Various simple PI and feedforward (FF) controllers were tested, as well as an advanced MPC controller, which was used as a reference for the other control strategies. In this way, the control strategy that produces optimal performance regarding OC and gives satisfactory removal of nutrients can be found.

The paper is organized as follows: In the following section a benchmark simulation model is presented. Then the applied control strategies are described. Next, the presented control strategies are assessed and compared in terms of OC. Finally, the most important conclusions are drawn.

2. THE BENCHMARK

The cooperation of the IWA Task Group and COST Actions 624 and 682 resulted in the development of a benchmark simulation model of an ASP. The benchmark (Copp, 2002) represents a pre-denitrification plant with two anoxic and three aerated compartments. In our case one anoxic and four aerobic reactors (Fig. 1) were used in order to achieve lower effluent ammonia concentrations. The activated sludge model no. 1 (ASM1) is used to describe the biological processes in the reactors (Henze *et al.*, 2000). The secondary settler is modelled as a non-reactive, ten-layer process with a double exponential settling velocity model proposed by Takács *et al*. (1991).

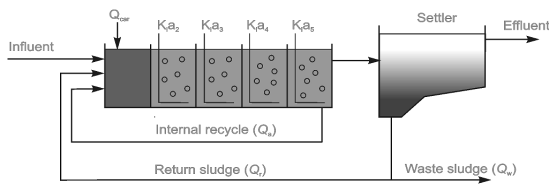

Fig. 1. Plant layout.

The benchmark defines three different weather situations, i.e. dry, rain and storm. All investigations of this paper are based on dry weather influent situation, given over a 14 day period. To calculate benchmark performance the plant is first run to the steady-state by simulating the plant with the defined constant influent file. Then, the plant simulation continues by twice (28 days) applying the dynamic dry influent file. The performance of the benchmark is then evaluated for the last seven days of dynamic data.

Various criteria have been defined in the benchmark to assess the performance of the plant (Copp, 2002). In this work, operating costs that include aeration costs, carbon dosage costs , sludge disposal costs and effluent fines (EF) were used to evaluate control strategies, while additional investment costs for the implementation of the control strategy (sensors, actuators) were not taken into account. Within the benchmark also pumping costs are defined, but were in our case not considered as all the pumping flow rates were kept constant.

EF are usually paid in proportion to the discharge of pollution into receiving waters. The cost function for EF which was used in our case is shown in Fig. 2 (Carstensen, 1994; Vanrolleghem *et al.*, 1996).

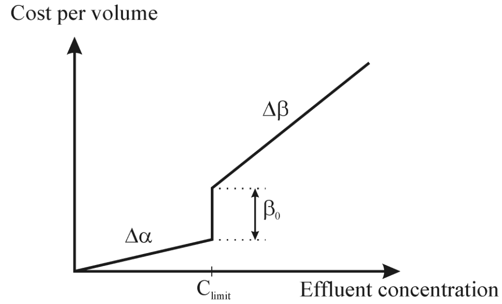

Fig. 2. Cost function for effluent fines.

Here, $\Delta\alpha$ and $\Delta\beta$ are costs per kilogram of discharge below and above effluent limit concentration C_{limit}, while β_0 is the cost for exceeding the effluent limit. In our study only effluent ammonia (S_{NHeff}) and total nitrogen (TN_{eff}) were considered in the calculation of effluent fines. The values of cost function parameters are shown in Table 1. Discharge limits for ammonia ($S_{NHlimit}$) and total nitrogen (TN_{limit}) were set to 4 mg/l and 12 mg/l, respectively.

Table 1 Cost function parameters

Parameter	Value
$\Delta\alpha_{NH}$	4 €/kg
$\Delta\beta_{NH}$	12 €/kg
$\beta_{0,NH}$	2.7 €/1000m^3
$\Delta\alpha_{TN}$	2.7 €/kg
$\Delta\beta_{TN}$	8.1 €/kg
$\beta_{0,TN}$	1.4 €/1000m^3

3. CONTROL ALGORITHMS

In this paper, the following manipulated variables were used in the control strategies: external carbon flow rate (Q_{car}), dissolved oxygen set-point (So_{set}) and oxygen transfer rate (K_La), which is related to the airflow rate. Other manipulated variables, such as internal recycle flow rate (Q_a), external recycle flow rate (Q_r) and waste sludge flow rate (Q_w) were set to the constant values of 55338 m^3/d, 18446 m^3/d and 300 m^3/d, respectively. It should be mentioned that the default benchmark value of Q_w was reduced from 385 m^3/d to 300 m^3/d in order to maintain sufficient nitrification capacity.

Boundaries of the manipulated variables were the same as in the benchmark. The maximum external carbon flow rate was limited to 5 m^3/d, with a COD concentration of 400000 mg/l, while the oxygen transfer rate (K_La) values were limited between 0–360 d^{-1}. The upper bound of the oxygen set-point was limited to 3 mg/l in order to reduce unnecessary aeration of the aerobic reactors. Because of the constraints of the manipulated variables, anti-windup protection, similar to that used in the benchmark, was applied in the PI controllers. To simplify evaluation of the control strategies, ideal sensors (without delay or noise) were used.

3.1. Oxygen PI control

One of the most basic control strategy that can be applied in WWTP is to use oxygen PI control. Oxygen PI control uses four PI controllers that control DO concentrations in the aerobic reactors to a desired set-point by manipulating the K_La values. This control strategy needs four DO sensors, which are the most commonly used in practice for online control or monitoring. The control scheme of oxygen PI control is shown in Fig. 3. As can be seen from Fig. 3 a constant external carbon dosage was applied in our case.

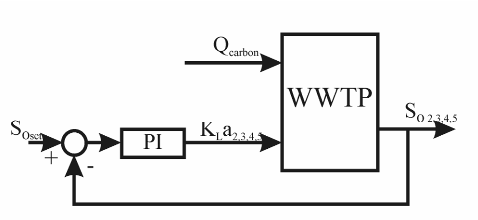

Fig. 3. Control scheme of oxygen PI control.

3.2. Nitrate PI and ammonia PI control

In this control strategy (Fig. 4), nitrate concentration in the last aerobic reactor (S_{NO5}) is controlled with a PI controller that manipulates external carbon flow (Q_{car}), while ammonia concentration in the last aerobic reactor (S_{NH5}) is controlled with a cascade controller. The outer PI controller in the cascade control adjusts the DO set-point value (So_{set}) based on desired and actual S_{NH} values, and the inner controllers manipulate K_La values based on desired and actual DO values. To apply this control strategy in practice, additional sensors for ammonia and nitrate concentrations are needed.

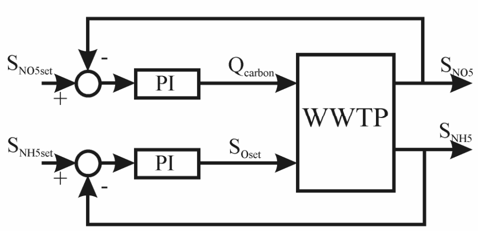

Fig. 4. Control scheme of nitrate PI and ammonia PI control.

3.3. Nitrate PI and ammonia FF-PI control

The idea of feedforward (FF) control is to act on the process when disturbances appear and before they cause changes in the effluent (Vrečko *et al.*, 2003). In the proposed strategy, the ammonia cascade PI controller was upgraded with an FF control that uses influent flow rate (Q_{in}) and influent ammonia concentration (S_{NHin}) as measurable disturbances. The control scheme of nitrate PI and ammonia feedforward-PI control is shown in Fig. 5.

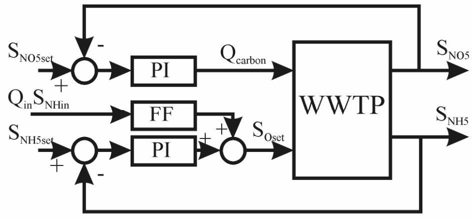

Fig. 5. Control scheme of nitrate PI and ammonia FF-PI control.

The DO set-point is calculated as the sum of PI and FF control:

$$So_{set} = So_{PI} + So_{FF} \tag{1}$$

where So_{PI} is the output of the ammonia PI controller and So_{FF} is the output of the FF controller. The response of the FF controller is proportional to the product of S_{NHin} and Q_{in} and is chosen to be non-zero only during high influent loads:

$$So_{FF} = \begin{cases} 0 & \text{if } Q_{in}S_{NHin} \le 1000 \text{ kg/d} \\ kQ_{in}S_{NHin} & \text{if } Q_{in}S_{NHin} > 1000 \text{ kg/d} \end{cases} \tag{2}$$

High influent flow rates reduce hydraulic retention times and therefore it is important to increase DO concentrations fast enough to counteract the influent disturbances. During low influent loads the PI controller is sufficient to reject small influent disturbances, and hence the FF part can be switched off. The proportional factor k in (2) was set to a value of $2 \cdot 10^{-2}$.

3.4. Model predictive control

The idea of MPC is to calculate a control sequence by minimizing a certain cost function. A control sequence is calculated based on set-points, an internal model, measured disturbances and outputs (Maciejowski, 2002). In our case the whole benchmark model was used as the internal model of the predictive controller and all influent disturbances were assumed to be known in advance (i.e. over the future prediction horizon). This "ideal" control algorithm was used as a reference for the other control algorithms presented above. Ammonia and the sum of ammonia and nitrate concentrations in the last aerobic reactor were used as controlled variables, while the manipulated variables were the same as above. The control scheme of the MPC is shown in Fig. 6.

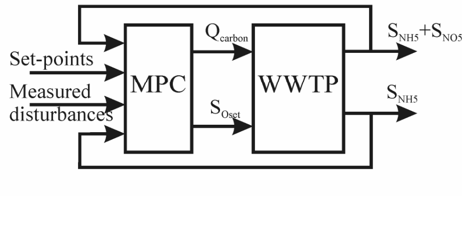

Fig. 6. Control scheme of MPC.

Various cost functions can be used in the MPC algorithm. In our cost function the deviation of the S_{NH5} concentration from the desired set-point was included, and the soft constraint on S_{NH5} was used to additionally penalize concentrations above the effluent limit. A soft constraint for S_{NH5} was implemented by using a so-called "slack variable", which is defined in such a way that it is non-zero only when the constraint is violated, i.e. when S_{NH5} values exceed 4 mg/l. The other controlled variable, the sum of ammonia and nitrate concentration in the last aerobic reactor (S_{NH5}+S_{NO5}), was considered in the cost function only with the soft constraint. The slack variable is in this case activated when the S_{NH5}+S_{NO5} exceeds 10 mg/l. In the cost function the values of the carbon flow rate were also included in order to penalize unnecessary external carbon dosing. The changes of the manipulated variables were penalized as well. This has the effect of reducing the oscillations of control signals. The complete mathematical expression of the cost function is the following:

$$
\begin{aligned}
J &= \sum_{i=1}^{H_p} \left\| z_{k+i|k} - r_{k+i|k} \right\|_Q^2 + \sum_{i=1}^{H_u} \left\| \Delta u_{k+i|k} \right\|_{R_{\Delta u}}^2 + \\
&+ \sum_{i=1}^{H_u} \left\| u_{k+i|k} - u_0 \right\|_{R_u}^2 + \rho \sum_{i=1}^{H_p} \varepsilon_{k+i|k} \\
z &= \begin{bmatrix} S_{NH5} \\ S_{NO5} + S_{NH5} \end{bmatrix}, u = \begin{bmatrix} So_{ref} \\ Q_{car} \end{bmatrix}
\end{aligned} \tag{3}
$$

where $z_{k+i|k}$ is a vector of the predicted controlled outputs, $r_{k+i|k}$ is a vector of the future set-point values, $\Delta u_{k+i|k}$ is a vector of the input future changes, $u_{k+i|k}$ is an input vector, $\varepsilon_{k+i|k}$ is the slack variable, H_p is a prediction horizon, H_u is a control horizon, Q is a weighting matrix to penalize the error between the predicted process output and the set-point, $R_{\Delta u}$ is a weighting matrix to penalize changes in the control signal, R_u is a weighting matrix to penalize deviations of the input vector from the desired steady-state value (u_0), while ρ is a weight to penalize soft constraint violations. The norm terms in the cost function are defined as follows:

$$
\|x\|_Q^2 = x^T Q x \tag{4}
$$

4. TUNING OF CONTROLLERS

4.1. PI controllers

Parameters of PI controllers were tuned from the step response experiments using the internal model control (IMC) tuning rules (Olsson and Newel, 1999). The values of the parameters of PI controllers are shown in Table 2.

Table 2 Parameters of PI controllers

	Oxygen controller	Ammonia controller	Nitrate controller
K_p	100	-1	-1
T_i	0.01 d	0.2 d	0.1 d

4.2. MPC controller

Parameters of the prediction and control horizon, the weights and the reference trajectory of the MPC affect the closed-loop behaviour of the plant. The weights in the cost function may be set according to the economic objectives of the plant, but usually they are adjusted in such a way that satisfactory control performance is achieved (Maciejowski, 2002). In our case, parameters were tuned based on experience gained from the simulations and from the tuning rules presented in Maciejowski (2002). Since the dynamics of nutrient removal processes are on a time scale of hours, the prediction horizon was set to 1.5 h, which is 6 time steps (each time step was 15 min). In order to simplify the calculation of the input sequences, only one control move Δu was optimized at each sampling instant (H_u=1), i.e. the control signal was constant during the prediction horizon. The parameters of the MPC can be summarized as follows:

$$
\begin{aligned}
&Q = \begin{bmatrix} 10 & 0 \\ 0 & 0 \end{bmatrix}, R_{\Delta u} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, R_u = \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix}, \\
&u_0 = \begin{bmatrix} 0 \\ 0 \end{bmatrix}, \rho = 10, H_p = 6, H_u = 1.
\end{aligned} \tag{5}
$$

5. RESULS AND DISCUSSION

The performance of the plant strongly depends on the selected controller set-points. In order to determine optimal operating points with respect to the OC, a number of dynamic simulations with different set-point values were performed for each control strategy. S_{Oset}, Q_{car}, S_{NH5set} and S_{NO5set} were changed in a range of 0.3-3 mg/l, 0-5 m^3/d, 0.5-7 mg/l and 5-16 mg/l, respectively. Set-point values that give the smallest OC are given in Table 3.

Table 3 Optimal set-point values

	Optimal values of set-points
Oxygen PI control	So_{set} =0.53 mg/l Q_{car}=1.6 m^3/d
Nitrate and ammonia PI control	S_{NH5set}=2.05 mg/l S_{NO5set}=8.8 mg/l
Nitrate PI and ammonia FF-PI control	S_{NH5set}=1.9 mg/l S_{NO5set}=8.8 mg/l
MPC	S_{NH5set}=2.0 mg/l

Each control strategy was simulated using the optimal operating set-point values (Table 3). The results of simulations from the 8th to the 10th days of influent data are shown in Figs. 7-10. Considerably better removal of ammonia was achieved by using control strategies where ammonia concentrations are controlled (Fig. 7). In these cases, DO concentrations are increased during high load periods (see Fig. 9) to enhance nitrification and to remove ammonia peaks more successfully. Ammonia peaks were lowered to approximately 4.5 mg/l and 3.5 mg/l with the PI and FF-PI ammonia controller, respectively. With ammonia FF-PI control, better reduction of ammonia peaks was achieved because the DO concentrations were increased approximately one hour earlier. Similar DO responses were also obtained with MPC, and therefore only a minor improvement in ammonia removal was achieved.

Even though the upper limit for the DO concentration was 3 mg/l, none of the controllers could manage to remove the effluent ammonia peaks completely. The problem is that the aeration volumes of the benchmark are too small and should be increased in order to achieve complete ammonia removal. An improvement in ammonia removal could be also achieved by increasing the sludge age (i.e. reducing the waste sludge flow rate); however, in this case sludge wash-out from the plant may occur during stormy weather.

Comparison of carbon addition flow rates in Fig. 10 shows that with oxygen PI control that uses a constant carbon flow rate too much external carbon is added during low influent loads, while too little carbon is added during high influent loads. External carbon can be dosed more efficiently with a PI controller that adds external carbon only when the nitrate concentration in the fifth reactor is high. The MPC controller starts to change external carbon dosing much earlier than the nitrate PI controller, and therefore a better reduction of effluent total nitrogen peaks is achieved (Fig. 8). Fig. 8 shows that during high influent loads the removal of TN_{eff} peaks is better with oxygen PI control than with nitrate PI control. Namely, in the first case, low DO concentrations during high influent loads enable simultaneous denitrification in aerobic reactors, leading to lower TN_{eff}. However, during low influent loads the TN_{eff} concentrations are much higher in the case of oxygen PI control because of higher DO concentrations (Fig. 9).

Control strategies were also evaluated with the criteria described in section 2. The obtained values of the evaluation criteria are given in Table 4. The largest OC and EF are obtained when only oxygen PI control is applied. The OC are about 5% (or 145 € per day) lower when nitrate and ammonia PI control was applied, which in addition also gives considerably better ammonia removal. With nitrate PI control and ammonia FF-PI control, the operating costs were reduced only slightly. However, the maximum values of effluent ammonia peaks were lowered even further. It should be mentioned that in reality even greater improvement can be achieved with FF control because of the delays of sensors and actuators. With MPC, almost the same operating costs were achieved as with simple FF control. The difference would be even smaller considering that an MPC with a perfect model, perfect measurements and perfect knowledge of the disturbances was used in the study. It appears that the additional information about the plant, along with the advanced multivariable and nonlinear control algorithm, would not improve the operation of the plant to such an extent that the investment in buying additional sensors and implementing more complex control algorithms would pay off.

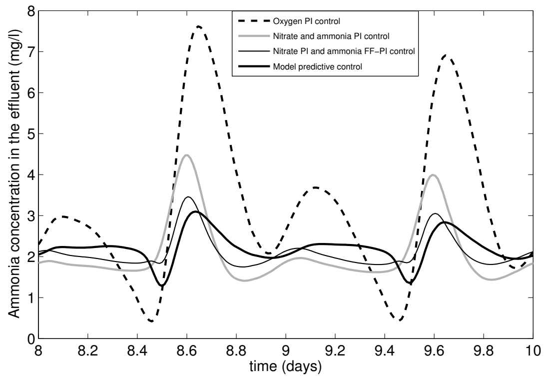

Fig. 7. Comparison of effluent ammonia concentrations.

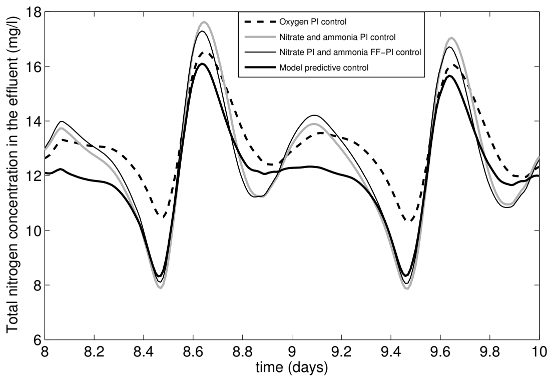

Fig. 8. Comparison of effluent total nitrogen concentrations.

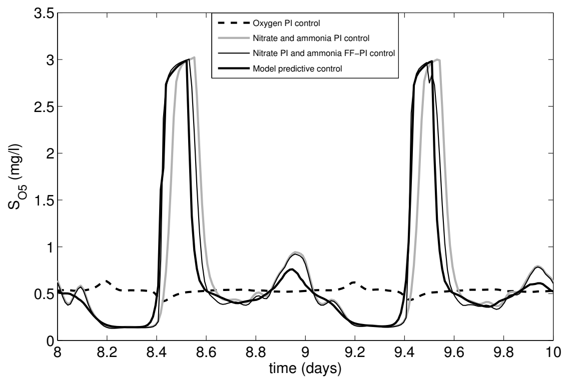

Fig. 9. Comparison of oxygen concentrations in the fifth reactor.

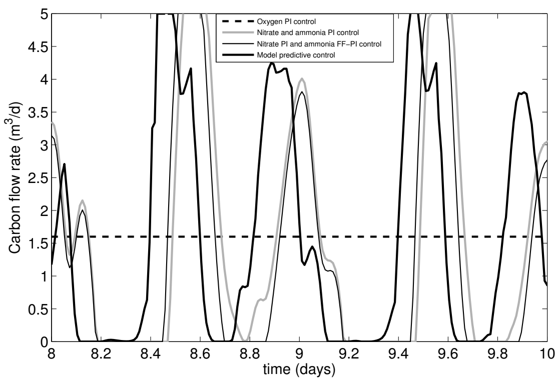

Fig. 10. Comparison of external carbon flow rates.

It should be also mentioned that the actual implementation of advanced control strategies strongly depends on the effluent fines imposed by legislation. For example, if softer effluent fines are applied even smaller improvements can be obtained with advanced control algorithms. On the other hand, even heavier effluent fines would favour advanced control algorithms.

Table 4 Evaluation criteria for different control strategies

	Oxygen PI control	S_{NO} and S_{NH} PI control	S_{NO} and S_{NH} FF-PI control	MPC
Aeration costs (€/d)	512	552	552	538
Sludge costs (€/d)	1227	1206	1199	1220
Carbon costs (€/d)	192	134	121	152
Effluent fines (€/d)	940	834	830	777
Operating costs (€/d)	2871	2726	2702	2687

6. CONCLUSIONS

In this paper, several control strategies for nitrogen removal in an ASP were evaluated using a benchmark simulation model (BSM1). The aim of the study was to investigate the differences between the controllers in terms of operating costs. In the study, various simple PI and FF controllers, as well as a more advanced MPC controller, were evaluated. Controllers differ in the information that is used about the process and in the complexity of the control algorithms.

It was shown that with nitrate PI and ammonia FF-PI control almost the same optimal operating costs can be achieved as with more advanced MPC algorithm. It is expected that in reality the differences between advanced MPC algorithms and relatively simple PI and FF control algorithms would be even smaller considering that an MPC with a perfect model, perfect measurements and perfect knowledge of the disturbances was used in the study. Hence, the improvement is thus more related to control structure, i.e. where the sensors and the actuators are located, than to the control algorithms.

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