Predictive Control of Intermittent Aeration in Activated Sludge Processes

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Abstract: - This paper presents a model-based predictive control for an intermittently aerated bioreactor of a medium-sized wastewater treatment plant. The main objective of the proposed method is to develop an intermittent aeration sequencing control strategy to minimize the aeration system energy consumption, with a subscription to the EU effluent standards and the plant operating constraints. A multilayer control system with two levels is implemented. The optimization level uses a model predictive control algorithm to determine the optimal value for the aeration fraction of the aeration cycle. The lower layer provides a feedback control loop of the bioreactor dissolved oxygen and secures intermittent aeration sequencing. The obtained aeration sequence guarantees that the effluent fulfills the requirements following regulatory standards for wastewater discharged. The control system demonstrates good performances for both setpoint tracking and disturbance rejection. Important energy savings are also obtained when comparing the developed control strategy to traditional control systems based on a pre-determined aeration sequence.

Key-Words: - wastewater, activated sludge, alternating aeration, process model, simulation platform, predictive control, optimization.

Received: June 19, 2024. Revised: November 14, 2024. Accepted: December 11, 2024. Published: December 31, 2024.

1 Introduction

According to the United Nations, it is expected that by the year 2050, six billion people will experience clean water scarcity, [1]. Droughts and floods brought on by climate change will worsen, further disrupting the water supply and resulting in contaminating events that might worsen public health and disrupt human society. Maintaining a clean and safe environment and promoting community health depend heavily on the efficient treatment and management of municipal and industrial wastewater. It is crucial that wastewater treatment plants (WWTPs) meet the standards for the quality of the water they discharge into the environment, [2], [3]

The biological treatment, which is part of most WWTPs, uses the activated sludge process (ASP) as its primary technology. The ASP provides high-level reliability, flexibility, cost-effectiveness, and capacity to achieve high-quality treated wastewater. However, the activated sludge process is particularly extremely complex, nonlinear, difficult to control, and requires a great consumption of energy. The development of accurate models for control algorithm design has been the subject of several studies, [4], [5]. Recent studies have also focused on developing various control methods as well as predictive [6], [7], [8], fuzzy [9], adaptive [10], [11], or fractional order PID control [12], [13]. Regretfully, this results in significant energy usage. Thus, optimizing energy efficiency is one of the key objectives for the WWTP, [14], [15], [16].

The recently increased interest in intermittent aeration systems relatively into a conventional multi-zone scheme is adopted by worldwide researchers due to its excellent efficiency in nitrogen removal and notable diminution of consumed energy, especially regarding medium and small size wastewater treatment plants. Alternating aeration systems are based on the same configuration as conventional activated sludge processes, using a single bioreactor, whereas nitrification and denitrification are obtained alternatively, the two phases being separated chronologically and not spatially. A salient characteristic of the alternating aeration-activated sludge process is its remarkable control potential which makes it appropriate for automatic control and improvement of operating costs. However, despite their widespread use, a large number of alternating aeration-activated sludge processes are still operated based on a pre-established air-on/air-off sequence, where the period of each phase remains unchanged, [17]. More efficiency of the alternating approach can be obtained by specifying switching on and switching off conditions based on the online measurements from the process. The proposed control strategies based on pH measurements [18], [19], online oxygen requirements (OR) estimation [20], effluent ammonium concentration measurements [18], [21], and oxidation-reduction potential (ORP) [22] as online control variables, can flexibly control the air-on/air off phases durations. To prevent extended air-on or air-off phase durations, completing strategies have been proposed. Maximum and minimum limit values were settled [21] for both aeration total cycle time and aeration fraction. Maximum dissolved oxygen concentration value, limits of air-on and air-off phase durations, and minimum oxidation-reduction potential value were settled to improve the aeration process management, [22].

Optimization and advanced control strategies are being developed to improve conventional resources in terms of both effectiveness and efficiency. An interesting approach is to determine air-on/air-off phase durations minimizing the energy consumed while preserving the effluent constraints by using dynamic optimization, [23], [24], [25]. An alternative method to improve the alternating aeration-activated sludge process performances taking into account the abovementioned problems is to use a receding horizon model based predictive control (MBPC) technique, [26], [27].

The purpose of this paper is to develop and evaluate the benefits of a hierarchical control system, with a higher layer implementing the optimization strategy and a lower layer containing the process level control loops and alternating aeration/non-aeration sequencing system. The main contribution of the hierarchical control strategy proposed in this paper is the possibility of exploiting the benefits of predictive control to improve process performance. The MBPC aeration strategy accomplished by the higher layer guarantees that the WWTP fulfills the effluent requirements and achieves significant energy savings. MBPC techniques have good disturbance rejection capabilities and are robust against unknown and variable time delays.

The paper has the following structure: the next section describes the design of a municipal wastewater treatment plant and the mathematical model of the ASP process. Section III presents the optimization strategies and the predictive control algorithm. Simulation results are presented and analyzed in Section IV and the last section outlines the conclusions.

2 Plant Description and Simulation Platform

2.1 Plant Structure

The wastewater treatment plant considered in this study is a municipal WWTP (max. flow - 4500 m3/day), designed for 20 000 population-equivalent. A plant for wastewater treatment usually includes three sections: the primary treatment, used to reduce large pollutants and suspended solids, a secondary stage which uses biological processes to further purify wastewater and tertiary treatment, used to improve the effluent quality.

Biological treatment is the most important process used in wastewater treatment plants. The frequently used procedure for biological treatment is activated sludge technology. This work focuses on the biological treatment stage shown in Figure 1. The biological treatment section is designed as two tanks disposed of as circular rings. The secondary settler provides the inner ring, while the bioreactor tank is represented by the outer cylindrical tank.

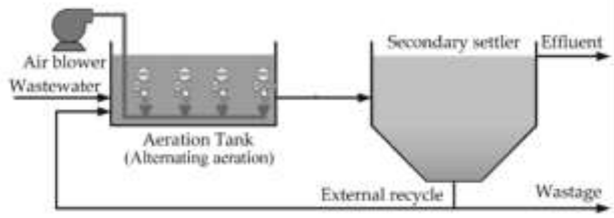

Fig. 1: Biological treatment process schematic configuration

The bioreactor aeration is controlled alternately for nitrification and denitrification by turning the blowers on and off. The bioreactor utilizes submersible mixers in order to maintain perfect mixing of its contents during the anaerobic phase. The blowers, which have a maximum aeration flow Qmax = 1380 m3/h and can operate at varying airflows, provide the necessary aeration flow to the biological treatment tank. In the secondary settler, following the bioreactor, the clean water from the settler's top will overflow into the effluent pumping station. The settled sludge is returned to the bioreactor by recirculation. The bioreactor volume is 3242 m^3 while the secondary settler has a 2048 m^3 volume. Usually, the aeration system is controlled based on a predetermined air-on/air-off duration with a total aeration cycle duration of 4 hours.

2.2 Mathematical Model and Simulation Platform

The Benchmark Simulation Model no. 1 (BSM1) [5], a well-known simulation platform, developed to evaluate different control methods, was used to simulate the biological treatment process. The BSM1 plant layout is composed of a group of anoxic reactors, aerobic reactors, and a secondary settler. The dynamic model describing the biological treatment process is based on two models: (i) for the simulation of bioreactors, the Activated Sludge Model No 1 (ASM1) [4], and (ii) for the simulation of the transfer between the various layers from the settler, the double exponential settling velocity model. Ten layers are used to model the settler. The modeled plant is designed to extract nitrogen from wastewater by means of nitrification as well as denitrification processes. Denitrification occurs in the anoxic tanks, whereas nitrification occurs in the aerobic tanks.

The BSM1 simulation platform mentioned before has been modified to accurately describe the dynamic of the activated sludge process for the WWTP considered in this work. Therefore, the internal recirculation and several bioreactors were eliminated from the standard BSM1 model. However, the model retains the biological reactor tank, alternatively operated with anoxic and aerated phases, chronologically alternated, the secondary settler and the primary recirculation.

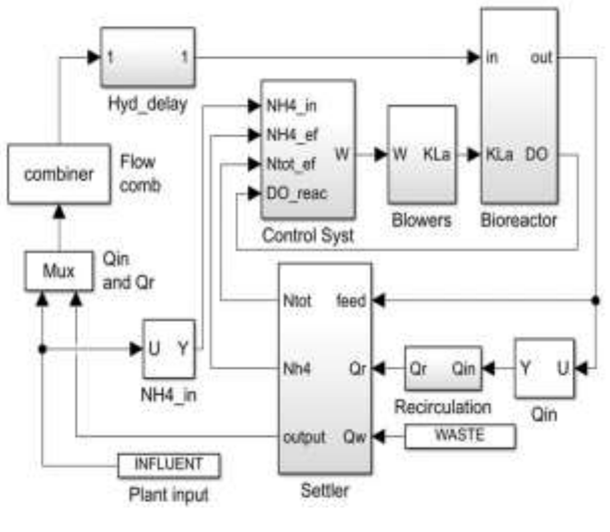

Fig. 2: Modified Benchmark Simulation Model 1

To develop the bioprocess model, the Activated Sludge Model no. 1 has been used. Eight basic processes and thirteen state variables are used to describe the biological behavior of the bioreactor. The state variables are divided into carbon-based components, nitrogen-based components, dissolved oxygen concentration, and alkalinity. The latter does not affect the other processes of the model and is only used as an indicator. Figure 2 presents the block diagram for the Simulink model that was derived from BSM1. To accurately represent the real plant characteristics, the model stoichiometric parameters as well as the model kinetic parameters and model initialization parameters are adjusted in accordance with the model calibration described in [28].

Several changes were made for the modeling of the blowers and aeration system to be as close as possible to the actual process. To control the bioreactor dissolved oxygen concentration, the transfer coefficient KLa is used in BSM1. However, since the real plant cannot use this variable, a new block is designed to transform the aeration flow rate (which is later utilized as the manipulated input of the bioreactor) into KLa.

To maintain the bioreactor's alternating phases for nitrification and denitrification, the blowers, controlled by the intermittent aeration sequencing system operate by switching ON-OFF. A PID controller at the process level is employed to control the dissolved oxygen concentration (DO) in the bioreactor at the setpoint value during the aerobic phase.

3 Optimization Strategy and Control Algorithm

3.1 Optimization Strategy

Only one bioreactor, in which the aerobic and anoxic phases alternate by having to start and stop the blowers, is required for the WWTPs which use intermittent aeration processes. By arranging the two phases in chronological order, nitrification and denitrification occur within a period known as the aeration cycle. As a result, the aeration cycle (TA = the total time of the aeration cycle) consists of an aeration time (TAN = air-on interval for nitrification) during which nitrification is permitted to continue, and an anoxic time (TAD = air-off interval for denitrification) during which denitrification occurs (TA = TAN + TAD). Additionally, the aeration duty cycle, or aeration fraction f, is added and may be calculated as f = TAN / TA.

The ratio between the total aeration cycle time and the hydraulic detention time of the bioreactor is determined using a particular parameter called the cycle time ratio (CTR).

An important characteristic of the alternating aeration method is its control flexibility, making it appropriate for the optimization of operational costs.

The control method developed in this work seeks to optimize the process operation and improve the control system's performance.

To decrease pollution by discharging in the effluent, the optimization system uses a predictive algorithm to control the alternate aeration system operation. However, an analysis of the energy consumption distribution at the WWTP level indicates that the aeration system's energy consumption accounts for almost 60% of the total energy consumed.

This implies that implementing the developed control method may help the process become more energy efficient. Figure 3 (Appendix) describes the control system as a two-level hierarchical structure: the level of the local process control loops and the optimization level which uses a model-based predictive control (MBPC) method to generate the control of sequencing aeration/non-aeration system.

At the process control level, a local control loop using a Proportional-Integral-Derivative (PID) control algorithm and the aeration sequencing system with a variable aeration fraction are implemented. The local control loop performs a fixed setpoint control of the bioreactor dissolved oxygen concentration at a fixed reference value (DOref) set by the operator and an aeration fraction value quantified by the optimization level.

The predictive control algorithm is designed for one input variable, the total effluent nitrogen concentration for which the reference value must be specified. The predictive control algorithm has one output variable, the coefficient of the aeration fraction, f .

3.2 GPC Algorithm

Different predictive control techniques were proposed. However, all MBPC algorithms compute the control actions vector using optimization of some cost functions. The Generalized Predictive Controller (GPC) is one of the most important design methods of Model-Based Predictive Control. The standard GPC design uses a linear model of the process, CARIMA - Controlled Auto-Regressive Integrated Moving-Average, and a quadratic cost index for the control law synthesis, using an incremental approach (the actual value of control output increment - Δu- is computed). This incremental realization provides offset-free operation in closed-loop systems.

The biological treatment process is the most energy-consuming process in the WWTP. An important approach in designing the optimization level proposed control strategy is the reparameterization of the cost function in the predictive algorithm to consider the energy consumed for the aeration process. This could use the fluctuation in the operating conditions of the plant to achieve important energy savings. Since the aeration fraction is the manipulated variable determined by the predictive algorithm, to minimize the algorithm output and not its variations the reparametrized cost index of the control algorithm must contain the output u, rather of the output increment Δu. A positional implementation of the predictive algorithm, based on a positional form of the GPC cost function will be obtained.

Consider the following modified cost function:

$$J = \sum_{j=N1}^{N2}[y(t+j) - y_r(t+j)]^2 + \sum_{j=0}^{Nu-1}\rho\, u(t+j)^2 \qquad (1)$$

where:

- y_r –represents the future setpoint sequence,
- N_1 - the minimum prediction horizon,
- N_2 - the maximum prediction horizon,
- N_u - the control horizon,
- ρ - the control output weighting coefficient.

In this paper the cost function presented in (1) and the CARIMA linear process model are considered:

$$A(q^{-1}) \cdot y(t) = B(q^{-1}) \cdot u(t-k) + C(q^{-1})e(t) \qquad (2)$$

Thus, the minimization of the cost function (1) when the controller output is replaced by u(t) = u(t-1) + Δu(t) where u(t-1) is known (u (t-1) = u') results to:

$$J = (y - y_r)^T(y - y_r) + \rho(u'+\Delta u)^T(u'+\Delta u) = (Gu + f + e - y_r)^T(Gu + F + e - y_r) + \rho(u'+\Delta u)^T(u'+\Delta u) \qquad (3)$$

with y, u, f and e vectors of form:

$$y = [y(t+1), \ldots, y(t+N)]^T, \quad N\,x\,1$$
$$u = [u(t), \ldots, u(t+N-1)]^T, \quad N\,x\,1 \qquad (4)$$

$$f = [f(t+1), \ldots, f(t+N)]^T, \quad N\,x\,1$$
$$e = [E_1(q^{-1}) \cdot e(t+1), \ldots, E_N(q^{-1})e(t+N)]^T, \quad N\,x\,1$$

and

$$f(t+1) = [G_1(q^{-1}) - g_0] \cdot u(t) + F_1 y(t)$$
$$f(t+2) = [G_2(q^{-1}) - q^{-1}g_1 - g_0] \cdot u(t+1) + F_2(q^{-1})y(t)$$

….

$$f(t+N) = \left[G_N(q^{-1}) - q^{-(N-1)}g_{N-1} - \ldots - g_0\right] \cdot u(t+N-1) + F_N(q^{-1}) \cdot y(t)$$

The polynomial G_j can be determined from a Diophantine equation:

$$G_j(q^{-1}) = E_j(q^{-1}) \cdot B(q^{-1}) \qquad (5)$$

$$1 = E_j(q^{-1}) \cdot A(q^{-1}) + q^{-j} \cdot F_j(q^{-1}) \qquad (6)$$

where j represents the prediction interval, N_1=0 and N=N_2 .

Taking in to account the derivative of the cost function regarding to Δu:

$$\frac{\partial J}{\partial(\Delta u)} = 2E[\,G^T(G\Delta u + f + e - y_r) + \rho I(u' + \Delta u] =$$

$$= 2E[\,(G^T G + \rho I)\Delta u + G^T(f - y_r) + \rho I u'\,],$$

this is zero for:

$$\Delta u = (G^T \cdot G + \rho \cdot I)^{-1} \cdot [G^T(y_r - f) - \rho \cdot I \cdot u'] \qquad (7)$$

where G is a lower triangular matrix of dimension N x N:

$$G = \begin{bmatrix} g_0 & 0 & 0 & \ldots & 0 \\ g_1 & g_0 & 0 & \ldots & 0 \\ g_2 & g_1 & g_0 & \ldots & 0 \\ \ldots & \ldots & \ldots & \ldots & \ldots \\ g_{N-1} & g_{N-2} & g_{N-3} & \ldots & g_0 \end{bmatrix} \qquad (8)$$

For the controller output vector Δu, only the first element Δu (t) have to be computed since it is the increment of the controller output at time t:

$$\Delta u(t) = \alpha^T(y_r - f) - \beta^T u' \qquad (9)$$

were

- α^T=[α_1...α_N] express the first row of the matrix $(G^T G+\rho I)^{1} G^T$;
- β^T = [β_1 ,... β_{Nu}] express the first row of the matrix $(G^T G + \rho I)^{-1}\rho I$.

Note that the Diophantine equation and determination of E_j and G_j polynomials has the same expression as that for the GPC algorithm in incremental form, and the equation for the controller output has a different form given by the equation (9).

4 Results

For this work, the process model and the control strategies proposed are implemented in MATLAB Simulink. The considered values of the stoichiometric and kinetic parameters are those determined after calibrating the model in [30]: Y_A= *0.24*, Y_H= *0.7*, f_P= *0.08*, i_{XB}= *0.086*, i_{XP}= *0.06*, μ_H= *4.0*, K_S= *20.0*, $K_{O,H}$= *0.20*, K_{NO}= *0.50*, b_H= *0.3*, η_g= *0.8*, η_h= *0.4*, k_h= *1.7*, K_X= *0.017*, μ_A= *0.475*, K_{NH}= *1.0*, b_A= *0.05*, $K_{O,A}$= *0.4*, k_a= *0.054.*

For the steady-state conditions, daily average values were considered for the inputs related to the influent (flow, concentrations, alkalinity). These values are: S_I=30, S_S=50, X_I=35 X_S=146, $X_{B,H}$=20.1, $X_{B,A}$=0, X_P=0, S_O=0, S_{NO}=1.5, S_{NH}=26, S_{ND}=7.3, X_{ND}=11, S_{ALK}=7, *Q=65.* All the values are represented in g COD/m^3, only the flow is represented as m^3/h and S_{ALK} , the pH of the influent is represented in mol/m^3.

The aeration flow rate W is controlled by a PID controller to obtain a dissolved oxygen concentration of 1.5 mg COD/l in the bioreactor at a value of 0.5 of the aeration fraction f.

Total effluent nitrogen ($N_{tot,e}$) was calculated with the following formula:

$$N_{tot,e} = S_{NH,e} + S_{NO,e} + S_{ND,e} + X_{ND,e} + i_{XB} \cdot (X_{B,H,e} + X_{B,A,e}) + i_{XP} \cdot (X_{P,e} + X_{I,e}) \qquad (10)$$

To handle with the EU WWTP effluent regulations on organic and nitrogen concentrations, maximum residual concentrations are imposed. The standards in terms of chemical oxygen demand (COD) and biochemical oxygen demand (BOD5) are given by: $COD_{e,max}$ = 125 mg /l, BOD5 $_{e,max}$ = 25 mg /l

The limit value for total nitrogen is 15 mg/l for WWTP with a capacity between 10 000 and 100 000 persons equivalent. In this work a limit value of 10 mg/l is assumed, aiming to make the plant more robust: $N_{tot,e,max}$ = 10 mg/l

The maximum of the residual concentrations fixed for both COD and BOD5 concentrations are easily satisfied for the WWTP considered in this paper, as a main part of the biodegradable organic matter is consumed during the denitrification stages. It was checked, and these requirements were fulfilled in all the presented simulations. Based on these considerations, only the constraints on $N_{tot,e,max}$ were considered in the optimization problem

It is considered that the total aeration cycle time of 0.2 days is an optimal value for this parameter.

The process output variable is set to $N_{tot,e}$. The $N_{tot,e}$ setpoint was fixed at 9 mg/l. For the GPC predictive control algorithm, the following values of design parameters are used: N=10, Nu=1, ρ(j)=0.1 and the sampling time T_s= 0.2 day.

To test the performance of the proposed control strategies, changes in the influent flow rate and the concentration of the pollutants (disturbance rejection) were considered.

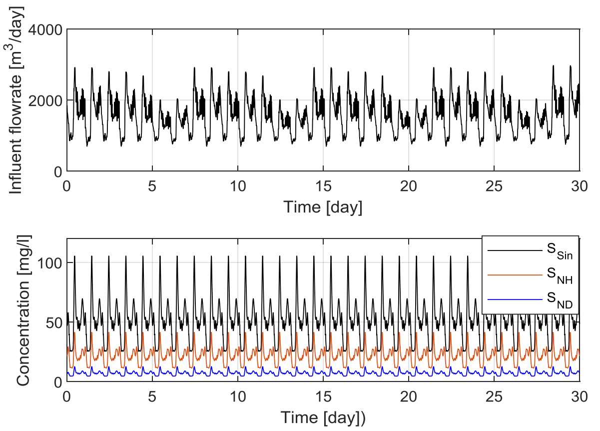

Fig. 4: Changes in the influent flowrate and pollutant concentration

The performances regarding the disturbance rejection, are presented in Figure 5 and Figure 6. Changes in the influent flow rate and pollutant concentration according to the profile presented in Figure 4 were considered.

The effluent nitrogen concentrations performances regarding the disturbance rejection, are presented in Figure 5. It can be observed that there are no issues with disturbance rejection in the closed-loop system. The maximum limit set for total nitrogen ($N_{tot,e,max}$) is not exceeded during the experiment. It can also be observed that during the experiment, the total ammonium nitrogen concentrations in the effluent ($S_{NH,e}$) do not exceed the maximum limit of 2 mg/l considered in this work.

The manipulated process input (aeration fraction) presented in Figure 6 operates within its constraint limits (0.25 - 0.75).

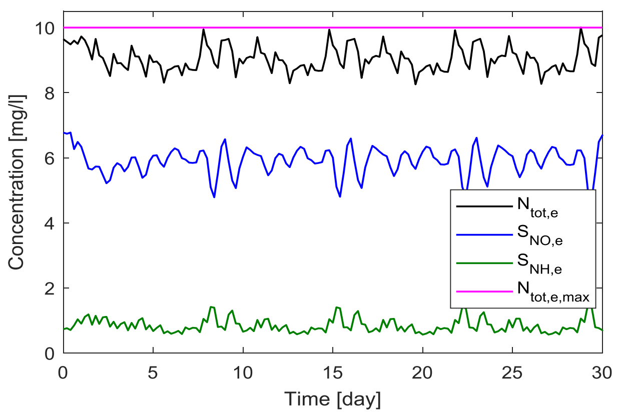

Fig. 5: Disturbance rejection – effluent nitrogen concentrations

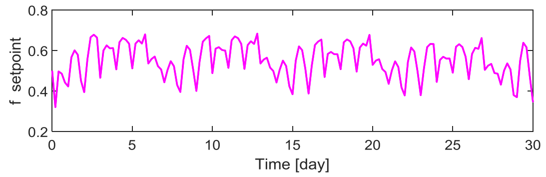

Fig. 6: Disturbance rejection - manipulated process input.

Taking into consideration the aeration flow, the blower efficiency, and the discharge pressure, electrical energy consumption over a period of 30 days was determined. Thus, implementing the optimization system, an improvement in the process efficiency was confirmed, with energy consumption decreasing by 9.2%.

5 Conclusion

In this paper, a predictive model-based control strategy was developed and implemented to optimize and control the aeration system of a municipal wastewater treatment plant that is alternatively operated by switching on and off the aeration. A hierarchical structure of the control system with two layers is designed: (i) uses a PID controller for the control of the bioreactor dissolved oxygen concentration and a sequencing system to provide the sequence of the aeration/non-aeration phases maintaining the aeration fraction coefficient at the value provided by the optimization level; (ii) the higher level uses a model predictive control algorithm to determine the optimal value for the aeration fraction of the aeration cycle. The control strategies developed in this work show excellent performance in rejecting disturbances in influent concentrations and flow, meeting EU effluent standards, as well as achieving considerable energy savings. Moreover, the aeration fraction is maintained within its constraints.

Acknowledgement:
This work was supported by a grant of the Ministry of Research, Innovation and Digitization, CCCDI - UEFISCDI, project number PN-III-P2-2.1-PED-2021-1147, within PNCDI III.

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Contribution of Individual Authors to the Creation of a Scientific Article (Ghostwriting Policy)

The authors equally contributed to the present research, at all stages, from the formulation of the problem to the final findings and solution.

Sources of Funding for Research Presented in a Scientific Article or Scientific Article Itself

This article was funded by a grant of the Ministry of Research, Innovation and Digitization, CCCDI - UEFISCDI, project number PN-III-P2-2.1-PED-2021-1147, within PNCDI III.

Conflict of Interest

The authors have no conflicts of interest to declare.

APPENDIX

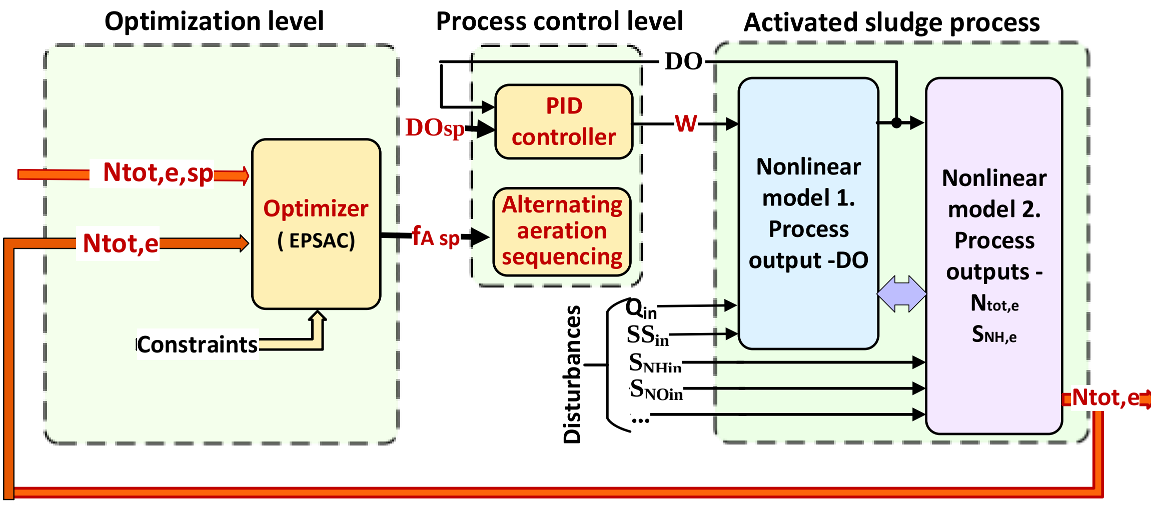

Fig. 3: Hierarchical control system – Schematic Representation