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The liquid waste of agro-food industry: characterization and modeling.

BEN ALAYA S., SHAYEB H.

LMHE, Laboratory of Hydraulics and Environment Modeling, ENIT; B.P 37, Le Belvédère, 1002 Tunis, Tunisia

saidaenit@gmail.com

Abstract **— The aim of this work is the development of an optimization model of the treatment system to manage the operation of the treatment process of an agro-food effluent in order to meet the standards of rejection and to minimize energy expenditure. The modeling was carried out by reducing the ASM1 biological model by simplifying the reaction scheme. The validity of the reduced model modelIAA has been highlighted.**

Keywords **— Agro-food industry, wastewater treatment, modeling.**

I. INTRODUCTION

Dairy and poultry slaughterhouse effluents are among the most rich in organic matter (protein, vitamin, blood, etc.) and microorganisms. This heavy load makes these effluents a source of environmental pollution. The management of this waste concerns producers, for this purpose the objective of this study is to contribute to the characterization of these effluents. A better knowledge of industrial waste makes it possible to orient and choose the optimal treatment to them apply. Our study is devoted to studying the effluent characteristics of the EL MAZRAA wastewater treatment plant, which collects effluent from the dairy industry (GIPA) and from the poultry industry (EL MAZRAA).

II. MEASURE CAMPAIGN

A measurement campaign was carried out on the industrial effluent treatment plant EL MAZRAA. The analyzed sewage samples were taken at the inlet and outlet of the station and at the inlet and outlet of the aeration tank. These samples are taken every 30 min. The evolution of the COD concentration of the influent is shown in Fig. 1.

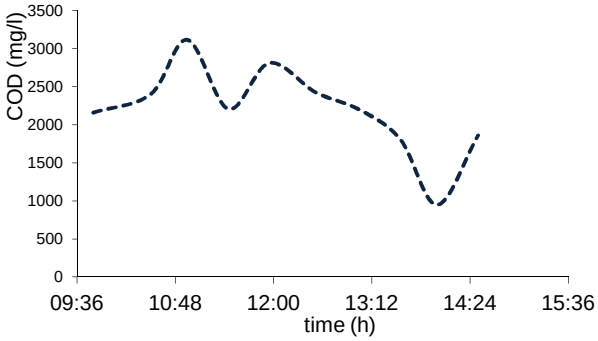

Fig. 1 Hourly evolution of the COD concentration of the influent

This parameter varies considerably over the same 5-hour cycle, reaching a maximum of 3114 mg/l at 11 am and a minimum of 948 mg/l at 14 h in the afternoon. The average COD concentration is in the order of 2192 mg/l. The evolution of the COD load is shown in Fig. 2. A significant fluctuation in the COD load is observed. This fluctuation can be explained by the influence of rinse and pre-rinse cycle in the dairy industry. Cleaning and disinfection operations account for most of the water consumption (Fig. 2).

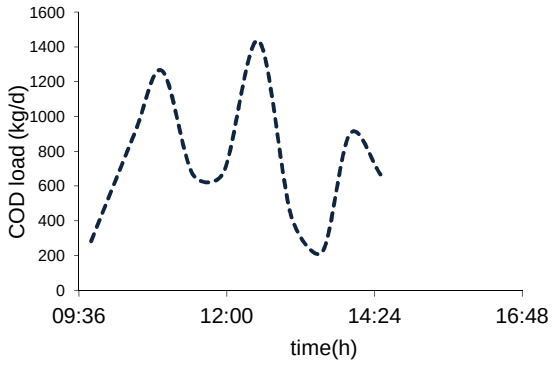

Fig. 2 COD load of the influent of EL MAZRAA

From Fig. 2, the load reaches 3 load peaks: the first has a value of 1263 kg/d at 11 am, the second is the largest with a value of 1434 kg/d at 12:30 pm and the third is lower with a value of 900 kg/d 2 pm. This explains why the effluent loads are in

close relation with the upstream production operations.

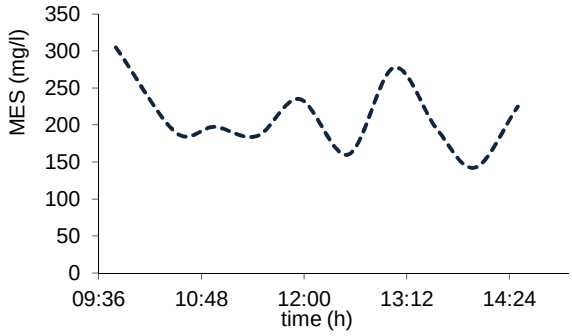

Fig. 3 MES concentration of the influent

The MES concentrations of the influent are shown in Fig. 3. Fluctuation of MES concentrations less than that observed for the COD concentration is noticed. The inlet and outlet of the aeration tank MES concentration was measured and shown in Fig. 4.

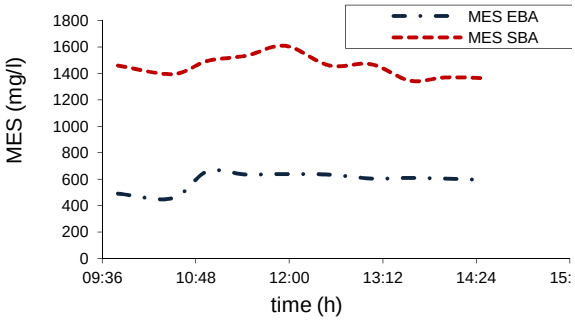

Fig. 4 The inlet and outlet of the aeration tank MES concentration

The mean ammonium ion concentrations at the inlet and outlet of the aeration tank are 20 and 30 mg / l, respectively. The concentration of NH4 + at the outlet of the aeration basin is greater than that at the inlet of the aeration basin. This is due to the accumulation of ammonium ions due to the absence of the anoxic phase for denitrification (Fig 5).

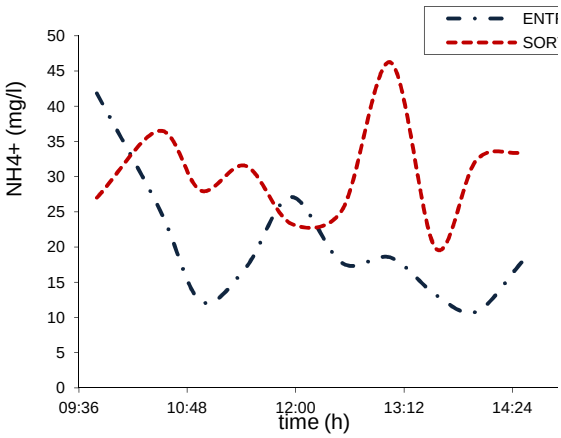

Fig. 5 NH4+ concentrations at the inlet and outlet of the aeration tank

As for oxidized forms (nitrites and nitrates), the analyzes indicate an average nitrite concentration of about 0.068 mg/l at the inlet of the aeration tank and 0.016 at the outlet of the aeration tank (Fig 6). However, for nitrates, concentrations are more significant with mean values of 76 mg/l at the inlet and outlet of the aeration tank (Fig 7).

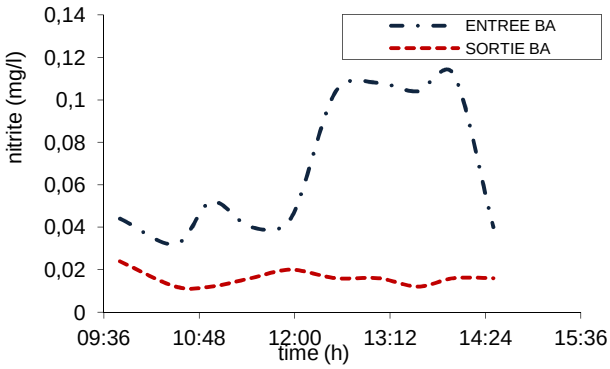

Fig. 6 nitrite concentration at the inlet and outlet of the aeration tank

It is noted that the values of nitrogen in oxidized forms and ammoniacal nitrogen are variable during a period of 5 hours of the day (Figures 5, 6 and 7). A concentration of kjeldahl nitrogen on the total effluent was measured, the value of the NTK concentration at the station inlet was of the order of 137 mg/l and the outlet was of the order of 90 mg / l. The concentration of NTK is higher than the Tunisian norm of discharge of water effluents. Nitrogen mainly comes from milk proteins (caseins) and mineral nitrogen from milk from dairy effluents.

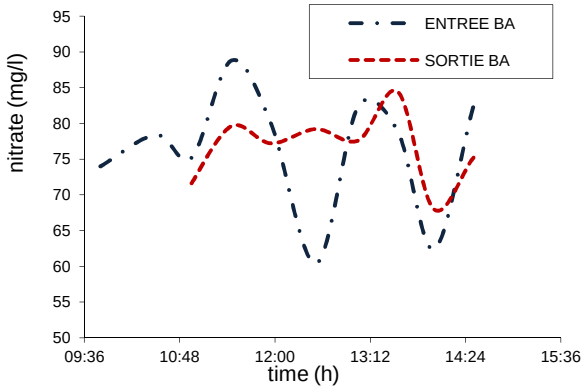

Fig. 7 nitrate concentration at the inlet and outlet of the aeration tank

Phosphorus comes from detergents used in washing and from blood. The phosphorus concentration of the average effluent was measured. The total P-PO_4^+ concentrations are about 4.6 mg/l of influent and 7.7 mg/l of effluent of the EL MAZRAA treatment plant.

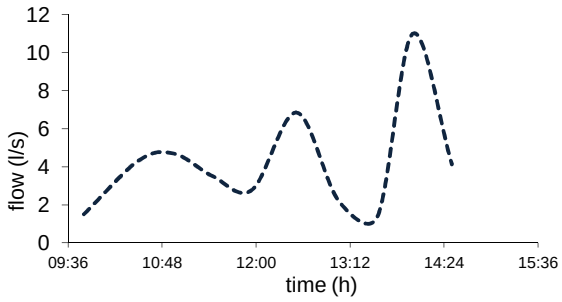

Fig. 8 flow evolution of influent to the EL MZRAA station

Flow is another important data to know about industrial effluents. The effluent does not have a constant flow during the day, it varies from one hour to the other. The variation of the discharge rate is mainly due to the irregularity of production of the various workshops. Similarly, the flow rate of discharge at each workshop is not known due to the obstruction of certain manholes. Fig. 8 shows the fluctuation of daily flow at the station entrance. The evolution of influent flow follows the production rhythm of the industry. A maximum value of 11 l/s was measured at 14 hours.

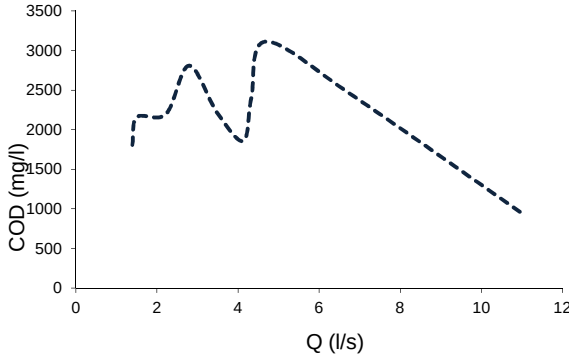

Fig. 9 COD load evolution as a function of flow

Fig. 9 shows the evolution of the COD concentration as a function of flow rate. It is clear that for low flow rates the COD concentrations are higher, the loss of dairy products or blood at the source. On the contrary, at a high flow rate, the COD concentration decreases considerably due to the effect of dilution of the effluent by the rinsing water in the industries.

III. BIOCINETIC MODELS OF ACTIVE SLUDGE (ASM)

The complexity of the dynamic models of wastewater treatment processes commonly used reflects the complexity of the processes themselves and the detailed knowledge gained over them over the past few decades. These actually include a large number of parameters to which a numerical value must be assigned either on the basis of an a priori knowledge of their value or on the basis of experimental data. The quality of the parameter estimation will inherently depend on the quantity and quality of data that are made available to the calibration (or identification) procedure of the model parameters. Another problem arises in the identification of the parameters of the model: the dynamic models of bioprocesses are intrinsically nonlinear and the parameters of the model can be strongly correlated with one another.

Modeling a treatment plant requires in fact the use of several models:

• A hydrodynamic model (representing the hydraulic behavior of the installation ...),

• A ventilation model,

• Models for physico-chemical processes (variation of pH and alkalinity, flocculation, precipitation, decantation ...),

• Biokinetic models (biological processes),

• A fractionation model: conversion of the measurements carried out on the affluent (COD, NTK ...) into state variables of biokinetic models (slowly and rapidly biodegradable substrate fractions ...).

The International Water Association (IWA) has produced a series of activated sludge plant models ([1], [2]) based on a detailed description of biological processes. The ASM1 model has been modified to take into account the biological and chemical removal of phosphorus in the ASM2 model [3] or to further include the denitrifying activity of phosphorus-accumulating organisms in the ASM2d model [3] . The ASM3 model is another extension of the ASM1 model which recognizes the importance of storage polymers in the growth of heterotrophic bacteria [3]. COD was chosen as a measure to share organic matter into categories based on biodegradability and whether it is soluble or particulate. Andy Vandekerckhove et al, 2008 used the ASM1 model to simulate effluents from the frozen potato production industry [4]. Van Hulle et al. (2004) used the modified ASM1 model by adding two other components to account for the toxic elements present in the wastewater of a chemical industry [5]. Lucas et al 2005 modified the ASM2d model to represent the biological reactions between the components of a wastewater from the agro-food industries [6]. Karahan et al (2008) used the modified ASM3 model, this model was adopted for the evaluation of components of waste water in the textile industry [7]. Zhongda Xu et al (2006) compared the ASM1 and ASM2d models for the sensitivity of various nitrogen fractions to the wastewater of a tomato processing industry [8]. Cindy Bassompierre, (2007) used the reduced ASM1 model to model paper effluents [9].

Given the low proportion of nitrogen and phosphorus in the effluents studied, their removal from ASM2d is of no particular interest to us. The ASM3 model mitigates certain disadvantages of No. 1 but does not yet benefit from the expertise acquired by its former. Thus the first model, ASM1,

seems to fit best. Moreover, this model has been used many times and seems to have proved its worth. It has become a reference for the treatment of carbon and nitrogen. Additionally, over the years, successive ASM1 versions have allowed the user to assign more confidence to the model.

A. THE COMPLETE ACTIVE SLUDGE MODEL (ASM1):

ASM 1 is a model simulating phenomena such as carbon oxidation, nitrification and denitrification within an activated sludge system by quantifying the kinetics and stoichiometry of each reaction. In ASM1 the organic matter is divided into biodegradable, non-biodegradable and biomass COD. The biodegradable COD is further subdivided into rapidly biodegradable (Ss) and slowly biodegradable (X_S) organic matter. The rapidly biodegradable fraction is supposed to consist of simple and soluble molecules that can be directly assimilated by the bacteria and then synthesized into new biomass or transformed into energy. The slowly degradable fraction is, for its part, made up of complex and particulate organic molecules which require enzymatic hydrolysis before absorption and use. In fact, slowly degradable organic matter may be partly in soluble form whereas it is considered to be totally particulate in the model. The non-biodegradable organic matter fraction is divided into soluble (S_I) and particulate (X_I). Finally, X_P represents the inert particulate products produced during biomass mortality. This model uses 13 variables that characterize the input effluent of the station. A set of parameters, 14 kinetic parameters and 5 stoichiometric parameters then complement the structure of the model [1]. A method for representing the interaction between state variables and internal processes is the Petersen matrix. This matrix is used to represent the reaction rate (growth or use).

B. MODELE SIMPLIFIE : APPROCHES BASEES SUR LE MODELE ASM1

The ASM1 model has been widely used, but the large number of state variables and parameters and the nonlinearity of these equations make it a complex model that does not allow it to be easily exploited for control and supervision. For all these reasons, many models, based on the ASM1 model, have been proposed based on the choice of the reaction scheme on the one hand and on the linearization of the equations of this model on the other hand. The common objective of these simplified models is to maintain the best compromise between ease of use (identification, computational cost, ...) and the precision of simulation results. In order to solve such problems, several methods of simplification and reduction have been proposed in recent years ([10] - [14]). A first attempt was made by Jeppsson [15]. A few years later, Steffens et al [13] proposed an algorithm for the elimination of state variables, based on the study of their dynamics over time. For this purpose, they are based on two mathematical methods: the association of the values proper to the state of the system, and the method of singular perturbations. Julien et al. (1997) have obtained a simplified model composed of two sub-models: one sub-model for the aerobic phase and another sub-model for the anoxic phase [16]. Gomez-Quintero et al (2004) proposed a reduced nonlinear model of four variables and thirteen parameters [17]. The reduction strategy adopted was based on considerations of biochemical simplification followed by a grouping of parameters. An improvement of this work was presented by Queinnec et al (2009) where a methodology of linearization of the model was detailed [18]. Benhalla et al (2010) proposes a linearization of the standard model for the study of interactions and simplifications [19]. This is a linear approximation of the terms representing the kinetics of reactions. The result is a locally linear model equivalent to the initial model. Nagy et al (2010) proposed an application of an analytical method of decomposition of dynamic nonlinear system in several linear sub-systems to the model of an activated sludge reactor [21]. The model discussed in this article is a reduced activated sludge reactor model representing the degradation process of carbonaceous pollution. It contains three state variables (the easily biodegradable substrate, heterotrophic biomass and dissolved oxygen). A linearization strategy is proposed to simplify the complexities of this model. In this strategy, the linear model obtained requires a certain number of specifications. The latter must retain without modification the size, inputs, outputs and state variables of the initial reactor model, with their biological interpretations. In Weijers et al (2000), a reduced nonlinear model containing five state variables was used [20]. The widespread use of these models across multiple application domains has allowed them to test their prediction capabilities. Loss of information is a first disadvantage of these techniques. One of the main difficulties in the modeling of a process is the determination of the essential reactions to describe it, while leading to the simplest possible equation. Obtaining a reduced model simplifies the analysis and simulation of the systems and the design of their controls. In the case of activated sludge processes, the problem of the complexity of the models makes the possibilities of control in the practical case very limited [14].

- The reduction of a model is based on two approaches:
- Approaches based on the choice of the reaction scheme

- Approaches based on linearization.

C. REDUCED MODEL:

1) Proposed approach

The use of reduced models is common in sewage treatment with activated sludge for the observation of the state, the estimation of the parameters or the control of the processes ([10], [9], [21]). Most often, these models are formulated by providing simplifications to the general ASM models of the IWAQ [3]. The model development approach has been designed to produce a tool representing the different characteristics of agro-food effluents: dynamic evolution is taken into account within the model, which allows us to follow, over time, Evolution of the behavior of the treatment process. The model most commonly used as a basis for describing the activated sludge process in the food industry is ASM1 ([8], [4]).

According to the study of characterization of the effluent of EL MAZRAA treatment plant [22], it is observed that the ASM1 model thus constitutes the starting point of this work.

In our study, certain assumptions are used for the model to be usable in practice:

- measurements of the oxygen concentration at different points of the reactor were carried out, an oxygen isoconcentration was noticed within the reactor. It was therefore assumed that the bioreactor is perfectly mixed.
- the biological reaction is carried out only in the bioreactor.
- the system operates at constant temperature.
- according to the pH measurements, it is observed that the pH varies very little, and especially remains in the zone where it does not affect the rate of growth. It is therefore not necessary to express its influence in the stoichiometric coefficients.
- the heterotrophic biomass is assumed to be homogeneous within the bioreactor.

2) Dynamics simplification :

In the literature, several simplifying hypotheses have been applied for the reduction of the ASM1 model, in our study we consider a simplification concerning the components of the model. Only biological degradation of carbon and nitrogen in wastewater is considered, involving the following five components: rapidly biodegradable substrate, slowly biodegradable substrate, dissolved oxygen, heterotrophic biomass, ammonia, nitrate and autotrophic biomass. Separation into two sub-models is also used depending on the aeration conditions. Two distinct sub-models are therefore proposed in order to take for each medium only the biological kinetics present and thus simplify the structure of the equations. In our case, the treatment of agro-food effluents is carried out only in the aerobic phase. Therefore, only the sub-model corresponding to the aerobic part is retained.

The other two nitrogen-containing fractions (particulate organic nitrogen and soluble organic nitrogen) have been simplified which describe the internal transformation in the hydrolysis and ammonification processes, since they represent only a small portion of the feedstocks, Nitrogen ([21], [9]). In practice, the process of measuring the chemical oxygen demand (COD) does not make it possible to distinguish the soluble part from the particulate part ([12], [21]), therefore a single organic component, referred to as X_{SS}, by adding the two soluble and particulate concentrations. This makes it possible to mask the hydrolysis reaction of the slowly biodegradable organic material which is a complex reaction (kinetics comprising three parameters to be identified). The association of X_S to S_S will slow the growth reaction of the heterotrophic biomass [9]. The state variables representing the inert compounds S_1 and X_I are deleted. These compounds only pass through the secondary treatment phase (S_1 is found in the purified water and X_I in the extracted sludge). This is also the case for the state variable X_P which is a terminal state variable for the biological model (only cumulative) [9].

Ammonia nitrogen is converted to nitrates / nitrites only through autotrophic biomass during the nitrification reaction. However, this biomass develops slowly and is present only for ages of high sludge, which is not the case in our study. We can therefore consider the hypothesis of the absence of autotrophic biomass within the mixed liquor.

Since the nitrate-nitrite transformation is produced only through autotrophic biomass, we also neglect their transformation within the treatment process, which is explained by the constant concentration of nitrate at the inlet and outlet Aeration tank and a low concentration of nitrite.

An increase in the concentration of ammoniacal nitrogen was observed, this increase can be explained by the phenomenon of ammonification.

3) Writing of the model of an agro-food effluent degradation

According to the simplification hypotheses studied previously, the model therefore has four state variables (X_{SS}, X_{BH}, S_{NH}, S_O). This model provides essential information to the operator:

• the state of the biomass, which is represented by the XBH state variables.

• the pollution abatement rate, which is represented by X_{SS} and S_{NH}.

The hypotheses set out above make it possible to establish a model whose number of state variables and biological kinetics is very limited. Due to the presence of the heterotrophic biomass, only three biological kinetics are to be taken into account:

• the growth of the heterotrophic biomass through the oxidation reaction of biodegradable organic matter ρ1;

• the death of the heterotrophic biomass ρ4.

• Ammonification ρ7;

This is reflected by the equations:

$$\rho_1 = \mu_h . \frac{XS_S}{K_S + XS_S} . \frac{S_O}{K_{OH} + S_O} . X_{BH}$$

$$\rho_4 = b_H . X_{BH}$$

$$\rho_7 = K_{NH} . X_{BH}$$

The overall biological kinetics is then given by the following formulas:

$$r_{XS_S} = -\frac{1}{Y_H} . \rho_1 + (1 - f_p) . \rho_4$$

$$r_{X_{BH}} = \rho_1 - \rho_4$$

$$r_{S_O} = -\frac{1 - Y_H}{Y_H} . \rho_1$$

$$r_{S_N} = 1 . \rho_7$$

The biological model therefore contains four state variables, three of which can be easily measured on-line (X_{SS}, S_{NH} and S_O) and seven parameters (two stoichiometric parameters and five kinetic parameters). The complete reduced model can be written as follows:

$$\frac{dXS_S}{dt} = \frac{[XS_{Sin}Q_{in} + XS_{Sr}Q_r - XS_S(Q_{in} + Q_r)]}{V} + r_{XS_S}$$

$$\frac{dX_{BH}}{dt} = \frac{[X_{BHin}Q_{in} + X_{BHr}Q_r - X_{BH}(Q_{in} + Q_r)]}{V} + r_{X_{BH}}$$

$$\frac{dS_O}{dt} = \frac{[S_{Oin}Q_{in} + S_{Or}Q_r - S_O(Q_{in} + Q_r)]}{V} + r_{S_O} + k_l a . (S_O^* - S_O)$$

$$\frac{dS_{NH}}{dt} = \frac{[S_{NHin}Q_{in} + S_{NHr}Q_r - S_{NH}(Q_{in} + Q_r)]}{V} + r_{S_{NH}}$$

IV. CONCLUSION

The agro-food industries are the main contributors to industrial pollution worldwide. The lack of information and effective supervision tools makes the task of monitoring even more difficult for the operator, who must then draw on his personal experience. Several tools for supervision and decision support have been proposed in recent years, mainly based on expert systems. They make it possible to sort the information collected on the process and to deduce the state of the process, using, if necessary, the knowledge of the operator. However, these tools do not respond to the primary concern, which is the lack of real-time information to anticipate variations in operation due, among other things, to fluctuations in the effluent to be treated (flow rate, composition). We therefore propose a global approach that can lead to a complete decision-making tool. We first studied the modeling of the activated sludge process for agro-food effluents on the basis of the ASM1 model in simulation.

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