Modern Environmental Science and Engineering (ISSN 2333-2581)
January 2019, Volume 5, No. 1, pp. 37-45
Doi: 10.15341/mese(2333-2581)/01.05.2019/005
Academic Star Publishing Company, 2019
www.academicstar.us

Inferential Sensor of Residual Moisture Content and Separation Efficiency Applied to Pilot-Scale Vibrating Screen

Mateus Sousa Freitas, Vinicius Pimenta Barbosa, Fernando Superbi Guerreiro, Anderson Lima de Menezes, Rubens Gedraite, and Carlos Henrique Ataíde

Chemical Engineering Faculty, Federal University of Uberlandia, Brazil

Abstract: Vibrating screening is still one of the main operations considering solid-solid and solid-liquid separation processes. Although it is an equipment of simple design and execution, the full description of a screening unit operation may be difficult to predict, considering that several operational variables can influence it. Therefore, the main objective of this work was to develop an inferential sensor to be used with an optimized control system in order to automate and improve the sieving process. Semi-empirical models were identified considering a pilot-scale vibrating screen by using a suspension of phosphate rock concentrate (with a density of 3.25 g/cm^3 and average particle size of 95 μm), water, and xanthan gum. The experiments for obtaining the models followed a factorial design 3^k and relate moisture content of retained solids and separation efficiency to g-force and solids concentration in the feed. The vibrating model was obtained by the disturbance in the rotation of the vibration motors and relates the g-force with rotation of these motors. The combination of the models was studied through simulation. The behavior of moisture content and separation efficiency was evaluated and an operation optimization was performed. For the studied range, the system worked properly, leading to g force to the best possible value, depending on operating conditions of the vibrating screen.

Key words: wet screening, inferential sensor, process control

1. Introduction

The drilling of oil and gas wells makes use of drilling fluids while the drill bit penetrates to the required depth. The advancement and the drill rotational movement breaks the rocky formation, creating small pieces of rock, called drill cuttings. Finally, the drilling fluid carries solid material along the annular region between the duct and the shaft wall, to remove it from the well and preventing the buildup of this material on the perforated region [1].

The size of the transported solid particles between 1 and 1,500 micrometers and its composition is the same as the perforated rocky formation. The presence of solid alter various properties of the drilling fluid which, in turn, affect the drilling time, the drill life, the recirculation pump and other mechanical equipment involved in the operation. For the reuse of this fluid and compliance with environmental constraints that prevent the disposal of solids contaminated, the separation of these materials is necessary [2-4].

The vibrating screens are the first devices that come into contact with the drilling fluid, being responsible for removing coarse solids, generally larger than 74 micrometers [3, 5]. The vibration obtained with vibrating motors introduces ascending and descendants forces in the material on the screen, which favors the separation. The upward movement of the sieve screen pushes the fluid in downward direction by inertia, causing it to drain by passing

Corresponding author: Rubens Gedraite, Ph.D., Chemical Engineer; research areas/interests: process automation. E-mail: rgedraite@ufu.br.

through the open area of the sieve screen by moving the solid up. When the screen cloth moves down, the solids have a tendency to be driven forward [3, 6, 7] The passing fluid (underflow) containing solid material with dimensions generally smaller than the screen opening of the sieve, which can be separated in other process steps [3, 8, 9].

Accordingly to Golovanevskiy et al. (2011) [7], the vibration phenomena in a granular bulk material represents a problem, due to the fact that material behavior depends on vibrating parameters, material properties and sieve feed system. The scientifically screening and its sub-processes are currently still not satisfactorily understood, often complicating the design and optimization of screening processes in both small scale laboratory and industrial applications [10].

The main variables that influence the performance of the vibrating screen operation are: magnitude of the acceleration of material on the screen (typically represented by the dimensionless number g-force), the sieve screen tilt, feed flow and characteristics of the screening cloth and solid fed [11-14].

Finally, seeking to reduce the loss of material and extend the life of the vibrating screen, some control strategies have been proposed [12, 15, 16]. However, these do not consider the use of process models identified able to infer the value of a particular property of interest in real time as shown by Itävuo et al. (2012) [17] for the case of the cone type mills. Liao and Dexter (2005) [18] also use a similar strategy to infer the operating temperature of a boiler and propose an alternative control strategy from these estimated data.

Makinde et al. (2015) [19] presented a study of vibrating screen development trends and the nature of the evolution through the years. According these authors, the survey considers a model that was developed to show the distinct novelties and technical features that have evolved in vibrating screen production trends in the mining machinery industries.

In contrast, for the control of vibratory sieving operation these ideas are still in the initial deployment phase. To contribute in this area, it was decided to study the residual moisture content of the behavior and the efficiency of separation in real time, considering the employment of identified mathematical model associated with the sieve control strategy that identifies the best operating point for the vibrating screen from the knowledge of its dynamic behavior.. The difficulty related with the measurement of the residual moisture of the retained material by traditional sensors is a problem that could be solved using a inferential sensor as proposed in this paper.

2. Materials and Methods

2.1 The Lab Scale Screen

A schematic diagram of the experimental unit used is shown in Fig. 1.

The main component of this unit is the vibrating screen with 1.65 m long, 0.81 m wide and 1.0 m high, equipped with two rotating vibrators and one screen

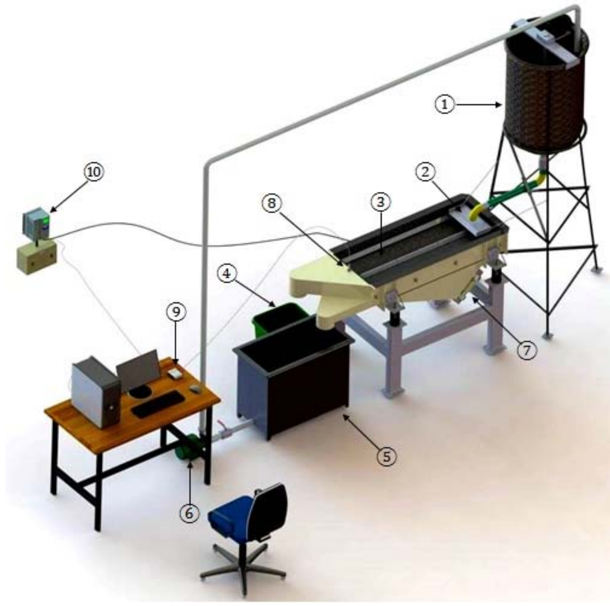

Fig. 1 Experimental unit used to perform the tests: (1) 500 L stired feed tank; (2) rail for the feed of the suspension; (3) screen surface; (4) tank to collect the retained material; (5) tank to collect the material that passes through the screen cloth; (6) centrifugal pump; (7) rotating vibrators; (8) accelerometer; (9) data acquisition board and (10) frequency inverter.

cloth, which is exchanged when necessary. The vibrating screen is linked to three tanks: a 500 L stirred feed tank that keep the suspension under constant mechanical agitation; a 200 L tank to collect the material that passes through the screen cloth and a 80 L tank to collect the retained material.

The vibrating screen was equipped with two 0.75 hp counter-rotating vibrating motors which produce rotation movements in opposite directions. This configuration ensures adequate vibration, providing a linear motion to the simulating drilling fluid discharged on the screen. A WEG model CFW700 frequency inverter adjusts the rotation of the vibrators. To perform the operation, the screen cloth was mounted and the suspension of phosphate rock concentrate stored in the feed tank was fed to the screen. The suspension was kept under constant agitation. The screening was started opening the valve installed at the tank base to allow flow of the suspension to be discharged onto a rail in order to enable a more uniform distribution on the screening surface. The g-force control was needed, since the value of the controlled variable decreases as the suspension is being fed onto the screen [12, 14].

2.2 Sensors and Controls

The experimental unit was equipped with a PCB model 646B00 piezoelectric accelerometer (Fig. 2A), responsible for sending a signal in the range 4 to 20 mAcc to a computer through National Instruments model USB-6008 data acquisition board (Fig. 2B). The signal magnitude is given in g-force in a range from 0 to 10 grms. The data acquisition, monitoring of experimental unit and g-force control was configured in the data base of LabVIEW® (Fig. 3). The current signal created by the accelerometer was collected and conditioned in a range from 1 to 5 V. The acquisition system collected 1000 data per second. The data collected mean for each time interval of 1 second was calculated and transformed to g-force. It was also possible to select a rotation value for vibrators

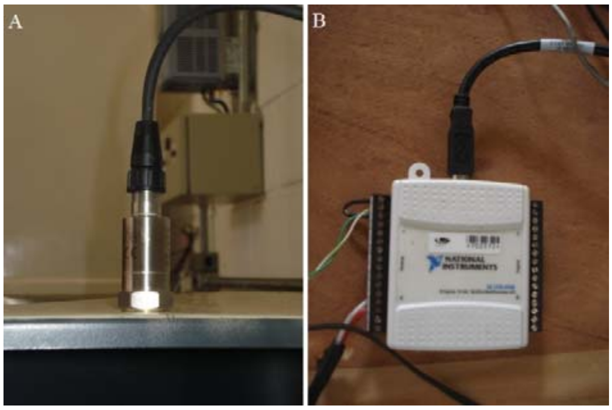

Fig. 2 (A) PCB model 646B00 piezoelectric accelerometer and (B) National Instruments model USB-6008 data acquisition board.

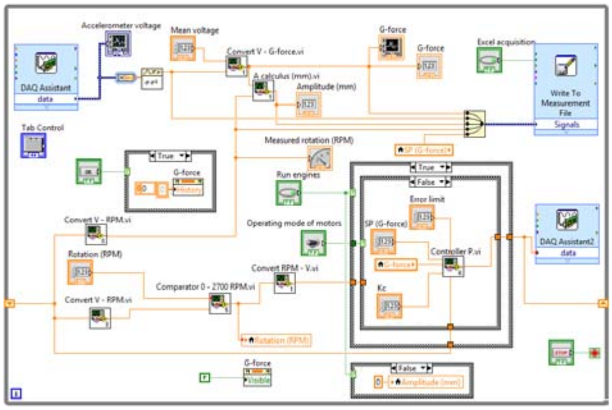

Fig. 3 G-force Controller Block diagram in LabVIEW®.

operation through a signal sent to the frequency inverter. For the experiments, it was necessary to establish a predetermined g-force (set point).

The g-force decreases as the suspension fills the basket and the total system mass increases, a proportional control algorithm was configured to compensate this disturbance. The collected data were exported to an Excel Spreadsheet. Experimental data used in this work was conducted by Guerreiro et al. (2016) [14]. The experiments were performed in batches considering a 3^k factorial design, in triplicate, for the variables (F_g) and volumetric concentration of particulate material in the feed (C_V).

3. Results

3.1 Inferential Models of a Dewatering Screening

The temporal behavior of the g-force value applied to the vibrating screen was evaluated using an identified model that relates the operating frequency of the vibration motors with the g-force applied to the material on the screen. This work was based on dynamic response analysis of the g-force to start the rotation frequency of the vibrators. The initial portion of the transient variation of g-force was studied, corresponding to the acceleration imposed on the oscillatory motion applied to the screen by the fact that it allows greater sensitivity in response to the system analysis. A first order plus dead time (FOPDT) transfer function was identified relating the g-force with the engine vibration, as presented at (1) and the simulation diagram developed in MATLAB/Simulink® is presented at Fig. 4.

To increase the performance of process systems, there is a need for differentiation between variables that can be measured easily and the variables linked to the efficiency of the equipment, many of which can not be measured quickly, or simply cannot be measured [20-22].

The identified models for the moisture content of retained solids and the prototype separation efficiency at a 175 mesh screen were developed and are presented in Eqs. (2) and (3). The evaluated responses were: moisture content of the retained material (M) and separation efficiency of the retained material (η). Besides, the independent variables chosen were: the

$$G_{screen}(s) = \frac{\left(\frac{1.9}{1490}\right)e^{-9s}}{3s+1} \quad (1)$$

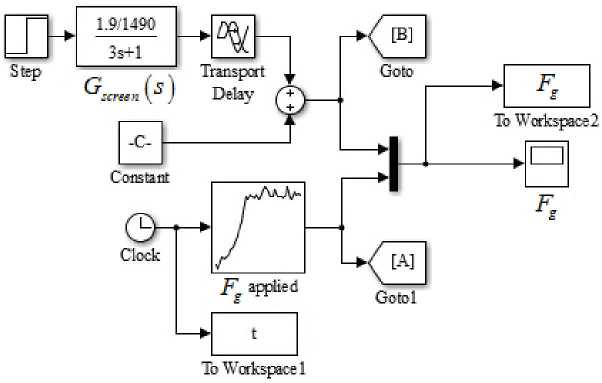

Fig. 4 Simulation diagram for g-force.

volumetric concentration of particulate material in the feed (C_V) and the g-force promoted by the screen (F_g). Each experiment was carried out in triplicate and one third of the outputs were used to validate the model. One barrel (159 L) of suspension containing phosphate rock concentrate diluted in water was prepared. Its particle density determined by helium gas pycnometry was 3.25 g/cm^3. The moisture content was determined from the samples collected, followed by oven-drying at 105°C for 24 h and the separation efficiency was evaluated from feed and fluid passing PSD analysis [11]. Eqs. (2) and (3) were evaluated from the experimental outputs and a full multiple regression to fit a second order model was executed [17, 23].

$$M(\%) = 30.833 - 8.847C_V + 1.238C_V^2 - 1.721F_g - 0.026F_g^2 + 1.090C_V F_g \quad (2)$$

$$\eta(\%) = 78.096 + 0.937C_V + 0.538C_V^2 + 4.593F_g - 0.682F_g^2 - 1.732C_V F_g \quad (3)$$

The optimal operation point for the studied experimental facility combines both low moisture content and high separation efficiency and take into consideration an auxiliary variable (Z), that is the objective function, subjected to the constraints1.00 ≥ F_g ≥ 3.50 and 1.0% ≥ C_V ≥ 3.0%, and defined by Eqs. (4) and (5):

$$Z(\%) = \eta(\%) - M(\%) \quad (4)$$

$$Z(\%) = 47.263 + 9.784C_V - 0.700C_V^2 + 6.676F_g - 0.657F_g^2 - 2.821C_V F_g \quad (5)$$

The optimal Z value, obtained from the experiments was 67.87 for a g-force of 1.00 and a solids concentration of 3.0%. Based on the identified models, it was proposed a control strategy that allows real-time optimization of the system considering disturbances in the concentration of solids in the feed stream and in the g-force applied to the screen. This system identifies the best g-force value to be applied depending on the solid concentration in the feed. Fig. 5 depicts the corresponding block diagram. This kind of technology

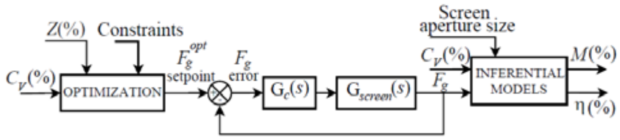

Fig. 5 Block diagram of the proposed inferencial control system.

can contribute to minimize the operator intervention in order to maximize screening performance [16].

The proposed control strategy defines a g-force set point that is required to provide a higher efficiency and also produce a retained solids stream with lower moisture content for a given solids concentration in the feed. This set point is compared with the measured g-force value, and the controller acts to compensate this difference. Considering Eqs. (2) and (3), it is possible to infer the screening efficiency and moisture content in real time operation. Similarly, a FOPDT (First Order Plus Dead Time) dynamic model was used in the simulation of the control system to represent the behavior of the sieve vibration. Also it was used a PID controller tuned with MATLAB PID Tuner®, considering a fast response time and a smooth answer for the equipment during transient behavior.

3.2 Model Validation

The model validation was realized applying the methodology proposed by Fair (1986) [24], considering that any experiment related to a high residual (also called an outlier) was removed from the regression. This procedure was executed until there were no more outliers, and at least two experiments of each experimental condition were kept for the analysis. In the sequence, a new regression was executed considering the mean values in each experimental condition with determination of R^2 after removing all outliers. The non-significant estimators were eliminated by the F-fisher statistical test at a 5% significance level.

The validation data set were compared with the results provided by the identified models considering the root mean square error (RMSE) and mean absolute error (MAE) criteria [24, 25]. Error values tending to zero indicate the validity of the equations. For g-force, varying between 1.00 and 3.50 and the volumetric concentration of solids fed varying between 1.0 and 3.0%, all calculated errors are smaller than 3%. For moisture content model, Eq. (2), the values of RMSE and MAE are 0.51 and 0.44. Similarly, for efficiency model in Eq. (3), the values of RMSE and MAE are 2.70 and 2.42. Eq. (3) higher errors occurs due to greater number of analyzes need to obtain efficiency values. Efficiency analysis involves measuring the flow, the concentration and the PSD of all screening stream [14].

The graphics presented in Fig. 6 and Fig. 7 depicts the behavior predicted by the models proposed on Eqs. (2) and (3), respectively. Considering Fig. 6, for volumetric concentration of solids in the feed equals to 1.0%, as the g-force values increase, the moisture content of the retained solids decreases. This occurs because for 1.0%, less solids are competing for the openings in the screen than for 2 and 3%, improving the fluid passage through the screen with increase in g-force, even though the residence time effect is lower due to a higher transport velocity. On the other hand, for 2.0% and 3.0% volumetric concentration of solids, the moisture content increases as the g-force values increase. This effect can explain by the fact of for 2.0 and 3.0%, there is more particulate material onto screen, which results in a smaller area available for liquid flow through the screen and, in addition, the resistance caused by the slurry concentration affect the liquid passage through the screen. Thus, the process is disadvantaged by increasing the g-force, since the residence time effect becomes a more significant variable. It is also possible to observe that, for each value considered for the g-force, the increase in the volumetric concentration of solids results in a decreasing in the moisture content. These results demonstrate the difficulty of relating the variables involved in the vibratory sieving process and the difficulty associated by the phenomenological description and simulation of process.

The inferential sensor is an appropriate choice to measure the values of variables that cannot be measured directly in the process or that are difficult to measure. In the case of this study, both separation efficiency and residual moisture are variables that are difficult to measure in real time, so the justification is to use the inferential sensor [26].

Considering Fig. 7, it is found that there is a trend of decreasing in the separation efficiency concerning the increase of the g-force values, except for C_V = 1.0%. Under the conditions used in the experiments, the g-force applied to the screen represents the driving force in the solid-liquid separation, and the volumetric concentration of the suspension fed to the equipment represents the resistance of the separation process. In this condition, the increase in the g-force value suggests that the particulate solid material will be subject to a more intense vibration which could increase the separation process. However, there is a tendency to promote higher conveyance of the solid material on the screen and this tends to neutralize or inhibit the most favorable effect of vibration applied to the screen [12].

The relationship between objective function, g-force and volumetric concentration of solids is depicted in Fig. 8. For C_V = 1.0%, the objective function value increases with increasing g-force. However, for higher volumetric concentrations of solids, an increase in g-force promotes decreases Z under the conditions used in the experiments. Similarly, for lower g-force values, an increase in volumetric concentration of solids increases the objective function value. However, for higher g-force, an increase in concentration causes

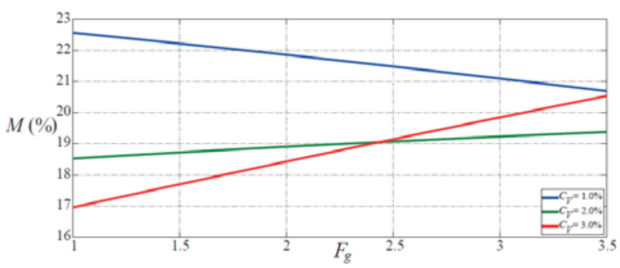

Fig. 6 Relationship between moisture content of the retained solids and g-force.

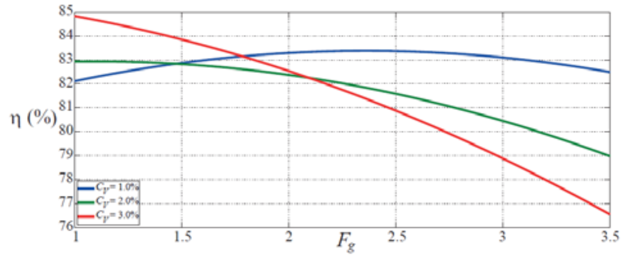

Fig. 7 Relationship between efficiency and g-force.

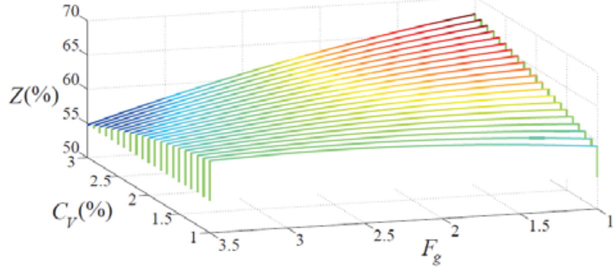

Fig. 8 Relationship between objective function and g-force and concentration.

a decrease in the Z values. The maximum point Z obtained was 67.87 for a g-force of 1.00 and a solids concentration of 3.0%. However, if a disturbance occurs in the volumetric concentration of particulate material in the feed stream, a new value of g-force may be required to maintain the objective function at highest value. This observation was used to calibrate the control system presented in Fig. 5. Eq. (6) was evaluated considering the maximum value of the objective function for each constant concentration from the annulment of Eq. (5) partial derivative with respect to g-force and it represents the best operating g-force (F_g^{opt}) for each concentration value [27].

$$F_g^{opt} = \begin{cases} 5.081 - 2.148 C_V, & 1.0\% \le C_V < 1.9\% \\ 1.00, & 1.9\% \le C_V \le 3.0\% \end{cases} \tag{6}$$

3.3 Control Simulations and Applications

Continuous monitoring of certain industrial processes is often difficult and, in some cases, impossible due to the lack of adequate equipment. In some scenarios, virtual sensors become adequate solutions for the online monitoring of these types of processes [28].

The proposed identified inferential models for the estimation of the moisture content of the retained solids and screening separation efficiency can be applied to an industrial control system considering the necessity to find the best value of g-force, according to concentration of solids in the feed stream. In addition to that, the identified FOPDT dynamic model was used to represent the behavior of the g-force on the screen over time.

The screening startup simulation of the optimized control system for different volumetric concentrations of solids in the feed is shown in Fig. 9. The control system identifies the optimal value of the frequency to be applied to the vibration motors and it is able to keep the g-force in the best value identified. Based on Eq. (6), the best operating value of g-force at 1.0% solids concentration is 2.93. Similarly, at 2.0 and 3.0% concentrations, the best g-force is 1.00. The exponential term of the FOPDT dynamic model in Eq. (3) represents the dead time concerning the beginning of the screen startup, experimentally observed. The dead time is followed by a rapid increase in g-force value, simulating the vibration motors operation start up. The response depicted in Fig. 9 shows that the control system is stable and robust as well, it is able to recognize the best g-force regardless the solids concentration. The static inferential models, showed by Eqs. (2) and (3), were not used to predict the moisture content and separation efficiency in screening startup because g-force value is lower than equations range.

It was also simulated disturbances in the solids concentration in the feed. These disturbances are shown as variations of step type. The temporal behavior of the concentration values, g-force, moisture content of retained solids, separation efficiency, and objective function are shown in Fig. 10. This simulation starts with the system running with a solids concentration of 1.0% and it pursuits a different set point. At a concentration of 1.0%, the optimum operating g-force is 2.93. Note that to achieve this value, the moisture decreases, efficiency and objective function increase as it was expected. A step from 1.0 to 2.0% occurs at 300 seconds in the concentration. At this point, the system identifies that the set point of the previous g-force is not the best and it looks for a new value. The efficiency tends to decrease after the disturbance, although the new set point and the controller action raise the efficiency to a higher level. As seen in Fig. 8 and Fig. 10, for C_V = 2.0%, the optimal g-force is 1.00. Once again at 600 seconds, a step disturbance occurs in concentration from 2.0 to 3.0%. In this case, the system identifies the best operating g-force value is still 1.00, and the set point is not changed. Finally, at 900 seconds a new step disturbance occurs in the concentration from 3.0 to 1.0% and the system returns to operate with 2.933 g-force. The results presented in Fig. 10 starts at 100 seconds because it is not possible to estimate moisture content and separation efficiency for g-force lower than 1.00.

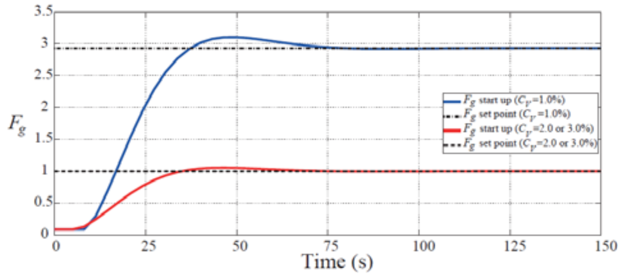

Fig. 9 Screening startup simulation.

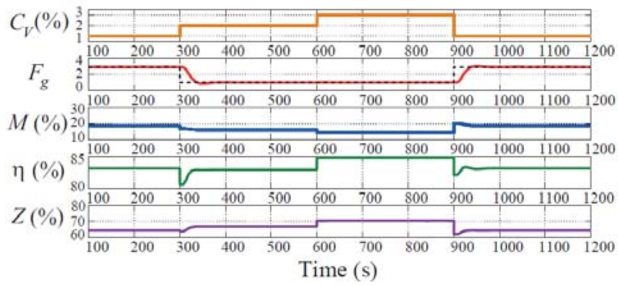

Fig. 10 System response simulation to step disturbances in concentration.

Likewise developed by Dorry and Dufilho (2012) [16], the proposed controller is also able to detect the best g-force from the screening feed data. The acting process in a controlled manner dispenses the operator intervention for choosing the best set point and prevents excessive loss of fluid from the separated solids.

4. Conclusions

It was possible to propose and simulate optimal control strategy based on identified models. This system was able to identify the best operating point that allows greater separation efficiency and lower moisture content in the retained solids. In addition, the proposed control strategy was able to drive and hold the g-force variable in the most appropriate operation condition.

A hybrid model was built with dynamic and static identified equations. Hence, a control strategy based on this model presented a smooth behavior, maintaining constant the g-force value in the presence of a disturbance. The importance of the inferential system is due to the fact that there is no efficient way to measure the concentration of the retained solids in real time, since the sieve operates with the solids distributed on the screen. The use of static models as inferential sensors for moisture content and separation efficiency can be assumed to be adequate.

References

[1] M. Charles and S. Sayle, Offshore drill cuttings treatment technology evaluation, in: *Proc. SPE International Conference on Health, Safety and Environment in Oil and Gas Exploration and Production*, Rio de Janeiro, RJ, Brazil, 2010.

[2] W. H. Marshal and L. K. Brandt, Solids control in a drilling fluid symposium on formation damage control of the society of petroleum of AIME, in: *Proc Lafayette*, TX, United States, 1978.

[3] American Society of Mechanical Engineer – ASME, *Drilling Fluids Processing: Handbook*, Gulf Professional Publishing, Burlington, MA, USA, 2005, pp. 11-115.

[4] L. Robinson, Economic consequence of poor solids control, in: *Proc. AADE Fluids Technical Conference and Exhibition*, Houston, TX, USA, 2006.

[5] Raja, Shale shaker model and experimental validation, doctoral thesis, Dept. of Eng. and Science Technology, University of Akron, Akron, OH, USA, 2012.

[6] American Association of Drilling Engineers, *"Shale Shaker Design" in Shale Shakers and Drilling Fluid Systems*, Gulf Professional Publishing, Houston, TX, 1999, United States, pp. 97-108.

[7] A. Golovanevskiy, V. A. Arsentyev, I. I. Blekhman, , V. B. Vasilkov, Y. I. Azbel and K. S. Yakimova, Vibration-induced phenomena in bulk granular materials, *Int. J. Miner. Process.* 100 (2011) (3-4) 79-85, doi: 10.1016/j.minpro.2011.05.001.

[8] M. Lal and L. L. Hoberock, Solids-conveyance dynamics and shaker performance, *SPE Drilling Engineering* 3 (1988) (4) 385-394, doi: 10.2118/14389-PA.

[9] W. Zhu, W. Wu, X. Hao and H. Wang, A novel solution to sieving model for a drilling fluid shale shaker, *Indonesian Journal of Electrical Engineering* 10 (2012) (6) 1357-1363, doi: 10.11591/telkomnika.v10i6.1399.

[10] F. Elskamp and H. Kruggel-Emden, Review and benchmarking of process models for batch screening based on discrete element simulations, *Adv. Powder Technol.* 26 (2015) (3) 679-697, doi: 10.1016/j.apt.2014.11.001.

[11] R. T. Fowler and S. C. Lim, The influence of various factors upon the effectiveness of separation of a finely divided solid by a vibrating screen, *Chem. Eng. Sci.* 10 (1959) (3) 163-170, doi: 10.1016/0009-2509(59)80044-0.

[12] K. Dorry, Effect of constant-G control on shale shaker performance, in: *Proc. AADE Fluid Conference and Exhibition*, Houston, TX, USA, 2010.

[13] V. Raja, G. G. Chase, B. N. Jones and T. Geehan, Computational modeling and experiments on shale shaker performance, in: *Proc. AADE Fluids Technical Conference and Exhibition*, Houston, TX, United States, 2012.

[14] F. S. Guerreiro, R. Gedraite and C. H. Ataíde, Residual moisture content and separation efficiency optimization in pilot-scale vibrating screen, *Powder Technol.* 287 (2016) 301-307, doi: 10.1016/j.powtec.2015.10.016.

[15] E. L. Scott, Automatic shaker control, in: *Proc. IADC/SPE Drilling Conference*, Miami, FL, USA, 2006.

[16] K. Dorry and B. Dufilho, Automation improves shaker performance, in: *Proc. Drilling Conference and Exhibition,* San Diego, CA, USA, 2012, pp. 501-506.

[17] P. Itävuo, M. Vilkko, A. Jaatinen and K. Villo, Dynamic modeling and simulation of cone crushing circuits, *Miner. Eng.* 43-44 (2013) 29-35, doi: 10.1016/j.mineng.2012.07.019.

[18] Z. Liao and A. L. Dexter, An experimental study on an inferential control scheme for optimizing the control of boilers in multi-zone heating system, *Energ. Buildings* 37 (2005) (1) 55-63, doi: 10.1016/j.enbuild.2004.05.009.

[19] O. A. Makinde, B. I. Ramatsetse and K. Mpofu, Review of vibrating screen development trends: Linking the past and the future in mining machinery industries, *Int. J. Miner. Process.* 145 (2015) 17-22, doi: 10.1016/j.minpro.2015.11.001.

[20] J. Bolder, T. Oomen and M. Steinbuch, Aspects in inferential iterative learning control: A 2D systems analysis, in: *53rd IEEE Conference on Decision and Control*, Los Angeles, CA, 2014, pp. 3584-3589, doi: 10.1109/CDC.2014.7039946.

[21] Jian Jiao, Yiguo Li, Jiong Shen and Shuanzhu Sun, The inferential predictive control method of coal mill, in: *2015 Chinese Automation Congress (CAC)*, Wuhan, 2015, pp. 968-973, doi: 10.1109/CAC.2015.7382638.

[22] Ž. U. Andrijić, I. Mohler, N. Bolf and H. Dorić, Development of inferential models for fractionation reformate unit, in: *21st International Conference on Process Control (PC)*, Strbske Pleso, 2017, pp. 143-148, doi: 10.1109/PC.2017.7976204

[23] B. Lennox, G. A. Montague, A. M. Frith, C. Gent and V. Bevan, Industrial application of neural networks — An investigation, ***J. Process Contr.*** 11 (2001) (5) 497-507, doi: 10.1016/S0959-1524(00)00027-5.

[24] R. C. Fair, Evaluating the predictive accuracy of models, in: *Handbook of Econometrics*, Vol. 3., Amsterdam, North Holland, Netherlands, Elsevier Science Publishers, 1986, pp. 1979-1995, available online at: http://www.sciencedirect.com/science/article/pii/S1573441286030131

[25] J. Leontaritis and S. A. Billings, Model selection and validation methods for non-linear systems, ***Int. J. Control.*** 45 (1986) 311-341, doi: 10.1080/00207178708933730.

[26] C. Bordons and M. L. Zafra, Inferential sensor for the olive oil industry, in: *European Control Conference (ECC)*, Cambridge, UK, 2003, pp. 1940-1946.

[27] J. P. Cardoso, A Simple model for the optimization of the extraction yield of antibiotics isolated from fermented broths by direct crystallization, ***Biotechnol. Bioeng.*** 42 (1993) (9) 1068-1076, doi: 10.1002/bit.260420908.

[28] V. Jain, P. Kishore, R. A. Kumar and A. K. Pani, Inferential sensing of output quality in petroleum refinery using principal component regression and support vector regression, in: *IEEE 7th International Advance Computing Conference (IACC)*, Hyderabad, 2017, pp. 461-465, doi: 10.1109/IACC.2017.0101.