Computers & Industrial Engineering 197 (2024) 110607

Contents lists available at ScienceDirect

Computers & Industrial Engineering

journal homepage: www.elsevier.com/locate/caie

Monitoring and control of air filtration systems: Digital twin based on 1D computational fluid dynamics simulation and experimental data

Federico Solari *, Natalya Lysova, Roberto Montanari

Department of Engineering Systems and Industrial Technologies, University of Parma, Parco Area delle Scienze 181/A, Parma, PR 43124, Italy

ARTICLE INFO

Keywords:
Digital Twin
Air filtration
Computational fluid dynamics
Industrial plant control
Cyclone separator
Clogging

ABSTRACT

This study presents the development of a digital model based on one-dimensional computational fluid dynamics for the monitoring and control of filtering systems used for removing flour, dust, and other particulates from the airflow arriving from various sections of industrial production plants.

Focusing on a pilot plant equipped with a cyclone bag filter, historical experimental data was integrated with the results of a one-dimensional fluid dynamics simulation model to create a digital twin capable of real-time control and regulation of industrial plants. In particular, measured pressure drop data under different clogging conditions were interpolated to generate the characteristic curves of the filter under various clogging conditions, to be implemented within the digital model of the plant. The generated model, validated through a dedicated experimental campaign, accurately predicted the airflow rate and pressure distribution across the plant. The system's capability to adapt to changing operational conditions, such as clogging, was demonstrated through simulation, highlighting the model's utility in maintaining the desired operation levels while minimizing the need for extensive sensor networks.

The analyzed case study in the field of air filtration systems aims to fill the gap in the scientific literature related to the application of Digital Twin technology to the control of industrial manufacturing plants. The findings highlight the potential of digital twins in monitoring and control, as well as predictive maintenance, of industrial systems. The findings highlight the potential of Digital Twins in monitoring and control, as well as predictive maintenance, of industrial systems. Future research activities will explore the model's applicability in failure and anomaly detection, to further enhance predictive maintenance of air filtering systems.

1. Introduction

The separation of heterogeneous mixtures is a widely used process in many industrial sectors (Sparks & Chase, 2016). In some cases, such separation is achieved by exploiting the action of a force field which, when phases have different densities, tends to separate them. When the applied force field is the gravitational one, it is referred to as sedimentation or settling (Souza et al., 2015; Wu and Chern, 2006); in this case, the process rate, being the magnitude of the force field fixed, is mainly driven by the difference in density between the phases. When, on the other hand, a centrifugal force is applied, it is referred to as centrifugal or cyclonic separation (Ogawa, 1997; Xie et al., 2018). In this case, the efficiency of the process and its rate can be influenced by acting directly on the force field and therefore on the operating and design parameters of the process.

In other cases, i.e., when phase densities are very similar, or when the size of the particles to be separated is very small, separation is achieved by passing the mixture through a porous media that traps suspended or dissolved particles, based on a cut-off dimension or chemical affinity. In the first case, the process is referred to as "filtration" (Löffler, 1988; Tanabe et al., 2011). In the latter case, when separation is achieved by exploiting the chemical-physical interactions (i.e., Van der Waals forces or intermolecular chemical bonds) that occur between the filter matrix and the species to be separated, the process is referred to as "adsorption" (Yu et al., 2021). In both filtration and adsorption, the filter matrix tends to become saturated over time and therefore must be periodically regenerated. Regeneration allows the matrix itself to be partially cleaned to extend its useful life. In the case of filtration, regeneration is carried out by flushing a countercurrent flow of fluid through the porous media to remove part of the trapped substances (Krammer et al., 2003; Andersen et al., 2016; Cirqueira et al., 2019). In the case of adsorption, on the other hand, desorption cycles are

* Corresponding author.
E-mail address: federico.solari@unipr.it (F. Solari).

https://doi.org/10.1016/j.cie.2024.110607

Available online 25 September 2024

carried out, to renew the filter matrix by purifying it from the adsorbed solute, either using a solvent (Tamon et al., 1990; Grajek, 2000), by thermal treatment (Ledesma et al., 2014), or by a pressure decrease (Pak and Jeon, 2016).

After a certain period, regeneration cycles are no longer effective, and the filter matrix must be replaced. Preventive maintenance techniques are generally adopted to schedule such substitution interventions by constantly monitoring the performance of the process. Generally, pressure drops at the ends of the filter are used as reference parameters to identify when regeneration is no longer able to re-establish acceptable operating conditions, i.e., when the reference parameter remains above a certain threshold value. This approach makes it possible to promptly intervene whenever the filter's performance is no longer acceptable, thus allowing it to always work under conditions of good efficiency. In some cases, however, for example in the presence of particularly abrasive materials or when non-homogeneous clogging of the filter matrix occurs, deviations from standard operating conditions could develop that could lead to sudden and premature failure of the filter matrix. In these cases, therefore, reactive, unscheduled maintenance must be carried out, resulting in considerably higher costs compared to a scheduled intervention. To avoid these situations, it is necessary to switch from preventive to predictive maintenance. To this end, it is necessary to develop analytical or numerical models, i.e., virtual representations based on the integration of real-time data, historical data, and data resulting from analytical or numerical sub-models (Lysova et al. 2022, van Dinter et al., 2022; Zhong et al., 2023). In Solari et al. (2023), the authors have described a predictive maintenance model for a cyclonic bag filter based on a digital model, built from both historical data and fluid-dynamic simulation results. By integrating pressure drop measurement with velocity measurements at a specific point within the filter, the authors developed a model that can detect in real-time both failures and malfunctions. The authors hence have focused on conditions internal to the filter to make predictions about the filter's remaining useful life, but they have not evaluated how the operating conditions of the filter impact the behavior of the whole system. Indeed, the filter is generally embedded within a more complex plant, and its operating conditions impact the overall fluid dynamic behavior (Viccione et al., 2019). Thus, it may happen that, while the clogging conditions of the filter are not yet sufficient to demand a replacement of the filter matrix, the behavior of the entire system does not reflect the desired one in terms, for example, of air flow rate; a tuning intervention would hence be necessary.

Since the clogging conditions of the filter and, as a consequence, the operating conditions of the system, are continuously changing, a continuous control and regulation system would be needed. In industrial settings, however, it is often difficult to monitor the actual operating conditions of the system because of specific process conditions which make it challenging to install sensors. This happens, for example, when the mixtures are highly heterogeneous, or there is a high percentage of suspended solid particles. It is therefore extremely difficult to detect deviations from the desired operating conditions and to develop automated adjustments based on standard feedback control.

In many studies, Computational Fluid Dynamics (CFD) has been adopted to accurately characterize both air suction systems and separation processes under different operating conditions, allowing for the monitoring of the parameters of interest at each point of the plant, even where the measurement with physical sensors is not possible (Misiulia et al., 2020; Elsayed & Lacor, 2010). Simulation results can be indeed used, in addition to, or in substitution, to real data, to evaluate corrective actions for the adjustment or improvement of the operating conditions. Liu, Bao, et al. (2022) have combined CFD simulations with field measurements to analyze dust pollution diffusion under different operating conditions and by varying suction port positions. The optimized parameters for air suction volume and suction port position were then applied to a construction site, leading to a significant improvement in dust control within the tunnel environment. However, traditional three-dimensional fluid dynamic simulations are very time-consuming and can not be used for real-time control. Many studies can be found in the scientific literature that have addressed this issue, to make the results of fluid dynamic simulations available more rapidly, thus making them more compatible with the development of real-time control systems and the implementation of digital twins. To this end, some of the existing studies adopted traditional 3D fluid dynamic simulation integrated with reduced-order models. Dwars and Mehring (2024) have presented a novel approach for the optimization of the design of cyclone separators for the separation of oil aerosols from gas streams. Starting from validated CFD simulations, the authors have developed a reduced-order model able to predict velocity profiles, pressure drops and separations efficiency with good agreement to experimental data. Although the main objective of the proposed approach was to reduce the computational time required by CFD simulation, the final aim of the authors was to speed up the design phase of cyclone separators and not to develop a model for real-time process control.

Some other studies have adopted simplified fluid dynamic models, such as Zhang and Liu (2022), who have developed a simplified calculation model based on CFD simulations, to rapidly calculate the dynamic process of particle capture, contributing to extending the service life of filter media and reducing the energy consumption in air purification systems. The authors have succeeded in reproducing the dynamics of particle deposition on a single fiber and the results appeared promising. However, being the method developed by assuming a single fiber and approximating it with a two-dimensional domain, it can hardly be applied with acceptable results in a much more complex industrial context. In both of the above cases, there is no connection between the real and the virtual system.

When a virtual model receives input from the real system and uses its results to provide feedback and maintain control over the real system, it is referred to as "Digital Twin" (Grieves, 2014).

Digital twin technology is increasingly transforming various industries by creating connected virtual replicas of physical assets, processes, or systems. A recent study by Liu, Ong, et al. (2022) has highlighted how the main applications of the Digital Twin can be found in the manufacturing sector, especially in the management of planning and scheduling phases of job shop activities and assembly processes. In another study, Son et al. (2021) have confirmed this evidence by highlighting how most of the studies focus on the pilot testing, monitoring, and improvement phases of the single machine or process. The application of the digital twin for industrial plant control appears to be an unexplored area of research.

In a recent study, Preite et al. (2023) have demonstrated that one-dimensional lumped-parameters fluid-dynamics simulation could be adopted to develop a Digital Twin of a complex system (i.e. an irrigation network) aiming to minimize water consumption and detect possible failures and malfunctions. Indeed, while 3D CFD simulations allow for detailed modeling of complex geometries and flow patterns, they can be notoriously very time- and resource-extensive. Furthermore, such a high level of detail may not be necessary for the development of Digital Twins and, more in general, for applications intended for real-time control of industrial plants. In contrast, 1D CFD simulations, offer a more computationally-efficient alternative by simplifying the system through lumped parameters. This type of simulation tends to reduce the overall computational cost, limiting the level of detail by simplifying the assumptions and averaging the system's parameters, variables, and flow characteristics. While this can reduce the accuracy of the results, as well as the applicability and flexibility of the method in particular contexts (e.g., complex geometries or turbulent flows), in several cases of industrial interest, 1D CFD simulation allows to optimize the trade-off between the information required to control the plants, the time available for the computation and the allocatable resources.

The present study will focus on an industrial air suction plant with a cyclonic bag filter such as the one described in Solari et al. (2023). In this device, an air stream with suspended solid particles is treated and separated by combining centrifugal separation and filtration on polyester filter bags. The adopted approach consists of integrating real data with one-dimensional fluid dynamics simulation to develop a digital twin for real-time control and regulation of an air suction system, which is commonly adopted in many industrial sectors.

After a characterization of the filter at different flow rates and under different clogging conditions, a 1D CFD lumped-parameter model of the entire system was developed. The digital model, validated with dedicated experimental measurements, accurately reproduces the system's behavior in terms of pressure and flow rate at each point when compared to the values detected by the field sensors. These values can be fed in real-time as input data into the digital model, which can then be considered a digital shadow of the plant. Specifically, it predicts in real-time the velocity and pressure ranges throughout the system and evaluates deviations from the desired operating conditions.

The proposed approach leverages modern computational capabilities for industrial applications and could be considered the base for future research and development in the field. Indeed, in future research activities, the digital shadow could be connected, via an application programming interface (API), to the actuators installed on the plant (i.e., the butterfly valves for flow regulation), allowing the use of the resulting digital twin for regulation purposes, aiming to maintain the deviations from the set-points within the expected limits. An in-depth economic analysis could also be performed, to assess the cost savings from reduced maintenance and improved efficiency.

The outline of the article is as follows: in Section 2, the equipment and methods used are described. In Section 3, the main results obtained are presented and discussed. In Section 4, the managerial insights related to the study are pointed out, and finally, in Section 5, concluding remarks are inferred and suggestions for possible future research activities are given.

2. Materials and methods

2.1. Description of the plant

The filtering device, installed at the University of Parma, Italy, consists of a cyclonic separator mounting 31 filtering bags, and it is characterized by a standard industrial scale (Fig. 2, Table 1). The cyclonic body allows for the separation of the bigger, heavier, particles, while the filtering bags trap the finer particulate. The bags are made of non-woven polyester needlefelt, with casual fiber orientation, thermally treated to lock all the fibers in place, and singed to ensure an appropriate surface finish (Fig. 3 a and b). The characteristics of the polyester needlefelt are reported in Table 2. The polyester fabric bags are mounted over a metallic structure (Fig. 3c) to ensure the correct shape throughout the filter's operation. The separator functions as follows: the particle-

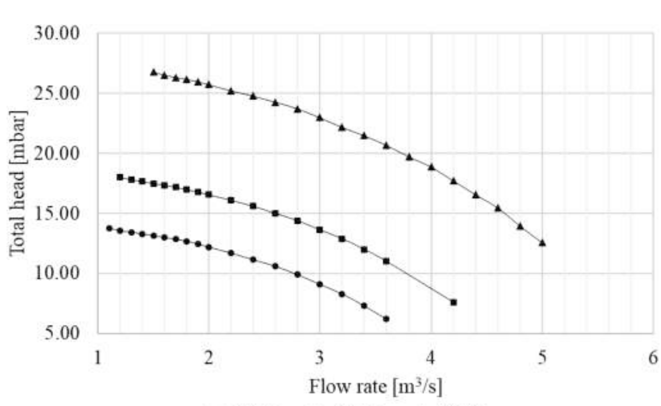

Fig. 1. Characteristic curves of the fan at different frequencies, which can be modified by means of an inverter. (Print in grayscale).

laden air from the processing line, drawn by a fan located after the filter, enters the system tangentially and proceeds towards the conical bottom of the cyclonic body in a spiraling motion. In this process, the heavier particles are separated from the airflow and collected in the conical bottom of the cyclone, from which they are periodically discharged. Afterward, the airflow is forced to pass through the filtering bags. While passing through the filtering material, the residual smaller particulate remains trapped in the fabric due to several phenomena ranging from inertial impaction, interception, and diffusion to electrostatic forces, and accumulates over time despite the periodic cleaning measures usually adopted.

Since the analyzed pilot plant is not connected to a real industrial line, the fan draws air from the external environment; after passing through the separation system, the filtered air is released back into the atmosphere. The total flow rate circulating in the system can be regulated by acting on the inverter of the fan through a PLC panel through a human–machine interface, and by adjusting the opening angle of valve V_1. In particular, by acting on the inverter it is possible to change the frequency of the electrical supply: by modifying the speed at which the motor's magnetic field rotates, this variation allows for more precise control over the speed of the fan blades. The adjustment in the opening angle of the valve, on the other hand, allows to regulate the processed flow rate. Fig. 1 illustrates three characteristic curves of the fan used in the pilot plant, each corresponding to a different inverter frequency, that show the relationship between the processed flow rate and the total head provided by the fan.

In this pilot plant, it is possible to draw air either exclusively from the main pipe section or also from a secondary branch by adjusting the opening angle of a secondary valve V_2. The valve opening angles can be regulated through the StepControl software, acting on dedicated stepper motors (aec M60SH86-TO0512P24C).

Several sensors are installed across the pilot plant to monitor the system's functioning. The data measured by the sensors are acquired every 0.5 s with a Data Acquisition Module (DAQ) connected to a NI LabVIEW project that allows to continuously log the data and write it to a file for further elaborations and analyses. In particular, the KIMO differential pressure device, equipped with a Debimo air flow measuring blade, measures the flow rate in the system. This device, installed on a straight pipe section after the inlet of the secondary branch and before the filter, generates a differential pressure, the square root of which is proportional to the flow rate according to Eq. (1) provided by the manufacturer, where C_M is a conversion coefficient which depends on the blade geometry and installation.

$$v = C_M\sqrt{\frac{2 \bullet \Delta p}{\rho}} \tag{1}$$

The pressure drop across the filter, and that across valve V_1, are measured with differential pressure sensors, while the pressure at the suction section of the fan is measured by a barometric pressure transmitter. Finally, a hot-wire anemometer is used to measure the air velocity in the secondary inlet branch. The locations of all the sensors, detailed in Table 3, are presented in Fig. 4.

2.1.1. Bags and clogging

During the standard operation of filtering devices, the porous material tends to become progressively more obstructed with particulate over time. Indeed, although compressed air systems are usually implemented to clean the bags by periodically injecting compressed air jets counter-current to the processed airflow, they are not able to completely remove all the particulate matter trapped in the fabric, besides the fact that their action is generally limited to the upper part of the bags.

This phenomenon takes the name of "clogging", and it is the main factor affecting the service life of filtering media. The effects of clogging at the macroscopic level can be summarized as a reduction in the permeability of the fabric, which results in an increase in the pressure

Fig. 2. Pilot plant with a cyclonic bag separator installed at the University of Parma, Italy. (Print in grayscale).

Table 1
Characteristics of the cyclonic body.

Dimension	Value	Units
Total separator height	5.308	m
Separator diameter	1.300	m
Height of the conical bottom	1.550	m

drop across the filter. This pressure drop is generally the only indicator of clogging monitored in industrial settings and used to schedule filter maintenance. In fact, when the pressure drop across the filter exceeds a critical value (10–15 mbar), the bags are usually dismounted and replaced altogether with a new set. At the microscopic level, clogging can be observed as the accumulation of particulate matter in the fabric, in particular on the fibers (Fig. 5).

2.2. Experimental testing

Experimental tests were performed in order to characterize the cyclone bag separator under different clogging conditions and with different air flow rates. The flow rate processed in the pilot plant was changed by acting on the fan inverter. The clogging conditions, on the other hand, were reproduced by manually disassembling the clean bags from the separator and substituting them with a given number (Table 4) of completely clogged bags, provided by an industrial manufacturer for research and testing purposes after dismounting them from the industrial filter. In Fig. 6, it is possible to qualitatively assess the difference between the two limit states of the bags, with clean filtering bags on the left side of the figure and completely clogged bags on the right side.

The characterization of clogging is based solely on the pressure drop across the separator, so it is assumed that, e.g., the presence of 40 % of clogged bags corresponds to a clogging level of 40 %. The clogging level, therefore, is calculated by dividing the number of clogged bags by the total number of bags (31). For each case, the range of inverter frequencies was determined based on the inlet air velocities commonly encountered under standard operating conditions, and the pressure drop across the filter, which had to be less than the upper measurement limit of the differential pressure sensor (10 mbar). The valve V_1 was left completely open (90°) for the two cases with clogged bags (Cases 2 and 3), while for Case 1 with clean bags, the opening angle was modified to have a comparable range of airflow rates.

To insert the clogged bags, the clogging sequence identified by Solari et al. (2023) was followed. In particular, the analysis allowed for the division of the 31 bags into 4 groups based on the airflow rates through them and thus the rapidity with which they tend to clog (Fig. 7). Namely, the bags in Group (1) are expected to clog more rapidly, while those in Group (4) are characterized by a lower clogging rate. The experimentally evaluated clogging configurations, therefore, were reproduced by first substituting Group (1) with clogged bags, and then all four groups.

During the experimental runs, as previously stated, the sensor data were continuously acquired and logged by means of a Data acquisition (DAQ) module connected to a project created with LabVIEW software. The analysis of the data allowed to derive the characteristic curves of the filter at the tested clogging levels by interpolating the experimentally measured pressure drops across the device. Moreover, the results of the analysis were used to predict pressure drop at intermediate, not tested clogging levels, allowing to generalize system's functioning under different conditions. An additional clogging state was then experimentally reproduced on the pilot plant to validate the results obtained by substituting Group (1) and Group (2) with clogged bags (Case 4 in Table 4).

2.3. Modelling the effect of clogging on the pressure drop

The sensor data logged during the filter functioning were exported and analyzed with MS Excel. By analyzing the data from the experimental campaign it was possible to derive characteristic curves of the filter under the tested conditions. In particular, to fit the trend in the filter pressure drop at increasing air flow rates, the following steps were followed: *(i)* cleaning of the data, by removing the transient conditions represented by the measured values logged during the change of the fan operating point; *(ii)* evaluation of the general trend in the data; *(iii)* fitting of the data with an appropriate model, which resulted to be a linear regression.

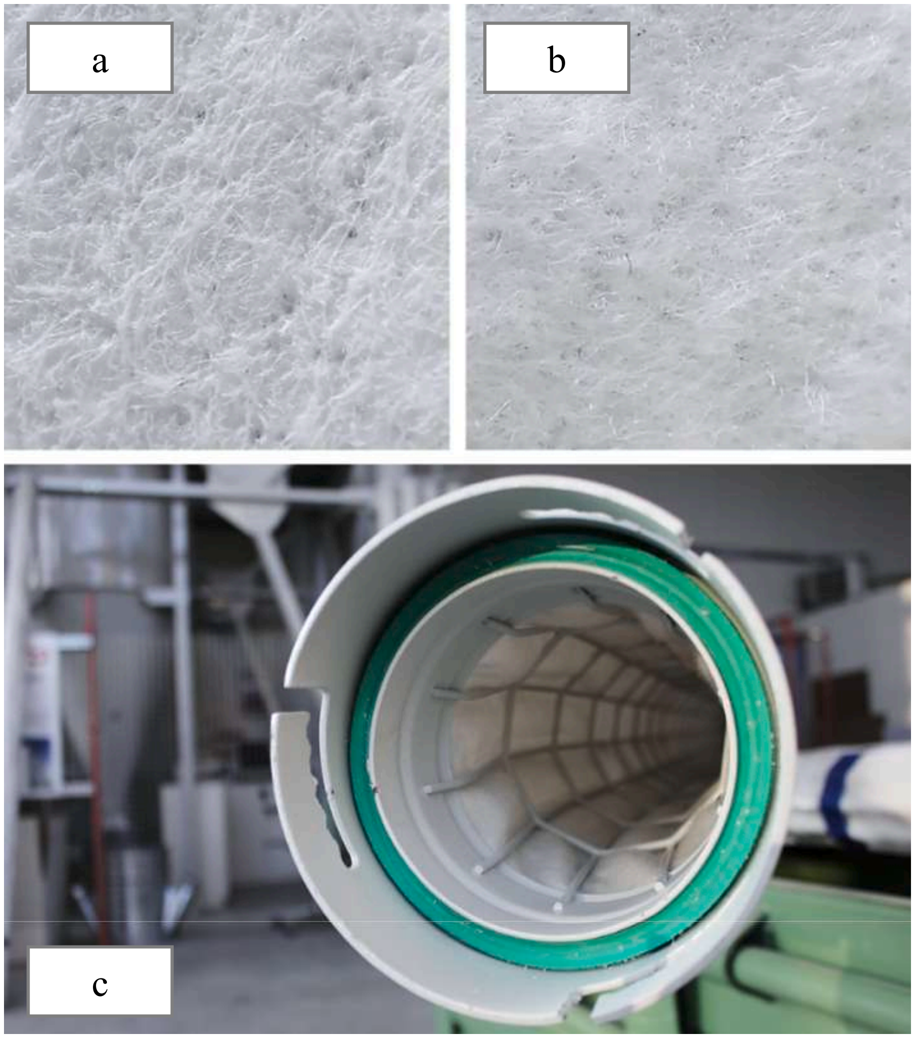

Fig. 3. Top (a) and bottom (b) sides of the filtering material. Inside of a filtering bag, showing the metallic support structure (c). (Print in grayscale).

Table 2
Characteristics of the polyester bags.

Characteristic	Value	Units
Length	3.000	m
Diameter	0.123	m
Thickness	1.4	mm
Weight	350	g/m^2
Density	0.26	g/cm^3
Pore volume	81 %	–
Air permeability	320	l/dm^2 min

$$y = m \bullet x + q \tag{2}$$

The results obtained made it possible to generate, for each clogging condition evaluated, an equation for the pressure drop in the general form of Eq. (2). The trend in the values of m and q were then observed and fitted with suitable models to generalize the system operation under different clogging conditions and predict the filter characteristic curves under non-tested conditions.

In industrial settings, the characteristic curves of the filter under different clogging conditions could be derived, for example, by monitoring and analyzing pressure drop value over the filter's useful life, or by characterizing it with three-dimensional CFD simulations.

Table 3
Overview of the sensors installed on the plant.

Sensor	Model	Measured quantity	Range	Accuracy
1	KIMO CP212 differential pressure transmitter	Pressure, converted to the velocity of the airflow entering the filter	±1000 Pa	±0.5 %
2	Endress Hauser Deltabar S PMD75 differential pressure transmitter	Pressure drop across the filter	±10 mbar	±0.05 %
3	Trafag Barometric Pressure Transmitter Absolute	Pressure at the suction section of the fan	800–1200 mbar a	±0.3 %
4	DELTA OHM HD402T2 differential pressure transmitter	Pressure drop across the valve	0–10 mbar	±0.75 %
5	EE650 hot-wire anemometer	Velocity of the airflow	0–20 m/s	±3.0 %

2.4. Digital model

The digital model of the plant was developed in Flownex®, a one-dimensional lumped-parameter fluid dynamics simulation software, typically used for the modeling of thermal-fluid networks and energy systems (Fig. 8).

The numerical model must be defined by setting valuable boundary

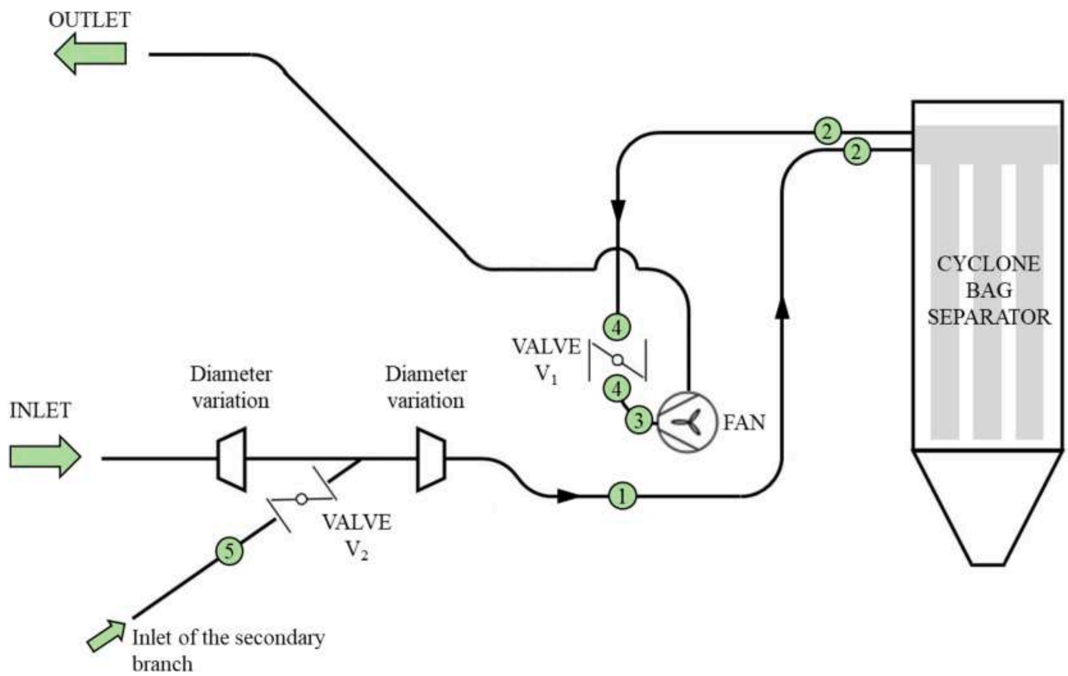

Fig. 4. Schematic representation of the pilot plant. The green numbered circles indicate the sensors described in Table 3. (Print in grayscale).

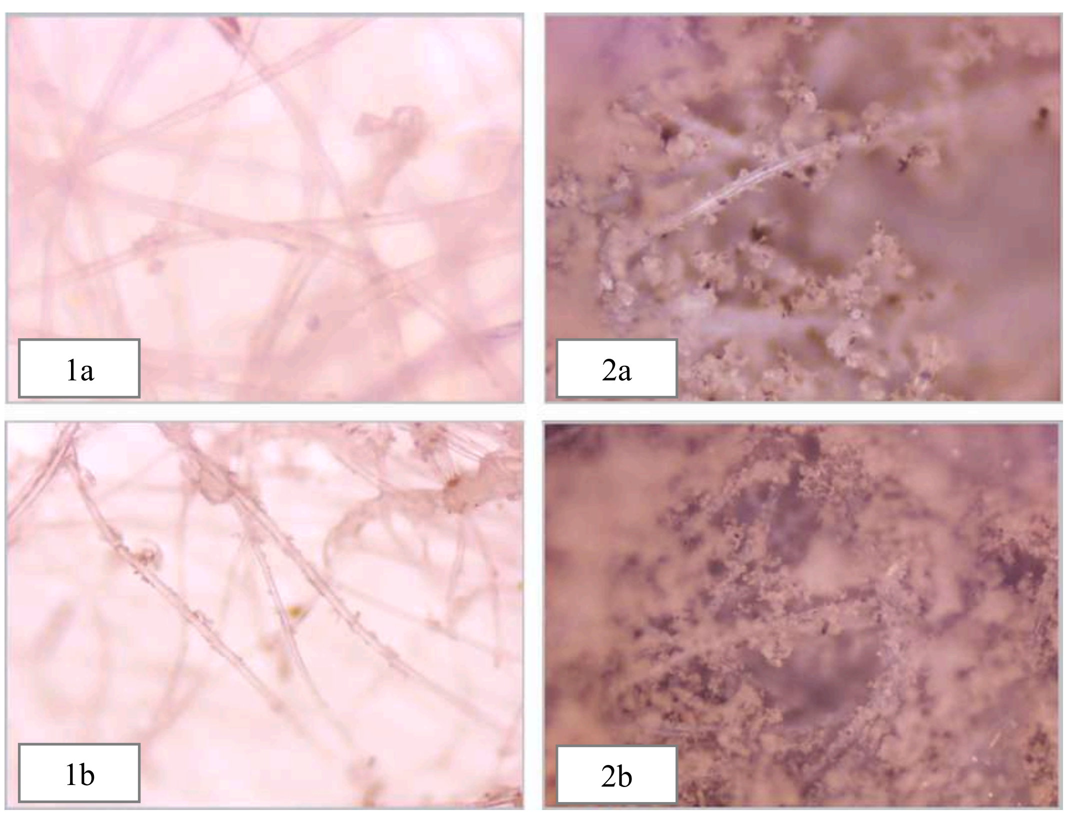

Fig. 5. Optical microscope images of 1) clean bags and 2) completely clogged bags at 20x (a) and 10x (b) magnification. The clogged bags were kindly provided by an industrial manufacturer for research purposes. (Print in grayscale).

conditions and by characterizing all the elements and the nodes involved in the network. The fundamental differential equations (i.e. mass, momentum, and energy equation) are then solved through an iterative procedure. Unlike traditional three-dimensional models, lumped parameter models do not require domain discretization with a computational grid since it is given by the individual elements inserted into the system.

In this study, atmospheric pressure was set at both the inlet and the outlet sections of the plant. Standard components (i.e., piping, valves, connections) were characterized using the existing components from the software library. For piping, diameter, length, material (steel) and surface roughness (35 μm) were specified. For bends, the ratio between the

Table 4
Clogging conditions reproduced during the experimental campaign.

Case	1	2	3	4 (Validation)	Units
Number of clogged bags	0	8	31	17	–
Clogging level	0 %	26 %	100 %	55 %	–
Range of inverter frequencies	35–50	35–45	35–41	35–45	Hz
Valve opening angle	55	90	90	90	°

radius of curvature and the internal diameter was also specified (1.5). The valve was represented using a standard butterfly valve, and the fan was characterized by its actual operating characteristic curves at different operating frequencies, provided by the manufacturer. The filter, which is not a standard component, was characterized by means of a proper experimental campaign. To have a characterization dependent on the clogging conditions, it was characterized at different clogging levels, which were reproduced by replacing a number of sleeves with fully clogged sleeves. Three different clogging conditions were reproduced based on which intermediate clogging conditions can be inferred by interpolation, as described in Sections 2.2 and 2.3.

In this work, the simulation model developed with Flownex was used to determine, for each clogging condition, the opening angle of the valves V_1 and V_2, and the operating frequency of the fan (f_{fan}), that would allow maintaining a constant airflow rate in the system. In particular, regulation is carried out by following the standard procedure generally adopted in industrial contexts: at first, regulation is carried out by acting on the opening angle of the main valve (V_1); in a second step, if regulation with valve fails to reach the set point, the supply frequency of the fan is increased or decreased, depending on whether the air flow rate in the system is to be increased or decreased. After the supply frequency is changed, the valve opening angles have to be adjusted to obtain the desired airflow rates in the different sections of the system.

The simulation model is extremely flexible and could be adapted to many industrial scenarios to optimize the management and regulation of complex air distribution networks with several branches conveying particle-laden air toward the filter. It allows, on the one hand, to achieve real-time results regarding air distribution across the system, according to the actual configuration, thus allowing a prompt and effective regulation; on the other hand, since it assumes uniform flow properties along the length of the system, it does not give any detailed information about the flow patterns within the machines and components constituting the plant. To overcome this limitation, the 1D lumped-parameter model can be integrated with detailed three-dimensional models of the single components, which allow the behavior of individual components to be deeply investigated. Indeed, it is possible to connect the 1D simulation software (i.e. Flownex) with the 3D simulation software (i.e. Fluent).

2.4.1. Digital model validation

The digital model was then validated with proper experimental tests in which, given the operating conditions of the fan (i.e., its characteristic operating curve), the valve V_1 opening was progressively changed and the overall flow rate and pressure values at various points in the system were monitored both in terms of mean values and standard deviation. In particular, the operating frequency of the inverter of the fan was set at 40 Hz, and four different valve openings were tested (fully opened, 60 degrees opened, 40 degrees opened, and 30 degrees opened) The same conditions were then reproduced on the digital model and the obtained results were compared.

Regarding the pressure, the comparison was made based on the

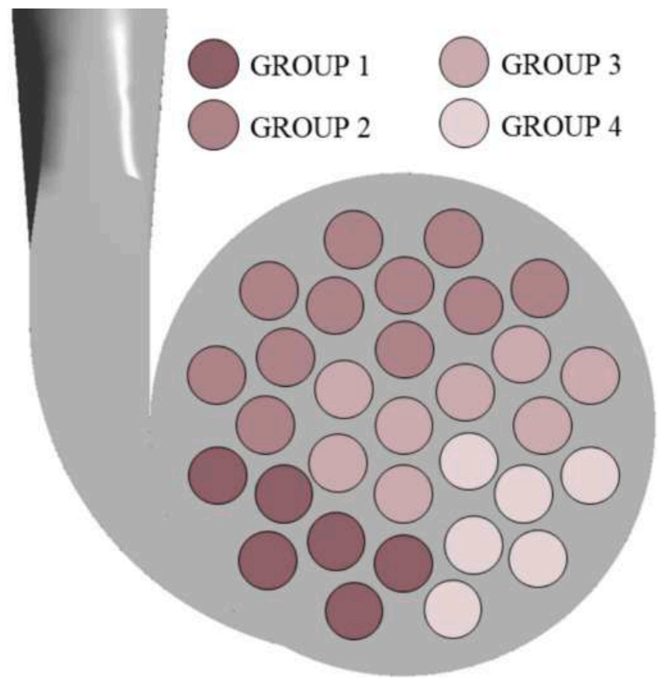

Fig. 7. Division of the bags into four groups according to the expected clogging rate. (Print in grayscale).

Fig. 6. Comparison between clean (on the left) and completely clogged filtering bags (right) disposed of by an industrial manufacturer. (Print in grayscale).

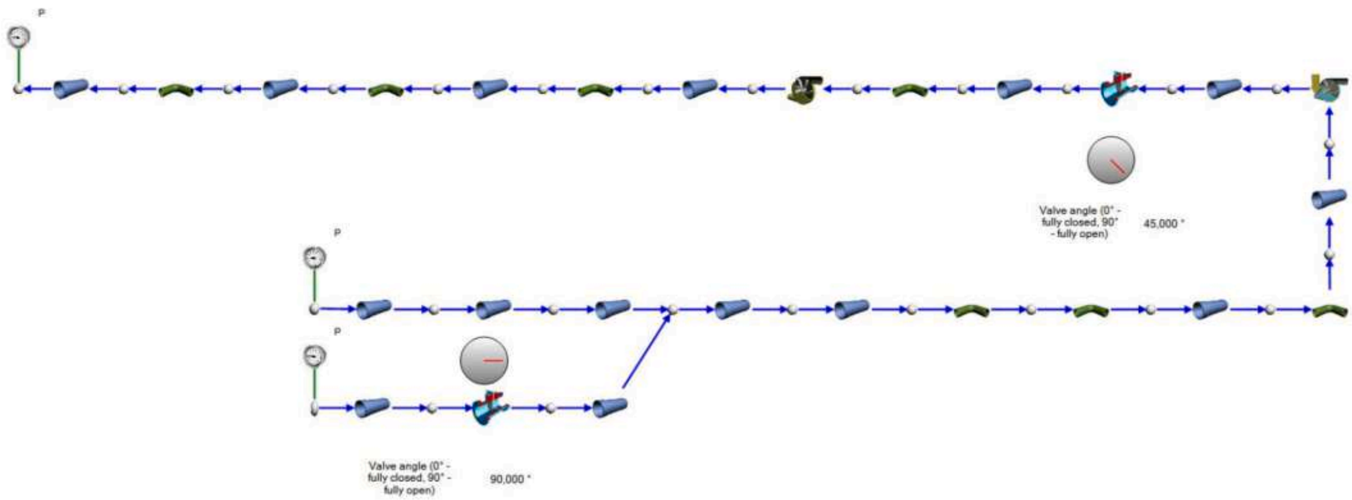

Fig. 8. Digital model of the plant. (Print in grayscale).

following values:

- Pressure drops across the valve V_1;
- Pressure drops across the filter;
- Depression at the fan intake section.

Flow rate value, as well as air distribution among the main branch and the secondary branch, were validated through two measurements:

- Air velocity in the main duct, upstream of the filter
- Flow rate percentage of air drawn through the secondary duct

2.5. Proposed digital twin framework

Once validated, the model, i.e., digital shadow, can be connected with the physical twin, i.e., real plant, through an API to generate a digital twin as represented in Fig. 9.

The digital twin (i.e. Flownex® model) receives input data from the physical twin in terms of the measured overall air flow rate (Q_{tot}) and the pressure drop across the filter (Δp_{filter}). In particular, the analog signals of the sensors will be converted into digital data using a Data Acquisition System (DAQ), and then real-time data will be fed into the digital model through a dedicated Python script. The signal acquisition frequency will have to be calibrated during the deployment phase. Based on these input

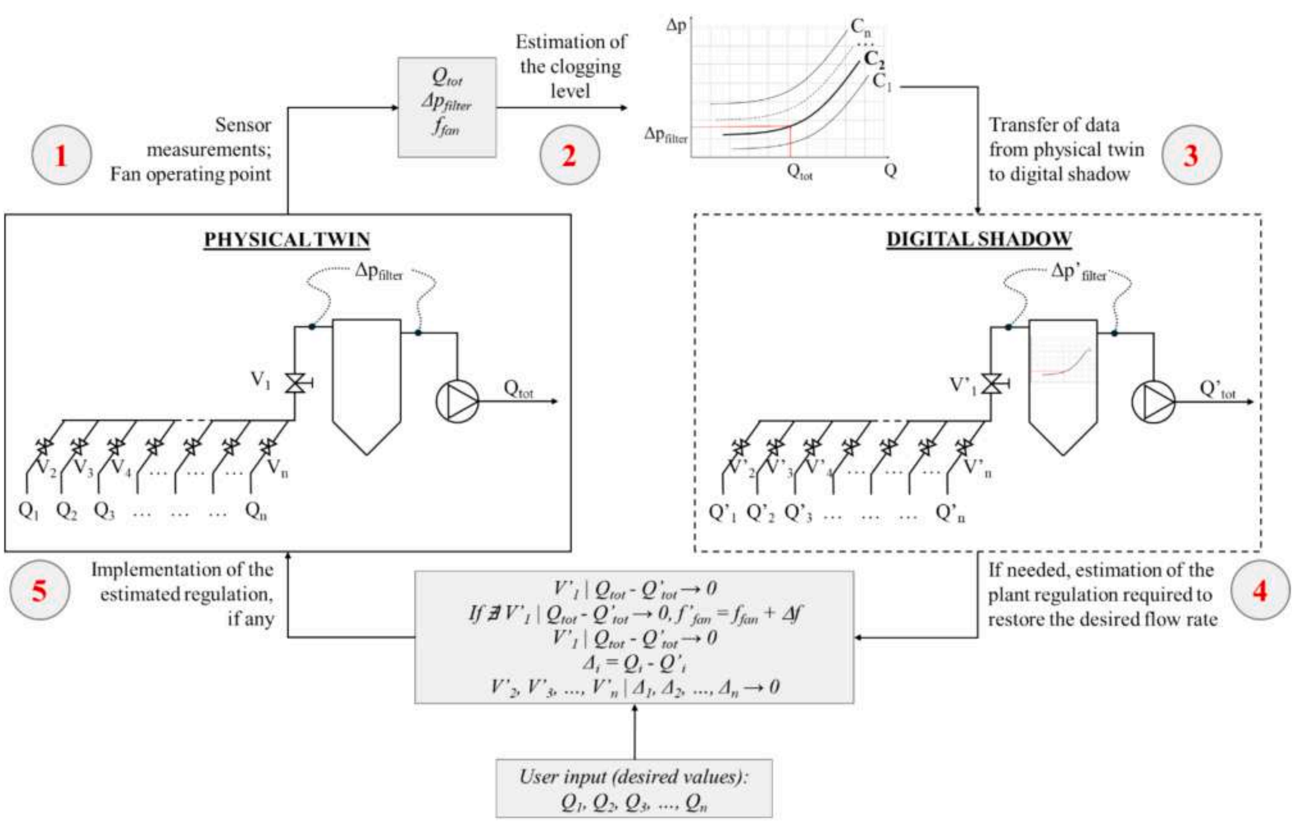

Fig. 9. Proposed digital twin framework. (Print in grayscale).

values, the filter clogging percentage and the resulting characteristic curve can be derived; assuming this curve, as well as the operating point of the fan, the digital model computes in real time the flow rate distribution across the plant. First of all, if the overall flow rate (Q_{tot}) is not sufficient to guarantee the desired values in the different branches, the fan supply frequency can be varied via an inverter, and the corresponding characteristic curve is then loaded within the model. Then, by comparing the obtained results with the set point values in the different branches, the digital model finds the adjustments to be made to the valves to have the desired flow rate values at each branch. To transfer the obtained results, in terms of opening angles, to the physical valves, the digital model can be connected to the physical plant by means of an application programming interface (API).

The described approach can similarly be applied to much more complex plants, where the airflow rate must be distributed over a very large number of branches. The proposed model, indeed, starting from two input values, then with only two sensors (overall air flow rate and pressure drop across the filter), calculates the adjustments to be made to fan supply frequency and to all valves to achieve the desired distribution over all the branches. In addition to a continuous adjustment of the system, the proposed method would allow for real-time monitoring of filter clogging conditions as well as its evolution over time, thus allowing for remaining useful life estimation and identification of possible failure.

3. Results and discussion

3.1. Experimental testing

The sensor measurements logged during the experimental tests summarized in Table 5 were cleaned from the transient data and interpolated with a linear regression model to generate the characteristic curve of the filter for each case in the form $dp = m \bullet v + q$, where dp is the pressure drop across the filter and v is the inlet air velocity (Fig. 10). The coefficients of the linear model were then interpolated with appropriate models to generalize the effect of clogging in the filter operation and derive characteristic curves of the non-tested conditions. With respect to q, the fitting was performed on its negative, $-q$, and 0 % clogging value was approximated with 1e-9 to use a power law model (Fig. 11). The generated model was then validated by reproducing an additional clogging condition, by mounting the clogged bag into the locations of Group (1) and Group (2), thus resulting in a 55 % clogging condition; the generated model had an average error on the pressure drop value of 4.8 % (approximately 0.3 mbar), and a maximum error of 9 % (0.5 mbar) (Fig. 12a).

For a given clogging condition, therefore, the linear model of the characteristic curve in the form of $dp = m \bullet v + q$, can be estimated by solving Eq. (3) and Eq. (4) where c is the clogging level ranging from 0 (clean bags) to 1 (100 % clogging). The trend in the filter pressure drop against filter inlet air velocity, calculated with the generated model, is reported in Fig. 12b for different clogging levels, while the coefficients are reported in Table 6.

$$m = 0.5726 \bullet c + 0.2524 \quad (3)$$

$$q = 4.4135 \bullet c^{0.039} \quad (4)$$

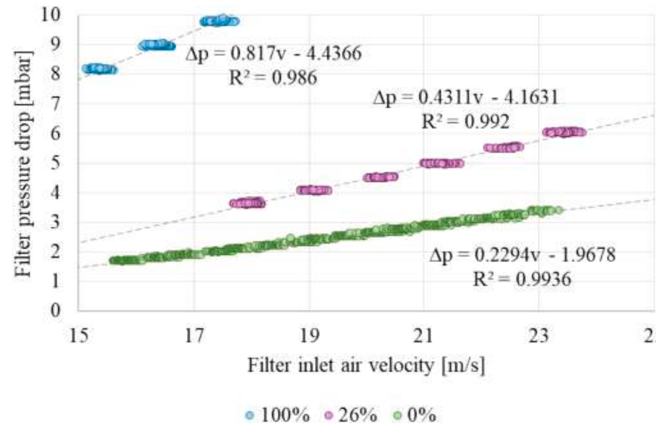

Fig. 10. Plot of filter pressure drop against inlet velocity with 100 %, 26 % and 0 % of clogging, and fitting with a linear model. (Print in grayscale).

3.2. Digital model

The digital model was used to assess velocity and pressure distribution across the plant (Fig. 13).

3.2.1. Digital model validation

In the following graphs, the comparison between the results of the digital model and the experimental data is reported (Fig. 14).

The pressure drops across the valve, as well as the pressure drop across the filter, are accurately predicted by the model. Regarding the depression at the suction section of the fan, there is a difference in the range of 0.65 mbar and 1.79 mbar between the experimental data and the simulated ones. This deviation, which increases as the valve opening changes, may be caused by the non-ideal installation of the sensor, which is located immediately after a bend and immediately before the fan. Turbulence, which increases at higher air velocity values, may therefore exist and significantly affect the measurement.

Regarding the air velocity in the main duct, the velocity measured by the sensor is always lower than that predicted by the model. To deeply explain this difference and identify which one of the two data is more reliable, a check can be made by analyzing the fan operating curve.

Within the considered range of total head (between 1400 and 1800 Pa), the fan provides a flow rate between 1.2 and 2.9 m^3/s, which, at the sensor location, corresponds to velocity values between 10 and 20 m/s. It can therefore be concluded that the velocity predicted by the model is more realistic than that measured by the sensor, which, probably due to a velocity profile that is not fully developed or slightly disturbed by the presence of bends in the vicinity, constantly underestimates air velocity.

For all configurations tested, the digital model predicts an air flow rate in the secondary branch equal, on average, to 2.63 % of the overall value. This result is confirmed by the experimental measurements (2.6 ± 0.045 %).

In light of these considerations, even considering the fact that measurements for air flows always suffer a certain degree of uncertainty, the fact that experimental data and simulated data show the same behavior and are also similar in terms of absolute value, it can be concluded that

Table 5
Overview of the filter operation under the reproduced clogging states.

Case	1	2	3	4 (Validation)	Units
Number of clogged bags	0	8	31	17	–
Clogging level	0 %	26 %	100 %	55 %	–
Range of inverter frequencies	35–50	35–45	35–41	35–45	Hz
Valve opening angle	55	90	90	90	°
Measured inlet air velocities	15.6–23.3	17.7–23.6	14.2–17.7	17.0–22.8	m/s
Air flow rates	117.6–176.0	133.4–179.1	107.2–133.7	128.5–172.1	m^3/min

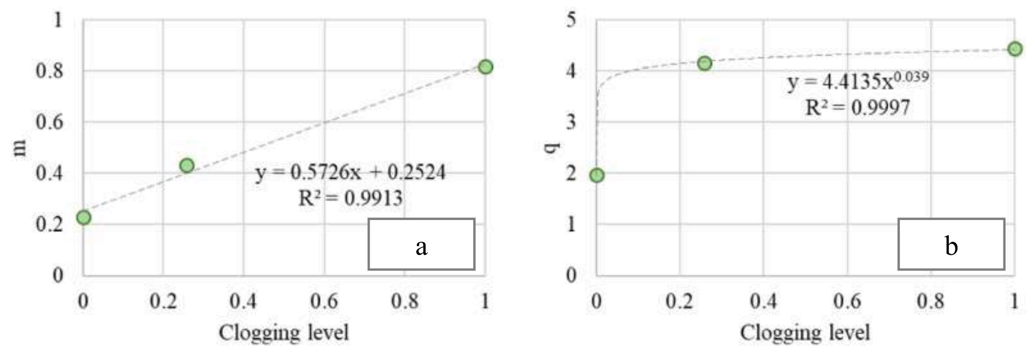

Fig. 11. Regression models for m (a) and q (b) coefficients of the characteristic curves of the filter under different clogging conditions. (Print in grayscale).

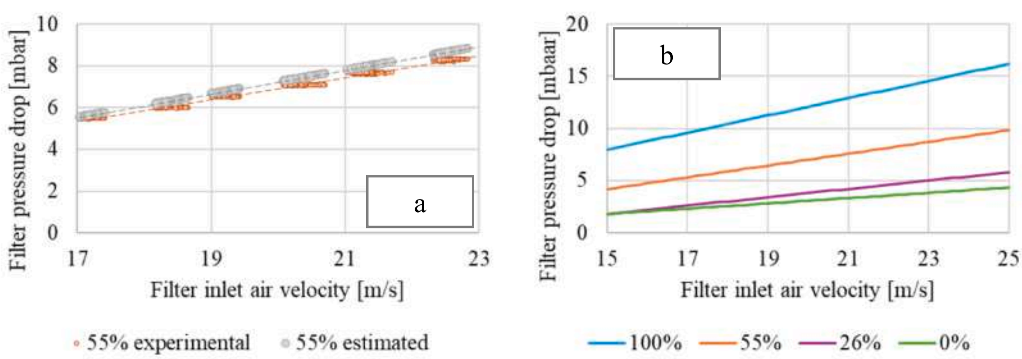

Fig. 12. Validation of the predictive model of filter pressure drop based on the clogging level (a); Characteristic curves of the filter calculated with the generated model based on experimental data (b). (Print in grayscale).

Table 6
Coefficients of the characteristic filter curves under different clogging conditions.

Clogging level	m	q
100 %	0.825	−4.414
55 %	0.566	−4.311
26 %	0.400	−4.186
0 %	0.252	−1.967

the model accurately reproduces the behavior of the real system. In a way, model-based assessments can even be considered more reliable, since they do not suffer the uncertainties that, naturally and inevitably, affect experimental measurements. As a conclusion, a digital model-based control can therefore be considered more reliable and more stable.

Finally, since the calculation times are very fast (less than 1 s), the developed model can be used for real-time evaluations.

3.2.2. *Simulation of a real operating cycle*

A working cycle was simulated using the virtual model, from clean filter conditions (0 % clogging) to fully clogged conditions (100 % clogging) (Fig. 15a and Fig. 15b). Within this range, the clogging

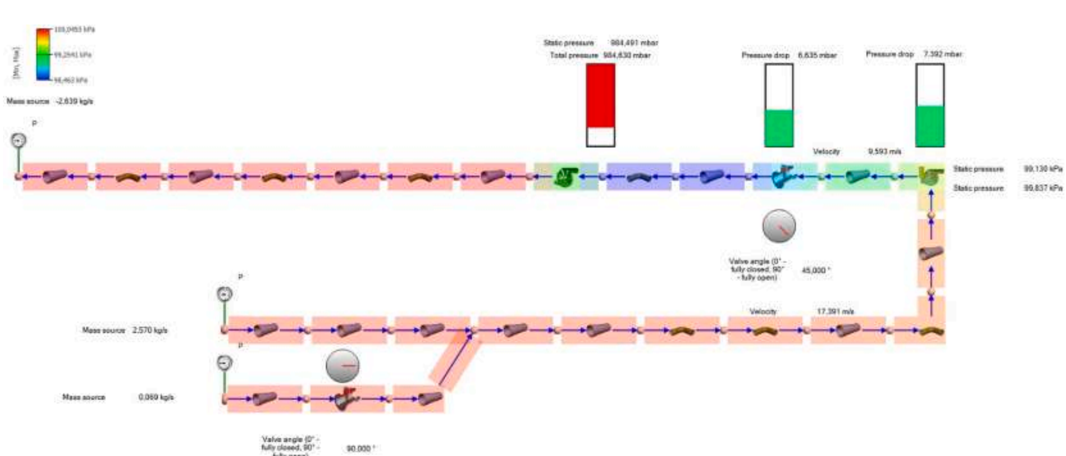

Fig. 13. Pressure drop distribution along the plant computed with the digital model. (Print in grayscale).

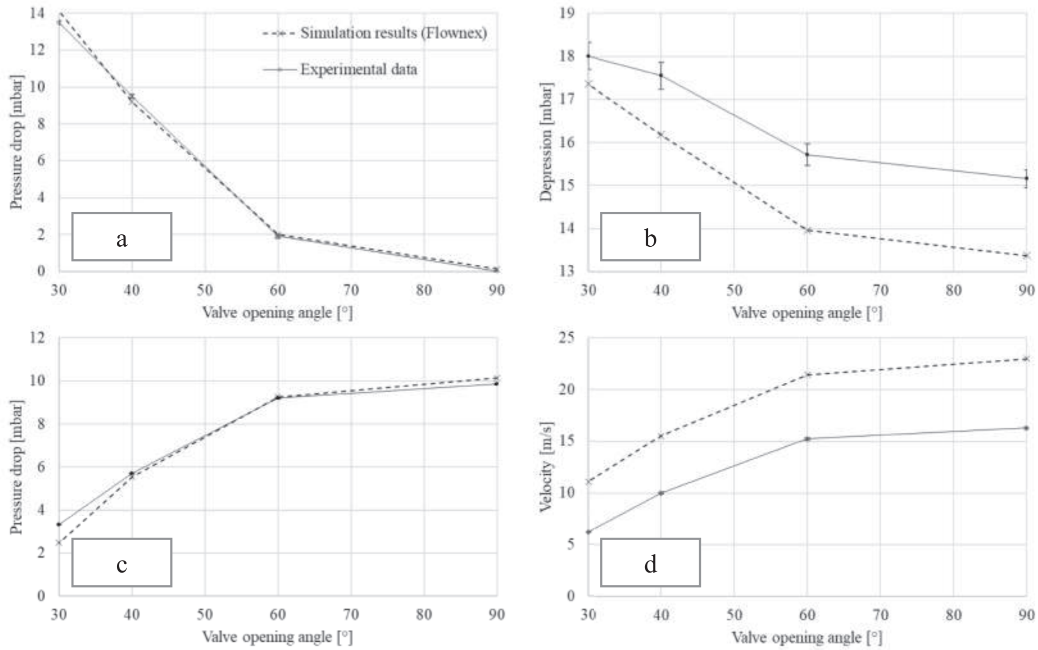

Fig. 14. Pressure drop across the valve (a); depression at the suction section of the fan (b); pressure drop across the filter (c); air velocity in the main duct (d). (Print in grayscale).

evolution was discretized by considering three intermediate clogging conditions: 25 %, 50 % and 75 %. Within this scenario, the filter characteristic curve is considered to be updated at discrete intervals, when the threshold clogging percentages are reached. Whenever the filter characteristic curve is updated, the system must be adjusted, both in terms of valve opening angles and fan supply frequency.

The set point values of velocity in the main duct and secondary branch were set, considering values that are generally adopted in industrial applications (22 m/s and 9 m/s, respectively).

Three frequency values were considered, namely 35, 40 and 49 Hz. At the initial time, under clean bag conditions, the fan operating frequency was set at 35 Hz.

As the filter clogging increased, the digital model calculated the opening angles of valves V_1 and V_2, and the operating frequency of the fan, to keep the velocity values close to the set-point values, as described in Section 2.5.

The calculation procedure for opening angle regulation is an iterative procedure with a maximum number of iterations of 25 and a convergence criterion of 0.001. In all configurations tested, the solution converged before reaching the maximum number of iterations.

Up to a clogging condition of 50 %, the set-point values can be guaranteed by simply regulating (opening) the valves (V_1 in particular). As clogging of 75 % is reached, at an operating frequency of 35 Hz, the fan was no longer able to reach the desired set-point, even by fully opening the valves, so the operating frequency was increased to 40 Hz and, at the same time, an adjustment of the valves was also performed. As clogging further increased, V_1 had to be further opened to keep the flow rate unchanged (Fig. 15a).

In the case considered, the adjustments on V_2 are undetectable because, as the flow rate on the main duct is kept constant, the flow rate in the secondary branch also remains unchanged. A more marked adjustment would be observed when, for instance, the set-point values are changed.

It is observed from Fig. 15b that the velocity in both pipes progressively decreases as clogging increases and, when adjusting, the set-point value is restored. To keep the velocity values closer to the set-point values, a higher regulation frequency would be required.

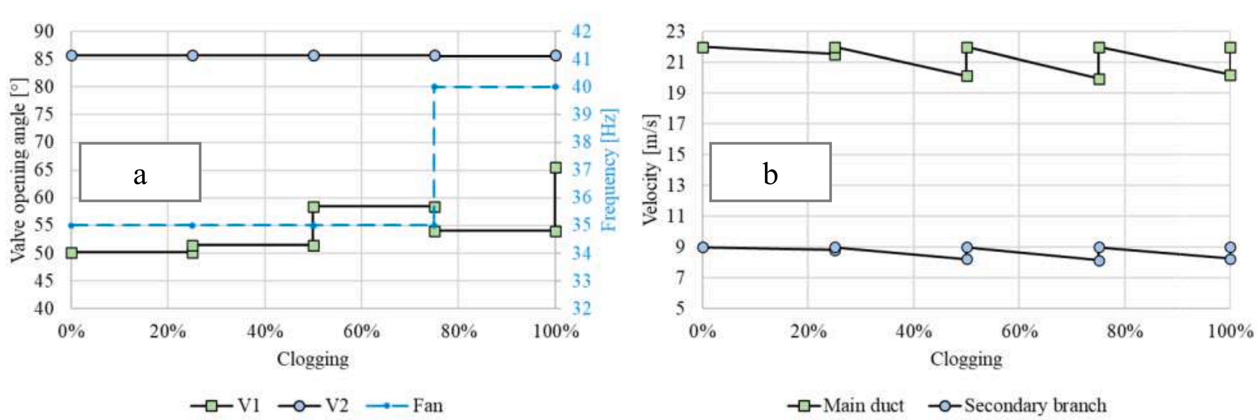

Fig. 15. Regulation of the valve opening angles and fan inverter frequency (a) and the resulting velocities is the main and secondary ducts (b). (Print in grayscale).

4. Managerial insights

Industry 4.0 technologies and paradigms can be of great support to industrial stakeholders in the pursuit of increasingly high-efficiency levels required by today's competitive market. To ensure efficiency, high quality, and optimized production, first of all, it is necessary to have deep knowledge of the system components and effective control over the plant. Indeed, the management of the system should be as much as possible informed and data-driven. In some industrial contexts, however, it is challenging to obtain useful and meaningful data to leverage for decision-making purposes.

The application discussed in this paper is one of these cases: the main issue affecting the optimal functioning of the plant, i.e., clogging of the filtering bags, can be only estimated indirectly through the value of pressure drop, and its effects on the plant and the distribution of flow rates across the system are generally unknown. Indeed, usually, there are no flow rate sensors on the different secondary branches of the plant, so it is not possible to directly assess whether the drawn flow rate is the one required for the correct system functioning. To overcome the complexities due to the nature of the specific application, the Digital Twin paradigm can be implemented in this context, supporting efficient control and management of the plant based on the availability of a digital model connected to the physical plant, that employs both historical and real-time sensor data.

First of all, it is necessary to characterize the critical component, in this case the filter, during its functioning, to generate its characteristic curves. This can be carried out in a few ways: it is possible to analyze historical data related to one life cycle of a set of bags, perform dedicated experimental campaigns like in the present study, or carry out simulation campaigns with a validated model replicating different clogging conditions. In the latter case, 3D Computational Fluid Dynamics (CFD) simulation can be adopted. This approach has the advantage of providing detailed insights into the functioning of the device but requires significant know-how, computational resources, and time. All three methods allow for the generation of characteristic curves of the filter under different clogging conditions, that can be then leveraged for the control of the whole plant.

With regards to the modeling of the whole system, 3D CFD simulation is not directly implementable: it would be highly impractical to simulate the whole distribution network, due to the resources and time required; besides, the added value of this approach would be extremely limited for the intended purpose.

1D CFD (lumped parameter CFD) simulation, on the other hand, appears to be the optimal approach in this case. By considering the overall behavior of the network components, it still reproduces the fluid dynamics inside the plant, allowing to quantify the flow rates in every branch of the system while at the same time neglecting the details not necessary for the application of interest. These details can however be included when needed by coupling 1D simulation of the entire system with 3D simulation of individual components Moreover, as demonstrated by the results of the study, the calculated values can be more precise and reliable compared to the measures of real sensors installed improperly or in non-optimal positions.

The lumped parameter CFD simulations can be performed with both open source and commercial software, with the latter ones featuring more user-friendly interfaces and less steep learning curves. These simulation models "evolve" over time based on the measured sensor data, aiming to faithfully reproduce the actual plant under different operating and clogging conditions. The commercial software used in this study, i.e., Flownex®, can communicate with the plant in two ways: it receives the data measured by the sensors and sends back to the actuators the details about the regulations to be performed to ensure the intended functioning of the plant. Indeed, in this case, the software is equipped with an optimization tool that allows to rapidly estimate the valve openings that would ensure the correct flow rate in the system based on the operating conditions.

The presented approach is not limited to the case under examination: the same general approach can be extended to several industrial applications and is particularly relevant in contexts where few data are directly available to assess and control the functioning of the plant.

5. Conclusions

In this study, a digital model, based on 1D lumped-parameters computational fluid dynamics, was developed for the simulation and monitoring of industrial air suction systems. These systems draw air at different locations within a production plant, to remove dust and other volatile substances. To ensure that such systems efficiently fulfill their function, the correct amount of air must be aspirated from each branch.

It is therefore necessary, on the one hand, that the fan supply the required total head, to aspire the required air flow rate. On the other hand, it is necessary to ensure that the flow rate is distributed correctly among the various branches of the system. This balancing should be done frequently since the operating conditions of such systems are constantly changing. For example, the continuous accumulation of solid particles on the filtration elements of the bag filter causes the pressure to drop and, consequently, the flow rate, to change continuously.

Such regulation is particularly complicated because these systems generally consist of a very high number of branches, since, typically, there are many suction locations within a production plant; adjustment made in one branch, therefore, impacts all other branches in the system, and vice versa. It is therefore necessary to perform an overall balancing of the system by adopting an iterative approach. Furthermore, this regulation is made even more difficult by the fact that it is difficult to monitor the actual operating conditions at the different points because, in the presence of dust, traditional velocity measurement systems (pitot tubes and hot-wire anemometers), are difficult to apply. Thus, the regulation of these systems represents a very challenging issue that still appears to be poorly investigated in the scientific literature.

In this study, a digital model was developed by reproducing an industrial-scale pilot plant installed at the University of Parma, which was subsequently used for testing and validation. The developed model resulted in accurate and real-time calculation of the airflow rate aspirated by different branches of the system, considering the real filter clogging conditions and the fan operating curve, both obtained based on real-time measured data. The model can thus be considered a digital shadow of the system. This developed model proved to be much more reliable in regulating the system than data measured with sensors, which are very sensitive to the installation position as well as to the flow conditions.

The digital shadow, through an application program interface (API), can then communicate with the physical counterpart and act on some components of the plant, thus effectively becoming a digital twin. As an example, depending on the results obtained, to keep the flow rates aspirated by each branch within the desired limits, the digital twin can be used to adjust with a feed-forward logic both the operating frequency of the fan and the opening degree of all the valves of the system.

The proposed approach can be applied for reliable and immediate regulation of very complex suction systems without installing sensors on all the secondary branches: the only sensors required would be a flow rate sensor on the main duct and a differential pressure sensor at the ends of the filter. By optimizing air suction systems, the proposed approach could directly contribute to reducing the environmental footprint of industrial operations as well as improving safety and workplace conditions.

The study presents some limitations, mainly related to the simulation approach. First of all, the presence of the particles (flour, dust, etc,) is not accounted for in the model. While this assumption is acceptable when the concentration of particles in the flow is low, in applications where it becomes significant some adjustments to the model should be made. In addition, the 1D simulation model is based on the reproduction of the system with standardized components; in the case of non-standard components and devices, like the functioning of the filter under different clogging conditions in the present study, these should be characterized by the end-user. While this may represent a limitation of the presented approach, it is also a sign of its flexibility, as it is always possible to include in the model personalized components with the level of detail tuned to the intended use.

Future research activities may focus on the development of models for failures and operating anomalies identification, thus targeting system predictive maintenance which could significantly impact the industry by reducing downtime and operational costs. Further exploration could also be done regarding the scalability of the model, its economic benefits, and environmental sustainability which could boost its applicability and relevance to industry.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors didn't use generative AI and AI-assisted technologies in the writing process.

CRediT authorship contribution statement

Federico Solari: Writing – original draft, Visualization, Validation, Supervision, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Natalya Lysova:** Writing – original draft, Visualization, Validation, Supervision, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Roberto Montanari:** Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgement

The authors wish to acknowledge the company OCRIM S.p.A. for providing the plant, the equipment and resources involved in the study.

References

Andersen, B. O., Nielsen, N. F., & Walther, J. H. (2016). Numerical and experimental study of pulse-jet cleaning in fabric filters. *Powder Technology, 291*, 284–298. https://doi.org/10.1016/j.powtec.2015.12.028

Cirqueira, S. S. R., Tanabe, E. H., & Aguiar, M. L. (2019). Experimental investigation of particle deposition in filter media during filtration cycles with regeneration by pulse jet cleaning. *Process Safety and Environmental Protection, 127*, 288–298. https://doi.org/10.1016/j.psep.2019.05.013

Dwars, G., & Mehring, C. (2024). Reduced-order model for predicting the performance of small-scale unidirectional cyclone aerosol separators. *Advanced Powder Technology, 35*(1), Article 104273. https://doi.org/10.1016/j.apt.2023.104273

Elsayed, K., & Lacor, C. (2010). Optimization of the cyclone separator geometry for minimum pressure drop using mathematical models and CFD simulations. *Chemical Engineering Science, 65*(22), 6048–6058. https://doi.org/10.1016/j.ces.2010.08.042

Grajek, H. (2000). Regeneration of adsorbents by the use of liquid, subcritical and supercritical carbon dioxide. *Adsorption Science & Technology, 18*(4), 347–371. https://doi.org/10.1260/0263617001493486

Grieves, M. (2014). Digital twin: Manufacturing excellence through virtual factory replication. White paper, 2014. Online:-03-01.

Krammer, G., Kavouras, A., & Anzel, A. (2003). Optimization of pulse cleaning frequency during bag filter operation. Chemical Engineering & Technology, 26(9), 951–955. Portico. https://doi.org/10.1002/ceat.200303032.

Ledesma, B., Román, S., Álvarez-Murillo, A., Sabio, E., & González, J. F. (2014). Cyclic adsorption/thermal regeneration of activated carbons. *Journal of Analytical and Applied Pyrolysis, 106*, 112–117. https://doi.org/10.1016/j.jaap.2014.01.007

Liu, C., Bao, Q., & Nie, W. (2022). The influence of ventilation parameters on dust pollution in a tunnel's environment using the CFD method. *Journal of Wind Engineering and Industrial Aerodynamics, 230*, Article 105173. https://doi.org/10.1016/j.jweia.2022.105173

Liu, Y. K., Ong, S. K., & Nee, A. Y. C. (2022). State-of-the-art survey on digital twin implementations. *Advances in Manufacturing, 10*(1), 1–23. https://doi.org/10.1007/s40436-021-00375-w

Löffler, F. (1988). Fundamental principles of particle separation in fabric filters. *Dust Collection with Bag Filters and Envelope Filters, 1–54*. https://doi.org/10.1007/978-3-663-07900-2_1

Lysova, N., Solari, F., & Vignali, G. (2022). Optimization of an indirect heating process for food fluids through the combined use of CFD and Response Surface Methodology. *Food and Bioproducts Processing, 131*, 60–76. https://doi.org/10.1016/j.fbp.2021.10.010

Misiulia, D., Antonyuk, S., Andersson, A. G., & Lundström, T. S. (2020). High-efficiency industrial cyclone separator: A CFD study. *Powder Technology, 364*, 943–953. https://doi.org/10.1016/j.powtec.2019.10.064

Ogawa, A. (1997). Mechanical separation process and flow patterns of cyclone dust collectors. *Applied Mechanics Reviews, 50*(3), 97–130. https://doi.org/10.1115/1.3101697

Pak, S.-H., & Jeon, Y.-W. (2016). Effect of vacuum regeneration of activated carbon on volatile organic compound adsorption. *Environmental Engineering Research, 22*(2), 169–174. https://doi.org/10.4491/eer.2016.120

Preite, L., Solari, F., & Vignali, G. (2023). Technologies to optimize the water consumption in agriculture: A systematic review. *Sustainability, 15*(7), 5975. https://doi.org/10.3390/su15075975

Solari, F., Lysova, N., & Montanari, R. (2023). Digital twin based on historical data and simulation results: Fault detection and estimation of the remaining useful life of a cyclone bag filter. *Applied Sciences, 13*(14), 8297. https://doi.org/10.3390/app13148297

Son, Y. H., Kim, G.-Y., Kim, H. C., Jun, C., & Noh, S. D. (2021). Past, present, and future research of digital twin for smart manufacturing. *Journal of Computational Design and Engineering, 9*(1), 1–23. https://doi.org/10.1093/jcde/qwab067

Souza, W. J., Santos, K. M. C., Cruz, A. A., Franceschi, E., Dariva, C., Santos, A. F., & Santana, C. C. (2015). Effect of water content, temperature and average droplet size on the settling velocity of water-in-oil emulsions. *Brazilian Journal of Chemical Engineering, 32*(2), 455–464. https://doi.org/10.1590/0104-6632.20150322s00003323

Sparks, T., & Chase, G. (2016). Filtration – Introduction, physical principles and ratings. *Filters and Filtration Handbook, 1–54*. https://doi.org/10.1016/b978-0-08-099396-6.00001-0

Tamon, H., Saito, T., Kishimura, M., Okazaki, M., & Toei, R. (1990). Solvent regeneration of spent activated carbon in wastewater treatment. *Journal of Chemical Engineering of Japan, 23*(4), 426–432. https://doi.org/10.1252/jcej.23.426

Tanabe, E. H., Barros, P. M., Rodrigues, K. B., & Aguiar, M. L. (2011). Experimental investigation of deposition and removal of particles during gas filtration with various fabric filters. *Separation and Purification Technology, 80*(2), 187–195. https://doi.org/10.1016/j.seppur.2011.04.031

van Dinter, R., Tekinerdogan, B., & Catal, C. (2022). Predictive maintenance using digital twins: A systematic literature review. *Information and Software Technology, 151*, Article 107008. https://doi.org/10.1016/j.infsof.2022.107008

Viccione, G., Evangelista, S., Armenante, A., & Ricciardi, V. (2019). Clogging process and related pressure drops in wire-wound filters: Laboratory evidence. *Environmental Science and Pollution Research, 27*(19), 23464–23476. https://doi.org/10.1007/s11356-019-05628-7

Wu, C.-H., & Chern, J.-M. (2006). Experiment and simulation of sludge batch settling curves: A wave approach. *Industrial & Engineering Chemistry Research, 45*(6), 2026–2031. https://doi.org/10.1021/ie0510730

Xie, B., Li, S., Jin, H., Hu, S., Wang, F., & Zhou, F. (2018). Analysis of the performance of a novel dust collector combining cyclone separator and cartridge filter. *Powder Technology, 339*, 695–701. https://doi.org/10.1016/j.powtec.2018.07.103

Yu, J., Cao, C., & Pan, Y. (2021). Advances of adsorption and filtration techniques in separating highly viscous crude oil/water mixtures. *Advanced Materials Interfaces, 8*(16), Portico. https://doi.org/10.1002/admi.202100061

Zhang, X., & Liu, J. (2022). Simplified model for the calculation of the particle capture process in air filter media. *Chemical Engineering Science, 249*, Article 117358. https://doi.org/10.1016/j.ces.2021.117358

Zhong, D., Xia, Z., Zhu, Y., & Duan, J. (2023). Overview of predictive maintenance based on digital twin technology. *Heliyon, 9*(4), e14534.