Dynamical Flow Rate and Pressure Artificial Neural Network Estimators for a Centrifugal Fan Driven by an Induction Motor Drive

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***Abstract*— To provide significant energy saving in the air and water supply systems, centrifugal fans/pumps are driven by variable frequency induction motor drives. To reduce the cost of the required energy saving close loop control, the necessary expensive flow rate or pressure (head) sensors can be replaced by estimators based on the monitored variables of the drives and imbedded into the drives' software. Available estimation techniques are based on the steady state experimental or data sheet fans'/pumps' curves which is justified by quasi-steady modelling of the fans and pumps. The present paper identifies the problem of this approach during transients. It develops quasi-steady and dynamical estimators for the flow rate and pressure of a centrifugal fan with induction motor drive based on the neural networks trained based on the steady state and transient experimental data. It uses the referred frequency of the stator voltages, the measured rms stator current and the estimated input active power of the motor as inputs of the estimators avoiding the velocity estimation as in the available approaches. It demonstrates better dynamical performance of the dynamical estimators with one sample time delayed feedback as the additional input which is justified by dynamical modelling of the fans/pumps. The details of a specifically designed test rig based on the Nicotra-Gebhardt industrial centrifugal fan equipped with a three-phase induction motor and estimators' design procedure are explained.**

Keywords—AC Motor Drives Control and Applications; Observers and Sensorless Methods; Artificial Neural Networks

I. INTRODUCTION

Energy saving control in air and water supply systems is achieved via using centrifugal fans and pumps driven by induction motor drives and it is based on the fact that the power consumed for the air/water transportation is proportional to the fans/pumps cubic velocity. It can be an open loop system which follows some consumption schedule, or it can be a close loop system, usually a stabilization system, which can accurately track consumers' demand. In the last case it requires corresponding sensors of the flow rate or pressure (head) which costs, for low power applications, are comparable with the costs of the fans/pumps with the driven motors. Therefore, the reduction of the costs for the close loop control implementation of the flow rate and pressure (head) can be achieved via replacing these sensors by corresponding estimators processing the available measurements from the electrical drives. It also reduces the maintenance costs.

Usually, the fans/pumps drives implement the scalar V/f^2=const regulation providing good matching between the critical motor torque and the load torque developed by the fans/pumps in the whole control range [1], [2]. It does not require velocity sensors and the motors are not equipped with them. Sensorless motor control more relates to the field-oriented control and includes the motor velocity estimation based on electrical measurements [3]–[6]. Modern industrial induction motor drives can monitor (estimate) the shaft velocity and shaft power both for the scalar and field-oriented approaches. The sensorless control of the centrifugal fans and pumps is defined as a close loop control without the flow rate, pressure (head) and velocity sensors [7]–[10].

Further analysis is dedicated to the estimation approaches for the flow rate and pressure (head) based on the available cheap measurements in the drives. Since the operation principles of the centrifugal fans and pumps are the same, the estimation methodologies are the same as well. Note that the estimations are impossible for inhomogeneous water or air systems because the power at any particular operating point will vary greatly depending on the quantity of solid particles in the water or air [11].

The standard (QP-curve-based) method [12] of the head and flow rate estimations of the centrifugal pump utilizes two (either experimental or data sheet) pump steady state curves for rated velocity: the dependence of the head on the flow rate (QH curve) and the dependence of the shaft power on the flow rate (QP curve). The main drawback is that this estimation is achieved via auxiliary estimations. The estimated motor velocity is used to modify the pump's curves and along with the estimated input active motor power (because of the PWM voltages) or shaft power to determine the flow rate and head from the modified curves. Besides there are possible flat regions of the pump curves preventing accurate estimations and the affinity laws are not accurate if the velocity changes more than 20% [13].

A set of experimental curves obtained for different velocities can be used instead in the form of look-up tables or polynomial or artificial neural network approximations.

The process-curve-based estimation method [12] is based on the process QH curve (the characteristic of the pump load), affinity laws and the estimated velocity. The method is applicable for the cases when the parameters of the process curve are constant during the estimation.

Paper [12] also proposes a hybrid method which means using the QP curve-based method for an allowed velocity range and where the QP curve is not flat, and otherwise the process-curve-based method is used. The main challenge of the hybrid method is in the selection of the areas where the two methods are switched. Note that all estimation methods in [12] are based on steady state curves and they are assessed only for steady state operation.

Paper [14] focuses on the accuracy of the QP curve-based and the process curve-based methods of estimation. The observations provided conclude that usually the data sheet QH curves are very accurate and the data sheet QP curves are less accurate which causes estimation errors if the data sheet curves are used instead of the experimental ones.

Paper [15] develops the estimation of the head and flow rate based on the measured stator current rms for the case when the motor is fed from a constant AC voltage source. 16% flow rate estimation steady state error is reported for this approach which is suitable for energy audit technique for a high power pump supplied directly from the grid.

Paper [13] proposes a QH/QP method of estimation. It combines a QH method, which in fact means using this curve for the flow rate determining based on the measured pressure/head and estimated velocity, and the QP curve-based method. Uncertainty factors are determined for the corresponding operating points and the best method is applied or an average estimate from both methods is computed. This combined method is applicable only for cases with the pressure/head measurements. It is validated experimentally only in steady states and no dynamics is presented.

The feature of this paper [16] is that it develops the flow rate and head estimation algorithms along with the estimation of the driving motor's velocity and load torque whereas other papers assume the motor's velocity and shaft power estimation known. The Extended Kalman Filter is designed to predict the motor velocity and load torque. The flow rate is estimated via real time solving of a cubic equation in flow rate whose parameters depend on the velocity, shaft power and head at zero flow rate. The efficiency is assumed to be constant restricting the possible sensorless control range. The head estimate is computed from the approximation of the QH curve whose coefficients depend on the velocity, head at zero flow rate and hydraulic resistance of the pump.

Paper [8] develops a quasi-steady model of a centrifugal pump using standard approximations of the QH and QP curves with added approximation for the pump efficiency as a third order polynomial. The estimation of the flow rate is based on the estimated velocity and shaft power using dual neural network architecture.

Paper [17] validates experimentally that in the well-known quadratic approximation of the QH curves the frequency of the motor voltage can replace the velocity with sufficient accuracy. However, this is not the case for the QP curves. Instead, the paper succeeds in development of a three layers feed-forward backpropagation neural network head estimator based on experimental data. The estimator is assessed during steady states and transients using a specially developed pump model.

Paper [7] designs neural network estimators for the flow rate and pressure of a centrifugal fan based on the experimental data of the steady state QH and QP curves (quasi-steady model) for various frequencies of the stator voltage. The velocity estimation is eliminated from the algorithm via using the frequency, measured stator current rms and active motor power as the inputs of the estimators. Like all methods discussed above it is based on steady state fan curves and experimentally assessed in steady states only.

The present paper extends the previous results of the authors in [7] via demonstrating the problems of quasi-steady estimations during transients and develops artificial neural (ANN) estimators based on dynamical data. A specially developed test rig and design procedure are explained. A comparison of the operation of the quasi-steady estimators and dynamical estimators is provided to demonstrate the advantage of the proposed technique.

II. Experimental Testing of a Centrifugal Fan

A. Test Rig Description

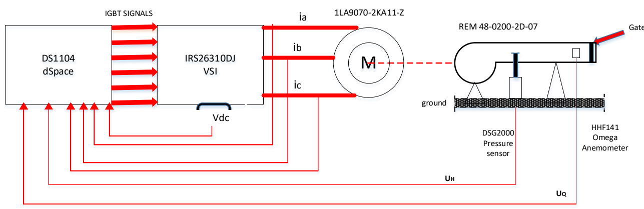

Fig. 1. Functional block diagram of the control prototyping test rig of the centrifugal fan.

The test rig is based on the REM 48-0200-2D-07 industrial centrifugal fan from Nicotra-Gebhardt (see Fig.1 and Fig. 2). The recommended operating point is at 1215 m^3/h flow rate, 680 Pa pressure and 2840 rpm velocity, which provides 53.5% efficiency. The fan is equipped with the 0.37 kW delta-connected Siemens three-phase squirrel-cage induction motor 1LA9070-2KA11-Z. The rated voltage is 230 V, and the rated velocity is 2840 rpm.

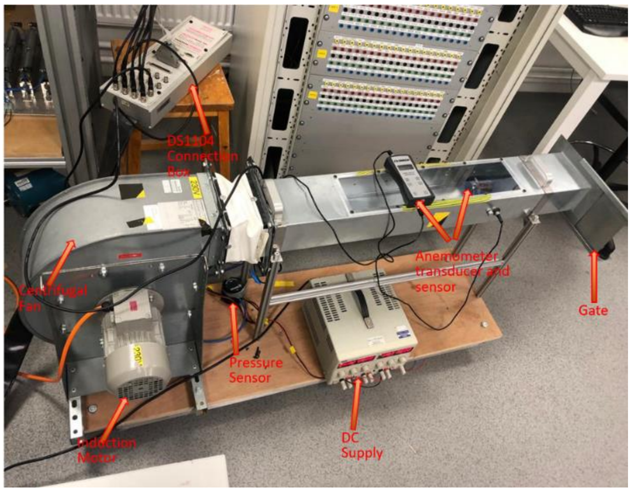

Fig. 2. The test rig of the centrifugal fan.

The IRS26310DJ gate driver evaluation board powers the induction motor through a two-level full-bridge three-phase voltage source inverter (VSI) based on IGBTs. The board also includes a single-phase full-bridge diode rectifier and a DC link capacitor. The rectifier's input rated voltage is 230 V RMS. The inverter's rated continuous output power is 400 W. The evaluation board's digital control is turned off. The dSpace DS1104 controller board implements the ramp unit for the linear frequency reference increase, the V/f^2=const control algorithm, sinusoidal PWM modulation, analogue-to-digital conversion of the output voltages of the DC voltage sensor (based on LV 25-P) and the stator currents sensors (based on LTS 6-NP). The PWM pulses are supplied to the board via digital isolators.

The fan's output is linked to an air duct. A gate is used to manually control the output area of the duct from fully open to fully closed. The Anemometer HHF141 Omega with the turbine installed inside the duct measures the air flow rate. The differential pressure sensor Ziehl Abegg DSG2000 measures the air pressure in the duct. The outputs of both sensors are DC voltages converted into digital signals via DS1104. The designed ANN estimators are run in real time by the DS1104 as well. The experimental data for ANNs' training are recorded through the ControlDesk software.

B. Experimental Data Acquisition

The gate is used to close the duct of the system. The width of the centrifugal fan's duct is 11cm and it has been marked for each centimetre as shown in Figs. 3.a and 3.b.

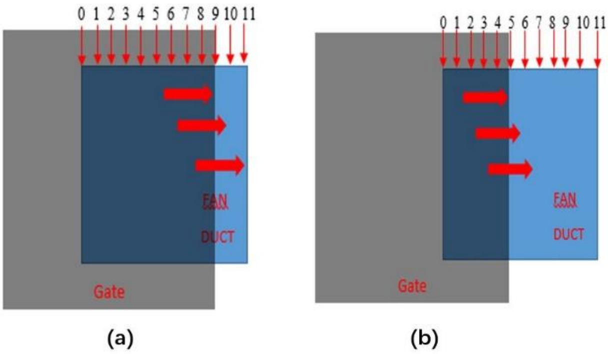

Fig. 3. Fan obstruction at position (a) 9 cm and (b) 5 cm closed, respectively.

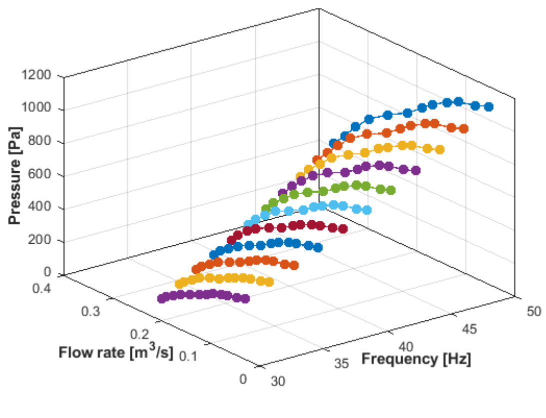

Fig. 4. Experimental f-*Q*-*H* characteristics of the centrifugal fan.

The steady state data were collected as follows. The frequency is kept constant at intervals of 2 Hz between 30 Hz and 50 Hz. The gate position varies between 0 and 11 with a step of 1 cm for each constant frequency. The obtained experimental centrifugal fan's Q-H characteristics are shown for 11 various frequencies in Fig. 4. In total, the data base includes 132 operating points. For each operating point the estimated input active power of the motor was computed based on the stator voltage references and measured stator currents in α-β stator stationary reference frame, in the dSpace controller. The RMS stator current was computed in real time based on the measured instantaneous stator currents.

For the dynamical tests, the fan was started smoothly till the frequency reached 50 Hz at a certain gate position. Then the frequency was changed by step several times allowing the flow rate and pressure to reach their steady state values. Then the gate position was smoothy changed which was followed by several step frequency changes. The frequency range covered is from 47 Hz to 50 Hz and the step changes used are either 1 Hz, or 2 Hz or 3 Hz. The step responses were recorded with the sample time of 0.0012 s which provides more than 200000 recorded points.

III. Artificial Neural Network Estimators Design

In the paper, three-layer feed-forward backpropagation ANNs are used for all flow rate and pressure estimators, with hyperbolic tansig as activation function of the first and second layers neurons and purelin for the third output layer neuron. The Matlab nntool is used for ANNs design. Bayesian Regularization (trainbr in Matlab) is used as a training function for all estimators. The gensim Matlab command converts the trained ANNs into Simulink blocks used for real time implementation in dSpace controller and for simulations.

We define three types of the estimators based on the trained data used. Quasi-steady estimators are the ANNs trained based on the experimental data of the 132 steady state operating points. The inputs are the reference frequency, the measured RMS stator current and the estimated input active power of the motor. For the flow rate estimator there are 3, 3 and 1 neurons in the corresponding layers whereas for the pressure estimator these are 5, 5 and 1 neurons [7]. The number of neurons in the first and second layers were selected iteratively, with the estimation accuracy meeting the ISO 13348 criteria [18]. The term quasi-steady is borrowed from the quasi-steady modelling of the centrifugal fan (without own dynamics) which flow rate and pressure are changed synchronously with the change of the motor velocity. The architecture of the estimators is shown in Fig. 5 and Fig.6.

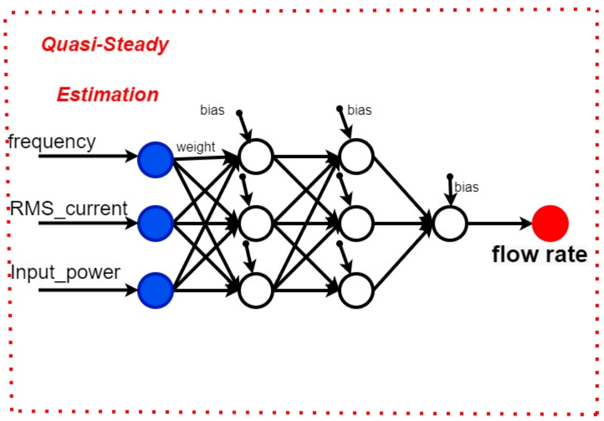

Fig. 5. Quasi-steady ANN estimation architecture for flow rate

The own dynamics of the pump/fan, additional to the motor dynamics, is introduced in the modelling via a nonlinear differential equation of first order for the flow rate [16]. Respectively, we introduce two types of dynamical estimators for the flow rate and pressure trained based on experimental transients. The first ones have the same inputs as the quasi-steady estimators. The second ones have an additional input with the flow rate/pressure estimated at the previous ANN sample time to account for the own fan's dynamics. All dynamical estimators have 5, 5 and 1 neurons in the corresponding layers. The architecture of the dynamical estimators is depicted in Fig. 7 where z^{-1} denotes one sample time delay of the ANN.

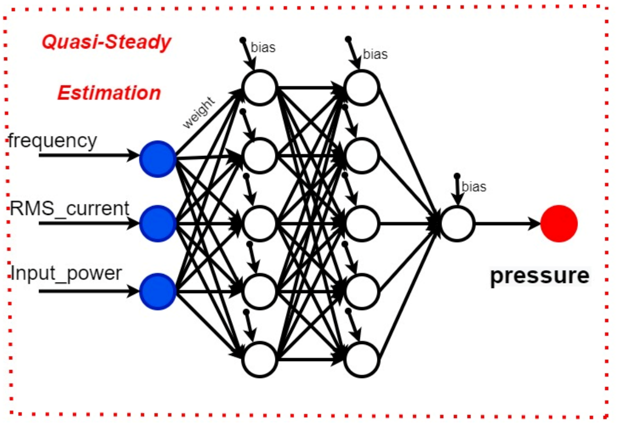

Fig. 6. Quasi-steady ANN estimation architecture for pressure

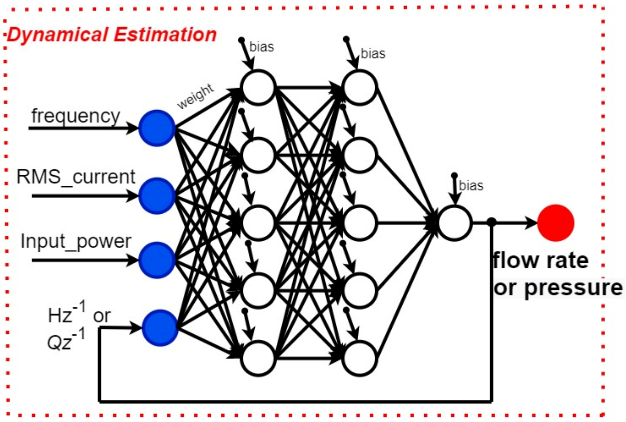

Fig. 7. Dynamical ANN estimation architecture

IV. Results

A. Steady State Estimations

The quasi-steady estimators demonstrated a high accuracy in steady states. The relative error obtained for the 132 operating points are shown in Figs. 8 and 9.

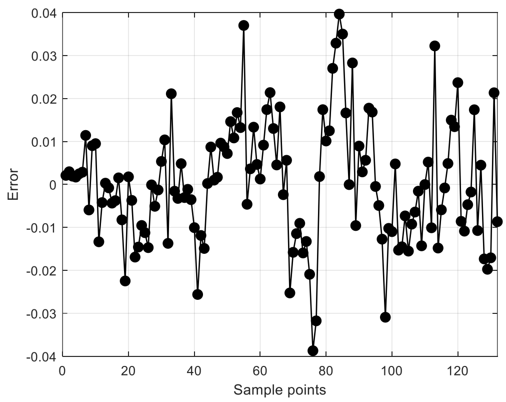

Fig.8. Steady state error between measured and estimated pressure.

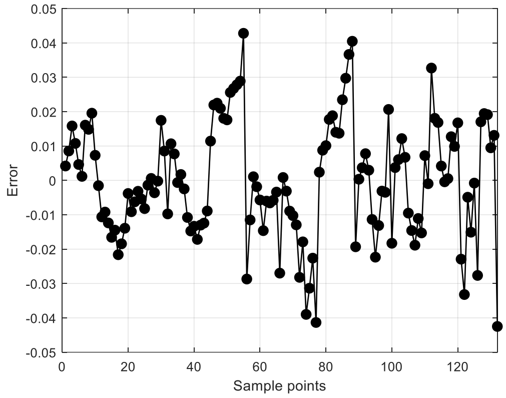

Fig.9. Steady state error between measured and estimated flow rate.

B. Estimation during Transients

The experimental transients are caused in the fan via step changes in the frequency as shown in Figs. 10-15 and in the middle of the process the gate smoothly changed position from 7 cm to 6 cm. These transient data were used for training the ANNs. Figs. 10 and 11 show the simulated operation of the quasi-steady estimators during the recorded experimental transients. It can be observed that these estimators fail to accurately predict the pressure and flow rate during transients. A sensorless control system based on them must be implemented quite slow to be considered quasi-steady.

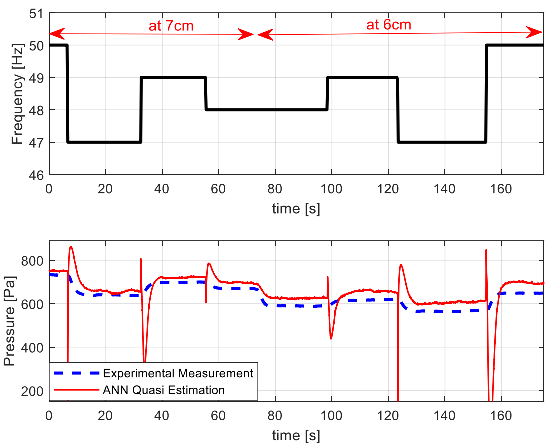

Fig.10. Pressure quasi-steady estimation compared with measured pressure.

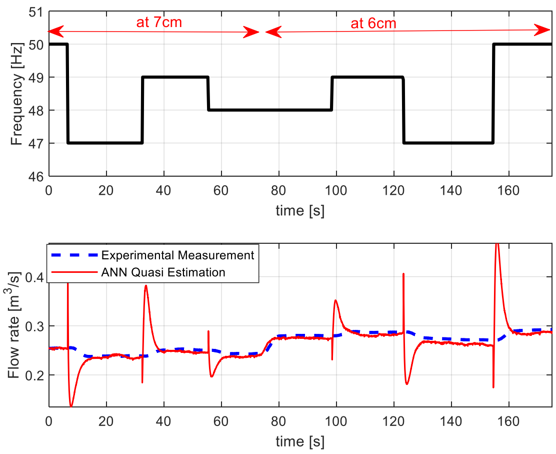

Fig. 11. Flow rate quasi-steady estimation compared with measured flow rate.

Figs. 12 and 13 illustrate the quality of the dynamical estimation without the one sample time delayed pressure/flow rate ANN feedback. Although the estimations are in general quite accurate, there appear some spikes which will cause disturbances in the pressure/flow rate close loops. The figures show the simulated estimation during the recorded experimental transients used for training.

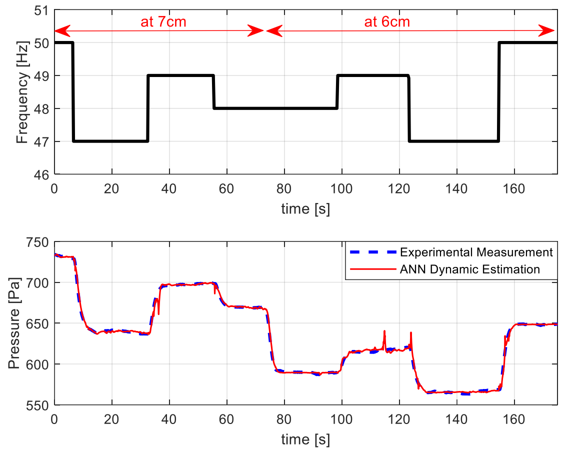

Fig. 12. Pressure dynamic estimation compared with measured pressure when inputs are frequency, RMS current and input power.

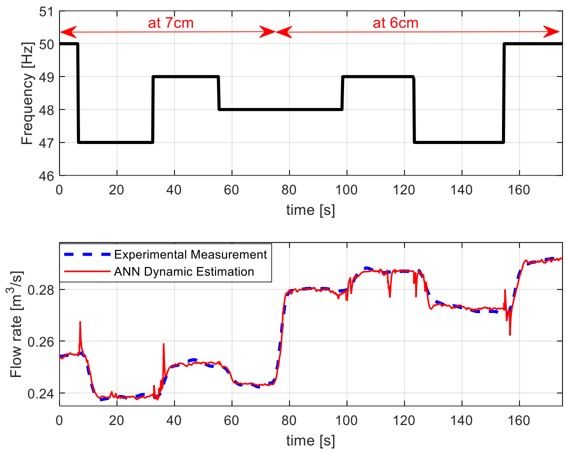

Fig. 13. Flow rate dynamic estimation compared with measured flow rate when inputs are frequency, RMS current and input power.

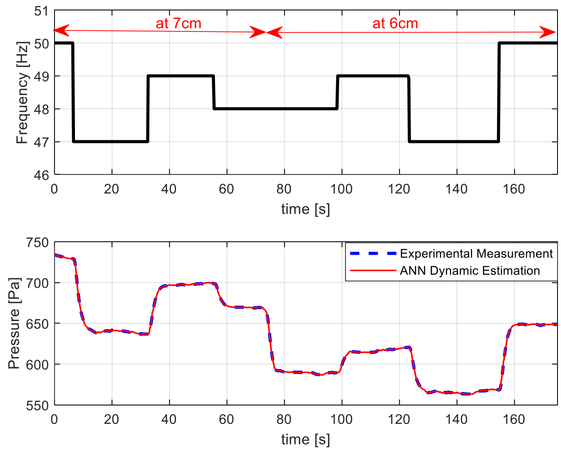

Fig. 14. Pressure dynamical estimation compared with measured pressure when inputs are frequency, RMS current, input power and measured pressure delayed by one sample time.

Figs. 14 and 15 report the results for the dynamical estimations with the one sample time delayed pressure and flow rate ANN feedbacks. The quality of the dynamical estimation is better than for two other types of the estimators. The figures show the simulated estimation during the recorded experimental transients used for training.

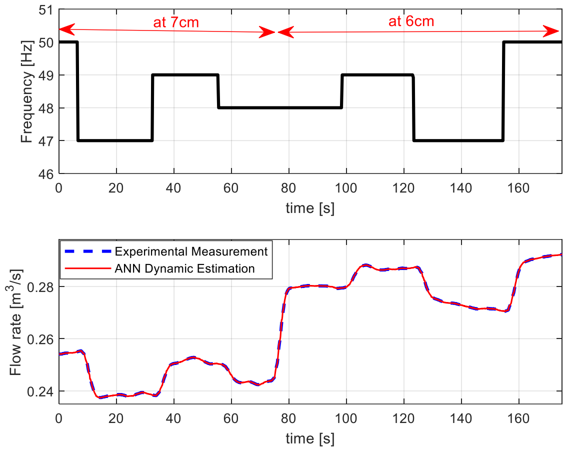

Fig. 15. Flow rate dynamic estimation compared with measured flow rate when inputs are frequency, RMS current, input power and measured flow rate delayed by one sample time.

C. Estimation during Untrained Transients

Figs. 16 and 17 show the results of the simulated dynamical estimation with the one sample time delayed pressure and flow rate ANN feedbacks during the recorded experimental transients not used for training at 8 cm gate position. The accuracy of the estimation remains high. Further improvement of the estimation will require more dynamical training data within the expected control range.

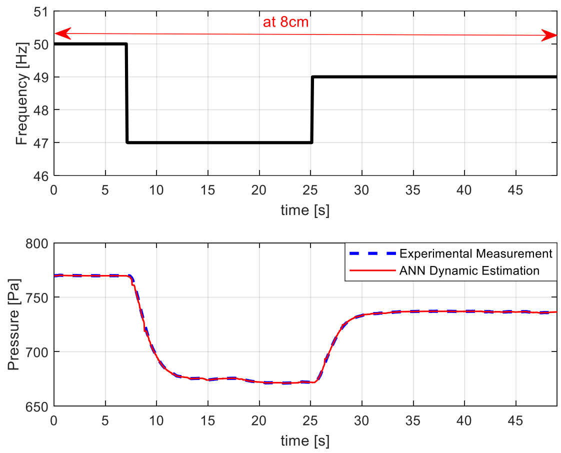

Fig. 16. Untrained dynamical pressure estimation.

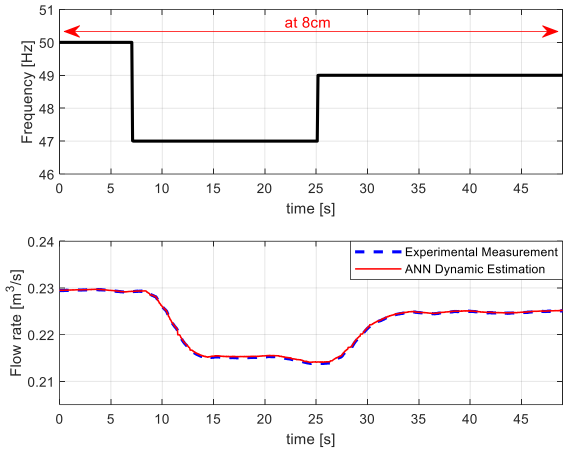

Fig. 17. Untrained dynamical flow rate estimation.

V. CONCLUSION

The paper identifies the problem of quasi-steady flow rate and pressure estimators of centrifugal fans with induction motor drives during transients. It develops quasi-steady and dynamical estimators based on the neural networks trained based on the steady state and transient experimental data. It uses the referred frequency of the stator voltages, the measured rms stator current and the estimated input active power of the motor as inputs of the estimators avoiding the velocity estimation as in available approaches. It shows better dynamical performance of the dynamical estimators with one sample time delayed feedback as the additional input which is justified by dynamical modelling of the fans/pumps. The methodology will be the same for any centrifugal fans or pumps which can also have different type of duct, but individual training data should be obtained.

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