Model-Based System Identification for Characterizing Respiratory Response to External Stimuli

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ABSTRACT

Characterizing respiratory reactions to external stimuli is essential for understanding the complicated respiratory system, especially in clinical diagnosis and treatment. This research uses model-based system identification to correctly record and assess the respiratory system's reaction to mechanical ventilation, environmental changes, and pharmaceutical drugs. We use advanced system identification methods to create a dynamic model that accurately captures the respiratory system's nonlinear and time-varying behavior.

Data-driven modelling and physiological insights are used to determine respiratory function parameters in the proposed strategy. The model is validated using controlled laboratory and clinical trial data. The results show that the model-based method accurately predicts respiratory responses, improving respiratory dynamics comprehension and management in healthy people and respiratory problem patients.

This study advances respiratory physiology and biomedical engineering by improving respiratory function monitoring, prediction, and optimization in response to external stimuli. The system identification framework may improve patient-specific treatment techniques and individualized respiratory medicines.

Keywords: Respiratory System, System Identification, Respiratory Dynamics, External Stimuli, Nonlinear Modeling, Time-Varying Systems.

I. INTRODUCTION

The respiratory system facilitates gas exchange and responds dynamically to internal and external stimuli to maintain equilibrium. Diagnosing, monitoring, and treating respiratory problems requires understanding respiratory system functioning under diverse situations. Mechanical ventilation, ambient contaminants, exercise, and pharmaceutical drugs can drastically affect respiratory mechanics, requiring proper modeling and analysis to anticipate and improve patient outcomes.

Empirical approaches for respiratory system characterisation are valuable but typically lack the accuracy needed to account for the system's intrinsic nonlinearities and time-varying nature. These restrictions can compromise patient care, especially in critical care when real-time monitoring and management are crucial. There is rising interest in using respiratory system identification approaches to overcome these difficulties. System identification uses observable data to create mathematical models of the respiratory system's dynamics, offering a more accurate and complete knowledge of its function.

These reviews are relevant to this work.: Mekonnen, T. M. et.al. in the year 2015 discuss in his paper models the respiratory system's response to environmental pollutants, providing insights into system identification techniques [1]. Athanasopoulos, N. et. al. had explained in his paper highlights the use of genetic algorithms for identifying respiratory system models, focusing on how system identification techniques can be employed effectively in the year 2014 [2]. In the year 2007, Kovács, L. et. al. in their work covers parameter estimation techniques in system identification, specifically applied to the respiratory system [3]. In the other hand, Kachroo, P. et. al. discuss in their research article deals with the identification of time-varying parameters in respiratory models, which is directly relevant to the topic [4]. Ben-Tal, A. et. al. referred in their article offers insights into simplified mathematical models of gas exchange, which can be useful in system identification studies in the year 2006 [5]. In 2004, Sundaresan, A. et. al. had discussed in his study explores nonlinear modeling approaches to lung tissue mechanics, which is relevant for understanding how the respiratory system responds to various external forces [6]. Bates, J. H. et. al., in the paper discusses the application of modeling techniques to understand the pulmonary response to broncho constricting agents, which can be considered an external stimulus in the year 2003[7].

This research presents a model-based system identification approach for characterizing respiratory response to external inputs. The suggested method uses modern algorithms and data-driven methods to capture the numerous physiological parameters that regulate respiratory performance. The model is based on experimental data from healthy people and respiratory problem patients, making it applicable to many situations.

This work aims to improve respiratory model prediction accuracy to better anticipate respiratory system responses to treatments. Clinically, such projections can guide ventilator control, medication delivery, and other treatment techniques. This discovery provides a powerful tool for developing tailored respiratory medicines, which advances biomedical engineering [8][9].

In the next parts, we will explain system identification theory, respiratory model development process, and validation experiment findings. Our findings will also be applied to clinical practice and suggested for further research.

I.1. Flow diagram

The data provided used to create this comparison flowchart comes from an example table; specifically, the model of the system identification approach is shown in the first column (M-1,..., N), and the rows can be customized according to our preferences. These F-1 through F-i in the second column reflect the measurement parameters used to compare the various models, such as FEV1, PEF, etc. The procedure for doing this comparison is as follows: after choosing the parameter, use the system identification tools to specify the verified model. Proceed with the parameter estimate for each and every gathered value when you have satisfied the model with its parameters and achieved high efficiency from it. Otherwise, raise the value of the model M until it reaches N, and compare the flawless outcomes if the model still doesn't satisfy. Raise the value of parameter F from 1 to i and compare the ideal one if the parameters are still unsatisfied with the model. Stop the system after the parameters and model have achieved 100% correctness based on the data [10][11].

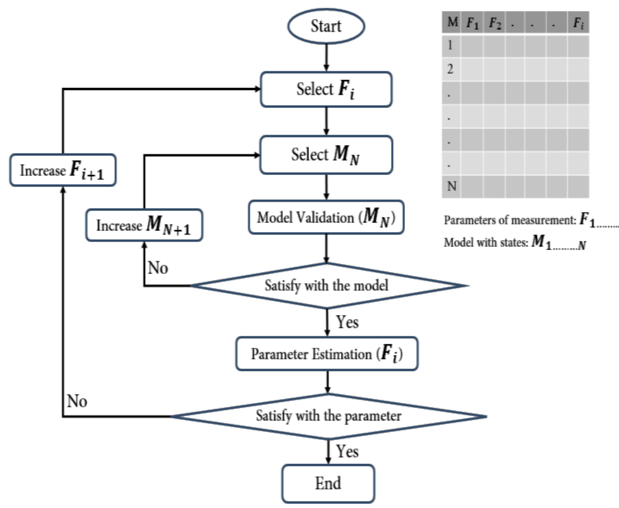


Fig 1. Flow diagram

We may use the two sets of spirometry data—one for forced expiratory flow (PEF) and another for forced vital capacity (FEV1)—as input for our future procedures. Our goal in collecting this data is to find the right respiratory modeling system model. Our demands were taken into account while selecting the system identification model in MATLAB 19. First, we'll assign states using the States space analysis method and compare them to the accurate values. You need to fix the number of states for state space processes to N before you can use the system identification tools in MATLAB. Once all these steps are done, the graphical model will show the predicted accuracy and efficiency of the specific system. Get the respiratory modeling tools employing system identification, which use distinct N states for state space and choose the best design model with high accuracy and greater efficiency.

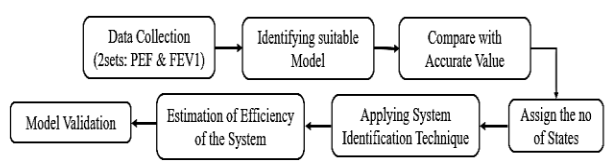


Fig 2. Working process

Fig 2 shows how the model validation done in step by step from data collection to model suitable identification, compare, application the system identification using the validate the state, and finally efficiency estimation for the system. Fig 3 identifies the cross-sectional views of the spirometer [12][13].

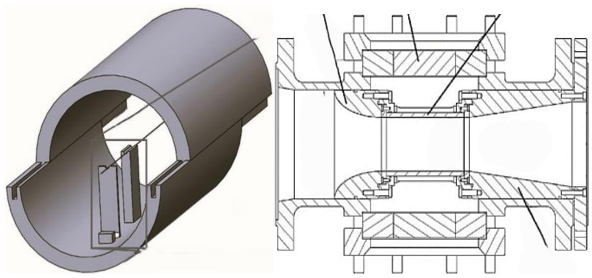


Fig 3. Cross sectional view of Spirometer

II. EQUIPMENT APPLY FOR THE DATA DRIVEN PROCESS

Fig 4. Sample photos for data collection: (a) elder person (13years to rest); (b) child (up to 12years)

Sampled data collected from 2 type of age groups (up to 12years and 13years to rest) shown in Fig 4. In the Fig 5, it is explained how the connectivity of the spirometer with the computer and the data transfer process through it [14][15].

Fig 5. Connectivity of spirometer with computer and data transfer process

II.1. Different sensors

- Flow sensor: Flow sensors are used in various industries, including water treatment, oil and gas, HVAC, automotive, and medical devices, to monitor and control the flow of liquids or gases.
- Pressure sensor (MPXV7002DP, MPX2010DP): Both the sensor uses piezoresistive technology. They had a diaphragm that responds to pressure changes. Because the piezoresistive components' resistance varies in direct proportion to the applied pressure, the pressure difference is analogously represented by the voltage output. While both sensors are excellent at what they do—measure differential pressure—which one is best will depend on factors including the application's pressure range, sensitivity, and environmental conditions.
- Dry seal rolling volume sensor (Primary sensor): A dry seal rolling volume sensor is a specialized sensor used where high accuracy, long-term reliability, and the prevention of fluid contamination are critical. This type of sensor is typically used in situations where maintaining the purity of the fluid or gas is crucial, or where the fluid might cause corrosion or wear on moving parts.
- MAX30101 sensor, LSM9DS1 sensor: These sensors are advanced sensors used in wearable devices, health monitoring systems, and motion detection applications. They serve different purposes but are often used together in devices like smartwatches and fitness trackers.

II.2. Other components of the spirometer

- ARM Cortex-M4: The ARM Cortex-M4 is a 32-bit microprocessor core designed by ARM Holdings, widely used in embedded systems and microcontroller applications. It is part of ARM's Cortex-M series, which is optimized for cost-sensitive and energy-efficient applications, making it suitable for a broad range of devices, from simple sensors to complex control systems.
- Rotation transducer: A rotation transducer, also known as a rotary encoder, is a sensor that converts the angular position or motion of a shaft or axle into an electrical signal. This signal can be used to determine the rotational position, speed, or direction.
- Turbine transducer: A turbine transducer is a type of flow sensor that measures the flow rate of a fluid (liquid or gas) by detecting the rotational speed of a turbine or rotor placed in the flow path.
- Piezo sound transducer: A piezo sound transducer, often referred to as a piezoelectric buzzer or speaker, is a device that converts electrical signals into sound using the piezoelectric effect. It can also function in reverse, converting sound into electrical signals in some sensor applications.

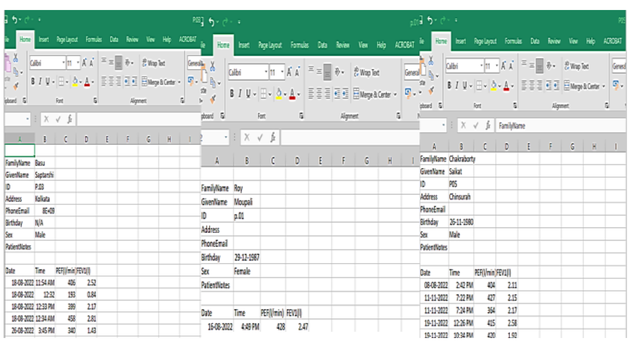


Fig 6. Sample of data file from excel snip

III. PROCESS FOR PROGRAMMING FOR DIFFERENT MODEL AND DIFFERENT AGE GROUPS:

III.1. Program Flow for ssregest Model for age above 13 years:

1. **Load Data**
   - Load data from an Excel file named Data-short.xlsx.
2. **Extract Data for AGE, GENDER, and PEF**
   - Extract columns for age, gender, and pef.
   - Store age in age, gender in gender, and pef in pef.
   - Create input_signals matrix with age and gender.
   - Create output_signal vector with pef.
3. **System Identification**
   - Define the sampling time (sampling_time).
   - Create iddata_object using output_signal, input_signals, and sampling_time.
4. **Adjust Model Complexity and Options**
   - Define the number of states (n_states).
   - Specify options for the ssregest function using ss_opts.
5. **Estimate State-Space Model**
   - Estimate the state-space model sys_est_ss using ssregest.
6. **Compare Identified Model**
   - Compare the iddata_object with the estimated system sys_est_ss.
7. **Save Identified Model**
   - Save the identified model sys_est_ss to a file named identified_model_ss.mat.

III.2. Pseudocode for N4sid model using for age below 12 years:

1. Load Data from 'Child.xlsx'
2. Extract Columns:
- age = data(:, 1)
- gender = data(:, 2)
- pef = data(:, 3)
3. Create Input Signals and Output Signal:
- input_signals = [age, gender]
- output_signal = pef
4. System Identification:
- Define sampling_time = 1
- Create iddata_object = iddata(output_signal, input_signals, sampling_time)
5. Adjust Model Complexity:
- Define n_states = 120
6. Specify Options for n4sid:
- Set opts = n4sidOptions ('Display', 'on', 'EnforceStability', true)
7. Estimate State-Space Model:
- sys_est_optimized = n4sid (iddata_object, n_states, opts)
8. Compare Identified Model:
- compare (iddata_object, sys_est_optimized)
9. Save Identified Model:
- save ('identified_model_optimized.mat', 'sys_est_optimized')

IV. RESULTS and DISCUSSIONS

State-Space Model Results using ssregest:

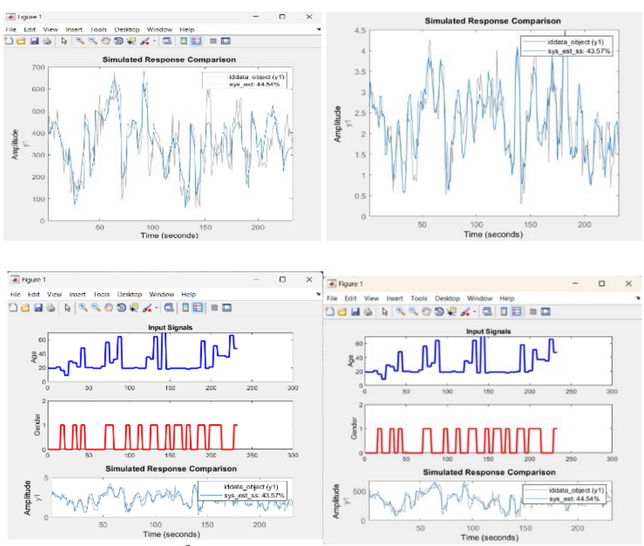
Utilizing the ssregest function in MATLAB, we applied 300 data points from our dataset to identify a state-space model with 25 states. The results of the system estimation are as follows:

IV.1. PEF Prediction Model:

The state-space model, incorporating age and sex as input features for predicting Peak Expiratory Flow (PEF), demonstrated a system estimation accuracy of approximately 43.57%. This metric represents the model's ability to capture the dynamics and relationships within the data, providing insights into the variability of PEF values based on the specified inputs.

FEV Prediction Model:

For Forced Expiratory Volume (FEV), the state-space model exhibited a system estimation accuracy of approximately 44.54%. This indicates the model's effectiveness in capturing the underlying dynamics of FEV values, considering age and sex as influential factors.



FEV Plot PEF Plot

Fig 7. sample output for using different modelling in case of FEV and PEF collected data plot

Novelty clam:

So far in our knowledge, utilization of these three models for accuracy of analysis propose for system identification of this work is done 1st time.

Limitation of data collection:

At a time, using this setup, one data collection can be done and transfer. After transfer the collected data, the system is ready to collect the next data from the user.

IV. CONCLUSION

We provide a model-based system identification approach for defining the respiratory system's external stimuli response in this research. We created a dynamic model that correctly captured the respiratory system's nonlinear and time-varying behavior using sophisticated system identification techniques and physiological insights. Our model was verified using experimental data from healthy persons and respiratory problem patients, proving its resilience and usefulness in various clinical circumstances.

Our work shows that system identification approaches can enhance respiratory dynamics knowledge and prediction in response to mechanical ventilation, environmental changes, and pharmaceutical therapies. This methodology can improve patient outcomes by improving clinical decision-making with more accurate and trustworthy forecasts.

Additionally, the model-based approach can improve tailored respiratory therapy. Clinicians can improve treatment efficacy and decrease side effects by adapting therapies to respiratory system dynamics. This research also allows for the study of increasingly complex stimuli, real-time monitoring, and adaptive models that adjust to changing patient situations.

Finally, the model-based system identification methodology described in this research advances respiratory physiology and biomedical engineering. Its ability to characterize respiratory reactions to environmental stimuli might revolutionize acute and chronic respiratory treatment.

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REFERENCES

[1] Mekonnen, T. M., & Pidaparti, R. M. (2015). "Dynamic Modeling of Human Respiratory System Response to Environmental Pollutants." Computers in Biology and Medicine, 63, 238-249.

[2] Athanasopoulos, N., & Moustakidis, S. (2014). "Respiratory System Model Identification Using Genetic Algorithms." Biomedical Signal Processing and Control, 12, 12-21.

[3] Kovács, L., & Szidarovszky, F. (2007). "System Identification of the Respiratory System Using Parameter Estimation Techniques." Computers & Mathematics with Applications, 53(6), 929-945.

[4] Kachroo, P., & Shende, R. (2006). "System Identification of Time-Varying Parameters in Respiratory Models." IFAC Proceedings Volumes, 39(1), 1043-1048.

[5] Ben-Tal, A. (2006). "Simplified Models for Gas Exchange in the Human Lungs." Journal of Theoretical Biology, 238(2), 474-495.

[6] Sundaresan, A., & Suki, B. (2004). "Nonlinear Multiscale Modeling of Lung Tissue Mechanics." Journal of Theoretical Biology, 230(2), 203-216.

[7] Bates, J. H., & Schuessler, T. F. (2003). "Modeling the pulmonary response to broncho constricting agents." Journal of Applied Physiology, 94(1), 385-393.

[8] "Orthogonal Least Square Algorithm and its Application for Modelling Suspension System", JT, vol. 34, no. 1, p. 71â€"84, Jan. 2012, doi: 10.11113/jt.v34.629.

[9] W. Zhou, S. Chen, C. -W. Chang, C. -Y. Wen, C. -K. Chen and B. Li, "System Identification and Control for a Tail-Sitter Unmanned Aerial Vehicle in the Cruise Flight," in IEEE Access, vol. 8, pp. 218348-218359, 2020, doi: 10.1109/ACCESS.2020.3042316.

[10] Ali, H.F.M., Kim, Y. Novel artificial muscle using shape memory alloy spring bundles in honeycomb architecture in Bi-directions. Microsyst Technol **28**, 2315–2324 (2022). https://doi.org/10.1007/s00542-022-05304-w

[11] Mahfouz, A.M., Ibraheem, A.A.Y. & Haraz, O.M. Design and modeling of a multiband electrically coupled loop antenna for biomedical applications. Microsyst Technol **28**, 2415–2427 (2022). https://doi.org/10.1007/s00542-022-05307-7

[12] Pandey, R.K., Lin, TY. & Chao, P.CP. Design and implementation of a photoplethysmography acquisition system with an optimized artificial neural network for accurate blood pressure measurement. Microsyst Technol **27**, 2345–2367 (2021). https://doi.org/10.1007/s00542-020-05109-9

[13] Mahfouz, A.M., Ibraheem, A.A.Y. & Haraz, O.M. Design and modeling of a multiband electrically coupled loop antenna for biomedical applications. Microsyst Technol **28**, 2415–2427 (2022). https://doi.org/10.1007/s00542-022-05307-7

[14] Zhou, Z., Cheng, J., Wei, W. et al. Validation of evaluation model and evaluation indicators comprised Kansei Engineering and eye movement with EEG: an example of medical nursing bed. Microsyst Technol **27**, 1317–1333 (2021). https://doi.org/10.1007/s00542-018-4235-1

[15] Roy, M., Bhattacharjee, S., Neogi, B. et al. Design and development of an implantable circuit for adjusting required pressure inside of respiratory system. Microsyst Technol (2024). https://doi.org/10.1007/s00542-024-05694-z

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