IN SILICO SIMULATIONS OF LUNG RECRUITMENT IN PATIENTS VENTILATED WITH AN INNOVATIVE DEVICE FOR CPAP THERAPY

A. Formaggio[1,2], M. De Luca[1,2], G. Putame[1,2], S. Borrelli[1,2], A. L. Audenino[1,2] and M. Terzini[1,2]

1. Department of Mechanical and Aerospace Engineering, Politecnico di Torino, Torino (Italy)
2. Polito[BIO]Med Lab, Politecnico di Torino, Torino (Italy)

Introduction

CPAP (continuous positive airway pressure) therapy, widely used during the COVID-19 pandemic, is traditionally delivered in an open-configuration, to treat patient with hypoxemic respiratory failure. Recently, a new non-invasive ventilation system was proposed [1], exploiting a closed-loop circuit, able to reduce the oxygen consumption and the viral load dispersion in the environment. In acute respiratory distress syndrome (ARDS), typical complication of COVID-19 disease, CPAP promotes the recruitment of non-aerated alveoli and improves arterial oxygenation [2]. In this study, an *in silico* model was developed and experimentally validated, to analyse the effect of different CPAP levels on lung recruitment, with the final aim of selecting the most effective therapeutic pressure for the patient.

Methods

The patient and the ventilation systems were reproduced as a lumped model (Figure 1) in Simscape (Mathworks).

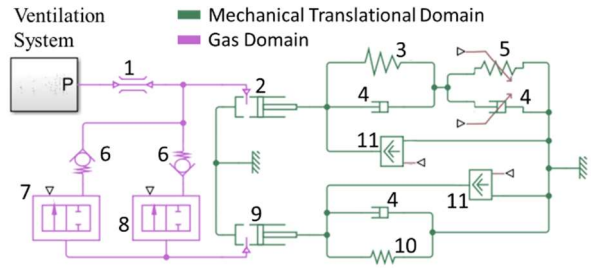

Figure 1: Schematics of the patient model 1) Airways; 2) Lung; 3) Non-linear lung compliance; 4) Tissues damping; 5) Variable compliance of recruitable alveoli; 6) Check valves; 7) Recruitment valve; 8) Collapse valve; 9) Collapsed alveoli; 10) Recruitment/collapse compliance; 11) Respiratory muscles.

Two conditions were evaluated, one involving external ventilation of a patient in apnoea, and the other involving treatment of a breathing patient using various CPAP levels in a closed-loop circuit. In this latter case, the device imposes CPAP at the patient's airway entrance, while a simulated muscles contraction generates the patient breathing. The recruitment valve opens when the alveolar pressure rises above a threshold (P_{rec}), to allow the recruitment of non-aerated alveoli and the increment of the variable compliance. The opposite mechanism occurs when the alveolar pressure drops below the collapse pressure (P_{col}). To validate the model, the ventilation systems were assembled *in vitro* using commercial components and connected to a lung simulator (TestChest® V3). Lung collapse and recruitable alveoli index (R/I) were set at 50% and 0.5, respectively [3]. The lung volume and the alveolar pressure were recorded and compared, computing the R^2 coefficient through regression with the 45-degline.

Results

In both passive and active patient conditions (Figure 2) the *in silico* model was able to capture the *in vitro* behaviour ($R^2 = 0.97$ and $R^2 = 0.95$, respectively). The *in silico* model allowed to analyse the effect of CPAP on aerated and collapsed alveoli separately (Table 1), estimating the efficacy of the therapy (ΔV_{lung} eff) as the lung recruited volume divided by the functional residual capacity increment (ΔFRC). Indeed, a high positive pressure limits the muscles work, reducing the tidal volume (ΔV_{tidal}); however, the alveolar recruitment increases the lung compliance, contrasting that effect.

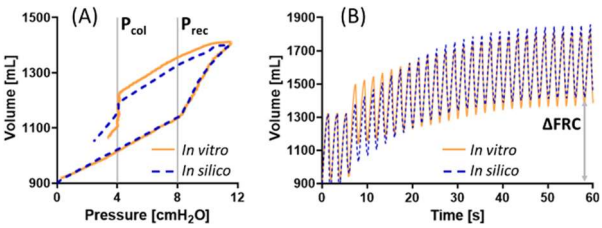

Figure 2: Pressure-Volume and Time-Volume curves for passive (A) and active (CPAP at 6 cmH₂O) (B) patients.

CPAP level	Recruitment	ΔV_{lung} eff	ΔV_{tidal}
4 cmH₂O	0 %	0 %	-11.9 %
6 cmH₂O	19.2 %	50.3 %	8.4 %
8 cmH₂O	37.5 %	54.1 %	21.9 %
10 cmH₂O	40.9 %	50.9 %	23.3 %
12 cmH₂O	43.2 %	47.8 %	21.7 %

Table 1: Comparison of the lung recruitment.

Discussion

This study introduces a novel *in silico* lumped model able to replicate the dynamics of alveolar recruitment during non-invasive ventilation. This innovative feature makes the model a viable tool to understand the most effective CPAP therapy for different types of patients.

References

1. M. Cavaglià et al. Artif. Organs, 45(7): 754-761, 2021.
2. A. Pagano et al. Respir Physiol Neurobiol, 280, 2020.
3. F. M. Beloncle et al, Ann. Intensive Care, 10(55), 2020.

Acknowledgements

This work is part of the NODES project (MUR – M4C2 1.5 of PNRR, grant agreement no. ECS00000036)