Ref. Ares(2020)2673495 - 22/05/2020

EUROPEAN COMMISSION

HORIZON 2020 PROGRAMME - TOPIC H2020-GV-05-2017
Electric vehicle user-centric design for optimised energy efficiency

GRANT AGREEMENT No. 769902

Design OptiMisation for efficient electric vehicles based on a USer-centric approach

DOMUS – Deliverable Report

D1.5 Efficient Cabin Model for Simulating Thermal and Acoustic Behaviour of Car Cabins

Deliverable No.	DOMUS D1.5	
Related WP	WP1	
Deliverable Title	Efficient Cabin Model for Simulating Thermal and Acoustic Behaviour of Car Cabins	
Deliverable Date	2020-04-30	
Deliverable Type	REPORT	
Dissemination level	Public (PU)	
Written By	James Brusey (COV) Matteo Rostagno (CRF)	2020-03-12 2020-04-30
Checked by	James Brusey (COV)	2020-05-06
Reviewed by (if applicable)	Sebastian Möller (ViF)	2020-05-12 2020-05-21
Approved by	IDIADA	2020-05-22
Status	Final	2020-05-22

Change Log

Version	Modifications of document	Author	Date
1	Creation of the document: table of contents, section headings, raw input in some sections (experimentation package, grant agreement, email exchanges)	James Brady	2020-02-13
2	Initial writing for public and sec 6	James Brusey	2020-03-12
3	Integrated input from CRF secs 5 & 7	James Brady	2020-03-23
4	Input from CRF in sections 1.4 and 7.1	James Brady	2020-04-14
5	New section 4.2 for general methodology to include reporting simulation accuracy	James Brusey	2020-04-15
6	Changes to template format and layout. Inclusion of new chapter (Chapter 4 in this version) “Purpose of the document” to be completed.	James Brady	2020-04-19
7	Remove numbering from all section headings before Chapter 1 “Purpose of Document”	James Brady	2020-04-22
8	Revise chapter 4	James Brusey	2020-04-24
9	Revised according to comments	Matteo Rostagno	2020-04-30
10	Inclusion of RMSE and NRMSE results	Matteo Rostagno	2020-05-06
11	Revision as per review	James Brusey and Matteo Rostagno	2020-05-14
12	Minor adjustment of explanation of delays	Alberto Merlo	2020-05-20

Disclaimer/ Acknowledgment

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 769902. The information and views set out in this publication does not necessarily reflect the official opinion of the European Commission. Neither the European Union institutions and bodies nor any person acting on their behalf, may be held responsible for the use which may be made of the information contained therein.

Publishable Summary

Background

The aim of this deliverable is to provide an efficient implementation of a thermal cabin model that can be used to rapidly and virtually assess cabin comfort making use of the assessment framework (D1.2) and the holistic comfort model (D1.3).

This deliverable aims to resolve a conflict that often occurs in computer aided engineering and design. Specifically, the need for accuracy and spatial resolution is in conflict with the computational speed required to optimize a system within a reasonable amount of time and using available computer resources.

In this case, high accuracy and spatial resolution is provided by simulating the car cabin thermal environment with computational fluid dynamic (CFD) simulation. For this project, the CFD model has been produced and validated as part of task 1.3 resulting in deliverable D1.4.

This high accuracy simulation typically takes around 10 minutes (elapsed time) to compute one second of transient simulation.

DOMUS, however, calls for much faster simulation for several key reasons:

1. The assessment framework requires simulation of 28 different scenarios that vary in length between 10 minutes to 30 minutes and thus the total simulation time for a *single assessment* is considerable.
2. Machine learning approaches that learn control algorithms such as Reinforcement Learning tend to require *months* or even *years* of simulation time to converge to the optimal solution.
3. Machine learning approaches that can evolve optimal cabin configurations may first require re-learning the control algorithm (point 2) for every new configuration and even then require thousands of assessments (point 1) to arrive at the optimal configuration.

Despite this severe contrast between the computational speed possible for high accuracy simulation and the computational speed required for full optimization, there is some cause for hope. This hope stems, firstly, from the possibility of using machine learning to approximate the high accuracy simulation and, secondly, the realization that a perfect simulation may not be needed to perform optimization on such things as the HVAC control algorithm.

Alongside work to speed up the CFD simulation (produced in Task 1.3), a back-up plan of using a 1D cabin model is also pursued. By 1D cabin model, we mean a model that is based on “lumped thermal capacity” that uses simplifying assumptions to produce approximate but reasonably fast thermal simulation.

This additional work provides a check and a safeguard. It is a check in the sense that the final accepted simulation should be at least comparable or better than the 1D simulator in terms of accuracy and computational speed. Thus, results for the 1D simulator are needed to perform this check.

Producing a 1D cabin model also safeguards the overall aims of the project by providing mitigation for the risk that the machine-learnt approach fails to produce a sufficiently capable simulator.

Task objectives

The objectives of the sub-task carried out are the following.

1. Produce a machine-learnt simulation of the thermal aspects of the car cabin focusing on those aspects needed to assess thermal comfort.
2. Produce a 1D thermal cabin simulation model focusing on the same aspects.
3. Compare the two models in terms of their accuracy against the CFD simulation provided in D1.4

4. Compare the two models in terms of their accuracy against available measurement data produced in a climatic wind tunnel.
5. Compare the two models in terms of simulation performance on roughly equivalent computational hardware.

Methods

All involved partners in the task engaged with defining overall methods through regular teleconference and face to face workshops (activity started as part of T1.4).

The methods consist of:

- Ordinary 1D modelling of the car cabin using AMESIM or GTSuite
- Machine learning to map current state and control values into next state values.

Results

The key results include:

1. The machine learnt cabin model has an average normalized RMSE over all sensors of 1.8%. The RMSE for the average air temperature for the front bench is 0.4 K (0.8%) over all trials.
2. The machine learnt cabin model computes a second of simulation time in 5.44×10^{-6} s.
3. The machine learnt cabin model is able to interface to the holistic comfort model and, in comparison with the CWT data, gives a misclassification rate that ranges from 1.3% to 3.4%.
4. The 1D cabin model predicts the cabin average air temperature within $\pm$ 1 K (1.52%) with respect to the reference temperature.
5. The 1D cabin model predicts AC pressure with an average error less than 0.6 bar (3%) at high pressure and 0.1 bar (6%) (steady state) at low pressure
6. The 1D cabin model computes a second of simulation time in 0.25 s (worst case – when the AC compressor is on) or 0.0076 s (AC compressor off).

These results meet the requirements set out in the objectives for this part of the project and provide a strong foundation for the remainder of the DOMUS work to build upon.