

Heat release rate calculation from indirect measurements

Application to vehicle fires

Mole-Antoniazza Renato¹, Paillat Jean-Luc¹, Suzanne Mathieu¹, Candelier Fabien², Vauquelin Olivier² and Jean-Baptiste Tramoni³

¹LCPP, Fire Engineering Division, Paris (FR), ²IUSTI, Marseille (FR), ³CTICM, Fire Research Section, Saint-Aubin (FR)

renato.anto.mole@gmail.com, jean-luc.paillat@interieur.gouv.fr, mathieu.suzanne@interieur.gouv.fr

ABSTRACT

This paper focuses on the calculation of the heat release rate from two different fires: 1) a load composed of building materials and 2) a light commercial vehicle. A methodology is developed which uses Computational Fluid Dynamic (CFD) modeling, machine learning method and three radiative heat flux measurements to determine the temporal evolution of the heat release rate. Once this heat release rate is rebuilt, the method provides by numerical simulation many other physical quantities.

KEYWORDS: optimization, CFD-modelling, heat release rate.

INTRODUCTION

The LCPP is a French laboratory responsible for fire investigation in Paris and its close suburbs. These investigations sometimes require numerical reconstructions based on CFD modeling. The heat release rate (HRR) is in this case the main unknown to perform accurate simulations and assure sufficient realism. The reconstruction helps in the assessment of the different hypotheses concerning the ignition location or the fire spread for instance. The estimation of a consistent heat release may be difficult because a lot of information is needed: the initial location of the fire, the physical characteristics of the combustible materials, and the influence of the built environment (enclosure size, location and dimension of the openings, combustion conditions...).

It is possible to measure the heat released by a vehicle fire using mass loss rate or oxygen consumption calorimetry. However, probably because of the cost and the lack of adequate experimental structures, such experiments are relatively rare in the open literature and often no longer up to date. Furthermore, for specific configurations involving several vehicles or when the vehicle is placed in a particular enclosure such as a car park for instance, performing these experiments may even be impossible. When full-scale experiments are nevertheless organized in these challenging conditions, a lot of additional measurements are usually performed: temperature, heat flux, velocity, gas concentrations (O₂, CO, CO₂...). These measurements are easier and much cheaper to realize than installing a weighting scale or a large-scale calorimeter. However, these measurements only characterize the thermal environment created by the fire and not directly the mass or energy released. But as it will be detailed in the present paper, these indirect measurements may be used to reconstruct the heat release rate.

The developed method was inspired by several studies. Overholt and Ezekoye [1] determined the HRR from hot gas layer temperatures using a predictor-corrected method based on numerical modeling with Consolidated Model of Fire and Smoke Transport (CFAST) [2] zone model and

analytical correlations from McCaffrey, Quintiere and Harkleroad [3]. Jahn et al. [4] created a methodology to forecast the fire growth based on data assimilation from temperatures and smoke layer height measurements, a numerical modeling with a zone model and a gradient based optimization. Arnold et al. [5] established an optimization method allowing the parallelization on high-performance computing systems of CFD modeling with Fire Dynamics Simulator (FDS) and optimization with Shuffled Complex Evolutionary Algorithm (SCE-UA) [9]. With this methodology, the authors successfully predicted several material decompositions from mass loss rate measurements obtained by Thermo Gravimetry Analysis. Lattimer et al. [7] established a methodology based on an artificial neural networks for real-time prediction of temperatures and velocities in a room. These networks were trained with a learning dataset composed of FDS simulations modeling different fire scenarios in the same geometry.

From these studies, many choices were made depending on two main criterions: 1) the accuracy and the flexibility of numerical model and 2) the numerical cost. Zone modeling is faster and less costly than CFD, however it is limited to closed geometry and calculate global quantities. The use of analytical correlations is less costly than optimization algorithm, but it depends on physical quantity studied. Evolutionary algorithm like SCE-UA or gradient based optimization require many simulations to work which represent a significant numerical cost.

From temperature, velocity or heat flux measurements, an optimization problem is defined as search for the solution (i.e. the evolution of HRR) that allows to numerically reproduce these experimental datasets. A numerical model whose main input data is a temporal evolution of HRR is used to reproduce the experiment. An optimization method named Optimization Based Iterative Workflow for A Numerical Experiment (OBIWANE) was developed. It is based on CFD modeling and machine learning method.

In this paper, the developed method is quickly described and applied to evaluate two experimental HRR: 1) the burning of a load composed of building materials and 2) a light commercial vehicle fire. The experimental data were measured during a recent test campaign organized by CTICM with the participation of LCPP, ArcelorMittal, Gagnepark. Renault provided the vehicles. The tests were performed on an EFECTIS experimental platform located in Saint-Yan (Bourgogne, France).

EXPERIMENTAL SET-UP

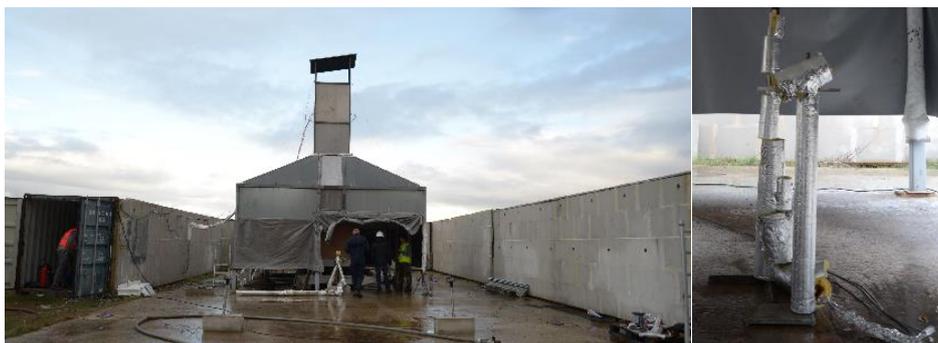


Figure 1: Experimental set-up -- (Left hand side) large-scale calorimeter -- (Right hand side) seven heat flux gauges.

The experimental platform is composed of a large-scale calorimeter determining the heat release rate by O_2 consumption corrected with CO_2 and CO concentrations. In addition, seven radiative heat flux gauges were installed (see Fig. 2): four sensors were in horizontal position at 1.1m high and placed 1.5m around the vehicle or the load of building material. The three other gauges were in vertical position and located at 1.5m from one side of the fire. These three measurements were placed in height at 0.6m, 0.9m and 1.2m. Video cameras recorded the experiments.

It was chosen not to perform any temperature measurement. The fire was located under a large-scale calorimeter where gas accumulation was not possible. It was therefore not possible to get any valid thermally stratified temperature measurements which may be successfully used in our model.

The first experiment was performed on a typical vehicle load (see Figure 2) composed of wooden and plastic pallets, bricks and steel bars. This assembly was placed in a tray to prevent the unwanted spread of melted or burned material. The fire was ignited with a small heptane container placed in the centre of the load. The positions of the horizontal heat flux gauges (black and green triangles) around the load (red square) are detailed in Figure 2.

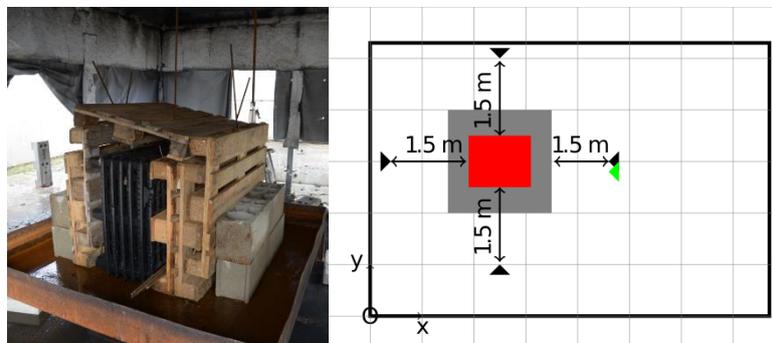


Figure 2: (Left hand side) photo of the load of building materials; (right hand side) diagram of the heat flux measurement set-up around the load (red square) -- three vertical gauges (green triangles) and four horizontal gauges (black triangles).

The second experiment was performed on a light commercial vehicle. Its tank was half-filled with diesel and its trunk was loaded with the materials from the first experiment (see Fig. 3). Initially, the vehicle was a passenger car. To convert it into a light commercial vehicle, the rear seats were removed, and the five back windows were blocked with plywood panels. The fire was ignited using a small heptane container placed on the floor in front of the front passenger seat. As shown in Fig. 3, a horizontal heat flux gauge and three vertical ones were installed in front of vehicle and one at the rear. The final two horizontal gauges were aligned with vehicle lateral windows.

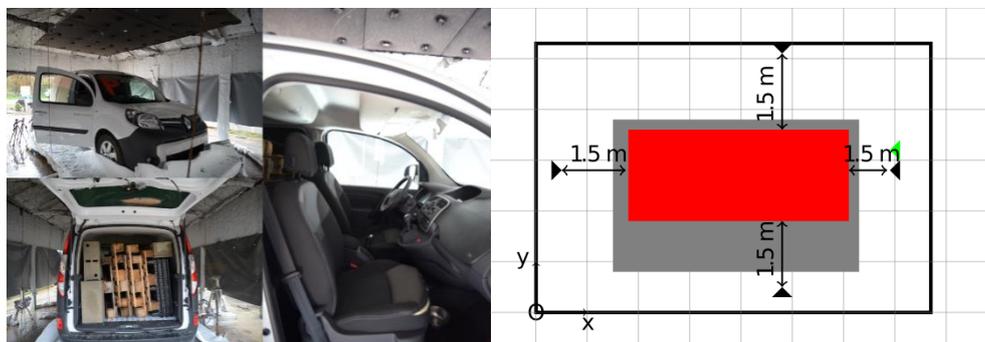


Figure 3: (Left hand side) photos of the light commercial vehicle and its load in the trunk; (right hand side) diagram of the heat flux measurement set-up around the vehicle (red square) with three vertical (green triangles, and four horizontal (black triangles) heat flux gauges.

OBIWANE: OPTIMIZATION METHOD

The Optimization Based Iterative Workflow for A Numerical Experiment (OBIWANE) method was employed to rebuild the HRR by numerical modelling of the experimental fire. It is hypothesized that if differences are slight between the experimental measurements and the output of a numerical model, then HRR numerically programmed is close to the value that would be measured by a method based on oxygen consumption or mass loss rate measurement. The problem whose consists in evaluating the HRR is formulated as an optimisation of the difference between experimental and numerical data.

The experimental measurements are assumed continuous which allows a discretization of the experimental time at regular intervals (much higher than the intervals of measurement acquisition). It is assumed that, if the discretization interval is small before the total fire time, the evolution of HRR is sufficiently slow to be quasi-linearized in this interval. This assumption helps calculating only the slope of HRR instead of several values in the same interval. It also makes easier to program the CFD model.

Over each interval, multiple HRR values are simulated with Fire Dynamics Simulator [6–8], a CFD model of fire-driven fluid flow. This program is chosen because it is widely used within the fire community; the LCPP uses it for fire investigation or fire safety design. In comparison with CFAST zone model, FDS allows calculating local physical quantities in open or close environment. The main disadvantage is the computational cost. With zone model, few minutes of fire require only few seconds of calculations. With FDS, few minutes of fire require hours of calculations. From an HRR slope within an interval, FDS calculate the same outputs as the measurements.

Once an interval has been computed with N different HRR slope, we dispose N datasets of simulation measurements. Thanks to a gradient Tree Boosting algorithm[11], [12], these datasets are compared to experimental measurements on this interval. This algorithm calculates the function which inputs the experimental measurements and outputs the expected best suited HRR evolution on this interval to reproduce experimental measurements. To calculate this function, the gradient tree boosting is based on successive establishment of regression trees [13].

FDS embed an interesting Restart option. It allows us to stop a computation and restart it after changing some inputs data. It is especially well suited to work with OBIWANE. Indeed, for the first-time interval, i.e. from $t=0$ to 60s, N HRR are evaluated. Then, OBIWANE gather all data and determine the best suited HRR. FDS is restarted from $t=0$ to 30s with this solution as input. This result will then be used as starting point for the next interval i.e. from $t=30$ to 90s using the Restart option.

As described in Fig. 4, the input data of OBIWANE are the experimental measurements (e.g. heat flux) and the modelling Figure 1 of the test geometry. From these two files, OBIWANE performs all the optimization operations automatically on HPC systems composed of 80 processors. The output data are the reconstructed HRR, and the comparison of the experimental measurements with the modelled values.

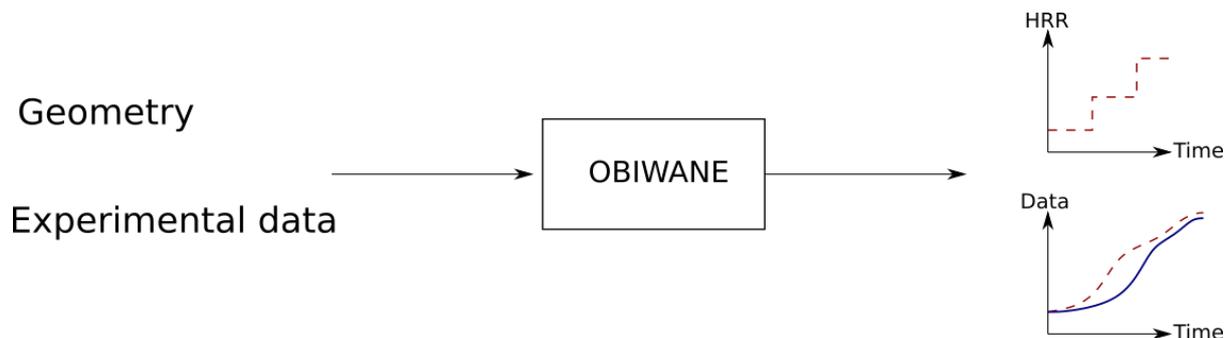


Figure 4: input and output data of OBIWANE.

The geometry file of FDS is basically composed of the experiment environment, as visible in Fig. 5, the material physical properties, and numerical information to perform the computation. In the present case, the experimental platform is modelled with its close boundaries (three maritime containers). The experimental data provided to OBIWANE are the heat flux measurements detailed previously.

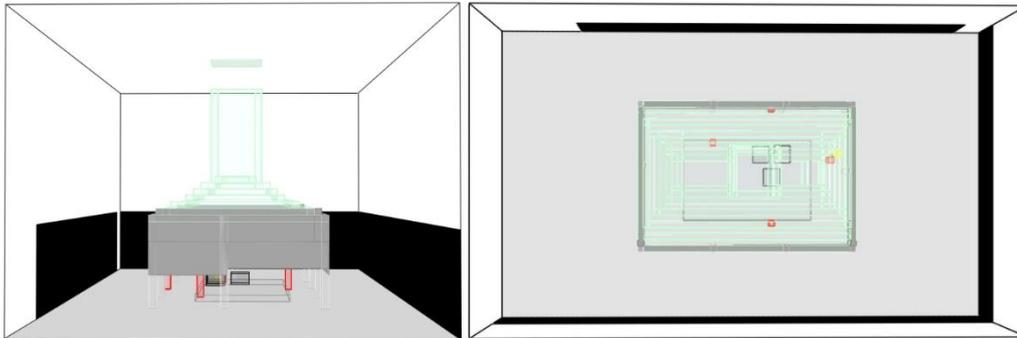


Figure 5: numerical modeling of the geometry with FDS -- (left hand side) side view and (right hand side) top view

Before any application to real configurations, OBIWANE was validated on purely numerical problems[14]. OBIWANE had to predict, from only five temperature measurements, the evolution of the HRR of an enclosed fire. This validation process helped defining the 60s time step mentioned previously over which the fire is modelled before further assessment of the results, as well as the number of HRR (20) modelled at each time step. These parameters can be modified if needed, but they remain the best compromise between computational time and accuracy of the predicted HRR.

RESULTS

Three results obtained with OBIWANE are described hereafter: one for the combustible load and two for the light commercial vehicle. For the vehicle, one configuration is more complex than the other. All the results are detailed as follow: on the first graph, the measurements (in solid line) used as input data are compared to its numerical rebuilt (dotted line) obtained with OBIWANE; on the second graph, the HRR (black solid line) based on O_2 consumption corrected with CO_2 and CO concentrations is compared to the rebuilt HRR (brown dashed line) determined with OBIWANE.

Load of building material fire

The load of building materials is modelled as an unalterable block (see Fig. 7). This means that the fire in the simulation keeps its cubic form although during the experiment melting of the plastic pallets and transformation of wood to char are observed (see Fig. 6). It is assumed that the physical properties of the block are a weighted average of those of wood and plastic material. The red surfaces of the block are the faces where the pyrolysis takes place. Only three heat flux measurements were used as input data for OBIWANE. The heat flux gauges are modelled by green, blue or orange parallelepipeds. The reconstruction of this heat release rate required seven days of OBIWANE calculations on 80 cpu.



Figure 6: sequences of the load fire; (top left hand side) fire starting in the center; (top right hand side) fire developing in the center; (bottom left hand side) fire is fully developed and flame impacting the protective ceiling of large scale calorimeter; (bottom right hand side) flame enveloping the load .

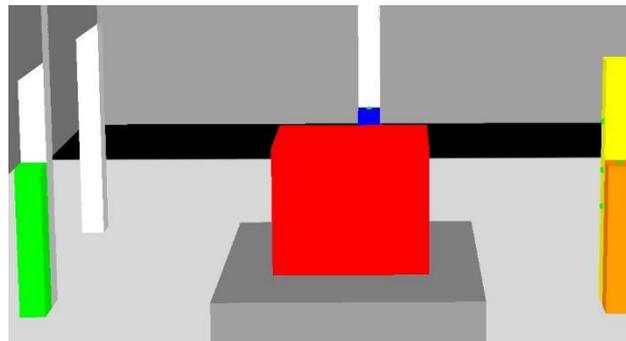


Figure 7: numerical modeling with FDS of the material load (red cubes); the three horizontal heat flux gauges used as input data are modeled by the green, blue and orange parallelepipeds.

This colour code is the same in Fig. 8 where the heat fluxes and heat release rates are plotted. It is observed (see the first graph in Fig. 8) that the three heat fluxes are well reconstructed with OBIWANE. The predicted HRR obtained with OBIWANE (see the second graph in Fig. 8) is close to the measurement. After 700s, the decrease is however not as precisely reproduced. It is due to the modification of the burning material which is not modelled in the simulation: collapse of the wooden pallet, melting of the plastic pallet, etc.

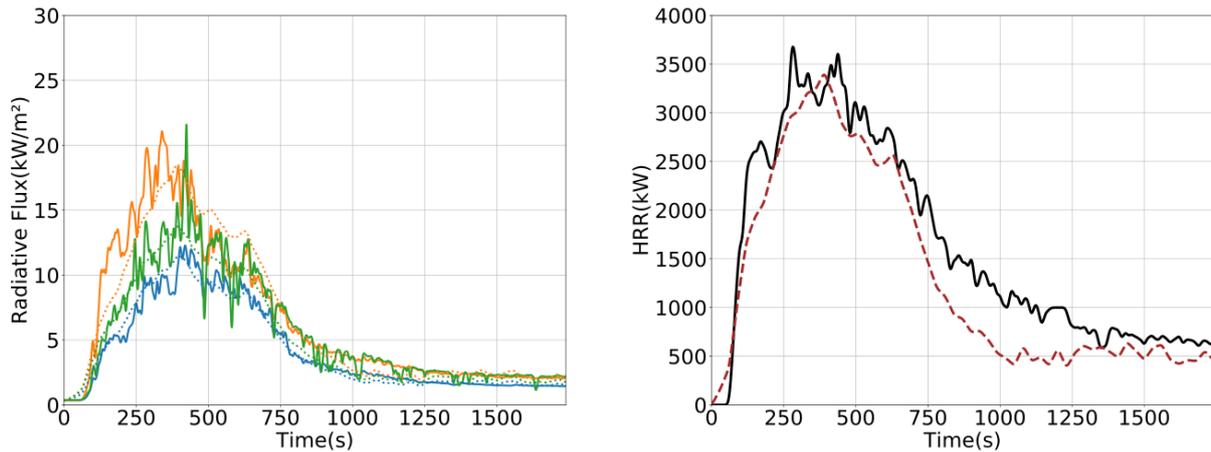


Figure 8: (Left hand side) comparison between experimental (solid line) and numerical (dotted line) heat fluxes; (right hand side) heat release rates obtained with OBIWANE (brown dashed line) and measured with the large-scale calorimeter (black solid line) for the load of building materials

Despite 1) a coarse modeling of the load of materials and 2) using only three heat flux measurements as inputs for OBIWANE, the reconstructed HRR is very close to the experimental value.

Light commercial vehicle fire -- simple design

The second reconstruction concerns the light commercial vehicle. The first try to determine the HRR is based on the same assumption as in the previous section. The vehicle is modeled using a parallelepiped shown in Fig. 9. The material properties are a weighted average of plastic, wood and foam. As a first approximation, the top surface of the parallelepiped (red zone) was considered to be the only pyrolysis area because it is assumed that the sides of the metallic car body do not burn. The reconstruction of this heat release rate required sixteen days of OBIWANE calculations on 80 cpu.

Only three heat flux measurements were used as inputs for OBIWANE. In Figure 9, the green parallelepiped represents the location of the heat flux gauge at the rear of the vehicle, the blue one in front of the vehicle and the orange one on the left hand side (driver's side) of the vehicle.

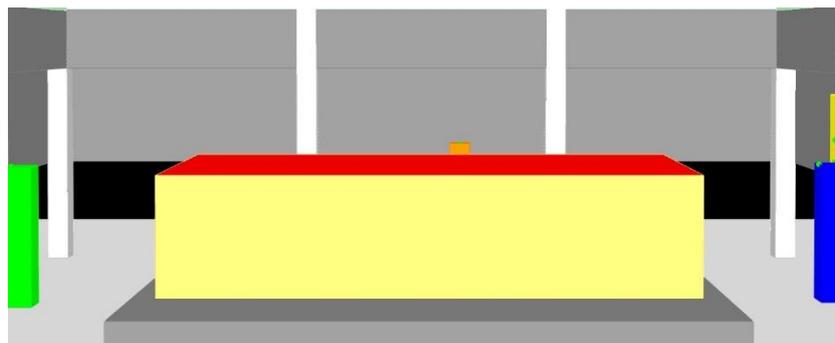


Figure 9: simple modeling of the light commercial vehicle (yellow parallelepiped) and pyrolysis zone (red surface) in FDS; the three horizontal heat fluxes used as input data are modeled by the green, blue and orange parallelepipeds.

In the first graph of Fig. 10, it can be observed that the measurement realized on left hand side of the vehicle is properly recovered with OBIWANE (orange lines). In front of the vehicle, the heat flux is slightly under-predicted for the first half of the experiment and over-predicted afterwards. At the rear of the vehicle, the opposite trend is observed: over-prediction for the first half and under-prediction afterwards. An interesting point to notice is that both modeled heat fluxes in front of the vehicle and at the rear are almost similar whereas measurements are much more different. The simple design of the light commercial vehicle in FDS is not precise enough to catch these differences. On the second graph

in Fig. 10, it appears that the overall shape of the HRR is well reproduced, but the measurement is under-estimated with this simple design of the vehicle in FDS.

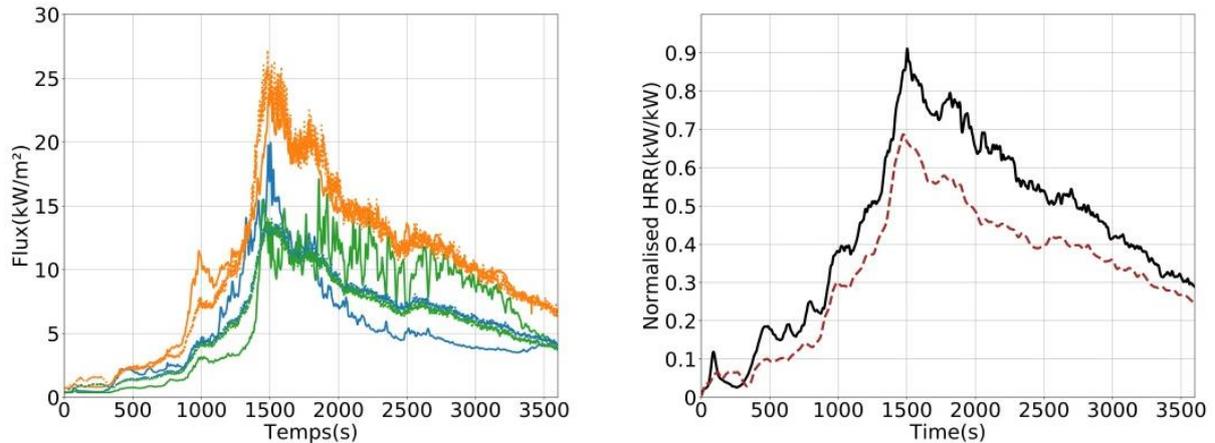


Figure 10: Results for the simple design of the vehicle: (left hand side) comparison between experimental (solid line) and numerical (dotted line) heat fluxes; (right hand side) comparison of the rebuilt HRR obtained with OBIWANE (brown dashed line) and the measurement from the large-scale calorimeter (black solid line).

Light commercial vehicle fire -- complex design

The study of the experimental video recordings (as shown in Fig. 11) revealed that the fire first developed at the front of the vehicle before decreasing gradually starting from half of the experiment. This explains that until 1600s the heat flux measured in front of the vehicle was higher than at the rear. The fire then spread progressively to the rear of the vehicle. This propagation is deduced from the successive ignitions of the plywood panels on the side of the vehicle. In the middle of the experiment, the rear window broke and flames appeared. This explains the increase in the heat flux at the rear of the vehicle around 1450s.



Figure 11: sequences of the light commercial vehicle fire; (top left hand side) fire developing at the front; (top right hand side) fire developing towards the rear of the vehicle with ignition of the right hand side plywood panels; (bottom left hand side) the fire is fully developed on the vehicle; (bottom right hand side) flame visible at the rear window.

In FDS, the vehicle is modified as shown in Fig. 12. More parts of the car are taken into account: the car body (white), the lateral front windows (blue), the lateral windows obstructed with plywood panels (gray). The ignitions of the plywood in FDS are based on those observed on video recordings. The red surface is the pyrolysis area. A second one is located inside vehicle and is not visible in Fig. 12. Only three heat fluxes were used as input data for OBIWANE; they are modeled in FDS with the same color code. The reconstruction of this heat release rate required twenty days of OBIWANE calculations on 80 cpu.

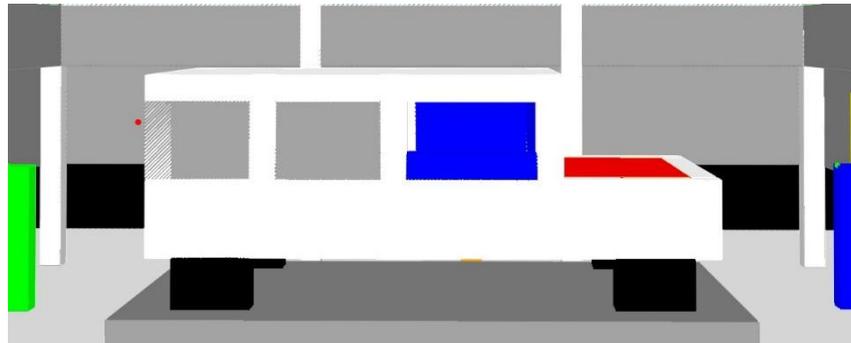


Figure 12: Complex design in FDS of the light commercial vehicle (white surfaces), its windows (blue and gray surfaces) and one pyrolysis area (red surface); the three horizontal heat fluxes used as input data are modeled by green, blue and orange (hidden) parallelepipeds.

It is observed in the first graph in Figure 13 that the heat fluxes measured on the left hand side and at the rear of the vehicle are properly reproduced by OBIWANE. The front measurement is over-predicted; it may be explained by the position of the burning surface on the top of front parallelepiped whereas some of the burning takes place from the floor during the experiment. The two burning surfaces are defined in FDS to burn simultaneously and with the same intensity, which is not the case during the experiment. This could be improved in a further modeling. The reconstructed HRR by OBIWANE is very close to the measurement in the large-scale calorimeter and this with only three incident heat flux measurements.

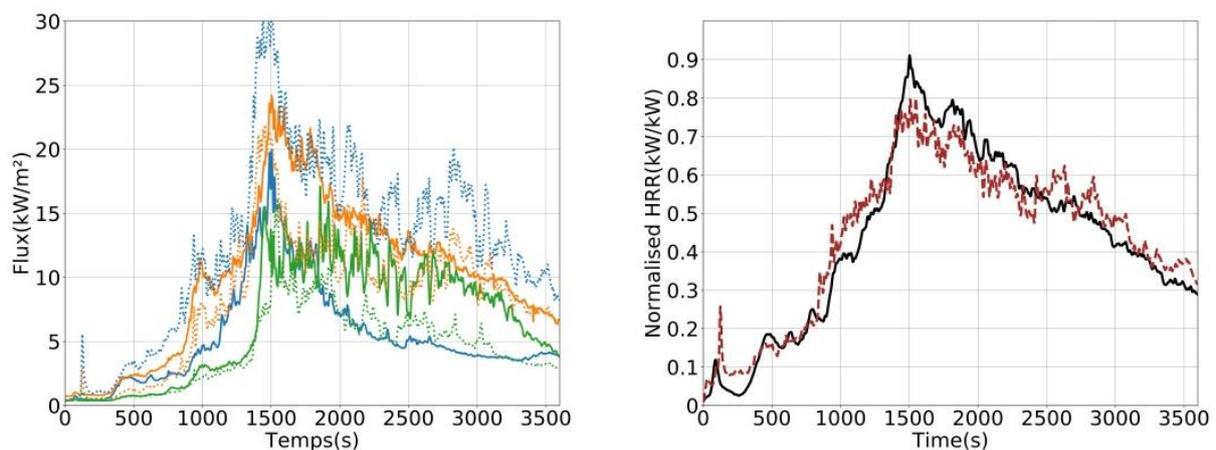


Figure 13: Results for complex design in FDS – (left hand side) comparison between the experimental (solid line) and numerical (dotted line) heat fluxes; (right hand side) comparison of the HRR reconstructed with OBIWANE (brown dashed line) and the measurement in the large-scale calorimeter (black solid line).

CONCLUSIONS

OBIWANE was first applied to a simple case: a material load composed of building materials placed on a platform under a large-scale calorimeter. Despite some complex burning behaviour which cannot be modelled such as the melting of the synthetic polymers and the resulting pool fire, or the collapse of the wooden pallet, this experiment was well-reproduced and the HRR rebuilt with a very good precision.

OBIWANE was then applied to a light commercial vehicle fire. The reconstruction of the HRR was first realised with a simple parallelepiped to represent the car. The shape of the HRR was well-reproduced, but the measurement was under-predicted. It however remains a correct first approximation of the measured HRR. One reason for this under-prediction is that the simple design in FDS is not able, by construction, to reproduce the asymmetry observed in the measurements.

A more complex design of the car was finally reproduced in FDS. For instance, this new model took into account the car body or the front windows. OBIWANE determined the HRR with an excellent accuracy with only three heat flux measurements as model inputs. However, one heat flux is over-estimated by OBIWANE. Improvements have to realize on heat flux modelling and taking gauges positions.

OBIWANE can determine the HRR under the same conditions as a large-scale calorimeter with only a few simple and cheap measurements. The main disadvantages of OBIWAN may be 1) its numerical cost which is mainly due to the CFD modelling and 2) the limits of the chosen modelling tool (FDS in the present paper) to properly reproduce some complex phenomena such as under-ventilated conditions, jet flames in case of hydrogen released from a fuel cell vehicle, changes in the geometry of the fire, etc. The developed method is an excellent tool to estimate the HRR of complex experiments.

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