Increasing the safety of rescue workers in fire events by merging fire simulations, structural models, and artificial intelligence

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***Abstract* – In the event of a fire, rescue forces must be able to evacuate as many people as possible from the burning building with minimal risk to themselves. On the one hand, this requires knowledge of where people to be rescued are located in the building, and on the other hand which escape routes are available. As a result of the fire event, heat-related material degradation occurs, which can lead to (sub-)structural failure. As a consequence, some rescue routes may be obstructed during the course of the rescue operation, so that the rescue forces need information about (still) possible rescue routes. This requires a multidisciplinary approach: Fire simulations form the basis for the description of the material behavior, from which the structural failure can be determined. If these computational data are analyzed by means of machine learning methods, a real-time prediction of potential rescue routes is possible in case of fire events in comparable buildings. In the DTEC project Kibidz, especially public buildings are investigated, so that a cataloging of comparable building types can take place and generally valid methods to be developed in the project can be specified for these building types. In this paper, first research results are presented.**

I. Introduction

According to the EU Fire Safety Guide each year approximately 5000 people are killed due to building fires [1]. Although deep investigations regarding fire simulation (fluid mechanics), material degradation (micro-mechanics), and successive collapse of buildings (structural analysis) took place especially after the tragic incident of 11th September 2001, there is still a lack of knowledge in combining these different approaches. Another issue in increasing the safety of rescue workers and those to be rescued during fire events is the necessity of real-time analyses, whereas the major focus in research so far is on analyzing critical situations after the incident. However, real-time simulations combining advanced methods of fluid mechanics, micro-mechanics, and structural analysis are still limited by the computational power available. Thus, the authors of the present contribution follow another approach: Further developing the techniques of fluid mechanics, micro-mechanics, and structural analysis as well as increasing the respective reliability, provide tools for a fast data exchange between these techniques in order to obtain both realistic and time-efficient simulation results. These simulation results serve as input data for machine learning (ML) approaches. Hence, numerous numerical experiments need to be conducted increasing the need for both realistic and time-efficient simulations at different scales. By means of artificial neural networks, general characteristics of fire events and the resulting consequences for the reliability and safety of rescue routes have to be analyzed. Once the artificial neural networks are properly trained, they allow for realistic real-time predictions based on (e.g., temperature) sensor data in the event of a fire incident. The respective predictions can be used on-site by rescue workers in order to increase their safety during the rescue campaign. This necessitates an applicability of the developed advanced methods to the concrete incident. To achieve this applicability, so-called digital twins of characteristic buildings are created. To keep these digital twins both realistic and (time-)efficient, the authors restrict themselves to standardized public buildings. The aforementioned aspects are dealt within the project KIBIDZ – *Intelligente Brandgefahrenanalyse für Gebäude und Schutz der Rettungskräfte durch Künstliche Intelligenz und Digitale Brandgebäudezwillinge*, which is thus introduced in the present contribution, too.

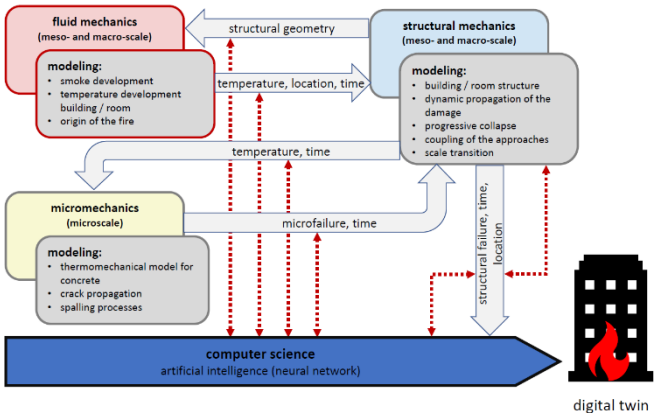

FIGURE 1: INTERACTION DIAGRAM.

The outline of this contribution is as follows: In Section II major aspects of fire simulations are discussed. The methods to be developed allow for detailed simulations of the temperature evolution and flue gas propagation. The respective results serve as time-dependent input quantities for both ML approaches and thermo-mechanical analyses at the micro-scale. The main objectives of these investigations at the micro-scale are presented in Section III. Once a damage is initiated, its extent and severity may increase due to (increasing) thermal loads and/or (sudden) mechanical loads. As a consequence, a structural member may fail. Additionally, a progressive collapse may occur. These aspects are dealt within Section IV. The ML approaches which allow for both the prediction of the temperature distribution and development as well as of a successive collapse are introduced in Section V. Finally, a summary and an outlook are provided in Section VI.

II. Fire Simulation and Evolution of Temperature Distribution

Fire, in general, causes a lot of damage to properties and the surrounding environment. Besides the fact that fire itself is dangerous for inhabitants, it can lead to heavy destructions, especially if public buildings are subjected to collapse due to the thermal load of the fire. Therefore, it is essential to study the fire characteristics and its impact on the structure of a building. The most important aspect of fire is the transfer of thermal load (in terms of heat energy) to the building structures. At first, the heat energy from the fire source is transferred to the surrounding fluid medium, i.e., the air plus the combustion products, by means of radiation from the fire itself and also from the smoke plumes that are covering the upper region of the room [2]. These hot smoke gases in-turn heat up the building through convection and conduction. Hence, the spread of the temperature along walls and ceilings plays a vital role in estimating the structural integrity of the building during a fire out-break. This study should not only help to understand the physical process of the fire but also in saving rescue workers from a partial collapse of the structure.

A. Fire Simulation

Fire simulations are carried out using the Fire Dynamics Simulator (FDS). FDS is a FORTRAN based numerical solver for large-eddy simulations (LES) using the NAVIER-STOKES-equations to solve low-speed thermally driven flows [3], especially fire. According to Rehm and Baum [4], for low-speed applications such as fire, the transport equations of fire-induced flows are simplified using the low-MACH number approximation to solve fire scenarios efficiently. Besides the governing equations, it considers a variety of sub-models (like combustion, radiation, pyrolysis, etc.). These sub-models help in emulating a realistic fire scenario. FDS is installed on the local high-performance computer and parallelized by domain decomposition and MPI. The domain is split into n domains, which is equal to the number of processors.

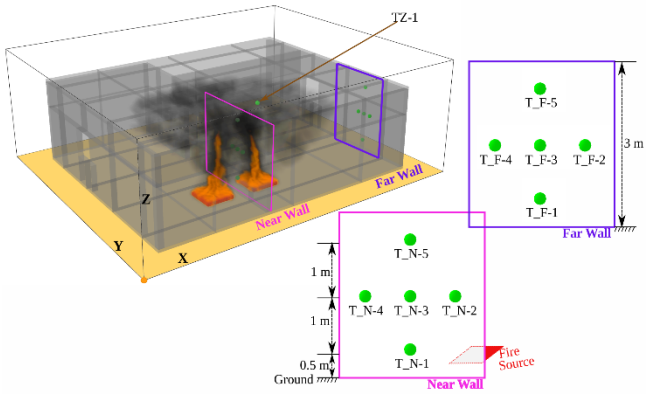

FIGURE 2: SIMULATED FIRE SCENARIO WITH GENERATION OF FIRE AND SMOKE DISPERSION SHORTLY AFTER IGNITION.

As an initial step, a basic fire scenario is considered. The setup shown in FIGURE 2 consists of two rooms with each having a fire source, a door and a window. The main objective of this model is to study the growth of fire, the dispersion of the smoke and the distribution of the temperature. In addition to the temperature also the velocity of the fluid medium and the propagation of smoke plumes and other gases are examined based on sophisticated large-eddy simulations.

B. First Results

During the set-up of the input file, the necessary output variables and planes must be chosen for post-processing the data of FDS. For example, the temperature and velocities at pre-defined planes have to be defined. In general, extracting output data for the whole domain is time consuming. Therefore, outputs are chosen sensibly at appropriate locations. Furthermore, monitoring points can be defined to assess time histories without increasing the overall run-time.

In order to provide results for the other groups, each output data is written in a particular format. The two sets of output data are the temperature within the fluid domain (at the spatial grids) and at boundary surfaces, which are delivered to the machine learning (ML) and structure group, respectively. FIGURE 2 exemplarily shows the generation of the fire and the spreading of the smoke inside the rooms. The evolution of the temperature with respect to time inside the rooms is extracted from the fire simulation and used in training the ML model of the project. The results are provided at every nodal point of the spatial grid. The development of the temperature at the surfaces of the wall due to the ignition of the fire is obtained and provided as the thermal load input for the thermo-mechanical simulations.

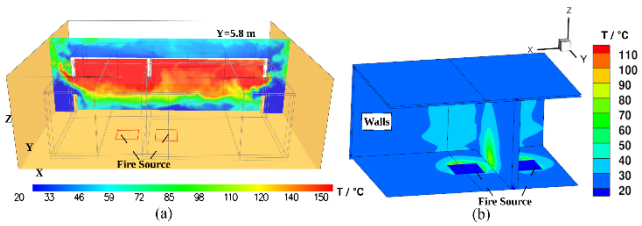

FIGURE 3: TEMPERATURE DISTRIBUTION AFTER 60 S.

FIGURE 3 (a) exemplarily depicts the distribution of the temperature along the y-plane of the room. This y-plane connects the windows of both rooms. Fig. 3 (b) shows the

distribution of the temperature at the walls that are near to the fire source (right side) after 60 s.

Two sets of monitoring points are placed at the near and far (opposite) wall of the fire as shown in FIGURE 2. TZ-1 is located on the roof exactly at the center of the fire source. FIGURE 4 (top) depicts the time history plots of the near wall, whereas the second plot depicts the results on the far wall. It is evident that the temperatures in both plots are rapidly increasing due to the fire. In FIGURE 4 (top, near wall), the temperature at T_N-1 is higher than at the other points as it is located closer to the fire. The temperature curves are getting flatter with increasing distance from the fire source. Nevertheless, the temperature at TZ-1 is higher than at the points T_N-3 to T_N-5 since the hot fumes from the fire directly hit the roof and heat up the surface. In FIGURE 4 (bottom, far wall) one can observe that the points located at higher elevations possess higher temperatures than T_F-1. This is due to the accumulation of the hot smoke gases in the upper part of the room. This is especially true for the point T_F-4, which shows the strongest temperature increase since it is most strongly exposed to the smoke gases compared to the other elevated monitoring points.

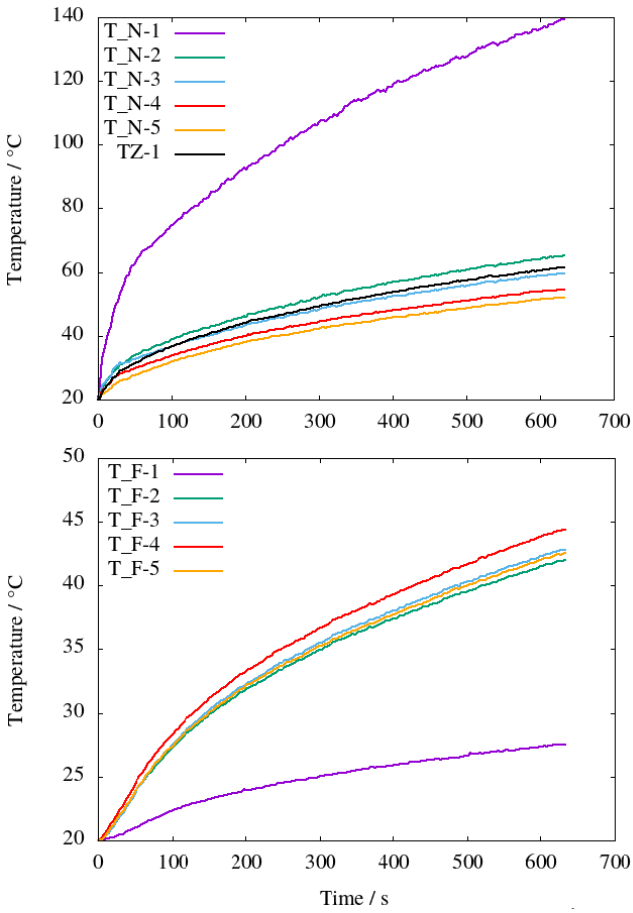

FIGURE 4: TIME HISTORY OF THE TEMPERATURE AT DIFFERENT MONITORING POINTS (SEE FIG. 2 FOR THE LOCATIONS OF THE POINTS).

C. Future Steps

Presently, the location of the fire is fixed and only the mass flow of the fuel is varied. In the next step, the geometry and the location of the fire source could be changed. Additionally, the spreading of the fire has to be taken into account. Furthermore, the dispersion of the smoke gases even poses a threat to the people stuck inside the building as well as to the rescue workers. Consequently, it would be useful to study the propagation of smoke within the building, thus leading to a less obstructed and safer escape route for the rescue.

III. THERMO-MECHANICAL MODELING AT THE MICRO-SCALE

At the micro-scale, a multi-field thermo-hydro-mechanical fracture model is formulated and simulated for the boundary conditions taken from the fire simulation carried out with the FDS software. Herein, concrete is modeled based on all three phases viz. solid – skeleton, liquid – liquid water, gas – water vapors and air. The main goal of this micro-scale simulation is to provide reduced stiffness at the given region due to micro-cracks resulting in material deterioration.

A. Multi-phase Concrete Model

Concrete is considered with all existing phases – solid, liquid and gas. Therefore, the total density ρ can be written as:

$$\rho = (1-\phi)\rho_s + \phi S_l \rho_l + \phi(1-S_l)\rho_g \,. \tag{1}$$

Here, ϕ denotes porosity, S_l is saturation, ρ_s is density of solid, ρ_l is density of liquid, and ρ_g is density of gas. In the above equation, the first term on the right-hand side is the mass of solid skeleton, the second term is the mass of liquid water, and the third term is the mass of gas phase. Further in gas phase, water vapors and air are considered and are derived using water vapor density ρ_v and air density ρ_a. In this multi-phase concrete model, both temperature and time dependency are taken into account for porosity, saturation and all densities.

B. Governing Equations and Implementation

Three phase model of the concrete leads to the mass conservation equations. Mass conservation equations for each phase are as follows:

$$\begin{aligned} \frac{\partial m_s}{\partial t} &= \dot{m}_{dehyd}, \\ \frac{\partial m_l}{\partial t} + \nabla\cdot(m_l v_{l-s}) &= -\dot{m}_{vap} - \dot{m}_{dehyd}, \\ \frac{\partial m_v}{\partial t} + \nabla\cdot(m_v v_{g-s}) + \nabla\cdot(m_v v_{v-g}) &= \dot{m}_{vap}, \\ \frac{\partial m_a}{\partial t} + \nabla\cdot(m_a v_{g-s}) + \nabla\cdot(m_a v_{a-g}) &= 0. \end{aligned} \tag{2}$$

Here, subscripts s, l, v, a, g indicate solid, liquid, vapor, air, and gas phases, respectively. The rate of change of mass due to dehydration is denoted by $\dot{m}_{dehyd}$, $\dot{m}_{vap}$ is rate of change of mass due to vaporization. Relative velocities of the respective phases are given as for example v_{1-2} is the velocity of the phase 1 with respect to phase 2. These relative velocities are modeled by using DARCY's law and FICK's law.

Mass balance equations given in Eq. (2) are further developed by substituting densities of each respective phase and by using chain rule for the time derivative. This results into primary variables as gas pressure p_g, capillary pressure p_c and temperature T. The final form of the balance equations is solved by using the finite-element method with C_0 continuous shape function for spatial discretization and NEWMARK time integration for the temporal discretization. Thereafter, each balance equation is solved in a staggered manner until global convergence is achieved.

C. Boundary Value Problem

A simplified one-dimensional boundary value problem is formulated according to [5] in order to simulate in staggered manner for the verification of the algorithm. A one-dimensional bar of length 20 cm is considered with 200 elements. Temperature profile according to standard fire curve [6] is given as DIRICHLET boundary condition on the left side and NEUMANN boundary condition of no fluxes on the other sides. Heat and mass transfer coefficients are taken as 18 Wm^{-2} K and 0.018 ms^{-1}, respectively. All material parameters and their temperature-dependent constitutive relations are taken from [7].

Results of the one-dimensional boundary value problem are plotted in FIGURES 5 and 6 for simulations running from 0 min up to 60 min. In FIGURE 5, temperature profile can be seen developing from the fire exposed side with a steep gradient. Temperature of the fire exposed face reaches 1200 K in 60 min while the temperature inside the concrete is still below 300 K. Temperature gradients are increasing significantly for the first 5 cm of the concrete.

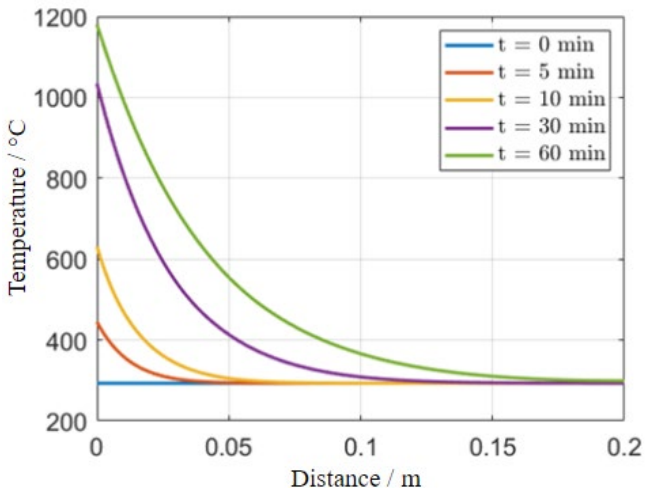

FIGURE 5: TEMPERATURE PROFILE OF THE 1D PROBLEM WITH THE LEFT FACE EXPOSED TO FIRE WITH STANDARD FIRE CURVE.

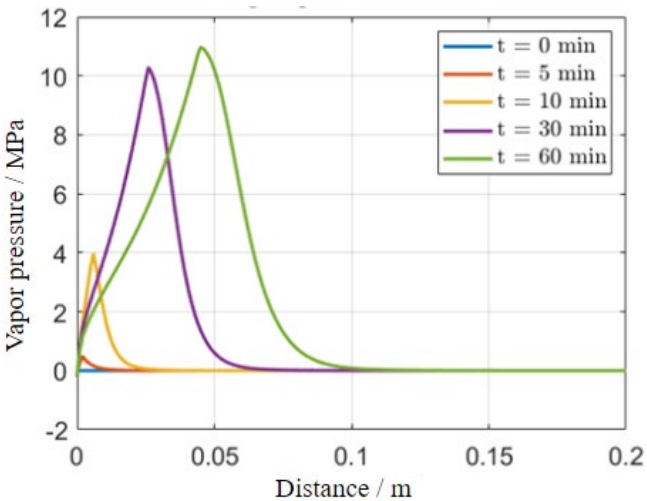

FIGURE 6: VAPOR PRESSURE PROFILE OF THE 1D PROBLEM WITH THE LEFT FACE EXPOSED TO FIRE WITH STANDARD FIRE CURVE.

In FIGURE 6, vapor pressure profiles are shown with respect to the distance at various time instances. Here it can be observed that vapor pressure peaks are increasing with respect to time and at the same time the curve is shifting towards right face side which represents colder regions. These curves are in agreement with the moisture clog theory and confirms that the vapor flux traveling towards both sides ends up forming peak pressures near the fire exposed face. This rise in vapor pressure also introduces significant pressure gradients within a small distance with respect to the total dimension of the bar.

D. Future Steps

This model will be extended with a phase-field fracture equation that will be solved also in a staggered manner. Fracture criteria for the phase-field equation will be based on the peak pressure limit and GRIFFITH's fracture energy. In this way, fire damage in the concrete will be computed and delivered to the macro-scale model using a scale transition algorithm.

IV. MODELING OF SUCCESSIVE FAILURE AT THE STRUCTURAL SCALE

Successive failure or progressive collapse due to fire is an important topic in the structural analysis of buildings. Especially since the devastating events of 11th September 2001 and the collapse of the World Trade Center (WTC), as well as more recent events such as the Plasco building disaster in 2017, show the extent of progressive collapse. In both cases, investigations have shown that the main cause of the collapse of the buildings could be attributed to fires and the high temperatures that accompanied them. As a result of these events, with the WTC collapse leading the way, there is a large interest in the scientific community to understand the mechanisms that trigger progressive collapse. Due to the very high cost of experiments and the highly simplified analytical solutions, which lead to inaccuracies, numerical simulations for the analysis of progressive collapses using finite-element methods (FEM) or applied element methods (AEM) are currently very common. The challenge to be met here is to build a model that provides accurate results without being too expensive from a numerical point of view. In the following, the terminology, failure mechanisms, and the general procedure of such simulations will be described.

A. Progressive Collapse

Progressive collapse results from the local failure of a structural element (e.g., column or beam) and the subsequent transfer of damage to other structural elements (dynamic propagation) until general structural failure [8]. This process can be seen in FIGURE 7, which shows the collapse of the Alfred P. Murrah building according to [8]. Even though the origin of the partial collapse was an explosion, the fundamental mechanisms of a progressive collapse are clearly visible here. First, a primary column fails. The lack of support from the column leads to the failure of the girder and the subsequent failure of the upper parts of the building. The characteristic of progressive collapse is that the final condition is disproportionately larger than the initial local failure [9]. Furthermore, it can usually be seen that after the failure of the first structural component, the parts that fail are in its vicinity, see also FIGURE 7.

B. Failure Mechanism

The failure mechanism of the structural components can be simplified to three causes. One cause is temperature change-induced thermal expansion (i), which causes the components to build up extra internal stresses in the fixed state and to exert displacements on surrounding structural elements in the simply supported state [10]. Both variants lead – directly

in the affected component or indirectly in surrounding components – to increased loads and in extreme cases to failure. According to [11], the second cause results from a temperature gradient in structural elements such as ceilings and walls. In real fire scenarios, building components have warm and cold regions until the thermal equilibrium state is reached. This temperature gradient across the component (ii) in turn leads to an increase in internal stress in the component, which can lead to failure. The third cause is material degradation (iii) due to the increased temperatures, which is described in Section III. In building fires, mechanisms (i), (ii), and (iii) occur in combination and must be considered together for an accurate simulation. It must be taken into account that (i) and (ii) mainly occur on the macro-scale (building scale, component scale) and (iii) on the micro-scale (material model) and thus a multi-scale approach is necessary. The relationship between the scales is shown in FIGURE 1.

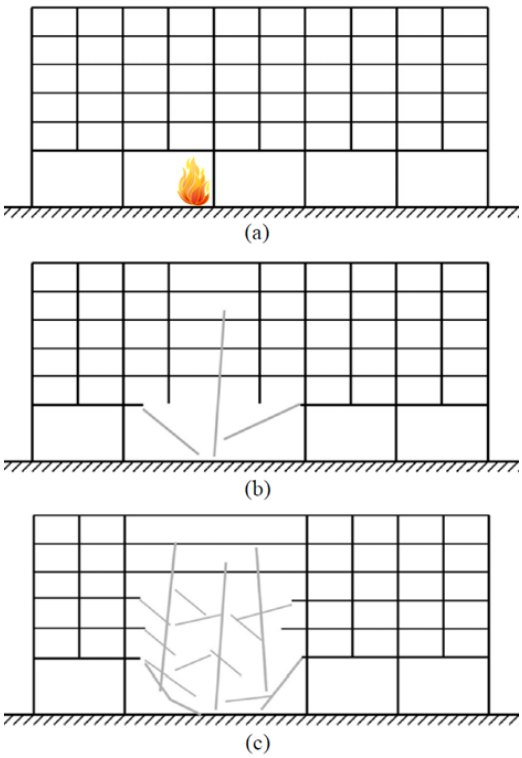

FIGURE 7: COLLAPSE OF ALFRED P. MURRAH BUILDING ACCORDING TO *[8]* (a) SOURCE OF THE COLLAPSE, (b) FAILURE OF THE FIRST ELEMENTS, (c) PROGRESSIVE (PARTIAL-) COLLAPSE.

C. *Future Steps*

Based on the fire simulation from Section II, which provides important temperature and smoke gas data, the local material failure can be determined in the micro-mechanical simulation (Section III). Both the temperature and smoke gas data, as well as the results of the micro-mechanical simulation, provide the input for the macro-mechanical model or structural model. In the structural model, the data are scaled to the macro-scale and used to determine the progressive collapses. The macro-model thus represents the necessary training data for the artificial neural network of Section V.

A detailed structural model (macro-scale) for burning buildings taking into account Sections II and III, and the coupling to an artificial neural network is missing so far. Especially the behavior of lightweight construction and the use of precast elements in case of fire have to be investigated. Furthermore, collapse topologies have often been considered separately, although mixed failure topologies occur under real conditions. The work should contribute to a better understanding of the phenomena mentioned [12].

V. FORECASTING TEMPERATURE AND DAMAGE EVOLUTION BY MEANS OF MACHINE LEARNING

This chapter shows current and possible future states of the development of artificial neural networks specialized on the task of temperature forecasting as well as the prediction of material behavior inside a burning room.

A. *Data and Temperature Forecasting*

Artificial neural networks (NN) are highly dependent on their training conditions and therefore rely heavily on their training's dataset. In order to create an effective NN, such data have to be obtained from the real world or reliable simulations. Since burning buildings are fortunately rare occasions, regarding the amount of data needed, and the reproduction of such occasions are extremely costly, within this project the desired amount of data is generated by true-to-life simulations.

Even though such simulations are just an approximation of real events, the opportunities of these simulations predominate the shortcomings. For the simulated datasets, rooms were designed with a high variation of properties like room cubature, number of doors or windows, whereas in real datasets such freedom of choice is not possible. Furthermore, numerical experiments with different boundary conditions and temperature distributions were carried out resulting in a well-balanced dataset.

The next step was to create a common interface such that the amount of simulation data can be sorted out and translated into input- and target tensors such that the NN is able to process those and learn from them. Since the numerical predictions for the fire simulations in Section II take several hours for each (numerical) experiment, the goal for the first NN was to approximate the results and, in the process, speed up their creation.

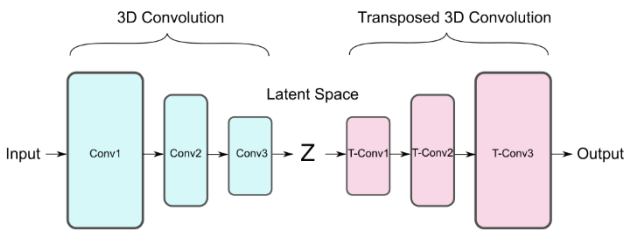

FIGURE 8: CNN ARCHITECTURE FOR FORECASTING TEMPERATURE DISTRIBUTIONS OF A BURNING ROOM.

The networks architecture was inspired by Xioxiao Guo et al. [13]. The method in [13] consists of Convolutional Neural Networks (CNN) combined with their transposed version of each layer. Each space component got its own transposed CNN layers resulting in the approximation of a steady laminar flow giving a geometry representation as input. For the suggested approach the overall architecture was adjusted such that the resulting network was capable of processing input data that represent a 3D temperature distribution of equidistant grid points. The resulting network architecture is shown in FIGURE 8.

The goal of the CNN was to forecast the temperature distribution at time $t + 1$ given the distribution at time t as

input. The output is then compared to the actual simulation; the mean-square error indicates the success rate of the network. Since each timestep t of the input generates outputs only one timestep ahead of the input, the CNN lacks the comprehension of proper time dependencies in the dataset. The network is focusing on the geometric behavior in the temperature alone at the current moment but is designed to be generalized in the future. As a consequence of the convolution process, grid points near the outer area show high errors, which is visible in FIGURE 9.

The method will be extended with 4D convolutional layers in order to convolute the datasets throughout the time dimension to implement a comprehension for time dependencies. Several other extension ideas like an additional one-dimensional convolution across the time dimension or additional Recurrent Neural Network layers like Gated Recurrent Units are yet to be tested.

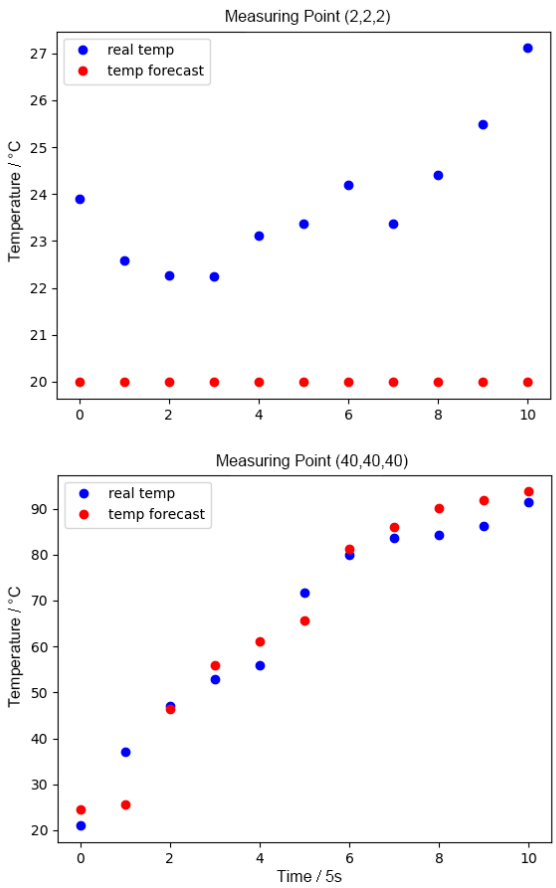

FIGURE 9: COMPARISON BETWEEN THE FAILED FORECASTING OF A POINT NEAR THE OUTER AREA (2,2,2) AND THE PROPER FORECASTING IN THE CENTRE OF THE ROOM (40,40,40).

B. *Material Behavior*

Even though the results of the proposed network can be used in order to approach the second task of forecasting damage evolution and material behavior, a second network architecture specialized for such task is needed.

Regarding anomaly detection for material behavior, several Autoencoder types were already tested and evaluated in order to detect sensor malfunction and distinguish them from material failure [14]. Based on these results, first approaches are already discussed combining two Feed Forward NN (FFNN) within the FEM to increase the simulation speed [15]. The first FFNN in this approach is trained to forecast the strain-stress behavior. Its output among other things is then processed as input by the second FFNN in order to calculate the fracture phase field behavior. Such an approach is in its infancy and will be expanded in near future. One of the end goals is ultimately the combination of both tasks, temperature forecasting and material behavior forecasting, with one generalized artificial neural network, that is suitable for variable space geometry. The possibility of such generalization is an open research question, which is targeted to answer.

VI. SUMMARY AND OUTLOOK

In this contribution, the dtec.bw project KIBIDZ is introduced. Based on the general motivation and the resulting necessary investigations at the micro-, meso-, and macro-scale, first approaches and results combining fluid mechanics, micro-mechanics, structural analyses, and artificial neural networks techniques are presented. These preliminary results show the general applicability of the joint work between the different engineering disciplines. As a next step, the methods developed so far will be further refined and connected with each other in order to obtain a methodology allowing for a real-time prediction of possible and safe rescue routes in case of fire within standardized public buildings. Additionally, selected small-scale experiments will be used to validate the (fluid) mechanical models.

ACKNOWLEDGEMENT

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