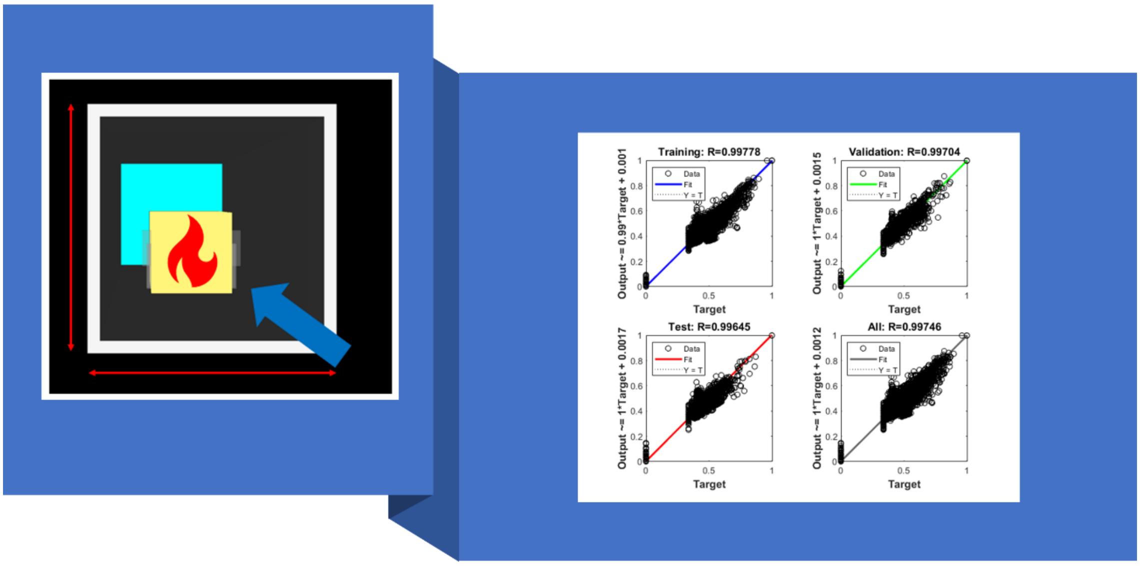
SAFETY AND TRANSPORT
FIRE RESEARCH



Investigating machine learning for fire sciences - literature review and examples

Johan Anderson, Axel Mossberg (Bengt Dahlgren), Eric Gard (Brandskyddslaget) and Robert McNamee

RISE Report 2021: 59

ISBN 978-91-89385-49-8

Användandet av självlärande algoritmer inom brandområdet - litteraturstudie och praktiska exempel

Johan Anderson, Axel Mossberg (Bengt Dahlgren), Eric Gard (Brandskyddslaget) and Robert McNamee

Abstract

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In this work, a review of current literature on artificial intelligence (AI) and more specifically machine learning (ML) is presented. ML is illustrated by two case studies where artificial neural networks are used for regression analysis of 110 spalling experiments and 81 Fire Dynamics Simulator (FDS) models of tunnel fires. Tunnel fires are often assessed by fire safety engineers using time-consuming simulation tools where a trained model has the potential to significantly reduce time and cost of these assessments.

A regression model based on a neural net is used to study small scale spalling experiments and similar accuracy compared to least-square fits are obtained. The result is a function based on 14 determining experimental parameters of spalling and result in, spalling times and depths. It is a relatively small effort to get started and set up models, comparably to regular curve fitting. In this first case study the training times are short, it is thus possible to establish how the model performs on average.

The 81 tunnel fire simulations are trained using a similar neural net however it takes considerable time to organize data, creating input, target data of the desired format and training. Here, it is also crucial to normalize the data in order to have it in a suitable format when training.

It should be noted that ML is often an iterative process in such a way that it may be difficult to know what settings will work before starting the process. It is equally important to illustrate and get to know the data, e.g., if there are large differences or orders of magnitude differences in the data. A normalization procedure is most often practical and will give better predictions.

Key words: Machine learning, Fire spalling, Tunnel fire, Fire Dynamics Simulator, FDS

RISE Research Institutes of Sweden AB

RISE Report 2021:59
ISBN: 978-91-89385-49-8
Borås 2021

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Preface

The Authors are grateful for the financial support from Swedish Fire Research Board (BRANDFORSK) which made this work possible. We have also benefitted from scientific input from an advisory group consisting of people with different backgrounds:

Mattias Delin	Brandforsk
Petra Andersson	RISE
Marcus Runefors	Lund University
Leif Andersson	

1 Introduction

Machine learning (ML) is a sub-field within the area usually called Artificial Intelligence (AI). Machine learning involves studies where a model is trained to identify certain rules for how a phenomenon behaves.

The field of Artificial Intelligence (AI) has a rich history going back to the 1950's, see Ketkar (2017). In the early days, training tasks consisted mostly of problems that are easily formalized, such as games with well-defined rules, a typical example here is chess. A chess game involves pieces that can move on a board according to well defined rules with starting positions and a termination condition, it is thus easily programmable. For this example, an algorithm can be developed that would yield a relatively good AI chess-player. The algorithms and more importantly the computing power increased tremendously over the coming decades. The early AI systems were general-purpose solvers in the sense that any problem that could be described formally could be solved using this generic approach. (Ketkar, 2017) The problem with this approach is that all these AI models solves problems that can be described by a well-defined set of rules. However, many problems are not easily formalized, but natural intelligence can still solve many such problems on daily basis. Consider the case of a physician diagnosing a disease. This is a problem that is difficult, to say the least, to formalize. A human may approach this by knowledge of previous known examples in the field. The big evolutionary step came when it was possible to imitate this intuitive process (not information in itself, but rather the ability to process data) by a mathematical function based on information with appropriate labels. Coming back to the physician, the process here is to collect information on the matter such as age, gender, test data that then can be turned into an assessment with the goal to determine if there is a disease or not. A proper ML model may be able to feed the same amount of data and give the same assessment with proper uncertainties, it may be that the patient exhibits most indicators for a certain condition but still don't have that particular disease yielding a false positive result resulting in the wrong treatment.

Fires are most often very complex with processes on many different time and length scales. Also, fire science is a quite young science giving that many of the underlying physical processes are not fully understood or resolved, i.e. all over the area semi-empirical models are used. Therefore, we believe that the potential to use ML in fire science is great and so far, quite under-developed. ML enables a possibility to create simplified models which is also called surrogate models of the complex model or experiment. When properly trained and validated such models yield predictions of certain outcomes based on the parameters that are available. The models often have a limited parametric domain of validity where it is trained. However, outside this domain, the prediction may strongly deviate from a realistic or true result. This may be due to two reasons, i) alternative physics can be present outside the training domain or ii) the trained model did not capture the actual physics in an accurate way. It is thus in many cases not possible to extrapolate results from a trained model, the model must have seen similar outcomes previously during training. However, it is viable to train sub-models that can be combined to a larger model and still have rather good predictive capability of the more complex model (Hodges, Lattimer, & Luxbacher, 2019). One important benefit is that artificial neural networks often performs better than regression in cases where nonlinear relationships are present. What we have found is that there are opportunities to develop two different levels for trained models in fire science:

1. Fire safety engineering/assessments. Fire safety engineering assessments are made based on experience in certain areas of fire science. ML is a way to automate and streamline the process when large data bases of data or images are available.
2. Scientific research. With the help of ML, the opportunity to make a more precise analysis of what governs complex phenomena is available. This new in-depth knowledge leads in the long run to us being able to develop more relevant test and assessment methods in the fire science.

ML has been used in several different parts of the fire area, especially when it comes to analysing large amounts of information. Some areas worth mentioning are the following:

• Nature of laminar flames (Pulga, Bianchi, Falfari, & Forte, 2020)

• Detection (Nakıp & Güzeliş, 2019), (Lamine Salhi, 2019) and fireplace fires (Tam, Fu, Mensch, Hamins, & You, 2021)

• Evacuation (Agnihotri, Fathi-Kazerooni, Kaymak, & Rojas-Cessa, 2018) and (Zohdi, 2020)

• Forest fire (Li, Fei, & He, 2018) and (Pourghasemia, Gayenb, Lasaponarac, & Tiefenbacherd, 2020)

• Fire resistance of steel, concrete and wooden structures (Fu, 2020), (Naser, 2018), (Naser, 2019) and (Naser, 2021)

• Tunnel fires (Zhang & Gao, 2018)

• Fire dynamics (Lattimer, Hodges, & Lattimer, 2020), (Hodges, Lattimer, & Luxbacher, 2019) and (Hodges J. , 2018)

• Probabilistic risk assessment for fires in nuclear power plants (Worrell, Luangkesorn, Haight, & Congedo, 2019)

However, it is pertinent to remember that AI in fire science is relatively new and some of the studies above are of a conceptual nature. It is also important to note that ML is used with the guidance of experts in the technical field so that the models are generally applicable in a specific domain.

In this report, the result from a literature study and application of ML on two test cases are presented. The test cases here are fire spalling experiments and tunnel fire assessment by Fire Dynamics Simulator models (McGrattan. K., 2021).

2 Literature review

As mentioned above, AI has been used in various science fields and engineering approaches. Different types of AI tools have proven useful in different fields, including fire dynamics, other CFD simulated fluid flows and material science. In many of the studies mentioned below, it can be established that learning an AI model can be both time- and data-consuming, while it usually results in a good-enough prediction tool with a significant speedup compared to traditional simulation tools.

2.1 Fire dynamics

Lattimer et al. (2020) published a paper proposing that machine learning can be used in the area of physics-based fire simulations. The authors identified the need of computationally efficient calculations in fire applications and explored how different machine learning models can be used in different fire scenarios. The results showed overall promising capabilities of predicting different outputs in several of the tested cases (dimensionality reduction and prediction of spatial distributions in fire conditions). It is also stated that a model trained in a simple geometry can predict certain conditions even in more complex geometrical configurations. By breaking down the geometry, it resembles the simple geometry in which the model was trained and thus, the model was applicable in the more complex configurations as well. Similarly, Naser (2021) reviews different kinds of AI techniques and applications and proposes further use of mechanistically informed models in fire research.

In a study by Dexters et al. (2020), a machine learning algorithm was used to study and predict the onset of flashover in a 1/5 scale ISO 13784-1 enclosure with sandwich panels. The goal was to evaluate whether a scale model could make more accurate predictions of a full-scale scenario compared to the existing single burning item (SBI) model. The experimental data that were used was referred to as the "historical data set" and were previously conducted by (Leisted, Sorensen, & Jomaas, 2017). A total of 14 experiments of the 1/5 scale were conducted with variations in burning intensities (1,79 kW, 5,37 kW or 10,74 kW), thickness of the sandwich element (0,06 m or 0,10 m) and planned duration of the burning intensity (465 s or 600 s). By letting the model analyse the historical data set and its results, the ML algorithm was also able to identify variables without any impact on the output. The output was binary (flashover or no flashover), and the authors argue that the model, in an early stage, can be seen as a rough estimation tool. The authors also predict that in later stages, with iterative training, the model can be used as an accurate prediction tool in the practice of fire safety design – even when facing previously unobserved conditions.

In a similar fashion, Garrity and Yusuf (2021) used an artificial neural network to recognize and identify patterns of swiftly rising temperatures before flashover. It was then possible to implement a thermocouple and the AI model in a wearable device that could warn firefighters of impending flashovers before they occur. Both historical data and experiments conducted by the researchers were used to train the model. The model itself used a single input parameter (temperature fluctuations) and were able to predict temperatures forward in time and, based on that, recognize whether any temperature rise patterns indicates an impending flashover. In a similar study, Nakıp & Güzeliş (2019) used data from different multi-sensor fire detectors to develop an algorithm that reduces the false positives in fire alarms.

In a study by Hodges et al. (2019), a transpose convolutional neural network was fed with data from more than 1000 FDS simulations of a simple two-compartment configuration to be able to predict temperatures and velocities of flow. The input parameters that were varied in the different scenarios were fire location, fire size, ventilation conditions and the compartment configuration. In similar two-compartment configurations, the model was able to predict 95 % of the values for temperature and velocity with an error within 17.2 % and 0.3 m/s compared to the FDS simulations. The model was also validated with more complex multi-compartment configurations by breaking down and processing each compartment separately, resulting in even smaller error margins than the validation of the two-compartment configuration. The authors argue that the results are promising when considering repetitive configurations such as tunnels, however, it is also stated that more research is needed to include other dependant input parameters such as fuel type and different boundary conditions.

In a paper by Zhang et al. (2021), the authors put together a database containing existing data from tunnel fire experiments based on an extensive literature study, and applied ML to train and predict the critical ventilation velocity to demonstrate the use of big data. The authors argue that the database facilitates the use of AI in fire safety in tunnels. Zhang & Gao (2018) also studied tunnel fires using AI. Using a 1:9 scale model of a tunnel and different configurations regarding heat release rate, ventilation velocities and fire locations, the authors trained a model that were able to predict temperature and smoke (CO_2) concentration. However, the authors also state that further experiment with more training data is needed to increase accuracy.

In a study by Su et al. (2021) a transpose convolutional neural network was used to predict smoke motion and thus the ASET (Available Safe Egress Time) in an atrium. The dataset used to train the model consisted of visibility profiles from CFD-simulations of atria with different configurations. The different configurations included variations in heat release rate, room width, atria height and smoke extraction rate (note that the fire location were constant). The full factorial design thus meant a total of 280 different simulation cases. The results show that the trained AI-based model was able to reliably predict the visibility profile and ASET much faster than the traditional CFD calculations. The obtained coefficient of determination, R^2, converged to 95 %.

Li et al. (2018) let four different ML models analyse a specific geographical location in order to identify the most important influencing factor as well as the most vulnerable location in a forest fire case. The results also identified similarities and differences between the used models. From the dataset of 517 forest fire records, the authors were successful in obtaining both the most important influencing factor (temperature) an the most vulnerable locations (certain coordinates).

2.2 Material science and structural behaviour in fire

In the area of material science, AI have proven useful in predicting and making quick analyses of different kind of structures. For example, Fu (2020) used artificial neural networks to recognize and predict failure in steel framed buildings in fire. The tool also made it possible to assess the risk of collapse. Naser (2018) also used artificial neural networks, to derive temperature-dependent models for structural steel. The trained model used a dataset of both experimental data as well as models in current standards. The author argues that one of the pros using AI models is that the result is an unbiased model based completely on the training set.

Hisham et al. (2021) also used artificial neural networks to predict temperature variation in fire exposed load-bearing structures, but in reinforced concrete columns instead of steel beams. Trained with 1200 samples and validated with previously published studies and experiments, the model proved successful predicting temperature variations with an accuracy of 85-90 %. It should be noted, however, that the accuracy decreased outside of the defined training range. In a study by Naser (2019), the phenomenon of fire induced spalling of concrete and fire resistance of reinforced concrete columns is studied using machine intelligence. Successfully, the model was able to accurately predict spalling in fire durations exceeding 4 hours.

In the area of timber structures in fire, Naser (2019) used AI to develop an assessment tool for evaluating fire performance of timber structures. The data set used to train the model was collected in a literature review of previously conducted fire tests where timber structures were exposed to fire and consisted of 12 000 data points. Although the limited amount of training data hindered full utilization of the model, it still proved successful in predicting performance of timber in fire, both on material and member stage.

2.3 Other physics and CFD flow cases

Lye et al. (2020) used a transpose convolutional neural network model to learn and predict observables based on certain input parameters in two cases of parametrized convection-diffusion. The studied cases were a two-dimensional finite volume airflow past an airfoil and a one-dimensional stochastic shock tube problem. The authors were able to produce a trained deep artificial neural network that were able to compute probability distributions faster than regular methods, with low prediction error. The authors discuss that, since the model was trained on obtained data and does not utilize the partial differential equations, the method can be expanded and applied to other partial differential equations such as the Navier-Stokes equations.

Guo et al. (2016) studied prediction of non-uniform steady laminar flow with transpose convolutional neural networks in two- and three-dimensional domains. The goal was a model that enables interactive and flexible aerodynamic design compared to the established (and data consuming) CFD modelling. Different obstacles were used in the simulations, such as cars or geometric shapes. The model can estimate laminar velocity fields with low margin of error in a more time efficient manner than traditional CFD calculations.

In a study by Heinonen and Diamond (2020), a supervised deep artificial neural network was used to predict turbulent fluxes based on direct numerical simulations of a two-dimensional system. In a similar way, Gopakumar and Samaddar (2020) used artificial neural networks to model plasma and other edge characteristics in a tokamak confinement device.

Liu et al. (2019) successfully used a feedforward deep learning artificial neural network to derive a new criterion for initial failure of fibre tows (yarns). With low error, the model was able to predict failure in fibre tows (microscale) using mechanics of structure genome applicable in textile composites (mesoscale) modelling. These studies all show promising results regarding strength prediction in the field of material science, both in fire situations and not.

2.4 Summary of literature review

In summary, the field of ML and AI is rapidly evolving where numerous new studies relevant for fire sciences are published every year. This work is not able to cover all aspects of ML and AI. However we have provided a basis for which further studies in fire sciences can be built. See also Naser (2021) and Lattimer et al. (2020) for guidance regarding design of models and specific techniques when studying fire science using AI.

Several of the studies focus on a simplified binary output such as flashover/no flashover. The literature review elucidated that there are not that many studies attempting to predict several parameters. Moreover, in the case of tunnel fire assessment, e.g., some data are vastly differing in magnitude such as soot density and temperature.

3 Previous feasibility study at RISE

An exciting area of development for ML is simulations based on fluid mechanics or Computational Fluid Dynamics (CFD) calculations, these calculations are often costly and have a relatively long running time where it is appropriate to optimize the process. RISE conducted a brief feasibility study on the applicability of how ML can be used to estimate uncertainties in CFD calculations. It takes the analysis a step further than using a surrogate model to calculate, for example, the velocities and temperature in a domain and instead provides the variations of the velocities and pressure directly, see (O. Penttinen, 2019). The study was done with a well-known case in fluid mechanics, a wind tunnel with a backward facing step in the flow direction inserted into the geometry, it also happens to be one of the tutorial cases in OpenFOAM. Variations in four input parameters (input speed, viscosity and the turbulent kinetic energy and dissipation) was employed. To estimate the variations a simulation scheme according to a so-called Full Factorial Design (FFD) (Olsson, Anderson, & Lange, 2017) and (NIST, 2012) with 81 simulations where the simulations are run to a steady state was used. The models were trained to predict the variations in results, see figure 1. A full factorial allows for estimation of main effects and interactions by a simple design. As the levels of a factor or the number of factors increase a large number of repeated simulations is needed.

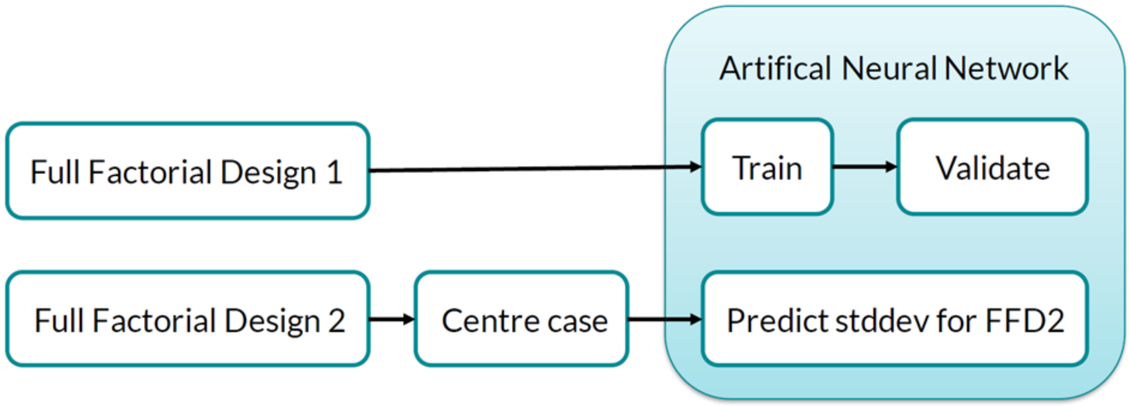

Figure 1. Schematic picture of how the feasibility study was conducted.

We use a subset for training and a subset for validation and repeat the process. To test the limits of the study, we take a lower speed than what was given in the training data and set up a similar FFD, which is motivated by the fact that in some parts of the domain we have lower speeds regardless. We estimate the variation from a simulation where all input parameters have been set to their mean value and compare with actual results from FFD. The lessons from the study are that, even though we pushed the model to the limit, the uncertainties in the velocity in the flow direction and the pressure are well captured while the uncertainty in the perpendicular velocity was difficult. The uncertainty in the parallel flow is displayed in figure 2. This is due to certain choices in the learning algorithms and can be improved by understanding the physics to be described, in particular the transfer functions seem to be important. The variations in the perpendicular direction are small and may thus be penalized too much by certain functions.

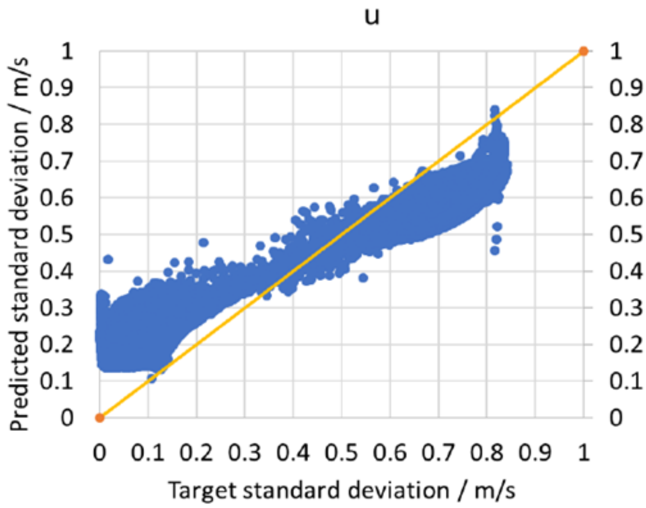

Figure 2. An overview of preliminary results from CFD - ML, which is shown in comparison between the prediction of the standard deviation against the calculated from 81 simulations in the flow direction (u).

4 Case studies

4.1 Concrete spalling in fire

Fire spalling of concrete is an issue that is constantly relevant and must be taken into account when designing tunnel sections made of concrete. The verification of whether you have a spalling proof concrete or not is done with experiments. A variety of factors influences the fire spalling propensity of a fire exposed concrete cross-section (Jansson R. , 2013), but little detailed knowledge about how the influencing factors interact exists (McNamee, 2019).

In a previous attempt to find correlations between amount of spalling a test series performed with a screening test method was analyzed more in detail. The size of the test specimens in the test series was 600 x 500 x 200 mm^3 and a loading system with three internal post tension bars were used to be able to load the specimens in compression. The heating was done on a small furnace where an area of 500 x 400 mm^2 of the specimens were fire exposed. In figure 3 one of the test specimens included in the analysis is shown after fire exposure.

Figure 3. Spalled test specimen after fire exposure. The three holes in the specimen were used for the post stressing bars in the loading system, (Boström & Jansson, 2008).

In the previous study, 14 potentially influencing parameters were analyzed and compared with spalling results of 110 fire spalling experiments, see parameters in table 1 (Jansson R., 2013) and (Jansson R., 2014). The average spalling depth of the individual specimens were between 0 and 53 mm with an average in the whole series of 20 mm. Of the 110 tests performed, 100 were performed in pairs (two identical tests). By analyzing these 50 pair we see that the average deviation between two identical spalling tests was 6 mm and that the greatest deviation between two identical tests were 21 mm.

The analysis was performed using a manually optimized least squares fit to the data of these fourteen parameters. The result of the fit, shown in table 2, compared with experimental values can be seen in figure 4.

Table 1. Span of values of the 14 input parameters analysed in the 110 fire tests on self-compacting concrete (Jansson R. , 2013). Tests from (Boström & Jansson, 2008).

Factor in experiments and model	**Span of values in experiments**		**Unit**	**Comment**
	min	**max**		
Water/powder ratio	0.25	0.55	[-]	
Water/cement ratio	0.3	0.71	[-]	
Cement type	1*	2 *	[-]	CEM I or CEM II
Water in mix	168	230	kg/m^3	
Cement in mix	300	560	kg/m^3	
Limestone filler in mix	0	252	kg/m^3	
Air content during moulding	2	12	%	Some mixes were designed to include much air
T 50 during moulding	1	7.5	sec	
Strength at 28 days	35	82	MPa	
Fire curve	1*	4*	[-]	10 °C/min, slow heating curve, standard fire curve and hydrocarbon fire curve
Applied stress during fire test	0	10.6	MPa	
Moisture content at test day	4.1	6.6	%	
Age at test day	88	400	days	
Strength at test day	39	105	MPa	

** This is numerical values given to be able to investigate with a least square fit whether an influence is detectable.*

Table 2. Formula for the best fit of 14 parameters to spalling test data of all 110 tests (reported to 4 significant figures). The table should be read row after row to give the

formula. The span of values for each parameter represented in the test series inside which the fit is valid can be seen in Table 1. Span of values of the 14 input parameters analysed in the 110 fire tests on self-compacting concrete . Tests from previous table.

	Fire curve ^	**1**	**X**	**-4.074**	+
+	**Stress^**	**0.001**	**X**	**14.38**	+
+	**Cement type^**	**1**	**X**	**21.86**	+
+	**Moisture^**	**0.04**	**X**	**490.7**	+
+	**Age/100^**	**2**	**X**	**-1.132**	+
+	**Air^**	**-3**	**X**	**-57.74**	+
+	**T50^**	**0.5**	**X**	**7.699**	+
+	**w/p^**	**10**	**X**	**3727**	+
+	**w/c^**	**-5**	**X**	**-0.039**	+
+	**Limestone filler/100^**	**0.4**	**X**	**10.58**	+
+	**Strength/100^**	**1**	**X**	**86.81**	+
+	**water/100^**	**-10**	**X**	**-1983**	+
+	**cement/100^**	**1.5**	**X**	**2.563**	+
+	**28d strength/100^**	**1**	**X**	**-26.74**	+
+	**-605.1**	=	**Average spalling depth [mm]**		

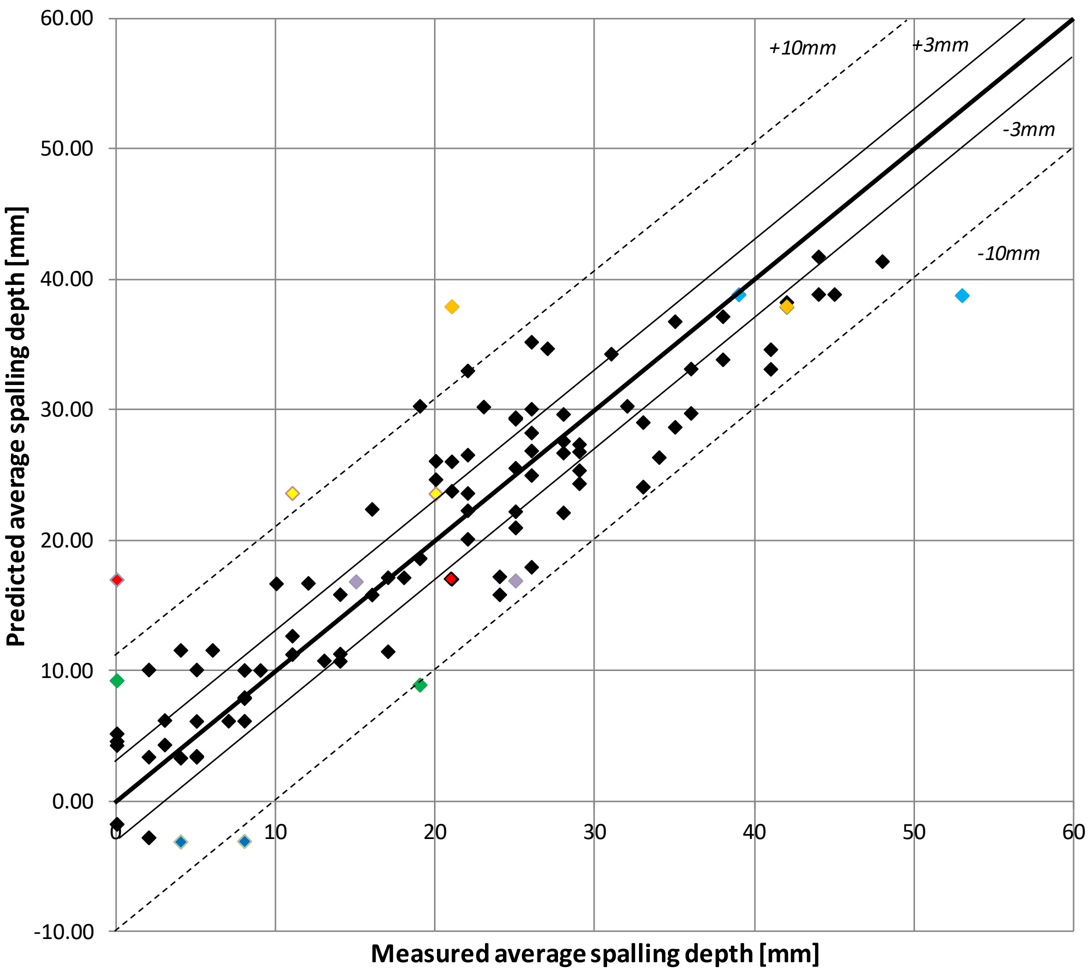

Figure 4. Measured vs. predicted values using the model in Table 2. Formula for the best fit of 14 parameters to spalling test data of all 110 tests (reported to 4 significant figures). The table should be read row after row to give the formula. The span of values for each parameter represented in the test series inside which the fit is valid can be seen in Table 1. Span of values of the 14 input parameters analysed in the 110 fire tests on self-compacting concrete . Tests from previous table. , R^2 =0.81. Coloured dots in same colour show pairs of two identical tests (these are the identical tests with the largest deviations, average deviation between two identical tests was 6 mm).

To see how sensitive the model was to test data, the model was redone ten times based on 95 randomly selected experiments in the test series to predict the results of the 15 which were not included in the model. It turned out that it was very difficult to rank the impact from different parameters relatively, but the model was quite robust, see R^2 values in table 3. The only clear parameter that could be distinguished was the influence of an external load, while the remaining 13 parameters seemed to depend on each other in different ways. In this project about machine learning we want to investigate if machine learning can be used to do better predictions than in this previous study.

Table 3. Prediction results (Jansson R. , 2013). In each prediction 15 random tests were removed from the analysis and then predicted based on the analysis of the remaining 95 test.

Prediction	R^2	Average deviation [mm]	Maximum deviation [mm]
1	0.84	6.7	14.4
2	0.81	3.8	14.1
3	0.81	4.2	13.3
4	0.85	6.5	19
5	0.81	4.7	11.7
6	0.81	5.2	18.1
7	0.83	6.5	17.1
8	0.85	6.6	19
9	0.83	5.1	19.2
10	0.81	3.3	8.3
Average	**0.83**	**5.26**	**15.42**

4.2 Tunnel fire simulation

In Sweden, the fire safety design of tunnels is often based on a risk-based approach. This is possible due to the scenario space being limited because of the restricted number of scenarios that can occur in a tunnel. Commonly, a few deterministic scenarios are selected based on different percentiles on a risk scale and then analysed thoroughly. Thus, the analysis is not fully probabilistic but rather semi-deterministic. This is mainly due to the fact that the calculation time for CFD calculations in tunnels is extensive, which means that only a handful of scenarios can be analysed within a reasonable time frame.

For this type of analysis, the number of outputs that are of interest is limited. In most cases, temperature and soot density in the tunnel is sufficient (from the soot density, both visibility and toxic components can be calculated). Also, the input data is often similar between different projects, although they vary at certain specific points, primarily:

• Tunnel geometry including length and slope

• Air velocity in the tunnel

• Heat release rate, fire growth rate and train design as well as placement of the fire in the tunnel

Assessing these parameters from a Fractional Design perspective, a basis for a machine learning algorithm can be formed. The benefits of such an algorithm would be great. As previous research on the subject (Lattimer, Hodges, & Lattimer, 2020) have shown, there are obvious time savings to be made, and such an algorithm could also enable a more fully risk-based approach when assessing tunnel fire safety. In this report, we aim to investigate if such an algorithm would be feasible to create.

To form a basis for the study, 81 different FDS calculations were performed with four different parameters varied between three different values for each parameter ($3^4 = 81$). The key parameters identified for this first feasibility study were, (1) tunnel height, (2) tunnel width, (3) tunnel air velocity and (4) maximum heat release rate. These are illustrated in figure 5.

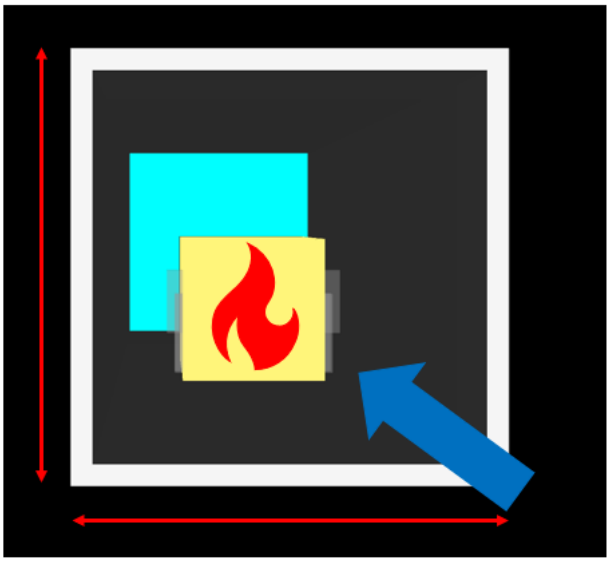

Figure 5. Illustration of the studied parameters in the tunnel case study.

The parameters were varied as follows:

1. Tunnel height [6; 7.6; 9,2] m
2. Tunnel width [6; 7.6; 9,2] m
3. Air velocity [0.5; 1.0; 1.5] m/s
4. Maximum heat release rate [2; 4; 6] MW

The output data collected was soot density and temperature, which were recorded in 12-21 locations (depending on the geometry) every 10 meters down-wind from the fire in the tunnel.

5 Machine learning models of case studies and approach

Here the machine learning models of the two case studies will be discussed. We perform regression analysis on two widely different data sets, the first is the 110 fire spalling experiments and the second is the 81 numerical CFD models of tunnel fires. There are several open source softwares for ML such as TensorFlow (2021) and PyTorch (2021), however in this study a commonly used engineering tool, Matlab 2021 (2021), will be used.

Using ML may often be an iterative process where the model and parameters are fine-tuned during testing and training of several models before a relatively good model with predictive capability is found.

In a first test, an earlier version, Matlab 2018, was used with the basic models suggested, e.g. logistic regression, support vector machine (SVM), k nearest neighbour, decision trees however using the suggested already prepared models and R^2 = 0.16 was the best performing model for the spalling case which is not very good. This can be compared with the previous used least squares model with R^2 = 0.83 for the fire spalling case. Thus, a new approach was needed where the artificial neural network was used and explored more deeply as described below.

5.1 Fire spalling model

In the case of fire spalling experiments the aim is to create a surrogate model that takes the 14 input parameters yielding the measured spalling time and depths. The surrogate model is created by neural net regression model using Matlab 2021.

There are premade applications available (although they use a number of regular Matlab commands) where a simple neural net is constructed. The network consists of virtual neuron which takes the input parameters assigning weights to each parameter and yield a matrix with the responding spalling parameters. A schematic layout of the neural net is presented in Figure 6. Note that from figure 6, it can be seen that the model takes 14 parameters (that may be correlated in different ways) as input, assigns ten virtual neurons, weights, the sigmoid activation function, defined below, and gives 5 output parameters. These defined output parameters were average spalling depth, maximum spalling depth, start of spalling (time), weight loss, and load increase during experiment. Although the primary target for the prediction was the average spalling depth using these extra outputs (results from the tests and related to average spalling depth) in the training model made the model more accurate.

The sigmoid activation function is,

$$\varphi(x) = \frac{1}{1 + e^{-x}}$$

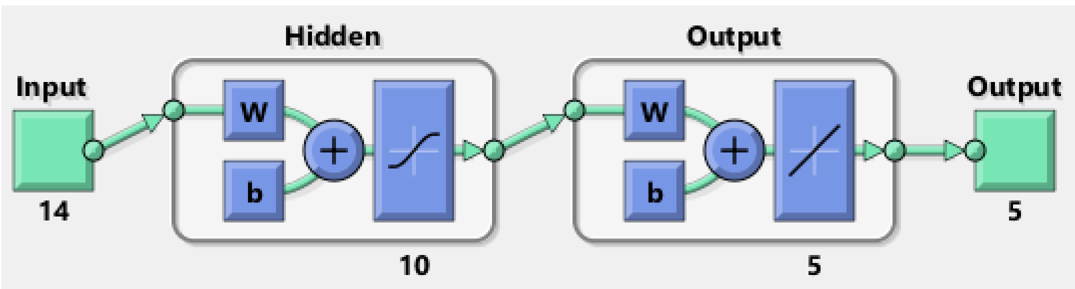

Figure 6. A typical neural net used during regression where w and b are weight and bias vectors.

The network is trained and solved by the Levenberg–Marquardt algorithm (LMA), which also known as the damped least-squares (DLS) method. This algorithm solves the nonlinear least squares problems. The model is usually trained and updated for 10-20 times or epochs.

During the setup of the model different numbers of virtual neurons, activation functions were used however this particular net yielded the best result in terms of R^2. The result for one training is summarized in figure 7. The data is divided randomly in a training set, validation set and test set, with 70 % of the data is used for training and 15 % for validation and 15 % for test. The regression coefficients are presented for all sets in figure 7.

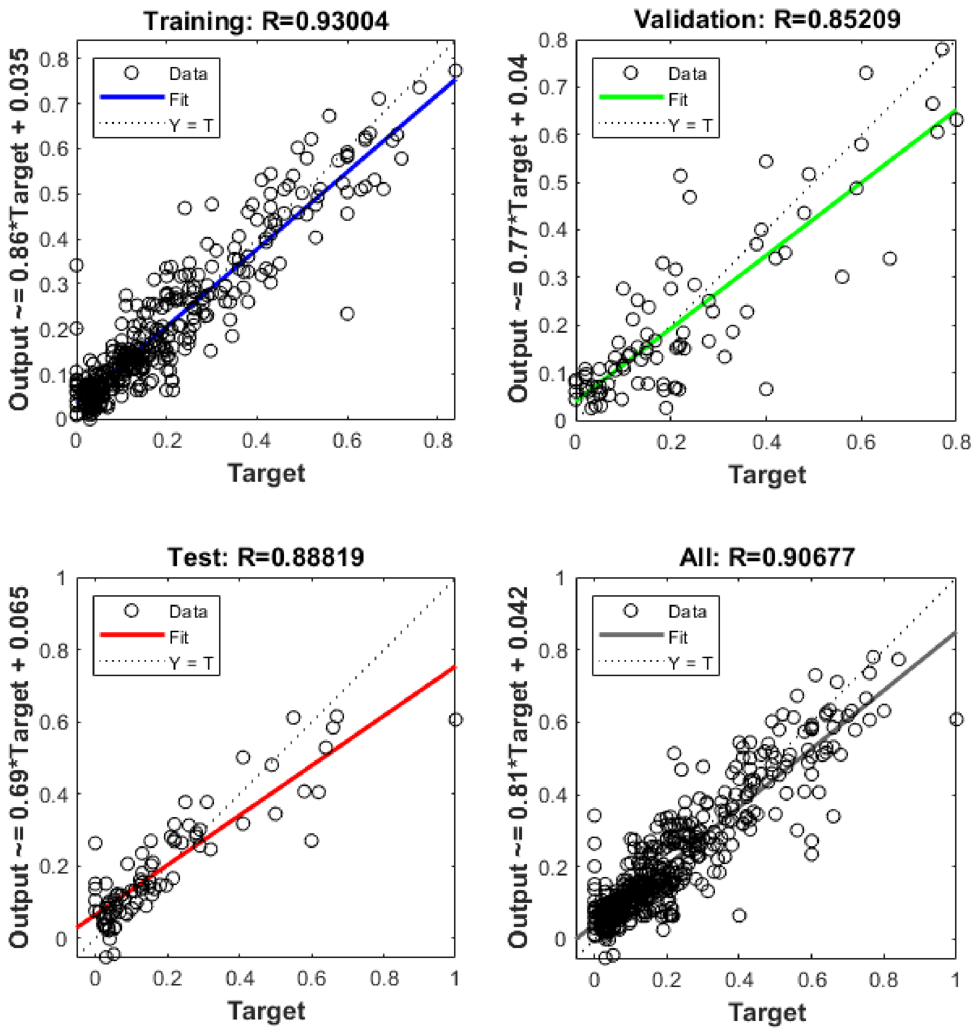

Figure 7. Regression using the full data set with all 5 target spalling data sets.

The error can be analysed using a histogram where incidences in different categories or bins for the three sets (training, validation, and test) are counted and plotted and then compared with the zero-error case, as seen in figure 8. In the repeated training of the model small errors are visible and the highest count or peak is close to the zero-error bar.

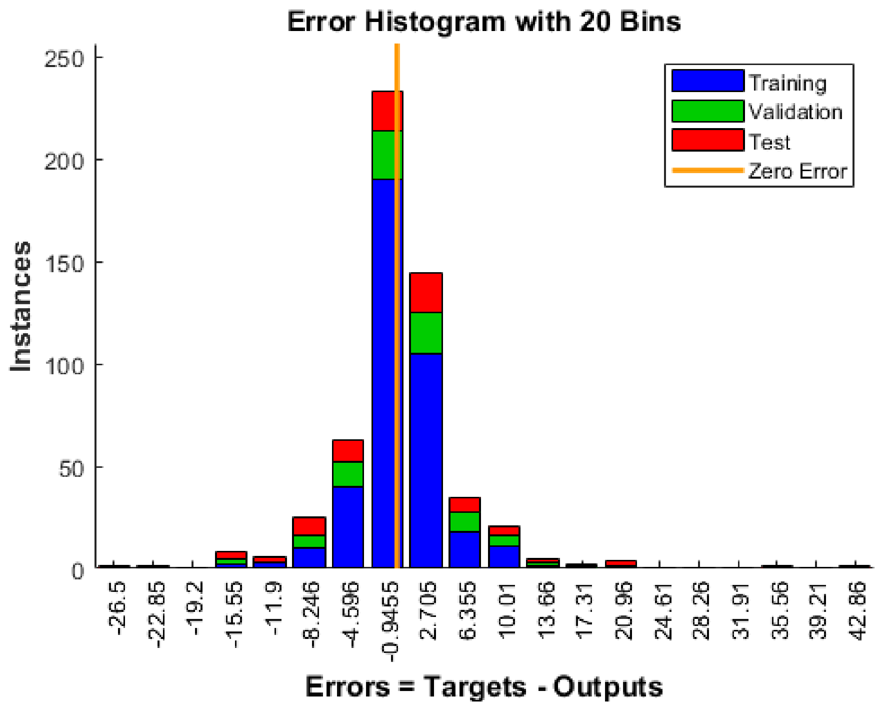

Figure 8. Error analysis of the trained model.

After each training or epoch, the mean square error is computed for the three data sets as is displayed in figure 9. The LMA solver need 10 – 20 epochs for training however as an example the Bayes method requires 100-200 epoch for training, that solver however gives similar precision in terms of R^2.

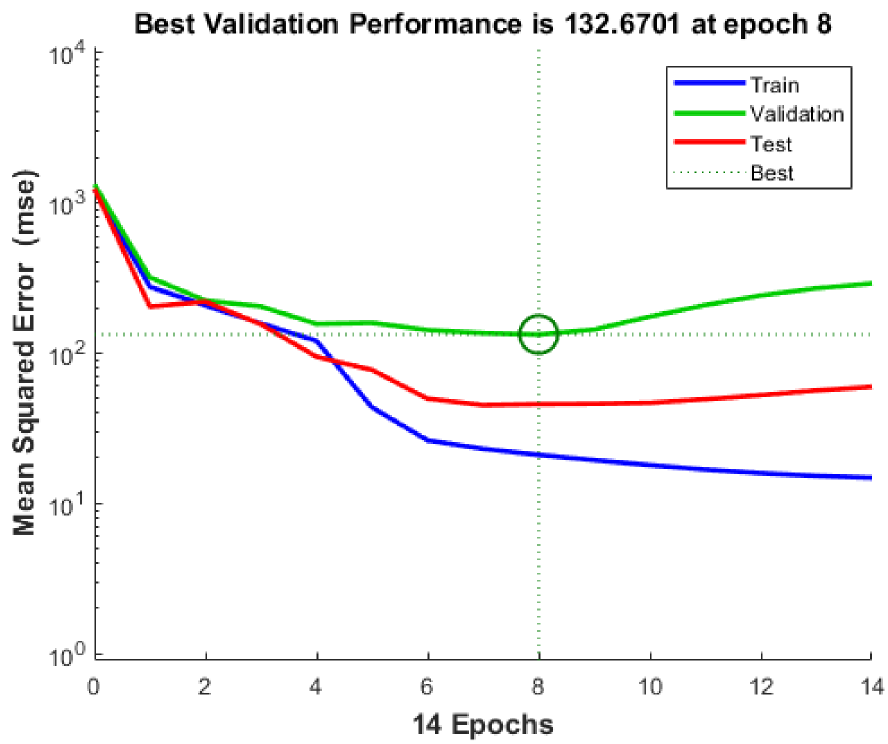

Figure 9. The mean squared error development for each epoch.

The model is then trained ten times, like the previous effort that used a modified least squares method. The data sets exhibited a few unknown entries, either no measurement was done or there was no spalling, thus no spalling time could be determined. Two different approaches were investigated, Model 1 and Model 2. In Model 1 unknown entries were set to 0 regardless of the meaning of that parameter, this leads a few instances with unphysical assumptions, e.g., where no spalling was measured, the spalling time was set to 0 minutes. In Model 2, the missing instances of spalling time were set to 60 minutes and other unknown data was taken as similar to other comparable experiments. In Model 3, the target data was taken to be the average spalling depth only disregarding the other 4 target parameters. The result of repeated training is showed in table 4, 5 and 6.

Table 4. Model 1, repeated regression where unknown data entries were set to 0.

Prediction	**R^2**	**Average deviation [mm]**	**Maximum deviation [mm]**
1	0.95	3.62	10.9
2	0.94	4.58	8.38
3	0.94	4.21	10.2
4	0.94	6.44	10.7
5	0.91	6.14	9.50
6	0.96	3.94	9.06
7	0.94	3.81	9.71
8	0.89	7.03	11.06
9	0.88	6.06	13.6
10	0.93	4.92	9.15

Table 5. Model 2, repeated regression where spalling time was set to 60 minutes and other unknown data was set to comparable data for other experiments.

Prediction	**R^2**	**Average deviation [mm]**	**Maximum deviation [mm]**
1	0.88	7.59	12.4
2	0.88	5.58	10.6
3	0.89	4.15	15.9
4	0.92	6.01	9.88
5	0.92	4.68	11.9
6	0.93	3.34	13.7
7	0.91	7.19	9.89
8	0.86	5.24	9.90
9	0.93	5.38	10.5
10	0.92	6.03	10.2

Table 6. Model 3, repeated regression where the target data was the average spalling depth.

Prediction	R^2	Average deviation [mm]	Maximum deviation [mm]
1	0.87	5.15	11.0
2	0.85	6.34	8.35
3	0.89	4.95	8.10
4	0.92	4.69	7.02
5	0.89	4.10	9.50
6	0.83	4.31	14.2
7	0.89	4.76	10.4
8	0.84	7.63	8.13
9	0.88	5.81	7.46
10	0.87	5.47	10.5

To summarize the repeated training, averages of the mean R^2, mean and maximum deviation is show in table 7.

Table 7. A summary of the results from the different models.

Model	Mean R^2	Mean dev. [mm]	Max dev. [mm]
Model 1	0.93	5.08	10.23
Model 2	0.90	5.52	11.49
Model 3	0.87	5.32	9.47

Comparing the Model 2 and experiment for all data points, estimating mean deviation and maximum deviation yields, 5.97 and 11.5 respectively. In summary, it is relatively small effort to get started and set up models, comparably to regular curve fitting. The result is a function that takes the 14 input parameters and predict the five measured outputs. The model has short training times (order of 10 s), it is thus possible to see how the model performs on average however it takes some time to organize data and create input files in the desired format. Note that although a Matlab function is created by the training it is possible to transfer this to other tools (Python, Excel etc), but it may need programming of already pre-defined functions available in Matlab.

The model provides similar estimates as the previous method but in general more time efficient. Approximately the same mean deviation 5.08 to 5.32 mm in comparison to 5.26 mm in mean deviation. Note that using only mean spalling depth as target gave less accurate predictions. This indicates that the other parameters give extra information on the physics of the spalling process and better predictions can be found even if they are not used directly in the predictions of e.g., mean spall.

There are also other possibilities with ML such as classification and evaluation of input parameters as well as parameter interactions that should be explored further.

5.2 FDS tunnel model

In the tunnel model case, 81 simulations were performed and generated data for the time evolution of the tunnel fire, as described previously. In each of the 81 simulations we have around 2000 output locations where mass flows, temperatures, soot density and average values of temperatures and soot densities are recorded. We present some of the data from these simulations below, such as the heat release rates, volume flows and soot densities at one location as functions of time obtained in the 81 simulations, see figure 10, 11 and 12.

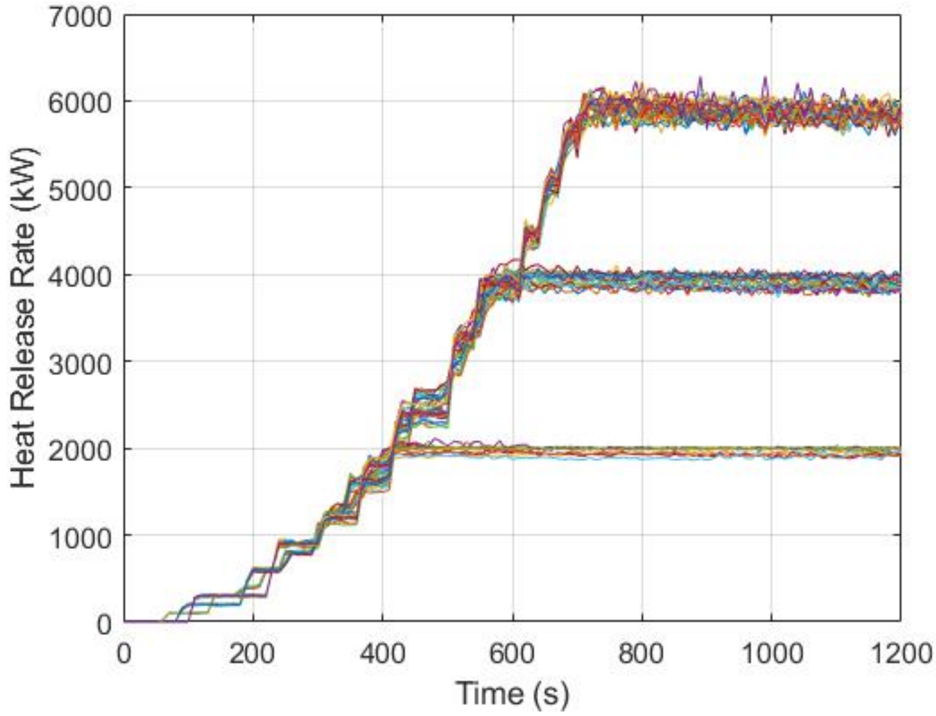

Figure 10. The Heat Release Rate (kW) as a function of time (s) from the 81 models, where the three target levels are visible.

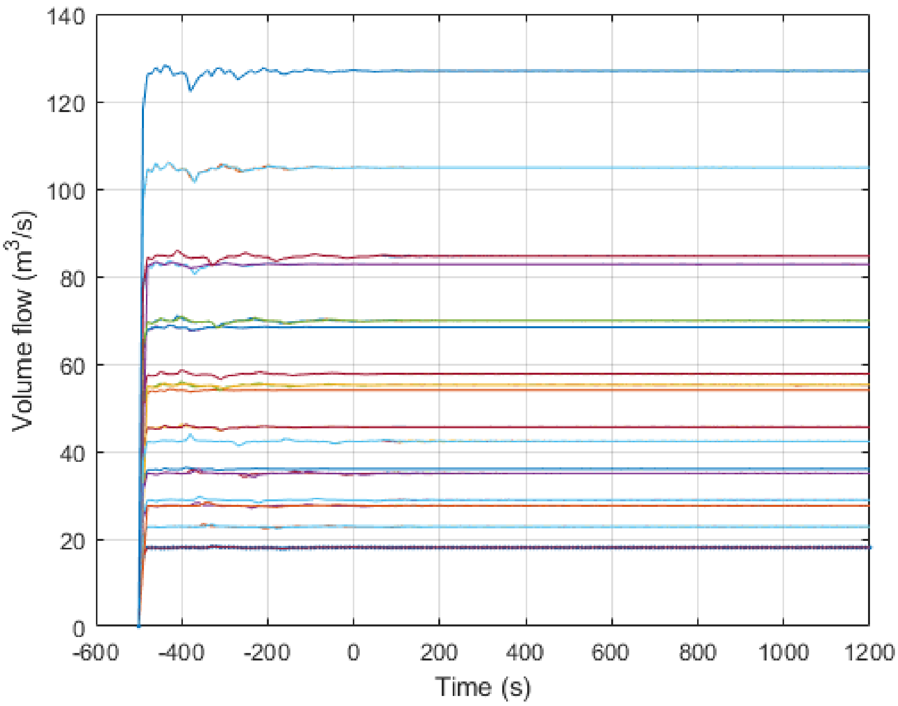

Figure 11. The volume flow (m^3/s) as a function of time (s) in all the tunnels as found in the simulations.

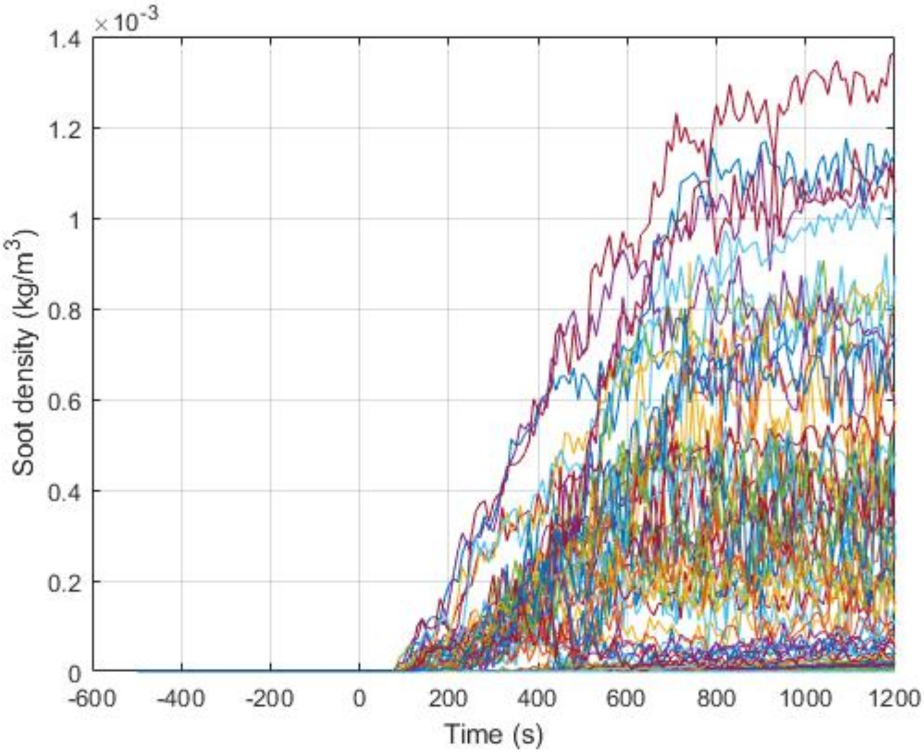

Figure 12. The soot densities (kg/m^3) as functions of time (s) for all simulations measured at one specific location.

The results from the simulation are long time series recorded each 10 seconds yielding 171 rows with at least 1839 columns. The data is organized into input data and target data where only the last time step is used. The input data consists of 81 rows, one for each simulation, and 16 columns describing the power balance e.g. the radiative and convective fractions of the HRR in the simulation and the tunnel dimensions in width and height [6.0, 7.6, 9.2] m, HRR (figure 10) and air velocity [0.5, 1.0, 1.5] m/s. The target data consists of 81 rows and 1839 columns describing the soot densities and temperatures at different locations along the tunnel. These last four columns describing the variations set in the simulation are simplified to be entries called 1, 2 and 3 corresponding of the minimum, mean and maximum of each parameter. Note that, the output data from these simulations differ quite widely in ranges soot densities ~10^{-4} (kg/m^3), see e.g., figure 12, to temperatures ~10^2 (°C) and in fire safety engineering assessments of tunnels the time evolution of temperatures and soot density is used. To make the training feasible, the data obtained in the last time step is used and scaled, often called normalized, using the logarithm and the min-max scaling algorithm,

$$y = \frac{x - min(x)}{max(x) - min(x)},$$

that takes the entry x and normalize it to y in the range [0,1]. The order of magnitude is rescaled by the regular logarithm. If no normalization of the data is performed the mean squared error will be dominated by the large values such as the temperatures whereas the error for soot density can be an order of magnitude off while the error will still be minimal, thus a normalization procedure is necessary.

A similar training procedure is adopted compared to the spalling case, where a neural net is trained consisting of ten neurons where the data is divided in a training set (70 %), validation set (15 %) and a test set (15 %). The same LMA solver is utilized, and the total training takes around 30 h on a laptop. The result from the training is shown is Figure 13, where the R^2 values are shown for the different sets.

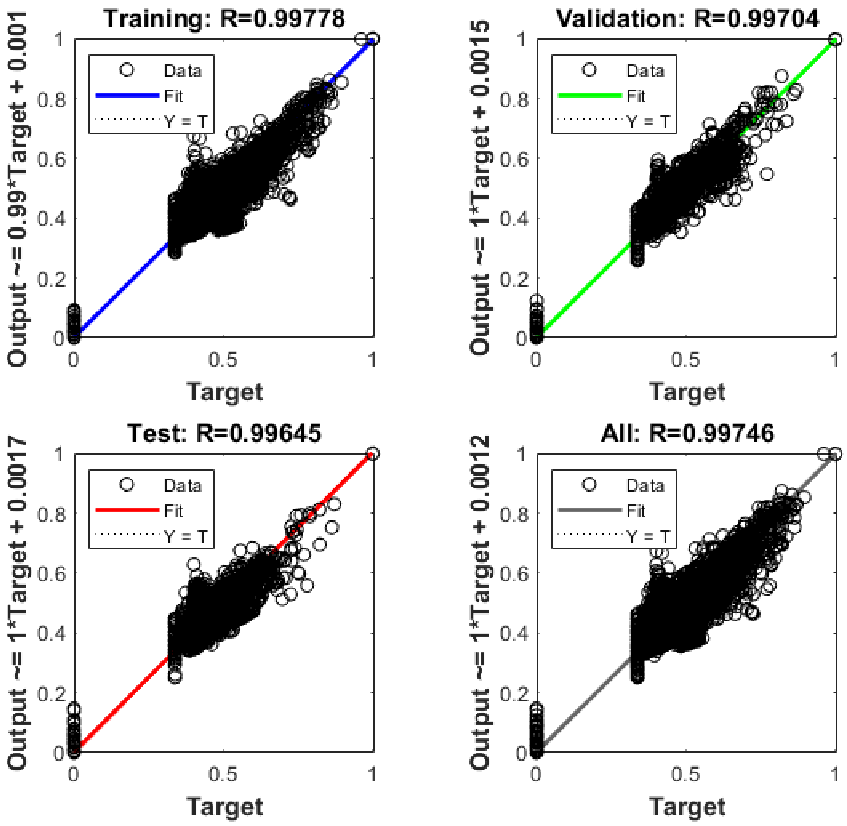

Figure 13. The regression of the normalized data from tunnel simulations.

Note that quite good regression is found however there are some deviations from the fit, see figure 13. The model is trained for 25 epochs and the best fit for the validation data is found at epoch 19, as is found in figure 14.

The result is a Matlab function that takes 16 inputs and yield 1839 columns of data for temperatures and soot densities. In the following the differences between the resulting function and the simulation data will be illustrated.

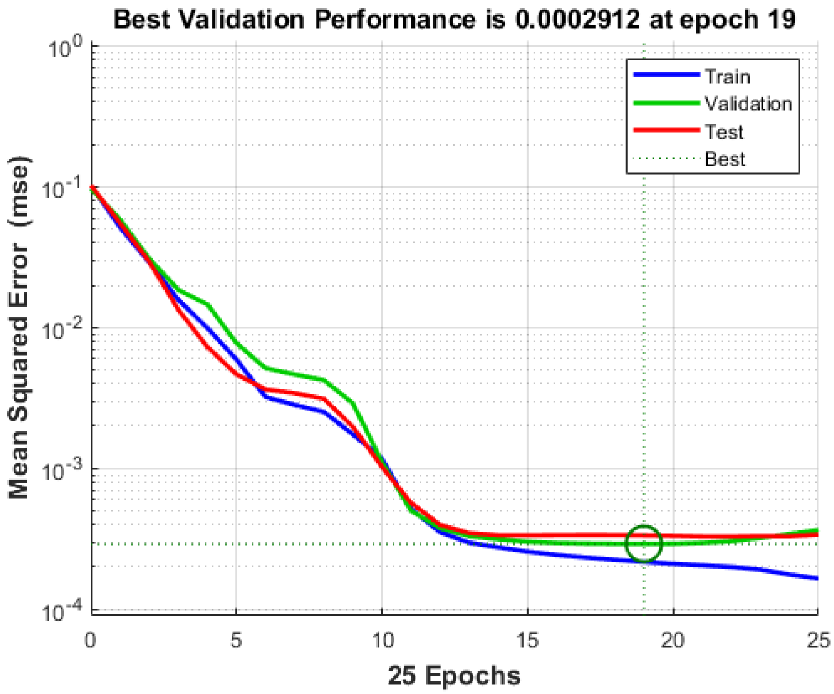

Figure 14. The mean squared error during the training process displayed at every epoch or iteration in the training.

In order to see differences between the simulation and the trained model a few cases will be explored, using first the 1111 case (minimum height, width, air velocity and HRR) and second a randomly chosen case, 3123.

The model gives a good prediction in both cases, 1111 and 3123, and reasonably good fits are found, see Figures 15 and 17. Slightly less good prediction, but still orders of magnitude better than using non-normalized target data, is found when the data is brought back by inversing the logarithm and the min-max scaling function, as can be seen in Figures 16 and 18. This indicates that the model has predictive capability and could potentially be used in fire safety engineering assessments.

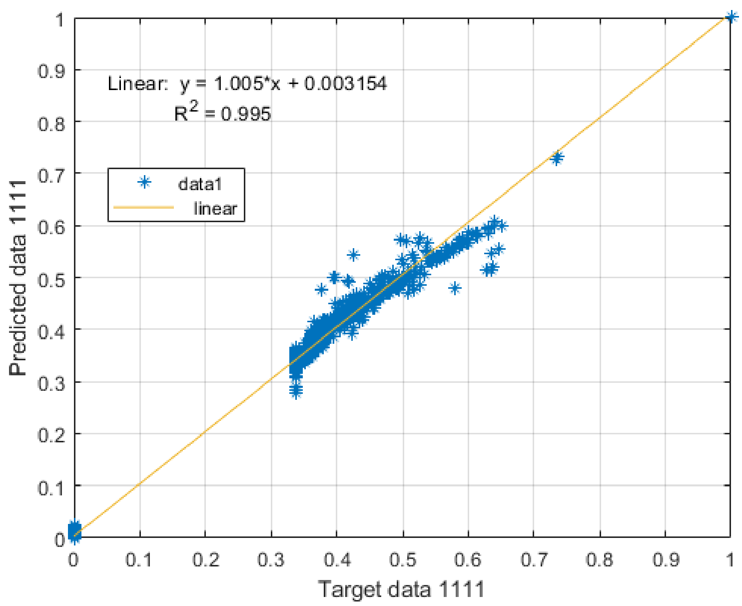

Figure 15. The fit between normalized target data and predicted model in the case 1111.

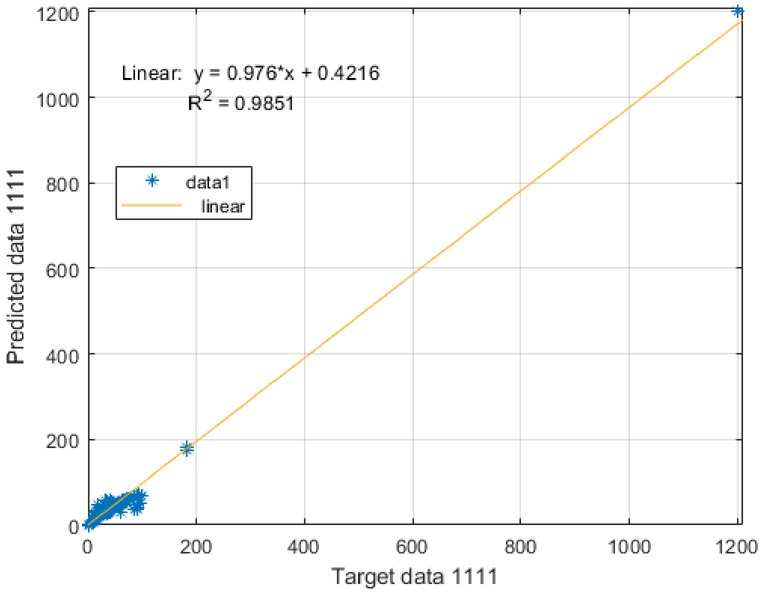

Figure 16. The fit between non-normalized target data and predicted data after in the case 1111.

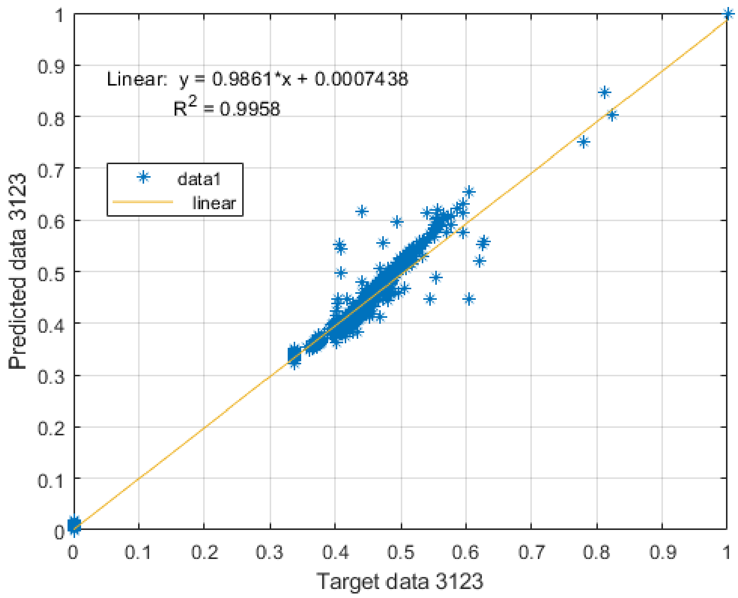

Figure 17. The fit between normalized target data and predicted model in the case 3123.

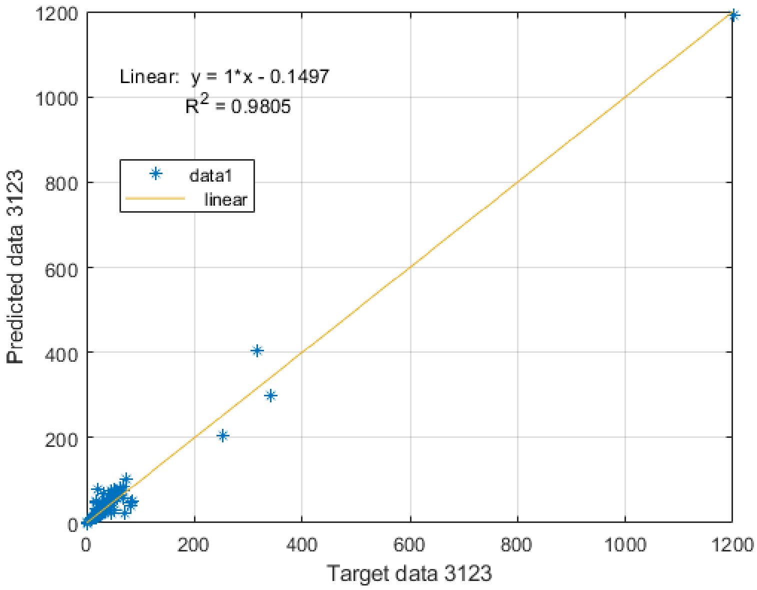

Figure 18. The fit between non-normalized target data and predicted model in the case 3123.

This shows that on average the model predictions are good however one further test was performed to look at some specific points and compare with the simulation data, see table 19.

Table 19. A comparison of predicted soot densities and the simulation data at 1200 s at a few locations for the case 1111.

Location	Simulation (10^{-4}) [kg/m³]	Model (10^{-4}) [kg/m³]
4	0.2	0.9
32	7.3	1.0
128	6.7	7.2

We see that location 4 and 32 are of the same order of magnitude but off by a factor four and seven, respectively. Location 128 on the other hand is quite well represented. Further, it should be noted that to be used for assessments a reasonable safety margin is needed, as there is no guarantee that the predicted data is conservative. However, it will give a good estimate.

Another test is to compare with analytical estimates using tunnel models. Starting with a tunnel that has a square cross-section of 7x7 m² and is 800 m long with a 4 MW fire, the maximum temperature is 106 °C and the mean temperature is 40 °C at 50 m from the fire. Note that this is interpolating between the simulated result since the models are solved for a tunnel with cross-sections of 6x6m², 7.6x7.6m²and 9.2x9.2m². The trained model yields a maximum temperature of 71 °C and mean temperature of 47 °C at the same location. Note that the FDS model with a slightly larger cross-section is close to the trained result with a lower maximum temperature (68 °C) compared to the analytical model.

In summary, the set-up of the models is quick however it can take a very long time to train the models. The process to find a useful model is often iterative where many small changes or tests are needed before a final model. It usually takes quite some time to organize data and obtain suitable input data and target data to the model. It is important to use normalization of data to get better fit between original and trained model. In this case it may be even more beneficial to divide the model into two different one for temperatures and one for the soot densities.

5.3 Approaching problems in fire science

One of the aims of this project is to develop a general method for approaching problems in fire science with AI and then more specifically ML. The process of deciding the strategy for a certain problem takes place on several levels, an overall level where AI could help choose the best method for tackling a particular problem and a more hands on-level where surrogate models are developed with ML. In comparison what has been the basis of this work with the two case studies described above. In the feasibility study carried out by RISE, it turned out that one of the most important components for the success of the project is the transfer of competence between the experts in the field of fire and the experts in ML modelling.

There is a general process for quality assurance of computational projects (Oberkampf, 2010). This process describes the relation between the intended use or problem at hand, model and the verification and validation process. Part of this work can be adopted here and would be applicable to most problems, see figure 20. The starting point is to define the intended use of the model, what the model should be able to describe. In ML problems identification and classification of the available data that describes the process to be modelled, is essential, define inputs and target data. During the training, an iterative process starts where different models and settings often must be tested to find a useful and predictive model. It may be difficult to know what settings will work before starting the process. Equally important is to illustrate and get to know the data, e.g., are there large differences or orders of magnitude differences in different parts of the data. A normalization procedure is most often practical and will yield better predictions. (Jansson R., 2013). Here it is important to verify that the model has predictive qualities and that it is not overfitted.

Before and during simulation production, the model is used to predict the cases of interest, however it is also convenient to investigate the predictive capabilities to look at the domain of the validation or if there are other data available that may give information on the predictive capability of the model. All this information must be documented and submitted to engineering assessment. Here, there are a number of questions that can be asked. Is it within the validation domain or are the other cases that needs to be evaluated? Is additional data needed? Are there other models that can be used for comparisons?

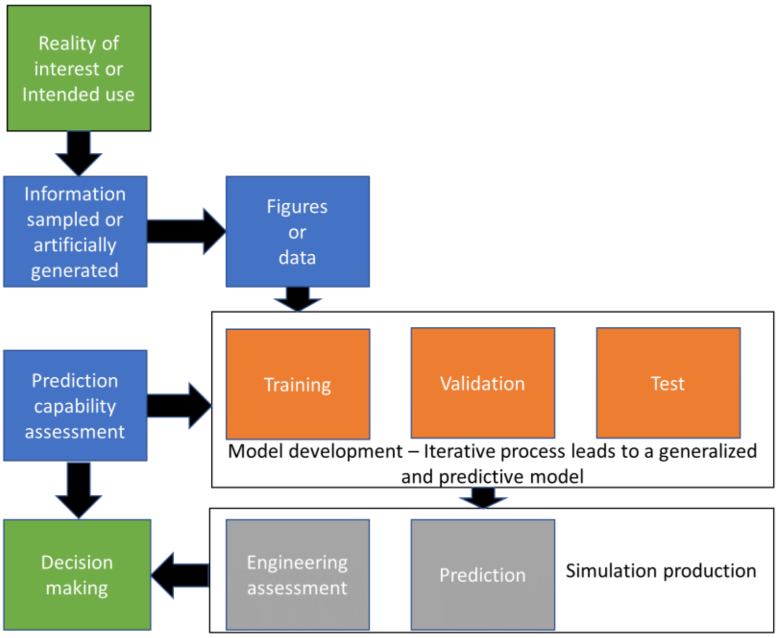

Figure 20. A flow chart describing the simulation and training process.

6 Summary

In summary, the basis of this work is a literature review and two case studies that explores regression by artificial neural networks. One of the more interesting finds during the literature review is the possibility of parameter exclusion where a certain parameter is found to have minimal influence on the result.

General observations are that current tools for ML are rather well developed and it is easy to create a model and get started, however, it is also evident that the user needs some background in how the models work and what can be expected and not only use pre-created models that may give low accuracy. The models may take extensive time to train but when trained the predictions are very fast. This opens up for different uses of these models such as a first prediction in an assessment of a design, but the final assessment is then complemented with some other tool such as CFD of the chosen design. This process also allows for data collection where the data base of cases is expanded.

A common problem in ML is the need for a lot of data in order to be able to have good predictive capabilities of the model. In the case studies we found that providing data on related parameters may give higher accuracy in the predictions due to that these parameters interact in a yet unknown manner and provide additional information on the system that restricts to training process to a better prediction.

We believe that ML models will be an important tool in fire science and fire safety engineering, in particular cases where repeated geometries or parameters are found. In the beginning data collection, training and validation of models are needed, which takes a lot of resources, but this may yield a very fast prediction of cases in the future.

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Fire Research
RISE Report 2021:
ISBN: