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Fire Risk Prediction Using Cloud-based Weather Data Services

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Abstract

Dry and cold winter seasons result in very dry indoor conditions and have historically contributed to severe fires in the high and dense representation of wooden homes in Norway. The fire in Lærdalsøyri, January 2014, is a devastating reminder of town fires still posing a threat to a modern society. In order to reduce conflagration probability and consequences, it is necessary to have an accurate estimate of the current and near future fire risk to take proper planning precautions. Cloud computing services providing access to weather data in the form of measurements and forecasts, combined with recent developments in fire risk modelling, may enable smart and fine-grained fire risk prediction services. The main contribution of this study is implementation and experimental validation of a wooden home predictive fire risk indication model, as well as outlining a wooden home fire risk concept. The wooden home fire risk model focuses on the first house catching fire (indoors) in a potential conflagration event. Such a fire would be critical to intervene prior to the fire developing exterior flames and embers post flashover, and thus high likelihood of fire spread. The implemented model exploits cloud-provided weather measurements and forecasts, to predict the current- and near future fire risk at given geographical locations. It computes the indoor wooden fuel moisture content of houses that may catch fire, using measured and forecasted outdoor temperature and relative humidity, and estimates the time to flashover. The latter is found through an empirical relation with the fuel moisture content, and can be used as an indication of the fire risk, beyond the modelled single house. The model implementation was integrated into a micro-service based software system and experimentally validated at selected geographical locations, relying on weather data provided by the RESTful API's of the Norwegian Meteorological Institute. The validation took place by applying the model to predefined cases, with an outcome known from observations or theory. The first part is a general evaluation of the outputs, considering three historical fires. Then, seasonal changes and natural climate variations were considered. Our evaluation demonstrates the ability to provide trustworthy and accurate fire risk indications using a combination of recorded weather data and forecasts. Further, our cloud- and micro-service based software system implementation is efficient with respect to data storage and computation time. Finally, the novel fire risk concept is demonstrated for a selected city, based on model output. It successfully depicts the implications following reduced indoor humidity by utilizing location specific fire risk contours.

Keywords: *Smart city and cloud data services, Climate related fire risk, Mitigating urban fire risk*

1. Introduction

In recent years, societies around the world have experienced large wildland-urban interface (WUI) fires [1]. Hundreds have lost their lives and thousands have been left homeless [1, 2]. Climate changes have become increasingly prominent and there appears to be consensus about future development, resulting in increased wildfire seasons and frequency [2–9]. Much attention is paid to these devastating fires. However, from the above 300,000 annual

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fatalities caused by fire, the majority occurs within enclosures, such as a residence [10]. Except from the mitigating measures implemented in the design and use phase, single-structure fire risk appears nearly unconsidered. The present work addresses the important under-examined topic of wooden home fire risk, through implementation and experimental validation of a dynamic predictive single-structure fire risk model. The model can be applied beyond a single-structure, i.e., utilized as a risk indicator for large fires and conflagrations by use of a modelled time to flashover (TTF). Attention was brought to the topic in the aftermath of the devastating winter fire blaze in Lærdalsøyri (Norway), January 18 - 19, 2014 [11–13].

It is known that the winter in cold climate regions brings along increased fire frequencies [13, 14]. In 1956, Pirsko and Fons suggested ambient dew point during the winter as an explanation for the increased fire frequency in buildings [15]. Post the Lærdal fire, the cold climate fire risk was again identified by Log [13]. It prompted further research, and indoor relative humidity was suggested as a fire risk indicator [16]. A cold climate structural fire danger rating system was suggested [10] and a mathematical model for predicting indoor relative humidity and wooden fuel moisture content (FMC) was developed [17]. Furthermore, Log et al. proposed a way forward for exploring and addressing novel dynamic fire risk assessment and management tools [2].

The overall aim of the present study is to contribute towards reduced conflagration fire risk through dynamic risk assessment and an early warning system. A main contribution is to report on implementation, validation, and further development of the model of Log [17]. Secondly, it is investigated what publicly available high-end weather data infrastructure and weather data services can be used to harvest data for the modelling of the indoor relative humidity. As part of this, a cloud-based microservice software architecture that utilizes the weather data representational state transfer (REST) application programming interface (API) provided by the Norwegian Meteorological Institute (MET) is developed [18, 19]. Additionally, the storage and computational efficiency of the proposed software system architecture and its implementation is evaluated.

Related research has been undertaken in the field of wildfire detection and environmental monitoring by use of Wireless Sensor Networks (WSN) and internet of things (IoT) devices. Some recent work can be found in [20–24]. Although promising, these systems suffer from economic limitations as well as difficulties related to the required infrastructure, and deployment and maintenance of equipment. For certain high-risk areas, such as the WUI around big cities, it is a viable solution. However, when monitoring forest or densely built wooden towns and cities nationwide, or globally, these solutions for data harvesting become comprehensive and costly. When parameters are modelled to assess the current risk level, the presentation of computed risk becomes important. The recent work of Yousefi et al. [25] aimed to produce an accurate multi-hazard risk map for the mountainous regions of Iran. They modelled the probabilities of snow avalanches, landslides, wildfires, land subsidence and floods, using machine learning models. Results were plotted as heat maps, similar to the mapping of road traffic accidents hot spots as done by [26]. Understandable visual presentations of current and future risk, is important when considering the implementation of the risk concept into new areas. Tsipis et al. [24] developed a complete system, summarizing and highlighting the possibilities within implemented technology related to wildfire risk. Utilizing a novel cloud/fog hybrid network architecture solution, similar to [27], combined with several wireless sensor networks for data acquisition of real-time data, they successfully indicated wildfire risk through the chandler burn index and communicated risk-levels through their web based graphical user interface, called "F.E.M.O.S", Fog- assisted Environmental Monitoring System.

Outline

In Section 2 we present the predictive fire risk indication model which served as a basis for the study. Section 3 presents our system architecture, and how we have implemented a software prototype by aggregating data from external cloud-services to provide a fire risk indication service. In Section 4 we present selected results of our experimental evaluation. In Section 5 we introduce the risk assessment concept and outline how the modelled single-structure TTF may be utilized as a risk indicator for a single structure as well as a major conflagration. Finally in section 6, we sum up the conclusions and discuss directions for future work. A preliminary workshop version of this paper appeared in [28], as well as a revised appearance in Procedia Computer Science [29], as a part of The 12th International Conference on Ambient Systems, Networks and Technologies, ANT 2021. In the present paper, a more complete presentation of the fire risk indication model is provided, as well as an improved software architecture. Further, the experimental results include evaluations of a recent fire in Norway, as well as consideration of historic fire risk variations. Furthermore, the effect of wind on fire spread in wooden towns is introduced, in accordance with the main objectives. Additionally, a novel fire risk concept is introduced, based on results from the model. For the interested reader, most of our experimental results and implementation details are available in the underlying technical report [30].

2. Predictive Fire Risk Indication Model

For compartment fires, flashover is the rapid transition between the growth phase and the fully developed fire. The onset of flashover indicates untenable conditions within the compartment (building), with typical heat flux at floor level quickly increasing beyond 20 kW/m^2. There are many factors influencing the TTF, such as ignition source, fuel, heat release rate, ventilation and compartment size. The modeling in the present study is based on a wooden home environment with indoor combustible hygroscopic surfaces, i.e., wooden floor, walls and ceiling. The latter two interact with smoke and hot gases produced in the fire, which in turn cause preheating and onset of pyrolysis for these surfaces. The rate at which this takes place is dependent on the fuel moisture content [31].

The predictive fire risk indication model estimates the TTF for a compartment based on the calculated FMC, which again is based on ambient temperature and relative humidity both fetched from the MET API (forecasted) and the FROST API (measured), as well as the indoor temperature, set to a constant of 22 ^oC [16]. The model computes the indoor RH by modelling the indoor air water vapor concentration, accounting for local production of water vapor, air changes due to ventilation or stack effect, and the effects of the hygroscopic wooden materials. Then, the FMC of the indoor surfaces is computed as a function of the indoor RH. TTF is then found through an empirical relation with the

FMC [31]. The main theoretical foundation of the implemented fire risk indication model is outlined below. The details can be found in [16, 17].

The indoor air volume water concentration is modelled by the following differential equation,

$$V_h \cdot \frac{dC}{dt} = \dot{m}_{wall} + \dot{m}_{ac} + \dot{m}_{supply} \tag{1}$$

where, C ($\frac{kg}{m^3}$) is the compartment water vapour concentration, t (s) is the time, V_h (m^3) is the compartment volume, $\dot{m}_{ac}$ ($\frac{kg}{s}$) is the ingress of air due to the ventilation and $\dot{m}_{supply}$ ($\frac{kg}{s}$) is the moisture supply from, e.g., people, pot plants, dishwashing, etc.

The contribution to the indoor water vapor concentration taking place through the wooden surfaces is accounted for through $\dot{m}_{wall}$. The term expresses the net transfer of water vapor from the wall boundary layer, to the compartment air volume by diffusion. The RH within the solid surface boundary layer is a linear function of the bulk air RH and the RH corresponding to the surface layer FMC. The indoor surface layer water concentration can be calculated by,

$$C_{1_{(t+\triangle t)}} = C_{1_{(t)}} + \frac{\triangle t}{\triangle x} \cdot \Bigg(\frac{D_{w,a}}{\delta} \cdot (RH_{in_{(t)}} - RH_{wall_{(t)}}) \cdot C_{sat,in} + \frac{D_{w,s}}{\triangle x} \cdot (C_{2_{(t)}} - C_{1_{(t)}}) \Bigg) \tag{2}$$

The equation represents the modelling of water concentration, kg/m^3, for layer $n = 1$, refer the subscripts. The wall panels are divided into N layers of thickness $\triangle x = L/N$, where L is the panel thickness. For the rest of the equation; $\triangle t$ is the time step, $D_{w,a}$ is the diffusion coefficient of water vapor in air at 22 $^\circ C$, $2.5 \cdot 10^{-5}$ m^2/s. $D_{w,s} = 3.0 \cdot 10^{-10}$ m^2/s is the solid wood water diffusion coefficient. The boundary layer thickness typically takes the value $\delta = 0.01$ m [17]. The water concentrations in the remaining panel layers are obtained by solving the second order partial differential "heat equation" [17]. The vapor barrier backing the wall panels in Norwegian homes, for rot prevention, is mathematically treated as a reflection plane.

The net vapor exchange related to the air change rate per hour (ACH), is modelled within $\dot{m}_{ac}$. The ACH depends on the ventilation principle of the specific building. In the case of natural ventilation, the model utilizes a rate based on the Bernoulli equation, as proposed by Log [17], but corrected here to account for summer conditions, $T_{out} > T_{in}$.

$$ACH = \gamma \cdot \sqrt{\frac{ABS\left(\frac{1}{T_{out}} - \frac{1}{T_{in}}\right)}{T_{out}}} \tag{3}$$

The value of γ was originally proposed at 300 h^{-1}, assuring that under normal temperature differences, Nordic climate, the ACH would equal 0.25. The present study justifies a value in the range of 300 - 380 h^{-1}, potentially resulting in an $ACH = 0.32$, i.e., in compliance with a Swedish study of 1200 homes [32].

Moisture supplied through local production, such as respiration, plants and cooking is accounted for through $\dot{m}_{supply}$. The model has mainly been applied for older wooden homes, assuming the kitchen as a separate compartment thereby justifying a 1 kg/day moisture supply.

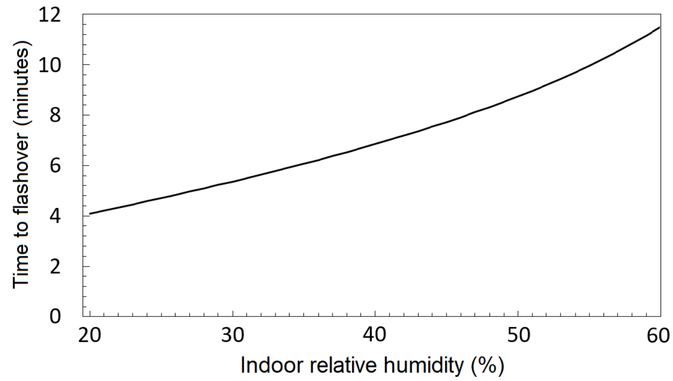

Fig. 1. Correlation between TTF and the indoor relative humidity according to Eq. 4 [31], where the FMC is taken as in equilibrium with the indoor RH [33], according to [17].

Accounting for the above mentioned terms, the indoor water concentration allows for calculation of the indoor RH by dividing C with the saturated water vapor concentration at a representative indoor temperature of 22 $^\circ C$. The computed indoor RH then becomes a part of the next iteration.

The model requires historical weather data to properly adapt, relative to days of previous weather. The original work of Log initiated calculations at 40 % indoor RH. A sensitivity study performed in the present work indicates 30 % RH to reduce the need of historical weather data and is recommended for future use. The FMC value at the first time step is taken as a function of the initial RH estimate.

Finally, the TTF is estimated by an empirical correlation to the FMC [31],

$$t_{FO} = 2 \cdot e^{16 \cdot FMC} \quad (minutes) \tag{4}$$

where FO denotes flashover and FMC is the water to dry wood mass ratio. Figure 1 presents the correlation between TTF and indoor relative humidity. The latter represents an indoor humidity level in equilibrium with the fuel moisture content of the specific house.

3. Cloud- and Microservice-based Software Implementation

A software prototype for a fire risk indication system was designed and implemented. The basic idea is to provide the fire risk indication as a REST web service relying on underlying weather data REST services [18, 19] provided by the Norwegian Meteorological Institute (MET) and Netatmo [34]. Figure 2 shows the overall software architecture of the developed prototype which has been organised into several smaller components following a microservice-oriented architecture [35] based on REST [36] web services. Since the external web services provide data in a JSON or XML representation, noSQL databases [37] were used for storing the weather data and fire risk indications. The application services and components were deployed on the Amazon EC2 platform and implemented using the Spark/Java microservice framework. The data storage uses a MongoDB database deployed on the Azure cloud platform. The main components of the software architecture are briefly explained below.

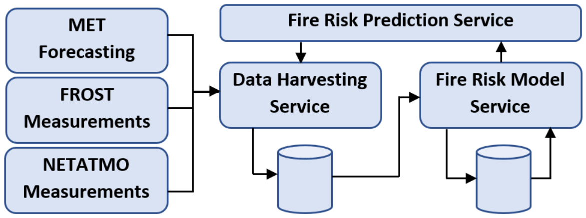

Fig. 2. High-level software architecture for the developed fire risk prototype application.

3.1. Fire Risk Prediction Service

This is the main service provided by the system. It constitutes a REST web service where a consumer provides longitude and latitude in order to trigger computation of a fire risk indication for the geographical location. Once the geographical location has been registered in the service, it triggers the data harvesting service to start collecting the required weather data elements for the location. In turn, it triggers the fire risk model service to start computing the fire risk indications based on the measurements and forecasts collected by the data harvesting service. As fire risk indications become available, they can be obtained via the fire risk prediction service.

3.2. Data Harvesting Service

This component is responsible for collecting weather data measurements and forecasts from the external weather data services and storing them in the associated database. The application uses two external web services to obtain weather data recordings, namely Frost (MET) and Netatmo, and one external web service to obtain forecast weather data, as to predict the fire risk in the coming days, namely MET Norway weather API. In this study, experimental results obtained using the Frost measurements and MET forecasting services are presented.

3.3. Fire Risk Model Service

This component implements the fire risk indication model (Section 2.) capable of computing fire risk indications based on historical data in the form of measurements from meteorological weather stations, forecast data, and a combination of the two. To initiate immediate monitoring of a location, measurements and predictions must be combined, so that measures adapt the model and allows for predictions the upcoming days. The current fire risk predictions are stored in the underlying database such that they can be retrieved via the fire risk prediction service.

3.4. External weather data services

The Frost API [19] is a REST web service providing historical weather data recorded by MET. Consumers of the service must provide the locations of where it shall retrieve weather data. This can be done by providing the identity of the source (station), or by giving the longitude and latitude of a position. Then, the service will find the nearest station. The service gives access to all the stored data that MET has recorded. The Frost API gives access to resources about locations, weather records, observations, lightning, sources (weather station metadata), elements (weather elements), climate normals, and frequencies. The application uses location, observation, and meta-data about the stations.

The Netatmo service [34] provides the same type of weather data as the Frost service, but relies on consumer grade weather stations typically installed inside and outside private homes. The consumers publish their weather data into a cloud service. Through this cloud service server, it is possible to retrieve the recorded weather data, which can then be used in the application.

The MET API [18] provides predictive analysis of the weather in terms of forecast data. It offers resources that estimate how the weather will be in the near future, as well as current weather data such as the lowest and highest temperatures over a certain period. The service is able to provide weather predictions for a nine day period into the future. The first three and a half days are provided as hourly measures. The next five and a half days are provided at six hour intervals.

4. Experimental Evaluation and Model Validation

The implemented cold climate fire risk model of Log [17] computes the TTF based on modelling of the indoor relative humidity and transient drying of wood wall panels. The model relies on applied physics and mathematics to arrive at indoor conditions, but utilizes an empirical relation correlating FMC with the TTF. The modelled indoor conditions are based on quantities representing a wooden home living room, the most common room of fire origin in Norway [38, 39]. Hence, the computed value is an estimated TTF for a specific enclosure within the building envelope.

In the present study, modelling results have been compared to three historical fires, as to evaluate how the system would have indicated the fire risk prior to these fires. Further, the model was applied at four selected locations during the winter 2019, two locations at the Norwegian coast and two inland locations. This was done as to evaluate whether modelling in different climates would give expected differences. Furthermore, the town of Lærdal was considered, by use of historical data, for as a long as eight winters in the period 2013/2014 until the winter 2020/2021. The purpose of this experiment, was to evaluate how the model depicts seasonal changes. The main aim of these initial experiments was to validate the fire risk indication model in terms of providing plausible indications, as an aspect of validation is to consider whether the software system outputs reasonable values based on the implemented model. The experiments were carefully chosen to represent cases where the outcome was partly known from theory or observations prior to being modelled. Modelled results could then be compared to expected results.

Additionally, since the cloud-based prediction service is intended to predict fire risk indications, the difference in predicted risk and historic risk is investigated. Finally, computation time and storage efficiency were evaluated. As one of the underlying objectives of this study is to contribute towards reduced conflagration risk, interesting observations will be commented.

4.1. Fire Risk Indications for Historical Fires

Three historical fires were chosen for comparison, two of older dates, and one recent fire in Risør 2021. All these fires developed rapidly, which should render low TTF values, and hence, high modeled risk. Historical weather data was loaded into the model, to determine how the fire risk was prior to and at the day of the fire.

The Lærdalsøyri town fire, 18th of January 2014 serves as the first example [11, 12, 40]. The town houses many wooden buildings worthy of preservation and experiences cold and dry periods during the winters. The estimated fire risk is presented in Figure 3 (top), with day 0 being the day of the fire. During a 12 days period prior to the fire, the ambient temperature and RH started dropping. This resulted in drier indoor air. In this dry period, the wood inside the homes released humidity to the indoor air, which was gradually ventilated. At the time of the fire (22:50), the fire risk model indicates a TTF of about 3.8 minutes. The fire department was notified at 22:53, and the fire fire truck was on scene at 22:59 [40]. Then, the home was fully involved in the fire, both inside and outside. The exact TTF for the evolving fire is difficult to determine, but the rapid fire development observed suggests TTF in the range of 3 - 7 minutes. The fire department apparently did not have sufficient time to respond to the fire. It should also be noted that there were shifting storm strength winds in the area [40] contributing to rapid spread of fire to adjacent and distant structures.

The second fire considered is the fire in Risør 24th of February 2021. The estimated fire risk is presented in the center of Figure 3. It can be seen that the fire occurred after about ten days of an increased ambient temperature. The associated TTF increased slightly during this period, hence a slightly lower risk. The relative humidity is not presented but in general, increased temperature is consistent with reduced risk as the potential for drier indoor air reduces. The fire was detected automatically at 04:41, by an IR-camera which continuously monitored the densely built wooden heritage cite [41]. As the house was partially hidden from the IR-camera behind taller structures, at the time of detection, it was already burning heavily on the outside. At 04:44 the fire had developed into the roof construction of a neighbouring house, evident through private video-recordings taken just outside the house of fire origin. When the emergency manager arrived as the first responder on scene, 04:52, he communicated flashover in two houses [41]. The fire developed very fast and observations and video recordings suggest a development somewhat less than the fire in Lærdal, but in the range of 4 - 10 minutes. The computed TTF at the day of the fire indicates flashover in about 5.2 minutes, consistent with the above observations. It can be seen from Figure 3 (center), that had the fire occurred a week or two earlier, conditions would have been even worse, and hence, considering how the fire department struggled the day of the fire, more buildings had probably been lost. This illustrates the importance of the developed model and the ability to predict high risk periods.

The last fire considered, was at a home care center in Kongsberg, 24th of December 2017, resulting in the loss of life [42]. The fire risk indication for this period is visualised in Figure 3 (bottom). During the December month of that year, the TTF averaged around 4.2 minutes, which is close to the indoor conditions in Lærdal. Since this is a home care center, the fire department must conform to the regulations, stating the required response time to be 10 minutes or less. If presented results are correct, they confirm the conclusion given in the aftermath of the fire in Lærdal 2014, i.e., that the TTF is considerably lower than the required response time from the fire department. This makes it likely that the model could have warned the fire department to be readily available. More generally, it suggests that the regulated response time does not take into consideration dry indoor conditions. However, being aware of high risk periods can initiate proactive measures, which could reduce the imminent risk.

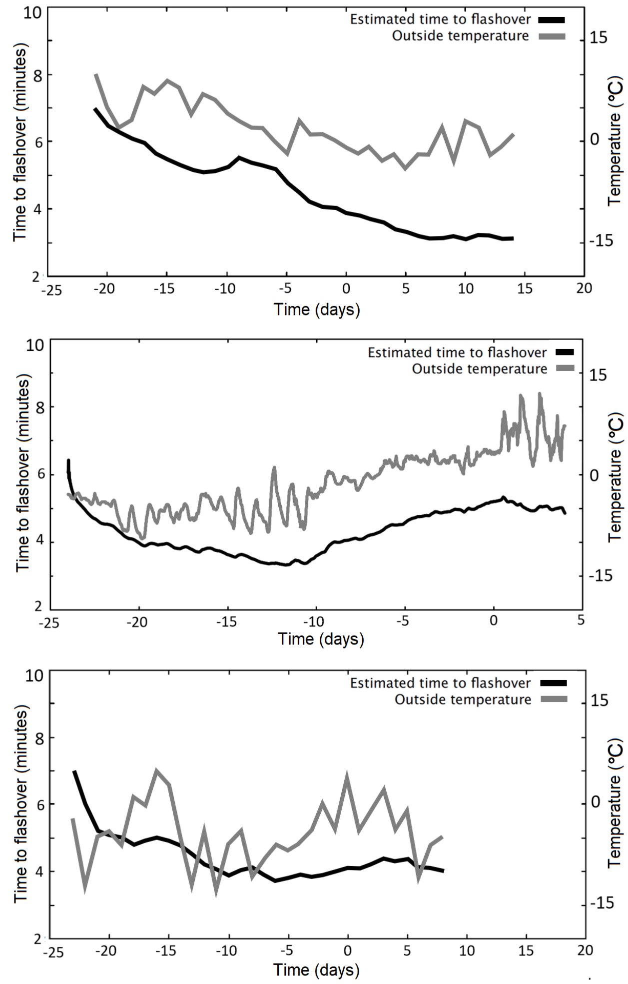

Fig. 3. TTF and temperature for the fire in Lærdal 2014 (top), Risør 2021 (center) and at a home care center in Kongsberg 2017 (bottom).

In general, and as initially expected, modelled TTF indications appear reasonable compared to identified range for these historic fires and results indicate low TTF values as initially stated.

4.2. Fire Risk Indications from Varying Climates

Historical weather data was collected from the winter of 2019 at four selected locations with different climate, i.e., Bergen, Haugesund, Gjøvik and Lærdal. At the west coast (Bergen and Haugesund) it is more humid than in the inland locations (Gjøvik and Lærdal), which in turn are generally much colder during the winter. Figure 4 presents the average fire risk indications based on measurements collected in the winter of 2019 (December 12 until May 05). It can be seen that the fire risk model generally indicates a greater fire risk (shorter TTF) at the colder inland locations. The average TTF for Bergen and Haugesund is 5.50 and 5.70 minutes, respectively, while for Gjøvik and Lærdal it is 4.48 and 4.77 minutes, respectively. Outputted values are as expected, the climatic variations are easily identified, as evident within the presented figure.

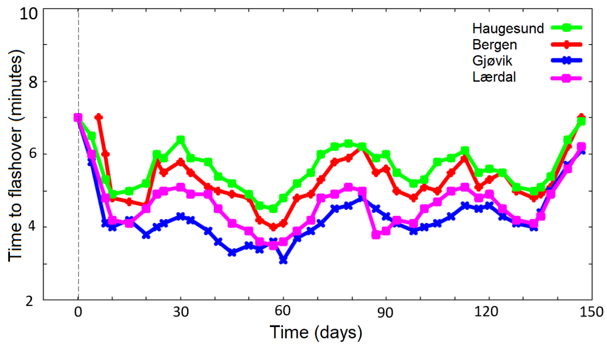

Fig. 4. Estimated TTF for the four selected locations, winter 2018/2019.

4.3. Fire Risk Indication and Periodic Variations

The aforementioned fire in Lærdalsøyri is a devastating reminder of city fires still posing a threat to a modern society. Generally, Lærdal has a very dry climate, but analysis of weather parameters in the aftermath of the fire, performed by the Norwegian Meteorological Institute, suggest that January 2014 was drier than average [11]. Possibly, as a result of this, it has been a common understanding that the Lærdal fire was due to exceptionally dry weather and strong winds. However, Figure 5 presents the computed TTF values for Lærdal prior to the fire in 2014 and throughout, until the winter 2021. It can be seen that the TTF value did not experience a particular low-point at the time of the fire in 2014, even though being dry. While the TTF value reflects the FMC of indoor wood panels, the FMC depends on the indoor relative humidity, which in turn primarily depends on the water content of the outside air and the indoor versus outdoor temperature. This is true, since other sensitive parameters are kept constant within the model, such as indoor humidity production. MET noted that the precipitation levels during January 2014 was about 30 percent of the average precipitation, while temperatures was about four degrees warmer on average, during December and January [11]. It should be noted, however, that Lærdal is known for low precipitation levels in general, in average 25 mm in the month of January [11].

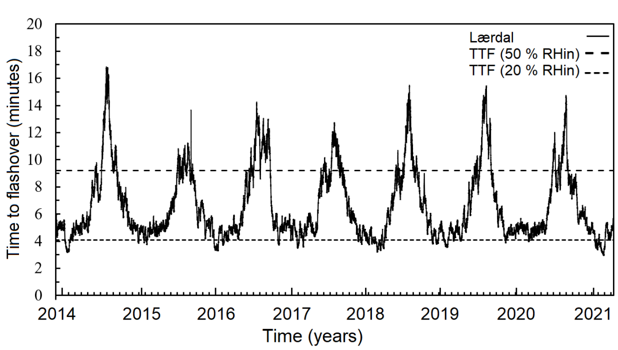

Fig. 5. Annual TTF variation in the town of Lærdal.

With regards to the outdoor relative humidity, the first half of January 2014 was approximately similar to the upcoming seven years, but about midways into the month, the 24-hour averaged ambient relative humidity dropped to below 40 %, continuing into the next month. Hence, observations indicate dry conditions. It appears that while outdoor conditions were drier than average, internal wood coverings (wall panels, roofing, flooring) did not experience a particular drought historically, as can be seen from Figure 5. Being a city fire, the condition of the wooden homes is of special interest. A possible explanation is the increased temperature that occurred simultaneously with the dry period. Increases in outdoor temperature reduces the potential of drying indoor hygroscopic materials, as the temperature difference decreases. Hence, winters of greater humidity and lower temperatures could have an equal effect on the indoor humidity and corresponding FMC as drier winters with greater temperatures.

Nevertheless, it needs to be differentiated between indoor and outdoor conditions. The conditions during the Lærdal city fire, were particularly dry outdoors, affecting outdoor conditions and fire spread. However, the results presented in Figure 5 indicate that the indoor conditions during the winter drought in Lærdal, is periodically low and approximately equally low each year for the period 2014 - 2021. Further, the fire in Lærdal did not even occur at the driest period that winter, but as it still was getting drier. Thus, the light drought identified by MET did not cause for exceptionally dry indoor conditions, and thereby did not cause a particularly low TTF compared to the period 2014 - 2021. However, it did result in outdoor wooden materials becoming dry and susceptible to fire, i.e., increasing the likelihood of fire spread to neighbouring homes.

Considering the modelled results, it appears to describe seasonal changes reasonably well. It is well known that the ambient air water concentration is higher in summer and lower in winter, and thus produce seasonal variations in indoor relative humidity and expected TTF [32].

4.4. Lærdal and Risør - Effect of Wind

In the end of the presented experiments, and as a part of the primary contribution of this paper, concerned with reducing conflagration risk, it is worthwhile to briefly address the differences between the Lærdal and Risør fires. The former was characterized as a town fire, while the latter fortunately was limited to only a few houses. From the presented data it was evident that the TTF value was somewhat lower for the Lærdal fire, indicating a more rapid fire development. Still, this primarily relates to the first house catching fire. Two additional parameters were also important for the Lærdal fire becoming so extensive, i.e., the dry external wooden claddings, and storm strength winds. Combined, these parameters contributed to the conflagration that developed.

In Risør, the houses stood much closer, as can be seen from Figure 6, which could partly outweight the calm wind conditions the day of the fire. However, even though the response time was higher during the Risør fire and the fact that the fire developed unnoticed for some time, the scenario did not develop to a major conflagration. As a town by the coast, the external cladding is likely to have greater moisture contents compared to the fire in Lærdal, but still, the wind appears a very important parameter in the context of conflagrations. It appears, by comparing the two cases, that fire spread by radiation and flame impingement to nearby structures, as was the case in Risør, is less critical if the fire department is on scene, compared to heavy winds and increased ember transport, as was the case in Lærdal. This is merely an observation post studying the two fires. Further, fire spread through ember transport, requires spreading firefighting resources over larger areas, thereby severely straining the emergency system capacity.

Fig. 6. Comparing the town of Lærdal, top, and the dense wooden houses in Risør, bottom. House of fire origin is marked with a red circle.

4.5. Combining Measurements and Weather Forecast Data

Being able to predict the fire risk for the coming days is a main objective. Therefore, risk indications based on measurements (historical data) and forecast data were computed separately and compared. Figure 7 presents the results from Bergen during the first days of January 2019. At the 3rd of January, the fire risk was predicted for the upcoming nine days, represented by the black line. That is, all data constituting the black line, was computed at day 3. The grey line represents the fire risk solely based on measured data. This means that calculations started at day 3, and was computed each day, based on measures, for the next nine days. By comparing the two, the deviation between predicted TTF and the measured TTF is obtained. From the figure it can be seen that the forecasted fire risk coincide with the historical fire risk for the first three and a half days. Then, predicted risk begins to deviate, but the deviation appears relatively stable. The average difference was approximately 0.26 minutes with the standard deviation at 0.24 minutes. The maximum difference was found to be 0.62 minutes.

In general, the degree to which the two curves coincide, is dependent on the degree to which forecasted weather occurs. The model is not very sensitive to changes in outdoor conditions, so there is a natural time lag before indoor wood moisture content is significantly affected. Further, the modeled risk indication is dependent on the occurring mean weather. That is, if the weather predicted the upcoming nine days occur in some arbitrary order, the crucial part is that the weather occur within these days. The nice fit the first 3.5 days, can be explained partly by the resolution of the retrieved external weather forecast and partly by the fact that the resolution decreases as a consequence of greater uncertainty in the weather predictions. The resolution of the retrieved weather data corresponds to 3.5 days of hourly predictions, while post this point weather data is given only per six hour, due to uncertainties in the predictions. For this reason, predicted fire risk appears to coincide well with measured risk the first 3.5 days. In turn, this implies that the model successfully predicted the upcoming fire risk in Bergen. It validates that the model can be used for predicting fire risk indications, but more data is still needed to further assess the model.

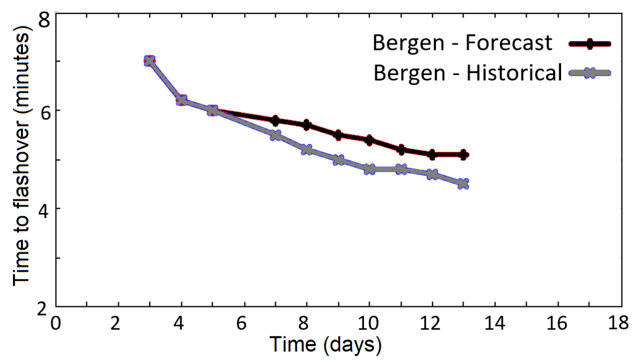

Fig. 7. Comparing time to flashover based on forecast and historic weather data separately.

4.6. Computation Time and Data Storage

During the evaluation period, the implemented model continuously harvested weather data for approximately five months. Every 24 hours, the application fetches historical data for the previous days and forecasts for the next nine and a half days. Whenever the application fetches new historical weather data, it will take the previously calculated fire risk indication and create an augmented fire risk indication based on the new weather data, and add it to the back of the previous one. This way, the storage efficiency depends not on the weather data, but only on how many fire risk indications are stored.

Each weather forecast stored in the database had a list of 87 objects containing weather information, such as temperature and relative humidity. The total amount of storage that these forecasts use, amounts to 12.5 Mb, with an average of around 25.4 kb per forecast. The weather data from the Frost stations was stored in 24 hour intervals and contains hourly recorded weather elements, mostly the same types as the forecast. The collection in the database that stores historical data finally contained 634 documents, each of these documents covering 24 hours worth of weather data. The total amount of storage used was 5.6 Mb with an average of 9.0 kb per document. A fire risk indication for a 24 hour period at one location requires 61.6 kb of storage. Given this, it is possible to calculate how much storage is needed when doing continuous fire risk calculations for several locations. For instance, with continuous fire risk calculations for 10 locations this will amount to 616 kb of fire risk indications every day. For a whole year this will require 225 Mb of storage. With 100 locations, each with a separate weather station as source, the total amount of storage for a whole year would be 2.24 Gb, which is a modest space requirement.

With regard to runtime efficiency, it took 0.07 s to compute fire risk indications for one year. Note that this excludes the time to retrieve the weather data from the external services and the time for converting the data. If everything is included for creating fire risk for one year, 4.1 s is required to retrieve the weather data and another 0.2 s to convert it. Then it is passed on to the fire risk component which adds another 0.6 seconds for conversions and it takes 0.07 s to compute the fire risk. The total time elapsed for creating a fire risk indication with weather data for a full year amounts to 5 s. If the same was done for half a year, the time is 2.5 s of which 2.36 s is used to fetch the data, and 0.04 s is used for conversion and computations. The remaining time is spent communicating between the components. This shows that with the proposed software architecture, fire risk indications can be computed and stored in both a space and time efficient way.

5. Risk Assessment Concept

In Norway, both the industry and the government promote the necessity of further introducing the concept of risk in safety related work. This became evident within fire safety preventive work in 2015, as a new preventive regulation was introduced [43]. Although a risk-based approach has always been used by first responders when units respond to emergencies, the new regulation introduced a risk-based approach for the preventive department within the fire services. Thus, allowing risk-based inspections on *buildings of special interest*, housing high risk activities. This was in contrast to the previous requirements of frequency-based inspections.

Among the main contribution of this study, is the introduction of an understandable risk concept, aimed at those without any technical background. The presented concept is developed for non-technical people as well as decision-makers and management controlling resources, particularly within the fire service, as to understand how changing weather conditions affects the current and near-future wooden house fire risk. Norway has more than 180 locations nationwide, of densely built wooden heritage sites. Thus, reflecting a long tradition of wooden homes, which still constitute the vast majority of new single family houses.

The model of Log [17], briefly presented above, is in itself a single-structure fire risk model. However, the results apply to all similar structures in an area, like all the houses at a wooden heritage site. Any conflagration is dependent on an initiating event, a source of ignition e.g., a house on fire. Most house fires in Norway originate in the living room or kitchen [38, 39], thus intervening before a fire reaches flashover and produces external flames and embers could be critical. In his study, Log proposed the modelled TTF to be used for risk assessment and compared the indicated TTF with the time needed for the fire department to get water on fire (WOF). Any imbalance in the time budget with regards to $t_{FO} < t_{WOF}$ indicates an increased risk. Considering this time budget, the single-structure fire risk model can be interpreted beyond the risk associated with the house of fire origin, and also serve as an indicator of an initiated major event, a possible conflagration. Such an indication would be especially helpful if it is known that outdoor conditions are dry. The fire department could then consider TTF indications with their expected overall time to get WOF. The TTF value is a fire risk indicator, just as existing forest fire indices, hence the degree of imbalance between t_{FO} and t_{WOF}, determines the conflagration risk level. The present study elaborates on the proposed concept and introduces conceptual location specific risk contours (LSRC).

The following description relates to wooden single family houses, representing the majority of single houses in Norway. The time needed for the fire department to initiate extinguishing and life saving work in case of fire, depends on a sequence of events of varying duration. The specific sequences in question depends on the particular case, for instance the presence of connected alarm service. In general, these sequences may be described through detection, interpretation, notification, turnout time, driving and on-scene preparations, in accordance with [44].

By considering a time budget, including the different sequences and comparing it to an indicated TTF, it is possible to arrive at the theoretical available time for driving. This in turn, can indicate the distance and area covered by the local fire brigade. In this case, TTF represents the maximum available response time, since it indicates time until critical conditions. Table 1 presents a simple time budget, including most of the presented sequences that constitute the overall time to WOF, i.e., the time until the actual fire fighting starts. The table compares two cases, i.e., at 50 % and 20 % indoor relative humidity, and subtracts the respective duration of each sequence from the available response time, until left with a theoretical time for driving from the fire station to the house on fire. Presented values and sequences are based on [44–46]. Values are not taken as worst-case, that is, the duration of the sequences presented, is generally equal to or lower then what the literature suggests.

Table 1. Time budget indicating area coverage assuming a driving spead of 60 km/h. TTF's are given with corresponding indoor relative humidities

Sequence of events	TTF 50%	TTF 20%
Time to flashover (min.)	8	4
Detection, notification and alarm-central processing (min.)	-1	-1
Turnout time (min.)	-1	-1
On-scene preparations (min.)	-0.5	-0.5
Time available for driving (min.)	5.5	1.5
Straight distance (km)	5.5	1.5
Area covered (km^2)	95	7
Relative coverage (%)	100	7

The results presented in Table 1 may illustrate the importance of indoor relative humidity on the area covered by the local fire department. During the winter, cold temperatures result in outdoor air having a low moisture content. When this air enters a heated building, the relative humidity of that air decreases and indoor hygroscopic materials desiccate, as modeled in the present study. The resulting low FMC results in reduced TTF and thereby reduced available response time. An indoor relative humidity of

20 % is common during the winter months in Norway, especially from December throughout February. The time budget indicates a reduction in area covered by 93 % compared to an indoor humidity at 50 %. This could render large portions of high-risk regions out of reach, prior to flashover, for the local fire department.

Figure 8 displays location specific risk contours for the city of Stavanger, Norway. The fire station is located at the origin. In general, the risk of uncontrolled fires increases as distance increases from the local fire station. The contours indicate the theoretical area covered by the fire department at a FMC in equilibrium with the specified indoor humidity. It is assumed that within each contour, the fire department will be able to reach the object of interest within the object reaching critical conditions during a fire, i.e., high risk of the fire spreading to neighbour homes. The location specific contours, indicating local fire risk, given a fire, do not take into account trafficability for first responders. When indoor FMC of the wooden houses of Stavanger corresponds to an indoor humidity of 20 %, the number of houses covered by the local fire station, compared to the case at 50% RH_{in}, is reduced by about 85 %.

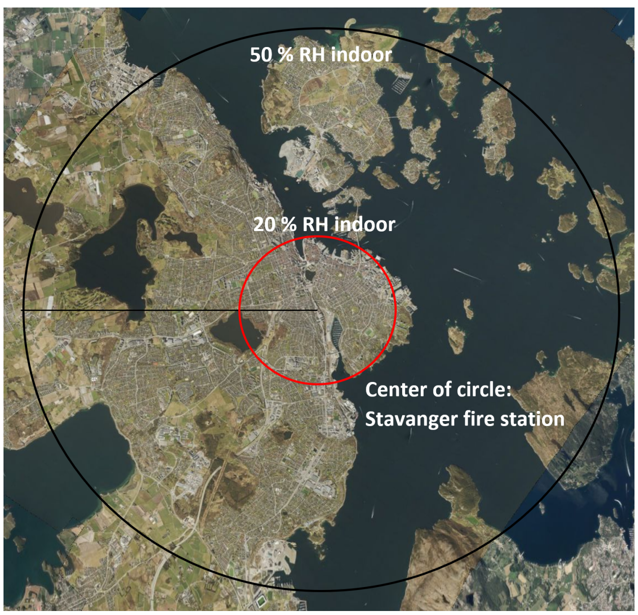

Fig. 8. Location specific risk contours, indicating area covered by the local fire department during specific conditions. High-risk regions are outside the contours.

The presented example illustrates how the implemented model [17], combined with cloud-based weather data services and the outlined risk concept, may serve as a tool enabling fire brigades to identify periods of increased risk locally. Thus, they may initiate proactive measures, especially when low indoor FMC coincide with forecasted high strength winds. The system may be used for predicting the fire risk in any densely built wooden neighbourhood and heritage sites in Norway. It may also be used internationally where sufficient quality weather services are available.

6. Conclusions and Future Work

An innovative and science-based predictive fire risk indication model has been implemented in a cloud-service context where external services were used to obtain the weather data required for the computation. Regarding storage efficiency, the application requires relatively little storage, i.e., the software architecture has adequate storage efficiency. Furthermore, it is evident that it does not accumulate large amounts of weather data. Regarding the run-time efficiency, most of the time is spent fetching data from the external services. The time for computing a fire risk indication was negligible. The most time consuming internal operation of the application was conversion of weather data. Fire risk for a whole year was calculated withing 5 s, i.e., the model is both storage efficient and fast.

With regards to the risk indication model, given the retrospective risk estimates for the fires in Lærdal, Kongsberg and Risør, combined with the reproduced natural seasonal variation in terms of the TTF, as well as consideration of the climatic separated locations, it may be concluded that the model produces sufficiently accurate fire risk indications and that variations in output reflects the modelled environment. Considering these results, many of the Norwegian fire brigades would not have sufficient time to respond to a fire during the winter period - even if they formally conform to current regulations during other periods of the year. Further, initial results show that predicted fire risk indications are well within the accuracy needed to notify local fire departments, at least 3-4 days in advance of high risk periods. Considering the historical fires presented in this study, the model could have predicted that the fire department would not be able to properly handle those fires. The current minimum response time that the fire department is expected to comply to, appears to be too high for the dry periods during winter time. In general, considering the overall performance, it can be concluded that the implementation, predicted TTF and the risk concept, constitute the initial stages of a sufficiently accurate risk predicting tool.

On the implementation side, end-user clients have not yet been consulted for, e.g., the graphical user interface. As part of future work it may be further investigated how to optimise the required storage and computation time. Despite producing accurate results when validated during the winter months, the model has potential for improvements regarding risk predictions during the summer months. This relates largely to the ventilation rates. Wind-speed, wind direction and building density could also be included for site specific fire and conflagration risk warnings. This would be very valuable for densely built wooden town areas also outside Norway, e.g., Japan, China, etc.

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References

[1] Morais J.C.M, Williams J, Albright D, Hoffmann A.A, Eritsov A, Moore P.F, San-Miguel-Ayanz J, Leonard M, Xanthopoulos G, and van Lierop P. Findings and

implications from a coarse-scale global assessment of recent selected mega-fires. Proceedings of the Vth International Wildland Fire Conference. Sun City, South Africa, 5. May, 2011.

[2] Log T, Vandvik V, Velle L.G, and Metallinou M. Reducing Wooden Structure and Wildland-Urban Interface Fire Disaster Risk through Dynamic Risk Assessment and Management. Applied System Innovation, 3(1):16, 2020.

[3] Bayham J, Thompson M.P, Belval E.J, and Dunn C. Weather, Risk, and Resource Orders on Large Wildland Fires in the Western US. Forests, 11(2):169, 2020.

[4] Cary G.J, Keane R.E, Gardner R.H, and Lavorel S. Comparison of the sensitivity of landscape-fire-succession models to variation in terrain, fuel pattern, climate and weather. Landscape ecology, 21(1):121–137, 2006.

[5] Enright N.J, Fontaine J.B, Bowman D.Mjs, Bradstock R.A, and Williams R.J. Interval squeeze: altered fire regimes and demographic responses interact to threaten woody species persistence as climate changes. Frontiers in Ecology and the Environment, 13(5):265–272, 2015.

[6] Eskandari S, Miesel J.R, and Pourghasemi H.R. The temporal and spatial relationships between climatic parameters and fire occurrence in northeastern Iran. Ecological Indicators, 118:106720, 2020.

[7] Flannigan M, Cantin A.S, de Groot W.J, and Wotton M. Global wildland fire season severity in the 21st century. Forest Ecology and Management, 294:54–61, 2013.

[8] Flannigan M, Krawchuck M.A, Wotton M, and Johnston L.M. Implications of changing climate for global wildland fire. International journal of wildland fire, 18(5):483–507, 2009.

[9] Ruffault J, Curt T, Martin-Stpaul N.K, and Moron V. Extreme wildfire events are linked to global-change-type droughts in the northern Mediterranean. Natural Hazards and Earth System Sciences, 18:847–856, 2018.

[10] Metallinou M and Log T. Cold Climate Structural Fire Danger Rating System Challenges. Challenges, 9(1):12, 2018.

[11] DSB. Brannene i Lærdal, Flatanger og på Frøya Vinteren 2014 (The fires at Lærdal, Flatanger and Frøya, winter 2014). Technical report, Norwegian Directorate for Civil Protection, 2014. ISBN 978-82-7768-342-3. In Norwegian.

[12] Hansen S, Hox K, Mikalsen R.F, Bøe A.S, Stensaas J.P, and Storesund K. Evaluation of fire spread in the large Lærdal fire 2014. Proceedings of the 14th Int. Fire and Materials Conf. and Exhib. Windsor, UK, 2-4 February, 2015.

[13] Log T. Cold Climate Fire Risk; A Case Study of the Lærdalsøyri Fire. Fire Technology, 52:1815–1843, 2014.

[14] Rohrer-Mirtschink S, Forster N, Giovanoli P, and Guggenheim M. Major burn injuries associated with Christmas celebrations: a 41-year experience from Switzerland. Annals of burns and fire disasters, 28(1): 71–75, 2015.

[15] Pirsko A.R. and Fons W.L. Frequency of Urban Building Fires as Related to Daily Weather Conditions. Technical Report 866, US Dep. of Agriculture, 1956.

[16] Log T. Indoor Relative Humidity as a Fire Risk Indicator. Building and Environment, 111:238–248, 2017.

[17] Log T. Modeling Indoor Relative Humidity and Wood Moisture Content as a Proxy for Wooden Home Fire Risk. Sensors, 19(22):1–22, 2019.

[18] Norwegian Meteorological Institute. Weather Forecast. api.met.no, .

[19] Norwegian Meteorological Institute. Historical Weather Data. frost.met.no, .

[20] Bushnaq O.M, Chaaban A, and Al-Naffouri T.Y. The Role of UAV-IoT Networks in Future Wildfire Detection. IEEE Internet of Things Journal, 2021.

[21] Hendra A, Palantei E, Syafaruddin, Hadin M.S, Zulkarnaim N, and Mansyur M.F. Wireless Sensor Network Implementation for IoT-Based Environmental Security Monitoring. IOP Conference Series: Materials Science and Engineering, 875:012093, 2020.

[22] Hidayatullah N.A, Putra R.G, Juliando D.E, and Kalam A. Volcano multiparameter monitoring system based on Internet of Things (IoT). Australian Journal of Electrical and Electronics Engineering, 17(3):228–238, 2020.

[23] Sharma A, Singh P.K, and Kumar Y. An integrated fire detection system using IoT and image processing technique for smart cities. Sustainable Cities and Society, 61:102332, 2020.

[24] Tsipis A, Papamichail A, Angelis I, Koufoudakis G, Tsoumanis G, and Oikonomou K. An Alertness-Adjustable Cloud/Fog IoT Solution for Timely Environmental Monitoring Based on Wildfire Risk Forecasting. Energies, 13(14):3693, 2020.

[25] Yousefi S, Pourhasemi H.R, Emami S.N, and Soheila-Pouyan. A machine learning framework for multi-hazards modeling and mapping in a mountainous area. Scientific Reports, 10(1):12144, 2020.

[26] Butt A, Ahmad S, Shabbir R, and Erum S. GIS based surveillance of road traffic accidents (RTA) risk for Rawalpindi city: A geo-statistical approach. Kuwait Journal of Science, 44:129–134, 2017.

[27] Debauche O, Elmoulat M, Saïd M, Mahmoudi S, Guttadauria A, Manneback P, and Lebeau F. Towards Landslides Early Warning System With Fog - Edge Computing And Artificial Intelligence. Journal of Ubiquitous Systems and Pervasive Networks, 15:11–17, 2021.

[28] Stokkenes S, Kristensen L.M, and Log T. Cloud-based Implementation and Validation of a Predictive Fire Risk Indication Model. Proceedings of the Norwegian Informatics Conference, Narvik, Norway, 25-27 November, 2019.

[29] Stokkenes S, Strand R.D, Kristensen L.M, and Log T. Validation of a Predictive Fire Risk Indication Model using Cloud-based Weather Data Services. Procedia Computer Science, 184:186–193, 2021.

[30] Stokkenes S. Implementation and Evaluation of a Fire Risk Indication Model. Master's thesis, Western Norway University of Applied Sciences, 2019.

[31] Kraaijeveld A, Gunnarshaug A, Schei B, and Log T. Burning rate and time to flashover in wooden 1/4 scale compartments as a function of fuel moisture content. Proceedings of the 14th Int. Fire Science and Eng. Conf, Interflam, Windsor, UK, pp. 553-558, 4-6 July, 2016.

[32] Geving S. and Thue J.V. Fukt i bygninger (Moisture in buildings). SINTEF Building Research, 2002. ISBN 82-536-0747-4. In Norwegian.

[33] Simpson W.T. Equilibrium moisture content of wood in outdoor locations in the united states and worldwide. Technical report, US dep. of Agriculture: Washingtion, DC, USA, 1998. RN-0268.

[34] Netatmo Smart Home API. https://dev.netatmo.com/apidocumentation, (accessed 6/9-2021).

[35] Dragoni N, Giallorenzo S, Lafuente A, Mazzara M, Montesi F, and Mustafin R. Microservices: Yesterday, Today, and Tomorrow. In Mazzara M, Meyer B. (eds) Present and Ulterior Software Engineering. 2017, pp 195-216.

[36] Pautasso C, Zimmermann O, and Leymann F. Restful Web Services vs. Big Web Services: Making the Right Architectural Decision. Proceedings of the 17th Intl. Conf. on World Wide Web, Beijing, China, pp. 805-814, 2008.

[37] Chen J-K and Lee W-Z. An Introduction to NoSQL Databases Based on Categories and Application Industries. Algorithms, 12:1–16, 2019.

[38] Bjerkseth M.S. Kjennetegn og utviklingstrekk ved dødsbranner og omkomne i brann: En gjennomgang av DSBs statistikk over omkomne i brann 1986-2009 (Characteristics and tendencies of fatal fires: A review of statistics from the Norwegian Directorate for Civil Protection), 2010. In Norwegian.

[39] Sesseng C, Storesund K, and Steen-Hansen A. Analyse av dødsbraner i Norge i perioden 2005-2014 (Analysis of fatal fires in Norway during the period 2005-2014), RISE-report A17 20176:1, Trondheim, Norway, 75 p, 2017. In Norwegian.

[40] Ighoubah F. and Solheim S. Slik var de første meldingene om Lærdalsbrannen (These were the first calls on the Laerdal fire). https://www.nrk.no/vestland/beboer-meldte-selv-om-boligbrann-1.11482695 (accessed 6/7-21), 2014.

[41] Østre Agder Brannvesen. Evalueringsrapport Brann i tett trehusbebyggelse i Risør (Evaluation report fire in densely built wooden homes in Risør) 36 p, 2021.

[42] Hunshamar C, Rønold I, Andersen G, and Holmes M. Brann i Kongsberg: En person funnet død (Fire in Kongsberg: One person found dead), vg.no/nyheter/innenriks/i/p6aode (accessed 5/5-2021), 2017.

[43] Norwegian Ministry of Justice and Public Security. Forskrift om brannforebygging (Fire Prevention Regulation), FOR-2015-12-17-1710, 2015. In Norwegian.

[44] Averill J, Moore-Merrell L, Barowy A, Santos R, Peacock R, Notarianni K, and Wissoker D. Report on Residential Fireground Field Experiments, NIST TN - 1661, 2010.

[45] Reglen D. and Scheller D. Fire Department Turnout Times: A Contextual Analysis. Journal of Homeland Security and Emergency Management, 13, 2016.

[46] Sintef. Nødvendig rømningstid ved brann (Available safe egress time), SINTEF Building Research Design Guides 520.385, 2016. ISSN 2387-6328. In Norwegian.