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Validation of a Predictive Fire Risk Indication Model using Cloud-based Weather Data Services

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Abstract

The high and dense representation of wooden homes in Norway, combined with periods of dry and cold climate during the winter season resulting in very dry indoor conditions, have historically resulted in severe fires. Thus, it is important 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 predication services. The main contribution of this study is implementation and experimental validation of a predictive fire risk indication model, which exploits cloud-provided measurements from weather stations and weather forecasts to predict the current and future fire risk for wooden homes at a given geographical location. The basic idea of the model is to estimate the indoor climate using measured and forecasted outdoor climate for computing indoor wooden fuel moisture content and an estimated time to flashover as indication of the fire risk. The model implementation was integrated into a micro-service based software system and experimentally validated during one winter at selected geographical locations, relying on weather data provided by the RESTful API of the Norwegian Meteorological Institute. Additionally, weather data from several historical fires were considered to relate our predictions to known fire incidents. Our evaluation demonstrates the ability to provide trustworthy and accurate fire risk indications using a combination of weather data measurements and forecast data. Furthermore, our cloud- and micro-service based software system implementation is efficient with respect to data storage and computation time.

Keywords: Climate related risks; Mitigating urban fire risk; Reducing vulnerability in cities; Smart city and cloud data services

1. Introduction

In recent years, societies around the world have experienced large wildland-urban interface (WUI) fires [9]. Hundreds have lost their lives and thousands have been left homeless [25, 9]. Climate changes have become increasingly prominent and there appears to be consensus about future development, resulting in increased wildfire seasons and frequency [7, 13, 4, 11, 10, 25, 8]. Much attention is paid to these devastating fires, however, from the above 300,000

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annual deaths caused by fire, the majority occurs within enclosures, such as a residence [26]. 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. Attention was brought to the topic in the aftermath of the devastating winter fire blaze in Lærdalsøyri (Norway), January 18 - 19, 2014 [3, 16, 22].

It is known that the winter in cold climate regions brings along increased fire frequencies [22, 31]. In 1956, Pirsko and Fons suggested ambient dew point during the winter as an explanation for the increased fire frequency in buildings [30]. Post the Lærdal fire, the cold climate fire risk was again identified by Log [22]. It prompted further research, and indoor relative humidity was suggested as a fire risk indicator [23]. A cold climate structural fire danger rating system was suggested [26], and a model for predicting indoor- relative humidity and wooden fuel moisture content (FMC) was developed [24]. Furthermore, Log et al. proposed a way forward for exploring and addressing novel dynamic fire risk assessment and management tools [25].

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 of the present paper is to report on an implementation, validation, and further development of the model of Log [24]. Secondly, we investigate 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 utilises the weather data representational state transfer (REST) application programming interface (API) provided by the Norwegian Meteorological Institute (MET) is developed [20, 27]. 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 [15, 5, 12, 32, 6]. 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 too 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. [14] 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. Developing understandable visual presentations of current and future risks, have a large potential when considering the implementation of the risk concept into new areas of the industry. Tsipis et al. [6] 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, 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 (GUI), 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 our research. 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. Finally, in Section 5 we sum up the conclusions and discuss directions for future work. A preliminary version of this paper appeared in [34]. In the present paper, we give a more complete presentation of the fire risk indication model and present an improved software architecture. Due to space limitations we cannot present all our experimental result and implementation details. These are available in the underlying technical report [33].

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 levels increasing beyond 20 kW/m^2. There are many factors influencing the time to flashover (TTF), such as ignition source, fuel, heat release rate, ventilation and compartment size. The modeling 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, resulting in a FMC dependent cooling and prolonged onset of pyrolysis [21].

The predictive fire risk indication model estimates the TTF for a compartment based on the calculated FMC, which in turn is based on ambient temperature and relative humidity (RH), and indoor temperature [23]. 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. Time to flashover is then found through an empirical relation with the FMC [21]. The main theoretical foundation of the implemented fire risk indication model is outlined below. The details can be found in [23, 24].

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 and dishwashing.

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 is calculated by,

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

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 $\Delta x = L/N$, where L is the panel thickness. For the rest of the equation; Δt is the time step, $D_{w,a}$ is the diffusion coefficient of water vapor in air at 22 °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 [24]. The water concentrations in the remaining panel layers are obtained by solving the second order partial differential ”heat equation”. 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 utilize a rate based on the Bernoulli equation, as proposed by Log [24], 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 [17].

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.

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 °C. The computed relative humidity 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.

Time to flashover. The time to flashover is estimated by an empirical correlation to the FMC [21],

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

where FMC is the water to dry wood mass ratio. Log [24] 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). The latter term includes; detection, interpretation, notification and emergency response (driving, rigging and initiating WOF). Any imbalance in the time budget with regards to $t_{FO} < t_{WOF}$ indicates an increased risk as a compartment reaching flashover quickly becomes threatening to neighbouring structures in densely built wooden structure areas. Thus, the degree of imbalance determines the risk level.

3. Cloud- and Microservice-based Software Implementation

A software prototype for a fire risk indication system was designed and implemented. The basic idea was to provide the fire risk indication as a REST web service relying on underlying weather data REST services [20, 27] provided by the Norwegian Meteorological Institute (MET) and Netatmo [28]. Figure 1 shows the overall software architecture of the developed prototype which has been organised into several smaller components following a microservice-oriented architecture [2] based on REST [29] web services. Since the external web services provide data in a JSON or XML representation, noSQL databases [1] 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.

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.

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: Frost Measurements and Netatmo Measurements to obtain weather data recordings, and one external web service: MET Forecasting to obtain forecast weather data to predict the fire risk in the coming days. Experimental results obtained using the Frost Measurements and MET Forecasting services were focused.

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. The latter is highly relevant as we want to compute the indications based on measurements for the last 1-7 days and forecast for the coming 1-7 days. The current fire risk predictions are stored in the underlying database such that they can be retrieved via the fire risk prediction service.

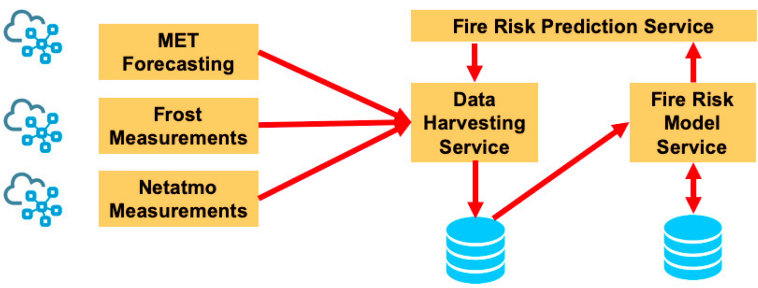

Fig. 1. High-level software architecture for the developed fire risk prototype application

External weather data services. The Frost API [27] 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, and the service will then 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 metadata about the stations. The Netatmo service [28] 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-based server. Through this cloud-based server, it is possible to retrieve the recorded weather data, that can then be used in the application. The MET API [20] 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 return the weather data for predictions of the weather 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

Weather data was collected in 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. The main aim was to validate the fire risk indication model in terms of providing plausible indications. The difference in computing fire risk indications based only on (historical) measurements versus using forecast data or a combination of the two was also investigated. It was also evaluated how the system would have indicated the fire risk prior to historical fires. Finally, computation time and storage efficiency were evaluated.

Fire risk based on weather data measurements. Figure 2 shows the average fire risk indications based on measurements collected in the winter of 2019 (December (12) until May (05)). From the graph it can be seen that the fire risk model generally indicates an expected higher fire risk (shorter time to flashover) at the colder inland locations. The average time to flashover 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.

Combining measurements and forecast weather data. Being able to predict the fire risk within the coming days is a main objective. Therefore, the combination of measurements (historical data) and forecast data was explored. An aspect to consider is that the fire risk model requires a few previous days of adaption before it can accurately begin to indicate the fire risk. To investigate this, the model was initially executed using only weather forecast data, and using a combination of historical data (for adaption) and forecast data. Figure 3(left), shows the results for the January-February period in Bergen without historical data adaption, including the corresponding fire risk indication obtained using only historical data as a reference. In Figure 3(right), historical weather data (measurements) is added to the

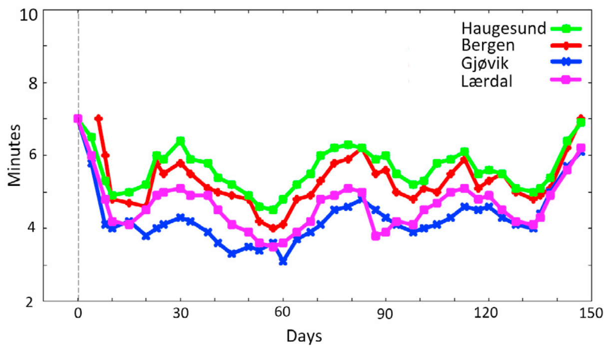

Fig. 2. Estimated time to flashover for the four selected locations

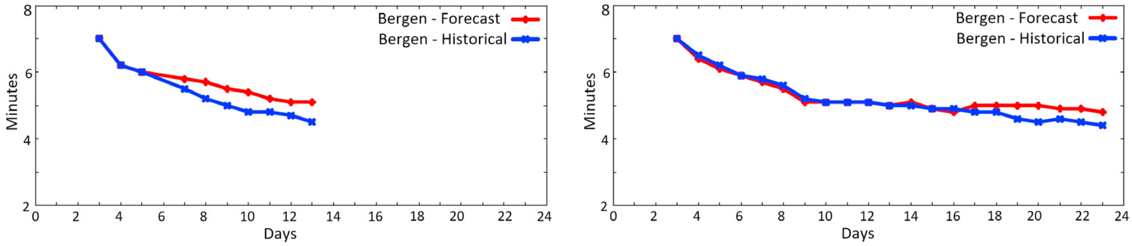

Fig. 3. Time to flashover for forecast and historical weather data - without adaption by historical data (left) and with adaption (right)

forecast data, and used for adaption. As can bee seen from the figures, the fire risk based on forecast follows roughly the same curve as the fire risk indication based on historical data in the first three and a half days. In this period, the forecast works with weather data at hourly measures. After that period it starts giving forecast data at a six hour interval, hence the greater uncertainty in the predicted weather.

The average difference between using only historical and forecast fire risk indication when additional data has not been added for adaption is approximately 0.26 minutes. The standard deviation for the difference is 0.24 minutes. The maximum difference between forecast and historical when adapted and not adapted is 0.58 and 0.62 minutes, respectively. These results demonstrate that using historical data for adaption results in a more accurate prediction. In practice this is also how we expect the model to be operating. When computing a fire risk prediction at a given day, historical data from the past days will be used in combination with the forecast data.

Fire risk indications for historical fires. Another aspect in terms of validating the fire risk model, is to consider fires in the past. This way it is possible to determine how the fire risk was at the time of the fire, and the period leading up to the fire. A recent fire that serves as an example, is the fire in Lærdalsøyri 18th January 2014 [3, 16, 19]. This is a place with many old wooden buildings and at a location that gets very dry during the winter period. The estimated fire risk is visualized in Figure 4(left), 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, resulting in drier indoor air. In this dry period, the wood inside the homes released humidity to the indoor air volume, which was gradually ventilated out. 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 [19]. Then, the home was fully involved in the fire, both inside and outside. The fire department clearly 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 [19] contributing to rapid spread of fire to close and distant structures.

Another fire that was considered, was at a home care center in Kongsberg, 24th of December 2017, resulting in the loss of life [18]. The fire risk indication for this period is visualised in Figure 4(right). During the December month of that year, the time to flashover averaged around 4.2 minutes. 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. Our results confirms the conclusion from the fire in Lærdal of 2014, that the TTF is considerably lower than that of the required

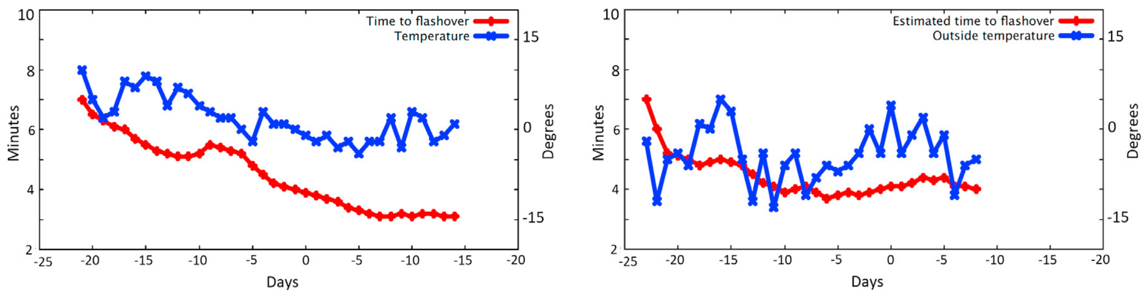

Fig. 4. Time to flashover for the fire in Lærdal 2014 (left) and at a home care center in Kongsberg 2017 (right)

response time from the fire department. This makes it likely that our model could have warned the fire department to be readily available. More generally, it suggests that the required response time does not take into consideration dry indoor conditions. Based on these results, the model could have predicted that the fire department would not be able to properly handle a fire during this period. 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.

Computation time and data storage. During the evaluation period, our implementation collected approximately five months worth of weather data. The application continuously harvest weather data. Every 24 hours, the application fetches historical weather data for the previous day 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 forecasts. The weather data from the MET stations were 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, the time is 4.1 s to retrieve the weather data and another 0.2 s to convert it. Then it is passed on to the fire risk component which add another 0.6 seconds for conversion and 0.07 s in computing 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 fire risk indications can be computed and stored in both a space and time efficient way.

5. 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. The results indicate that it can obtain a reasonably accurate fire risk prediction in terms of the estimated TTF. Given the retrospective risk estimates for the fires in Lærdal and Kongsberg, it may be concluded that the model gives accurate fire risk indications. 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.

The results show that it is feasible to use a combination of measurement data and forecast data for computing a viable fire risk indication. The results demonstrate that the best option is to combine the two using measurement data to properly adapt the model relative to days of previous weather. 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.

On the implementation side, end-user clients has 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. Future work may also include continuous experimental evaluation through whole years. 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 and China.

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