

Cloud-based Implementation and Validation of a Predictive Fire Risk Indication Model

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Abstract

The high representation of wooden houses in Norwegian cities combined with periods of dry and cold climate during the winter time often results in a high risk of severe fires. This makes it important for public authorities and fire departments to have an accurate estimate of the current fire risk in order to take proper precautions. We report on the implementation of a predictive mathematical model based on first order principles which exploits cloud-provided measurements from weather stations and weather forecasts from the Norwegian Meteorological Institute to predict the current and future fire risk at a given geographical location. We have experimentally validated the model during the winter 2018-2019 at selected geographical locations, and by considering weather data from the time of several historical fires. Our results show that our cloud and web-based implementation is both time and storage efficient, and capable of being able to accurately predict the fire risk measured in terms of the estimated time to flashover. The paper demonstrates that our methodology in the near future may become a valuable risk predicting tool for Norwegian fire brigades.

1 Introduction

The large amount of forest in Norway has provided the foundation for a very long tradition of constructing houses using wood as the main material. These houses can be extremely susceptible to fire under weather conditions that typically occur during the winter time when there are long periods of dry and cold weather. When the air gets colder and drier, the water concentration in the wood decreases [17], meaning there is a high probability of the wood to catch fire. As identified by Log [12], it is the period during December - January when the weather is usually cold that have the highest frequency of fires in Norway. The very severe fire in Lærdalsøyri January 18-19 2014, resulting in the loss of more buildings in a single conflagration since 1923, may serve as an example [5, 11].

This paper was presented at the NIK-2019 conference; see <http://www.nik.no/>.

The long-term aim of the work presented in this paper is to address the research question as to whether there is a way to reduce the impact of fires by means of an early warning system that can for example warn the local fire brigade when a high fire risk is expected in the coming days. This would enable them to stay alert and be better prepared in case a fire incident occurs [14]

The first contribution of this paper is to investigate whether the predictive model developed by Log [12, 13] for estimating the relative humidity in wooden structures based on first order principles can be used in combination with weather data measurements and forecast data to obtain a reliable and useful fire risk prediction. In this work, we use the estimated time to complete flashover as an indication of fire risk. The time to flashover is in practice in the order of minutes. To be useful, our predictions should be within similar order of magnitude in terms of time and be consistent with observed weather conditions [10]. A second contribution is to show how the fire risk prediction can be provided as a cloud-service and be implemented based on cloud-services. We have implemented the fire risk indication prototype as a distributed application based on the architectural principles of micro-services [3] and REST [16]. For the implementation of the fire risk prediction service we have used the Spark/Java framework [18], and deployed the application on the Amazon EC2 platform. For data storage, we rely on the MongoDB noSQL database deployed in the Azure cloud platform. As the data source for meteorological data we rely on the Frost[15] and MET [9] REST web-services of the Norwegian Meteorological Institute (MET) providing data from high-end weather stations and weather forecast data. In addition to these professional meteorological services, we have also investigated the consumption of meteorological data from Netatmo consumer-grade weather stations.

The remainder of this paper is organised as follows. In Section 2 we briefly outline the predictive fire risk indication model which has served as a basis for our investigations. Section 3 explains how we have implemented a software prototype by aggregating data from external cloud-services to obtain the input data required for the predicative fire risk indication model. In Section 4 we present selected results of our experimental evaluation. Finally, in Section 5 we provide the conclusions and discuss directions for future work. The paper is based on the master’s thesis [19].

2 Predictive Fire Risk Indication Model

The predictive fire risk indication (FRI) model [12] is based on computing the relative indoor humidity of a wooden structure using the measured and/or predicted indicators for the outdoor climate [13]. Obtaining the relative indoor humidity makes it possible to determine the concentration of water in the wood which in turn makes it possible to estimate the time to complete flashover in case of a fire.

The basic observation underlying the model is that as the air gets dryer the wood releases moisture and when the relative humidity increases the wood will absorb moisture. In addition to this, the predictive model takes into account decay periods related to the transport of water in and out of the wood. The decay period gives a delayed effect in terms of fire risk. Due to space limitations, we only outline the theoretical foundation of the FRI model below. Details can be found in [12, 13].

Outdoor Climate. The FRI model requires the outdoor air temperature, outdoor relative humidity, and the outdoor water concentration of the air. The first two

elements are typically measured. The outdoor water concentration can be estimated by calculating the water saturation vapour pressure as:

$$P_{sat} = 610.78 * e^{\frac{17.2694 * T_c}{T_c * 237.3}} \quad (1)$$

where T_C ($^{\circ}C$) is the the outdoor air temperature. The outdoor water concentration can now be obtained as:

$$C_{wa} = RH_{out} * \left(\frac{P_{sat}(T_c) * M_w}{R * (T_c + K)} \right) \quad (2)$$

where RH_{out} is the outdoor relative humidity, $M_w(0.01801528)(kg/mol)$ is the molecular mass of water, $R(8.314J/Kmol)$ is the molar gas constant, and K is the absolute temperature $273.15K$.

Indoor Climate. The indoor climate is dependent on the outdoor climate [13] in addition to factors such as the humidity released by people, plants and animals inside the house, and also the air change rate. Log found [12, 13] that it is reasonable to assume that 1 kg of moisture is released daily and that older wooden houses have a lower air change rate compared to newer houses. Based on the investigations of Log [12, 13], the concentration of water in the air inside a house with forced ventilation can be computed iteratively using the following formulas:

$$C_{in,0} = RH_{inside} * C_{sat,in} \quad (3)$$

$$C_{in,i} = ((1 - \beta) * C_{in,i-1} + \beta * C_{wa} * \left(\frac{T_{out}}{T_{in}} \right)) + \frac{m_{wall,loss}}{v} + ms * \frac{\Delta t}{v} \quad (4)$$

where RH_{inside} is a base relative humidity set to 40% as a starting point; $C_{sat,in}$ is found using Eq. 2 without RH and T_c is set to $22^{\circ}C$; β accounts for the ventilation (air changes per hour), T_{out} and T_{in} is the absolute outdoor and indoor temperature where we set the indoor temperature to an estimated $22^{\circ}C$; m_{wall} is the sum loss of water concentration in the walls, $volume$ is the volume of the room, ms is the moisture supply which is $\frac{1}{24 * 3600} kg/s$ and Δt is the calculation interval set to 720 s.

The second order partial differential diffusion equation, i.e. analogous to the heat equation, is then solved for the wooden wall layers involved in the moisture transport. The innermost layer is for simplicity treated as a mathematical reflection surface. This is well-founded based on moisture diffusion barrier requirements in Norwegian houses preventing rot formation as a result of wall and thermal insulation cold weather temperature gradients. The Bernoulli equation based air change rate as recommended by Log [13] was used in the modeling. It should be noted that the methodology relies on basic physics, with no empirical constants. Parameters such as the moisture diffusivity coefficient is taken from the literature [1].

With the indoors concentration of water calculated, the relative humidity can be computed using the following equation:

$$RH_{inside} = \frac{C_{in}}{C_{sat,in}} \quad (5)$$

where C_{in} is then obtained using Eq. 4.

Fuel Moisture Content. Based on the computed indoor climate figures, it is possible to estimate the concentration of water in each of the layers of wood, and based on this in turn estimate the *fuel moisture content* (FMC) of the wood at a given moment of time. Having computed FMC, the time to flashover t_{FO} can be computed as [10]:

$$t_{FO} = 2 * e^{0.16 * FMC} \quad (6)$$

The time to flashover is in practice in the order of minutes where the lower the time to flashover, the higher the fire risk. It should be noted in the current version of the model, we do not take into account further risk elements such as wind-speed and wind-direction which may contribute to a high risk of a fire spreading.

The advantage of the FRI model is that it can estimate fire risk based on outdoor climate elements. Measurements and predictions of outdoor climate elements are publicly available as measurements and forecasts covering all of Norway, whereas it is not yet realistic to assume that all houses would be equipped with sensors making indoor climate elements publicly available.

3 Cloud- and Microservice-based Implementation

We have made an implementation of the FRI model capable of computing fire risk indications and providing the indications as a REST web service. The application and the web service has been designed such that it can be used both for our experimental evaluation, and also be consumed by clients in general that need to access to fire risk indications for a given geographical location.

Figure 3 shows the overall software architecture of our prototype system which is divided into several smaller components following a microservice-oriented approach. The Fire Risk Prediction Model (FRP) component implements the FRI model, and the data harvesting and collection component (DHC) deals with collecting weather data, both forecast and historical weather data (measurements). The fire risk web service acts as a controller service that handles communication from clients to the other two components. All components are to be deployed on a cloud platform where we additionally store collected weather forecasts and measurements in order to be able to run the controlled experiments required to validate the FRI model.

The implementation is able to compute fire risk indication 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 in practice as one often want to compute the indications based on measurements for the last 1-7 days and forecast for the coming 1-7 days. Figure 2 illustrates the interaction between the components of the application when providing a fire risk indication based on a combination of measurements (historical data) and forecast data.

Part of our evaluation goal is to compare the fire risk computed using different weather data sources. In order to have consistent data sets throughout the evaluation, the weather data from all external services are stored in databases. This allows the model to use a consistent data set when testing occurs at a later date for instance as the fire risk model is being refined. The data is stored using the original format as it was retrieved from the external services in order to have the complete data available. Since external services provide data in a JSON or XML representation, we are using a noSQL database [6] for storing the weather data.

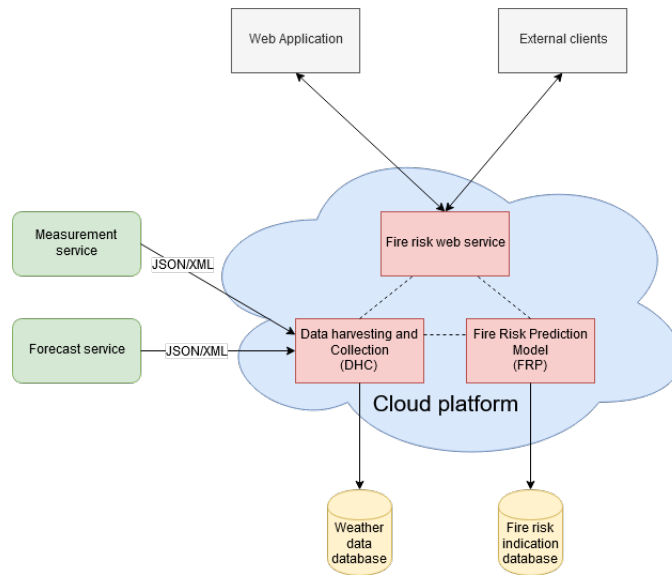


Figure 1: Software architecture of the FRI prototype application

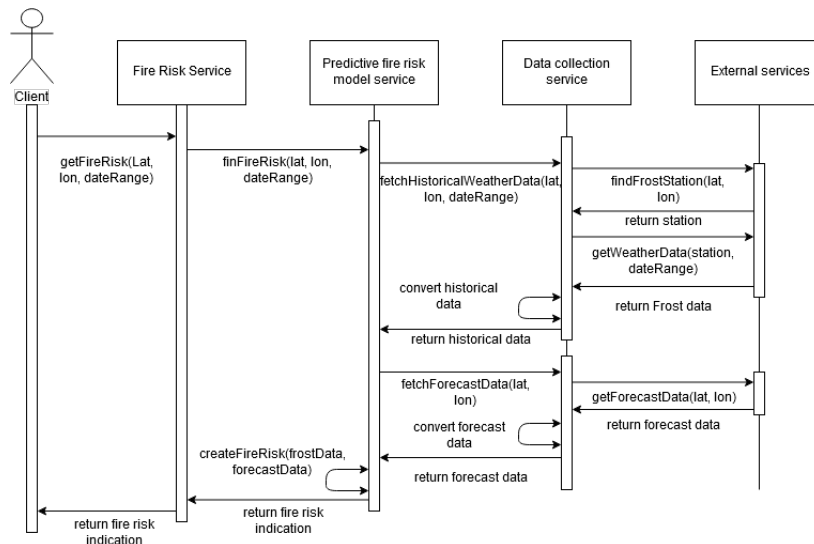


Figure 2: Sequence diagram for fire risk indication with historical and forecast data

The FRI application services and components have been 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 FRI application uses three external web services to obtain weather data from several sources. Two of the sources provide historical weather data while the third one provides forecast weather data to predict the fire risk in the coming days.

Frost. The Frost API [15] is a REST web service that provides 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, lighting, sources (weather station

metadata), elements (weather elements), climate normals, and frequencies. The FRI application uses location, observation, and meta-data about the stations.

Netatmo. The Netatmo service [2] deals with the same type of weather data as the Frost service, but relies on consumer grade weather stations typically installed in private homes. The consumers publish their weather data into a cloud-based server. Through this cloud-based server, it is possible to retrieve the measured weather data, that can then be used in the FRI application. The Netatmo API offers different services based on the types of Netatmo product. In the case of the FRI application, only temperature and humidity is used. The meta-data for the stations contains the identification of the indoor and outdoor module, and general information about the stations such as location which is used by the FRI application.

MET. The MET API [9] 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 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. The forecast data is offered in XML and JSON format.

4 Experimental Evaluation

We have collected weather data in the winter period 2018 - 2019 at four selected locations in Bergen, Haugesund, Gjøvik, and Lærdal. The reason for choosing these locations were due to the varied climate. At the west coast it is more humid in the winter than in some of the inland locations which in turn are also generally a lot colder during the winter. The collected data includes weather data from Netatmo stations, placed in Bergen and Gjøvik, MET stations, and weather forecasts from Frost. Part of the evaluation has been to investigate whether the data source used impacts the fire risk indication, and to validate the fire risk indication model in terms of being able to provide plausible indications. We also investigated the difference in computing fire risk indications based only on (historical) measurements versus using forecast data or a combination of the two. We also considered historical fires to see how the FRI model implementation would have indicated the fire risk at the time of fire, and in the days leading up to the fire. Finally, we have evaluated the computation-time and storage efficiency of our implementation.

Historical Weather Data. Figure 3 shows the average fire risk indications based on measurements collected in the winter period 2018 - 2019 (December (12) until May (05)). From the graph it can be seen that the FRI model generally indicates an expected higher risk of fire (shorter time to complete flashover) at the colder inland locations. This is also shown in Table 1 which summarises key figures for the complete period. It should be noted that at 50% and 60% indoor relative humidity, the time to flashover is around 9 and 11 minutes, respectively.

Historical and Forecast Weather Data. Being able to predict the fire risk within the next coming days is a main objective. We therefore explore the

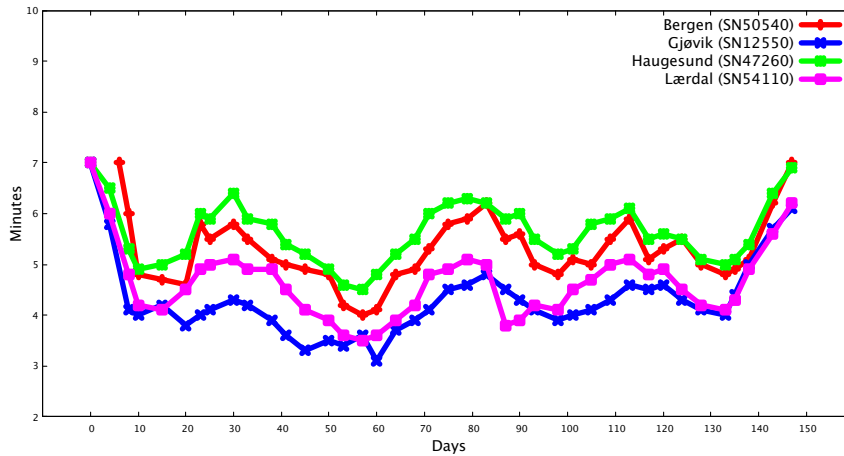


Figure 3: Estimated time to flashover for the four selected locations

Location	Average	Std. dev	Max	Min
Bergen	5.50	0.67	7.64	4.13
Haugesund	5.70	0.63	7.59	4.32
Gjøvik	4.48	0.90	8.02	3.32
Lærdal	4.77	0.74	7.57	3.56

Table 1: Key figures for fire risk indicates from the four locations

combination of measurements (historical data) and forecast data. An aspect to consider is that the FRI model requires a few days of self-calibration before it can accurately begin to indicate the fire risk. To investigate this we ran the FRI model using only weather forecast data (no calibration) and using a combination of historical data (for calibration) and forecast data. Figure 4(left) shows the results for the January-February period in Bergen without the use of historical data for calibration. The corresponding fire risk indication obtained using only historical data is also visualised as a reference. In Figure 4(right) historical weather data (measurements) is added on to the forecast data, which is used for the calibration. As can be 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 of time, the forecast works with weather data at hourly measures. After that period it starts giving forecast data at a six hour interval. When it starts the six hour interval, the FRI model has less data to work with and predict the fire risk until the next measure in six hours.

Table 2 provides the key figures. It can be seen that the average difference between using only historical and forecast fire risk indication when additional data has not been added for self-calibration is estimated to around 0.26 minutes. The standard deviation for the difference is at 0.24. The maximum difference between forecast and historical when calibrated is 0.58 and when not calibrated is 0.62. The results demonstrates that the use of historical data for calibration results in a more accurate prediction. In practice this is also how we expect the FRI model to be used. 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.

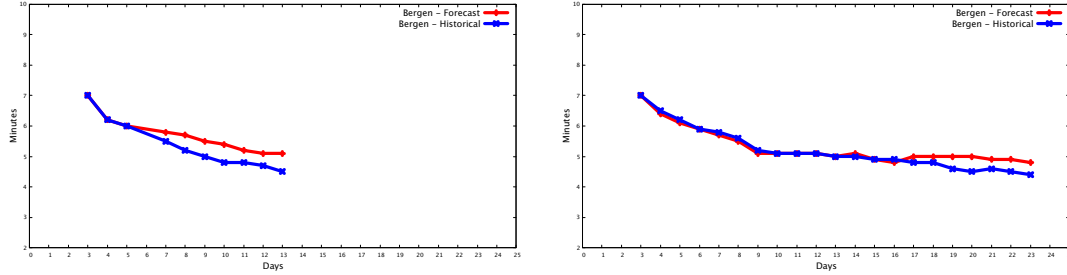


Figure 4: Time to flashover for forecast and historical weather data - without calibration (left) and with calibration (right)

Location	Avg. Diff	Std. Div	Max. diff
Bergen (no calibration)	0.26	0.24	0.63
Bergen (calibration)	0.12	0.18	0.58

Table 2: Fire risk information from four locations

MET stations and Netatmo stations. The results above were based on using MET data from high-end measuring stations. We also investigated the use of low-end measuring stations in the form of Netatmo stations. These stations are typically placed closer to the houses than that of the MET stations. Figure 4 shows the difference between using a Netatmo station and a MET station for two locations.

As can be seen in Figure 4 (right), the fire risk indication based on the Netatmo station in Gjøvik follows almost the exact same curve as the one based on the MET station. In Figure 4 (left), the Netatmo fire risk indication from Bergen is not exactly the same as the one from MET. The curve itself follows almost to the point of what the MET-based fire risk indicates. This may be due to the fact that the Netatmo station is not correctly calibrated and measures temperatures higher than the MET station, or that the Netatmo station in Bergen is placed around $1.76km$ north east of the MET station. The MET station in Bergen is located close to the water with an open field surrounding the station whereas the Netatmo station was placed in the inner city with surrounding houses.

Table 3 summarises the numerical differences between the use of Netatmo stations and MET stations when computing the fire risk. At Gjøvik, the difference between the Netatmo stations and the Frost stations is almost negligible, whereas the result from Netatmo and Frost Bergen is more varied for certain periods. Still the overall difference is 0.5 minutes on average, and at most around 1 minute.

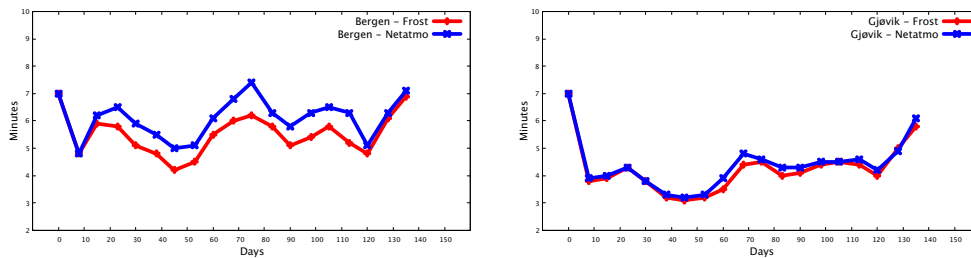


Figure 5: Time to flashover for input data based on the MET and Netatmo stations in Bergen (left) and Gjøvik (right)

Location	avg.diff	std.dev	Max diff	Max	Min
Bergen	0.53	0.28	1.06	7.09	4.13
Gjøvik	0.07	0.07	0.19	6.14	3.32

Table 3: Difference between MET stations and Netatmo stations

Fire Risk for Historical Fires. Another aspect in terms of validating the FRI 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 will serve as an example, is the one in Lærdalsøyri on 18th January 2014 [4, 5, 8, 11]. This is a place with many old wooden buildings and at a location that gets very dry during the winter period. The fire risk estimated for that time is visualised in Figure 6(left) with day 0 being the day of the fire. During a period of around 12 days before the fire, the temperature started dropping which results in the climate getting drier. In this dry period, the wood inside the houses released humidity to the indoor air, and was gradually ventilated out of the houses. At the time of the fire at around 22:50 the FRI model indicates that it would take around 3.8 minutes until complete flashover. The fire department learnt about the fire at 22:53pm, and the fire fire truck was on scene at 22:59pm [8]. At this time it was reported that the house was in complete flashover. Since the FRI model indicate a complete flashover in 3.8 minutes, the fire department did not have sufficient time to put out the fire. It should also be noted that at the time, there was storm strength winds in the area [8] which also contributed to higher risk of fire conflagration.

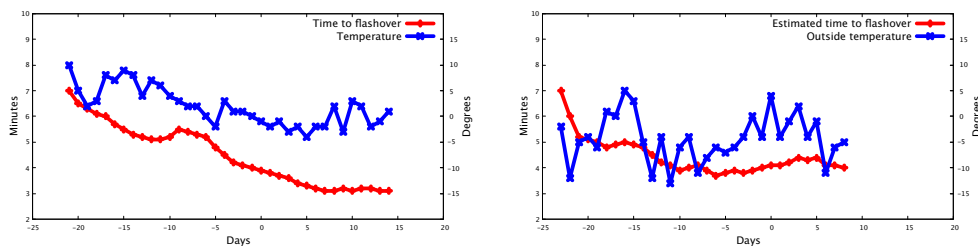


Figure 6: Time to flashover for the fire in Lærdal 2014 (left) and at a home care center in Kongsberg 2017 (right)

Another fire that we considered was the one in Kongsberg, at 24th December 2017, at a home care center[7]. The fire resulted in the loss of life. The fire risk indication for this period is visualised in Figure 6(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 response time given by the Norwegian law which states the required response time is to be 10 minutes or less. Our results indicates the same as the fire risk from the fire in Lærdal of 2014, that the time it takes for a complete flashover is considerably lower than that of the required response time from the fire department.

Given these results, the FRI model could have warned the fire department to be readily available. It also looks like the required response time does not take into consideration dry indoor conditions. Based on these results, the FRI model could have predicted that the fire department could not properly handle a fire that would flashover that quickly. The current minimum response time that the fire department is expected to comply to hence seems to be too high for the dry periods of winter.

Storage and Computation Time. During the 2018-2019 winter period, the FRI application collected approximately five months worth of weather data. This includes forecast data and historical data from four locations, and weather data from two Netatmo stations. The FRI application performs continuous harvest of weather data. Every 24 hours, the FRI application fetches historical weather data for the previous day, from MET and Netatmo, and forecasts for the next nine and a half days. Whenever the FRI application fetches new historical weather data, it will take the previously calculated fire risk indication and create an augmented fire risk indication for the new weather data, and add it to the back of the previous one. By doing it 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 humidity. The total amount of storage that these forecasts use, amounts to 12.5Mb, with an average of around 25.4 kb. per forecasts. The weather data from the Frost 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 ended up containing 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. The measurements from the Netatmo stations were stored in the same way as the Frost stations, where each document contains 24 hours worth of weather data. The total number of documents containing weather data from Netatmo totalled at 336.7 kb of storage with a average of 1.3 kb per document.

A fire risk indication for a 24 hour period at one location uses 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 224.84 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 amount of space.

With regard to runtime efficiency, it took 0.07 seconds to compute fire risk indications for a full year. Note that this excludes the time it takes to retrieve the weather data from the external services and the time for converting the data. If everything is included for creating a fire risk for a whole year, the time is 4.1 seconds to retrieve the weather data, another 0.2 seconds to convert it. Then it is passed on to the FRI component which add another 0.6 seconds for conversions and it takes 0.07 seconds to compute the fire risk. The total time elapsed for creating a fire risk indication with weather data for a full years amounts to 5 seconds. If the same was done for half a year, the time 2.5 seconds of which 2.36 seconds is used to fetch the data, and 0.04 seconds used for converting and computations. The rest of the 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

We have implemented an innovative and science-based predictive fire risk indication in a cloud-service context where external data services provided by MET and Netatmo have been used to obtain the weather data required for the computation. The results indicate that we are able to obtain a reasonably accurate fire risk

prediction in terms of the estimated time to flashover. In particular given the result of the fires in Lærdal and Kongsberg, we conclude that the FRI model gives accurate fire risk indications. Furthermore, information gathered from the fire department in Bergen, stated that they had a minimum requirement of 10 minutes response time to certain critical buildings. This included hospitals, nursing homes, historical buildings and shopping centres. With the result regarding the Lærdal and Kongsberg fires, many of the fire departments around Norway 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.

Our results also shows that it is feasible to use a combination of measurement data and forecast data in order to compute a useful fire risk indication. In fact, our results demonstrate that the best option is to combine the two using measurement data to properly calibrate the FRI model. With regard to storage efficiency, the FRI application requires relatively little storage, and we can conclude that the software architecture has adequate storage efficiency. Furthermore it has been shown that it does not accumulate large amount of weather data. With regard to the run-time efficiency of creating fire risk indications, most of the time was spent fetching data from the external services. The time for computing a fire risk indication was negligible. This indicates that the implementation of the FRI model is adequate regarding the run-time efficiency. The most time consuming internal operation of the FRI application was conversion of weather data.

On the implementation side, we have not yet considered end-user clients. In addition to this, future work may also include further improving the implementation of the FRI model for fire risk indication aimed at making it more efficient. However, the time it takes to compute the fire risk itself is very low, and for that reason it would be more relevant to consider the time it takes to retrieve data from external services possibly by using background fetch of the data.

Based on the result of indicating the fire risk of the four locations, we can identify a period from the start of January to the middle of February as the period with the highest fire risk. After this period the fire risk reduces steadily with a few periods where it goes up again before it starts to decrease from the middle of April. It is at this point the weather climate gets warmer, but that does not necessarily mean that the fire risk will be lower. The reason for this is because of, e.g., heathlands and forests that can easily catch fire. This may also have an impact on the fire risk for later periods of the year. The current FRI model considers only colder climate conditions and would have to be mathematically refined in order to cover also the warmer periods of the year. Another aspect that may be improved in the future is to take into account more parameters when calculating the fire risk. This could be done by weather elements such as wind-speed and direction to get a more accurate result regarding conflagration risk. There is also the possibility of combining the wind with a parameter that may indicate how densely the houses are located.

Acknowledgement. This study was partly funded by the Research Council of Norway, grant no 298993 *Reducing fire disaster risk through dynamic risk assessment and management (DYNAMIC)*.

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