Remaining Useful Life Estimation for Air Filters at a Nuclear Power Plant

Olli Saarela[1], John Einar Hulsund[2], Aimo Taipale[3] and Morten Hegle[4]

[1,2,4]*Institutt for Energiteknikk, OECD Halden Reactor Project, PO Box 173, NO-1751 Halden, Norway*

John.Einar.Hulsund@hrp.no
Morten.Hegle@ife.no

[1,3]*VTT Technical Research Centre of Finland, PO Box 1000, FI-02044 VTT, Finland*

Olli.Saarela@vtt.fi
Aimo.Taipale@vtt.fi

Abstract

The exhaust ventilation air from nuclear power plants and other nuclear facilities is carefully filtered, as aerosols are a potential vector of contamination. Monitoring the condition of the air filters improves radiation safety. In this paper the progression of differential pressures over air filters at a nuclear research reactor have been studied. Technical properties and possible environmental influences have been checked in order to understand the variation of the pressure over time. The differential pressure has been decomposed into different components as a result of an analysis of environmental conditions. The gradually increasing component, representing gradual accumulation of aerosol particles in the filter, is modeled as a gamma process and an estimate for determining the remaining useful life of the air filters has been computed.

1. Introduction

At most nuclear power plants there are relatively long periods of operation, typically about one year, before the plant is shut down for an outage period of several weeks for inspection, maintenance and possibly also refueling. For economical and safety reasons it is desirable to avoid unplanned shutdowns and keep the outage period as short as possible. The estimation of the remaining lifetime for air filters at a nuclear facility can therefore help in planning the optimal outage period for changing air filters. In addition to advancing safety and improving maintenance planning, this also helps to minimize radioactive waste.

The OECD Halden Reactor project is an international research program with 20 member countries. One of the research themes deals with condition based maintenance at nuclear power plants. This paper describes methods developed within this project for estimating the remaining useful life (RUL) of air filters at nuclear power plants.

The air filter data described in this paper is measured at one of the two research reactors belonging to the institute. The data contains measurements of the differential pressure over the air filters for air originating at two different locations in the reactor building. One of the locations is the reactor hall, and the other location is a laboratory where radiation experiments are held.

2. Towards risk-informed decision making

Filtration of exhaust air from nuclear facilities forms a barrier against nuclear contamination. High-efficiency particulate air (HEPA) filters are used as the final filtration stage due to their high particle removal efficiency. Another requirement for filters in these applications is durability even in unlikely scenarios, including e.g., earthquakes and explosions. Glass fiber media in HEPA filters is brittle and loses strength with aging (First, 1996; Winegardner 1996). With the current state of the art filter changes are based on conservative pressure difference and age limits (e.g., 10 years from the date of manufacture) defined with the main focus of maintaining adequate physical strength. (U.S. Department of Energy, 2003). This is in contrast to most air filtration applications, where the energy cost of ventilation is a major factor in determining filter replacement policies (Gustavsson, Ginestet, Tronville & Hyttinen, 2011).

As aerosol particles are accumulated in a filter, its permeability decreases, and consequently forces acting on the aging material increase (Brown, 1993). As increasing forces due to filter loading and the weakening of the material aren't considered jointly in the current state of the art (Gustavsson et al., 2011), filter replacement limits have to be set quite conservative. Prediction of pressure drop development, and consequently RUL facilitates time-based maintenance procedures to be superseded by condition based maintenance. As a further advantage, comparing actual pressure drop to predicted development facilitates monitoring of increased aerosol emissions.

Prediction of pressure drop development is also a step towards risk-informed decision making. In this approach, complex safety-related issues are evaluated where probabilistic risk assessment is used as a tool in design, operation, and regulation to achieve an acceptable overall risk level (U.S. Nuclear Regulatory Commission, 2011; Varde & Pecht, 2012). In the case of air filtration this would involve, e.g., defining monitoring and replacement procedures based on predictions of filter strength and permeability developments combined with estimated probabilities of pressure shocks and evaluated consequences of mechanical failures.

3. COLLECTED AIR FILTER DATA

3.1. How the air is filtered at the reactor site

The inlet air is split in three tubes where the air is filtered and heated or cooled down before it is sent to the destination rooms. The target temperature is regulated and supposed to be constant at 20°C all year, which means that the air is cooled down occasionally during summer and heated otherwise. In addition to the reactor hall and laboratory, the air is sent to adjacent rooms, but data in this paper is collected only for air from the reactor hall and laboratory.

The outlet air is filtered through three types of filters; a coarse filter, a fine filter and a micro filter (HEPA filter). All three filters are changed at the same time based on the value of the pressure difference, $dP(t)$, which is measured over all three filters.

3.2. Differential pressure

The collected data are from 1974 until now (2014) and are written down on paper schemas. In this first phase, data from the end of 2000 until the end of 2013 have been converted to digital form suitable for computer analysis.

The differential pressures over the air filters from the two different locations, plotted in Figures 1 and 2, have different signatures. The differential pressure over the air filters for the laboratory has clear seasonal variation, so that the pressure drop decreases each spring. This is especially visible when the air filters have a high load of particles, with pressure drop decreasing up to about 20 % from winter to the following summer.

The two locations are used very differently. While the entrance and exits to the reactor hall are practically sealed, the laboratory is a working environment with direct exits to the outdoor area where unfiltered air from the external environment can enter the room. To prevent leakage of radioactive particles, the indoor air pressure is kept adequately below the outdoor air pressure.

Filter changes can be seen in the pressure difference graphs as sharp drops down to ca. 20 mmH_2O and are indicated with vertical dashed lines in Figures 1 and 2. The filter pack was changed only once for the reactor hall and twice for the isotope laboratory during the studied period.

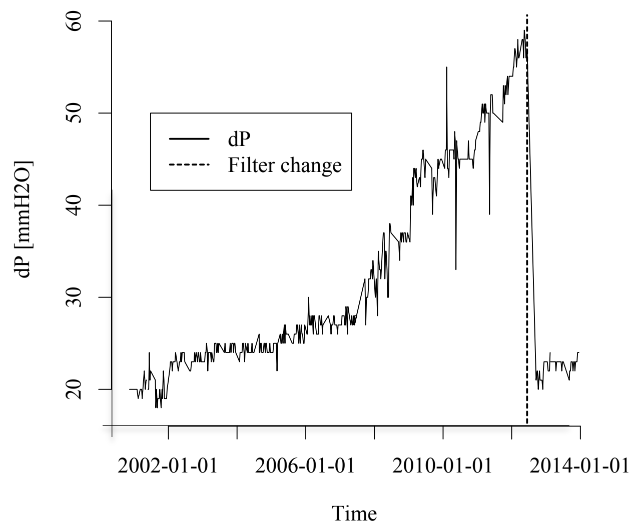

Figure 1. The differential pressure over air filters for air coming from the reactor hall.

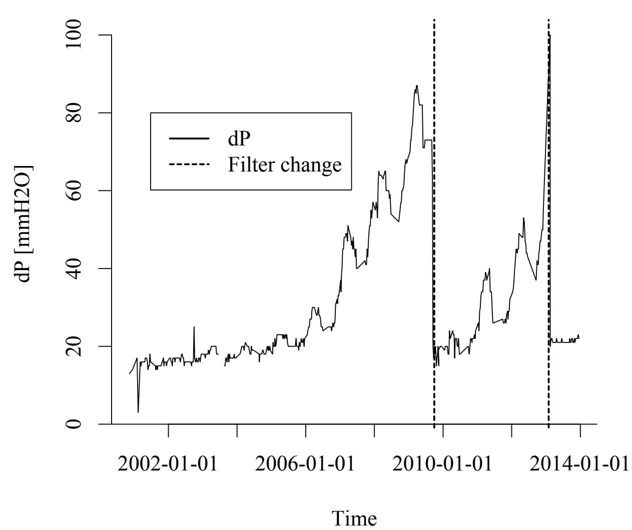

Figure 2. The differential pressure over air filters for air coming from the isotope laboratory.

Some step-like increases of the differential pressure occur occasionally at both locations. It is not known what is causing these jumps, but it can be e.g. maintenance operations that contribute to extra loading of the filters.

The differential pressure for air filters is commonly assumed to be monotonically increasing as particles accumulates in the filters under constant environmental conditions. The observed data, however, is clearly non-monotonic. The decreases in the data are assumed to be caused by both changing environmental conditions (especially humidity), measurements errors, and possible variations in air flow.

3.3. Air quality

As changing environmental conditions were hypothesized to influence the observed pressure drop, measurement data from a nearby weather station was retrieved. Available data included time series of outdoor air pressure, temperature, and humidity (Norwegian Meteorological Institute, 2014). Indoor humidity was estimated by computing the absolute amount of water in the incoming air and transforming it to relative humidity at 20 °C, which was the regulated indoor temperature.

Data on particle concentrations in the outdoor air in the vicinity of the studied facility was not available. Availability of such data would have aided in understanding the observed phenomena. However, its interpretation wouldn't have been trivial due to both the large number of different particles assumedly present and most of the particle concentrations showing a seasonal variability that correlates with the seasonal variability in the pressure drop data.

3.4. Radioactivity measurements

Radioactivity is also monitored in addition to differential pressures. It is measured at four different locations in the vicinity of the metal casings of the air filters. As particles accumulate in the air filters, the radioactivity readings will increase. The activity measurements can give an indication of unusual radioactive pollution in either location.

4. METHODS USED FOR RUL ESTIMATION

In RUL estimation the development of the differential pressure $dP(t)$ is modeled as an aggregation of three phenomena, each occurring at different time scale:

$$dP(t) = dP_1(t) + dP_2(t) + dP_3(t) + dP_0 + \varepsilon(t) \qquad (1)$$

The modeled phenomena are:

1. $dP_1(t)$: Gradual accumulation of aerosols
2. $dP_2(t)$: Sporadic large aerosol emissions.
3. $dP_3(t)$: Seasonal variation.
4. dP_0: Differential pressure of a new clean filter.
5. $\varepsilon(t)$: Residual variation, comprising e.g. measurement errors.

Gradual accumulation of aerosols causes the differential pressure to increase with a functional form that is characteristic to each combination of (not fully known) aerosol and filter characteristics. This phenomenon is modeled as a stochastic gamma process, where the gradual development of the pressure drop $dP(t)$ is identified as a large number of small mutually independent gamma distributed increments (van Noortwijk, 2003):

$$dP_1(\tau) - dP_1(t) \sim \mathrm{Ga}(v(\tau) - v(t), u) \;\forall\; \tau > t \geq 0 \qquad (2)$$

The shape function $v(\tau)$ of the gamma process represents the above mentioned functional form. Utilizing data from preceding filter lifetimes in shape function identification improves the reliability of the RUL estimates especially for long prediction horizons (Saarela, Nystad, Taipale & Ventä, 2013). In this study a fit that was subjectively considered as adequately good (see discussion in Section 5.2) was achieved with a power law shape function

$$v(t) = ct^b \qquad (3)$$

where parameters c and b are identified from measured data. The expected value of the gamma process can then be calculated as

$$E\{dP_1(t)\} = \frac{v(t)}{u} = \frac{c}{u}t^b \qquad (4)$$

which is then extrapolated to future time values in RUL prediction.

Sporadic large aerosol emissions are caused by, e.g., some maintenance operations. They are modeled as stepwise increments in the differential pressure. A statistical identification of these larger increments could be based on, e.g., identifying a probability distribution of the observed increments and determining a classification threshold based on a predefined significance level (Box, Hunter & Hunter, 2005). Instead of such a data-driven approach, however, classification based on a priori knowledge (especially times of maintenance operations) was seen as preferable. These sporadic phenomena were modeled as

$$dP_2(t) = \sum_j dP_{2,j} * (t > t_j) \qquad (5)$$

where t_j are the times and $dP_{2,j}$ the magnitudes of these sporadic large increases of the pressure drop. The logical expression $(t > t_j)$ is here interpreted to produce a value 1 for true and 0 for false.

Seasonal variation of the pressure drop is hypothesized to be caused by changes in relative air humidity as the heating of the input air varies. In filter loading laboratory experiments an increasing humidity has been observed both to decrease differential pressure (by facilitating especially larger particles already captured in the filter to rearrange) and to increase differential pressure (due to particles of various hygroscopic salts expanding especially in high humidity) (Joubert, Laborde, Bouilloix, Chazelet & Thomas, 2011; Miguel, 2003).

A detailed modeling of humidity-related air filtration phenomena would require comprehensive data of, e.g., the time history of aerosol composition. Most importantly, distributions of the hygroscopic properties of the particles would have to be known for past and assumed to remain relatively unchanged for the future. As such information was unavailable, seasonal variation observed in the data was modeled with a data-driven approach. Applying the principle of Occam's razor (Burnham & Anderson, 2002), the simplest possible model with adequate modeling accuracy was sought for. A simple, yet reasonably accurate (see discussion in Section 5.2) model found turned out to be a sinusoid whose amplitude was directly proportional to $dP_1(t)$:

$$dP_3(t) = e * dP_1(t) * \sin(2\pi t_d/365 + t_{d0}) \qquad (6)$$

where t_d indicates the number of the day from the beginning of each year. Coefficient e and day offset t_{d0} were identified from data using differential evolution (Storn & Price, 1997) to minimize least squares cost function. In this optimization, term $dP_1(t)$ in Eq. 6 was replaced by its expected value (Eq. 4) identified from the same data set.

5. Estimated Lifetimes for the Air Filters

5.1. Reactor hall

Three distinctive steps were identified from the historical data for the differential pressure over the filters for air from the reactor hall. Their magnitudes were determined by visual inspection to be 3 mmH_2O, 3 mmH_2O, and 5 mmH_2O. After the last step the differential pressure had increased by 11 mmH_2O due to sporadic stepwise changes since the start of the data series.

The stepwise increase of the data was subtracted from the data before a median filter was applied to reduce the effect of noise and to have a monotonically increasing data series.

The data then looks to be close to a parabolic curve. The actual form of the curve is not known since it is expected to change depending on the type distribution, size distribution and amount of particles in the air and the total airflow. A RUL estimation of the data using the gamma process model (Eq. 2) with power law shape function (Eq. 3) was carried out using the algorithms described in (van Noortwijk, 2003; Saarela et al., 2013). Values for the shape function parameters c and b were identified using the maximum likelihood approach, giving:

$$c \approx 0.066, \quad b \approx 1.92 \qquad (7)$$

Figure 3 shows the data series after subtracting the stepwise increases and applying the median filter (solid line). The predicted power law function $v(t)$ is plotted as a dotted line.

The threshold for the end of life should be determined from the recommended maximum pressure or operational performance in the specification of the filters. This information has not been obtained and it is set to 24 mmH_2O (dashed line), which corresponds to the threshold when the filter is changed.

At filter age 3600 days, the model gives a predicted end of life at filter age 4580 days with a 95 % confidence interval of [4160, 5120]. This prediction was made more than a year before the filters were changed.

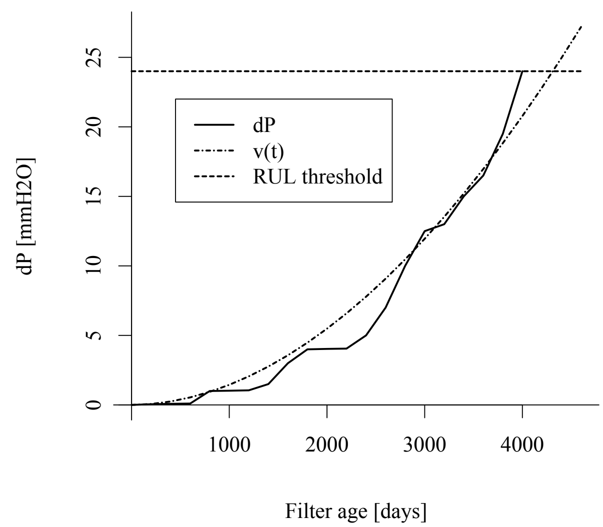

Figure 3. Predicted power law function, differential pressure and a RUL threshold.

5.2. Isotope laboratory

The differential pressure measured at the isotope laboratory exhaust air filter had a distinct seasonal component. This data was modeled as a sum of the three components discussed above. The identified components, representing phenomena of different time scales are plotted in Figure 4. The identified seasonal variation $dP_3(t)$ has its minima at each summer, when input air is not heated and consequently indoor humidity is high. The straight line segments in the seasonal variation are time intervals for which original measurement data was not available.

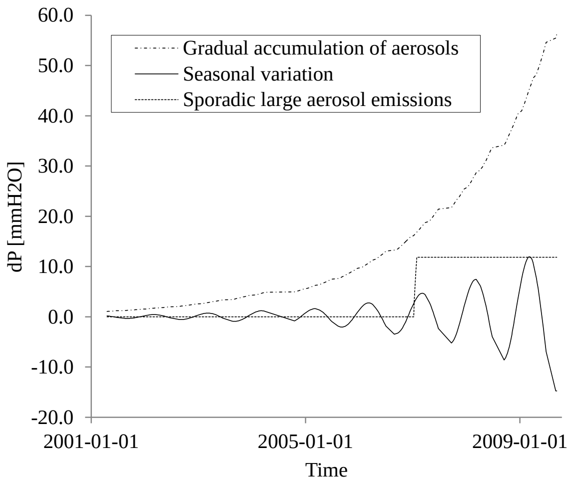

Figure 4. Three components of pressure drop development identified from the data measured at the isotope laboratory exhaust air filter.

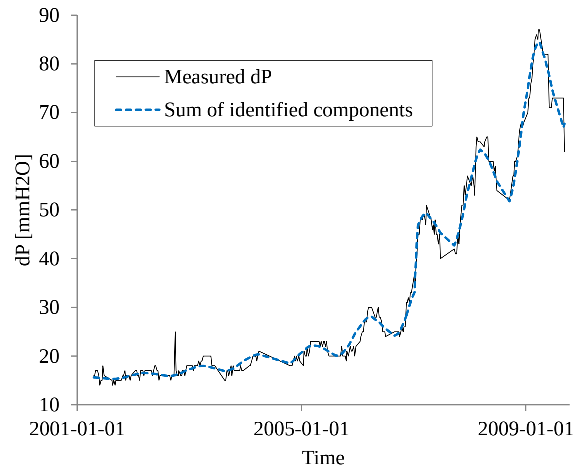

Figure 5. Measured and modeled differential pressure at the isotope laboratory exhaust air filter.

The modeled differential pressure, i.e., the sum of the three identified components is plotted together with measured data in Figure 5. The standard deviation of the residual $\sigma(\varepsilon(t))$ was ≈ 2.6 mmH_2O for six months preceding the RUL prediction time. The reading-to-reading variability in the measured data had roughly an equal standard deviation $\sigma\left(dP\left(t_{j+1}\right) - dP\left(t_j\right)\right) \approx 2.8$ mmH_2O in the same time interval. This was subjectively considered as accurate enough to represent the pressure drop trend, while keeping the number of identified parameters reasonably small to reduce the risk of overfitting. This assessment also implies that the used functional forms (seasonal sinusoid and power law shape function) were considered as adequately applicable. However, the impact of modelling accuracy to the RUL estimation accuracy (Saxena, Celaya, Saha, Saha & Goebel, 2010) must be studied in further phases of this work.

Identified values for the shape function parameters

$$c \approx 0.017, \quad b \approx 2.45 \tag{8}$$

differ from those identified from the reactor hall data. Since the filtration system is equivalent, the difference reflects the dissimilarities of aerosol concentration and composition.

Figure 6 depicts RUL estimation using the data series after subtracting the identified seasonal variation and the stepwise increase and applying the median filter (solid line). The predicted power law function $v(t)$ is plotted as a dotted line.

RUL was estimated at filter age 2600 days, assuming 45 mmH_2O as the filter change threshold. The gamma process model representing gradually accumulating aerosols gives a predicted end of life at filter age 3040 days with a 95 % confidence interval of [2760, 3500] days.

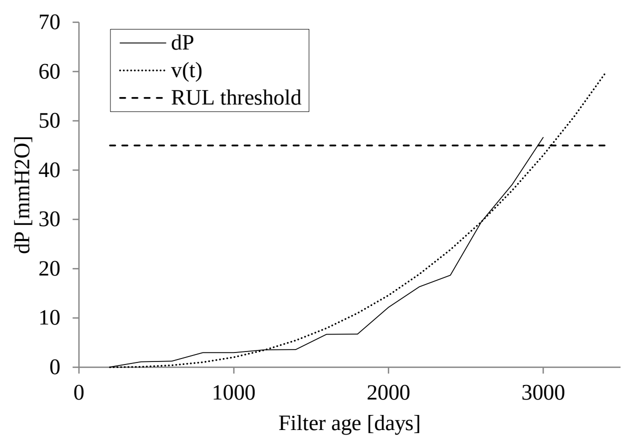

Figure 6. Predicted values of the power law function at the isotope laboratory exhaust air filter.

The seasonal variation is predicted simply by extrapolating the identified sinusoid and using the prediction from the gamma process model in computing the increasing amplitude. For final prediction, depicted in Figure 7, these predicted pressure drop components are added together.

The 95 % confidence interval in Figure 7 was computed from the identified gamma process model, Eq. 2. In this simplified approach the uncertainties of the identified seasonal and sporadic component were not considered separately. Further study is required for understanding their impact on the reliability of the RUL estimate. Especially, inaccuracies in the identification of the seasonal component influence the identification of the gamma process in a way that is not compliant with the assumption of mutual independency of increments made in the theory of gamma processes.

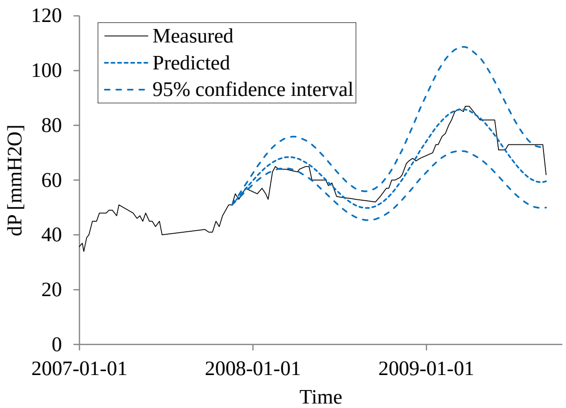

Figure 7. Predicted values of the pressure drop development at the isotope laboratory exhaust air filter.

6. CONCLUSIONS

Historically HEPA filters were developed for the removal of radioactive particles from air streams in nuclear facilities. Monitoring the loading of the air filters and estimating their remaining useful life can enhance the facilities ability to plan ahead and optimizing their maintenance schedule.

In this study the measured differential pressure was decomposed into components representing phenomena of different time scales. RUL was estimated from the decomposed time series. The results suggest the applicability of this approach for estimation of RUL of air filters. Gamma process models are seen suitable for modelling gradual lifetime expenditure, especially as it easily adapts to the steeper increase of the differential pressure towards the end of filter life. Naturally the shape function representing the functional form of differential pressure development and values for model parameters have to be identified for each application separately.

In this analysis, measured differential pressure at one location was found to have a strong seasonal variation. The amplitude of this variation increased as more particles accumulated in the filter. The phase of this variation was such that its minima coincided with the highest values of relative humidity of the indoor air.

Modeling large sporadic aerosol emissions and seasonal variations separately facilitated increased accuracy in modeling the gradual pressure drop development. Evaluation and quantification of the RUL prediction accuracy will be topics in further phases of this work, where data from multiple filter life times will be utilized.

Besides more accurate RUL estimates, modelling relevant phenomena separately allows more reliable detection of sporadic aerosol emissions when actual pressure drop deviates significantly from what is predicted. Consideration of high humidity values in pressure drop calculation is also relevant to fault scenarios involving release of steam.

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BIOGRAPHIES

Olli Saarela has a PhD degree in automation technology from Tampere University of Technology, Finland. He is a Senior scientist at VTT and works currently as a visiting scientist for OECD Halden Reactor Project. The main focus of his career has been the development and application of data mining and statistical techniques especially for industrial processes.

John Einar Hulsund has a MSc degree in experimental particle physics from the University of Bergen, Norway. He has been working as a Research Scientist at the Institute for Energy Technology (IFE) and OECD Halden Reactor Project (HRP) since 1997 within the Computerized Operations and Support Systems department. His main areas of work has been the development of a computerized procedure tool for control room operations and research within condition based maintenance for nuclear power plants and oil installations in the North Sea.

Aimo Taipale has a M.Sc degree in mechanical engineering from Tampere University of Technology. He is a research team leader of clean air and acoustic solutions team. He has been working in the field of air filtration for 18 years.

Morten Hegle has a degree in mechanical engineering from the college of Sør-Trøndelag in Norway. He has been employed at Institute for Energy Technology (IFE) in Norway since 1998 and is now working as section head for the Mechanical Maintenance section in the Reactor Operation department at the nuclear research reactor at Kjeller, Norway.