**Abstract**

Despite frequent occurrence of wildfires around the world, the role of wildfires has rarely been taken into account in risk assessment of process plants in wildlands, especially that large inventory of flammable petroleum products in contact with the heat of wildfire can lead to severe domino effects. We have developed a dynamic risk assessment framework by integrating available models of fire spread and domino effect analysis with online maps of wildfire characteristics such as ignition probability and heat intensity to investigate the impact of wildfires on oil facilities. The framework is modular, so one can readily enhance its accuracy by replacing the current techniques with more sophisticated ones. The application of the methodology is demonstrated on an oil terminal.

**Keywords:** Wildfire; Natech risk assessment; Domino effect; Oil terminal; Dynamic Bayesian network; Cost-benefit analysis.

# Introduction

Natechs are referred to technological accidents such as release of hazardous materials, fires or explosions in industrial plants which are triggered by natural disasters like earthquakes, floods, and hurricanes. Compared to normal technological accidents, which are a matter of random failures or human error, natechs usually give rise to more catastrophic consequences since the likelihood of simultaneous damage to hazardous units (e.g., large storage tanks) and domino effects (chain of accidents) is much higher. Substantial release of petroleum products due to Hurricane Katrina in 2005 in the United States (the second largest oil spill disaster after the BP spill in the Gulf of Mexico in 2010) and fires in a refinery in Turkey due to the Kocaeli earthquake in 1999 are some examples among the others. Aside from direct damage to industrial plants caused by natechs, simultaneous damage to other infrastructures such as communication and power grids, pipelines, and transportation network hampers emergency response procedures, and thus aggravate the extent and severity of consequences (Campedel, 2008, Krausmann and Mushtaq, 2008).

Due to an ever-increasing growth of industrial facilities and thus the prolonging interface with nature on one hand, and anticipated increase in the frequency and severity of climatic disasters (floods, hurricanes, forest fires, etc.) on the other hand, the occurrence of natechs have been foreseen an increasing trend (Parry et al., 2007). According to a research conducted by the European Joint Research Centre (Forzieri et al., 2017), weather-related disasters such as heatwaves and cold spells, wildfires, droughts, floods and windstorms are expected to affect around two-thirds of the European population annually by the end of this century, potentially leading to a 50-fold higher fatalities (compared to today).

The hazard of wildfires has long been recognized, and there has been an exhaustive amount of work devoted to their modeling and ecological risk assessment (Preisler et al., 2004; Scott et al., 2012, 2013; Lozano et al., 2016). Wildfires can be categorized as hydro-geological events which are bound to increase especially due to climate change: every degree in warming associates with a 12% increase in lightning activity, as one of the triggers of wildfires (Romps et al., 2014). Likewise, for every degree in warming, 15% more precipitation is needed to offset the risk of wildfires (Flannigan et al., 2016). Despite the risk of wildfires (Figure 1), their hazard has not yet, to our best knowledge, been accounted for in natech risk assessment of industrial plants. In Europe, for example, Seveso Directive III (2012) has only recently mandated the member states to consider the probability of natural disasters in the risk assessment of major accident scenarios when preparing safety reports (Article 10), with an explicit mention of floods and earthquakes in the Annex II. The most of European countries that consider natechs have likewise limited their programs to only a few natural hazards, mainly flood and earthquake (Krausmann and Baranzini, 2012).

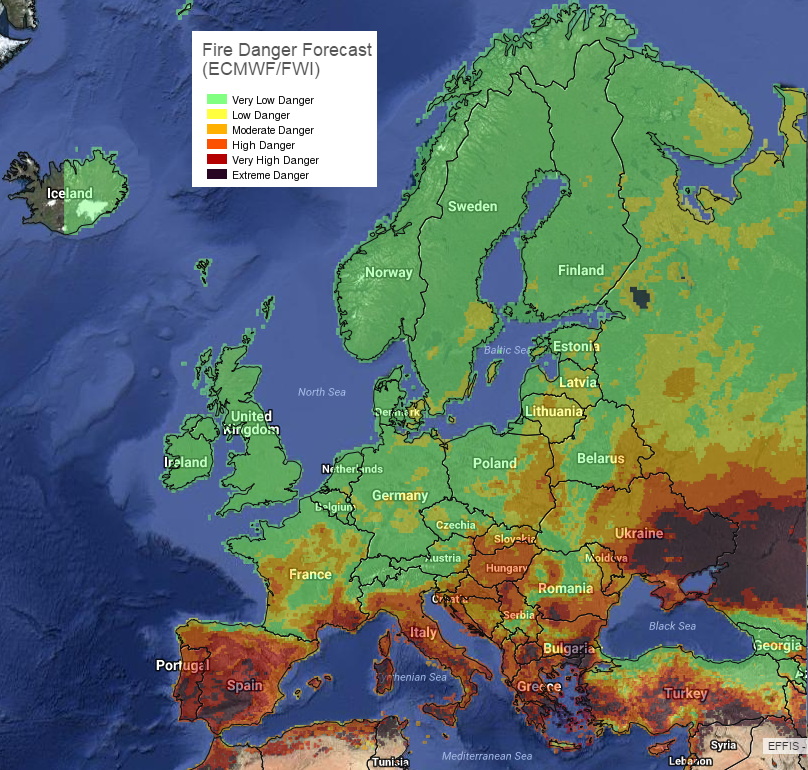


Figure 1. Wildfire danger forecast as of August 17, 2017 (The European Forest Fire Information System).

Wildfires, like other types of fire, can be defined using the fire triangle, consisting of fuel (trees, grasses, shrubs, houses, etc), oxygen, and heat source. Lightning, burning campfires or cigarettes, hot winds, and even the sun can ignite a wildfire although four out of five of wildfires have reportedly started by people (National Geographic). Wildfires are more complicated than other fires in the sense that as they grow large enough they create their own weather and increase their speed. A wildfire can move at a speed of up to 23 km/hr and the flames can reach a height of up to 100 m. A favorite wind not only speeds up the wildfire spread but also can carry sparks and embers kilometers away, helping fire jump over roads and rivers.

In wildfire risk assessment, the ignition likelihood, burn probability (the probability that wildfire spreads to a certain spot), fire intensity, flame height, and type of exposure (people, the environment, assets) are the main factors to take into account (Scott et al., 2013). In wildfire-related risk assessment of process plants, the foregoing factors seem to play the key role although due to the large inventory of hazardous chemicals the severity and extent of the envisaged consequences could be far worse especially with the possibility of domino effects. Domino effects in process plants refer to a chain of accidents (fires and explosions) triggered by a primary fire or explosion so that the total consequences are much severer than that of the primary event. In domino scenarios, the escalation of a primary fire, for instance, to an adjacent unit takes place if the magnitude of heat intensity received by the unit is larger than a respective threshold (e.g., 15 kW/m2 for atmospheric storage tanks); the neighboring unit is then expected to be damaged and thus be engaged in the chain of fires.

Many methodologies have been developed to model the spread of different types of wildfire such as surface fire (Rothermel, 1972), crown (or canopy) fire (Rothermel, 1991), and transition between surface and crown (van Wagner, 1977). Subsequently, a number of software tools such as FARSITE (Finney, 1998), FlamMap5 (Finney, 2006), FSPro (Finney et al., 2011a), and FSim (Finney et al., 2011b) has been developed to predict the likelihood and model the spread of wildfires based on historical records of wildfires in the region, weather conditions, type and density of vegetation in the landscape of interest (also known as fuelscape), and also the topology of the landscape.

There have been extensive studies on wildfire modeling (e.g., the ones mentioned above), vulnerability assessment of process equipment to external fires (Vilchez et al., 2001; Cozzani et al., 2006; Mingguang and Jiang, 2008; Landucci et al., 2009; Casal, 2017), and domino effect modeling in process plants (Bagster and Pitblado, 1991; Gledhill and Lines, 1998; Khan and Abbasi, 2001; Cozzani et al., 2005; Abdolhamidzadel et al., 2010; Khakzad et al., 2013, Dadashzadeh et a., 2014; Khakzad, 2015). However, to the best of our knowledge, there has been no work devoted to the wildfire-related risk assessment in industrial plants.

In the present study, we aim to develop a methodology for wildfire-related natech risk assessment in process plants with an emphasis on domino scenarios. To this end, we will integrate in a framework the available techniques for wildfire spread modeling and domino scenario modeling to investigate the potential impact of wildfires on process plants in wildfire-prone areas. It however should be noted that the mutual impact of process plants on wildfires (due to their inventory of combustible and flammable materials) are beyond the scope of the present study. Wildfire characteristics and spread mechanism are discussed in Section 2. Domino effect modeling using dynamic Bayesian network is explained in Section 3. The application of the methodology is demonstrated in Section 4 while the conclusions are presented in Section 5.

# Wildfires

## 2.1. Ignition probability

Weather conditions such as temperature, relative humidity, and wind speed are key factors in the probability estimation of an ignition (small fire) which can lead to a wildfire. In addition to the weather conditions, the vegetation moisture content (also known as Fuel Moisture Content, FMC) plays a key role not only in the initiation of fire (the ignition probability) but also the continuation and spread of fire (fuel flammability) (Chuvieco et al., 2004).

FMC can be calculated as the amount of water per day mass of fuel (vegetation):

(1)

where Ww and Wd are, respectively, the wet weight and dry weight of the same sample of vegetation. FMC has been used either to define thresholds above which a wildfire cannot maintain (moisture of extinction) (Rothermel. 1972) or to predict the ignition probability (Jurdao et al., 2012). For example, based on the measurement of FMC in different periods before a potential wildfire and using logistic regression, Jurdao et al. (2012), developed the following relationship to roughly predict the probability of ignition (PI) in Spain’s Meditteranean grasslands:

(2)

where PI is the probability of ignition, FMC8 and FMC16 are the fuel moisture contents of the grassland measured 8 and 16 days, respectively, before the wildfire of interest.

Similar efforts have been made to find the correlation between the PI and FMC (Larjavaara et al., 2004). Lawson et al. (1996) developed an application called Wildfire Ignition Probability Predictor (WIPP) to predict, on an hourly or daily basis, the igniting probability of man-made wildfires (e.g., those caused by matches, campfires, etc.) in British Columbia forests. Based on the calculations of FFMC (Fine Fuel Moisture Code) and 10-meter wind speed, WIPP estimates PI in three categories as low (0-50%), medium (50-75%), and high (75-100%) for dry/moist lodge pole pine and spruce forests.

Taking into account various spatial and temporal parameters, Preisler et al. (2004) used a logistic regression technique to predict the probability of small fires (equivalent to PI), that is, fire in an area of 0.04 ha, based on parameters such as burning index, fire potential index, drought index, thousand-hour fuel moisture, wind speed, relative humidity, dry bulb temperature, day of the year, and elevation.

## 2.2. Fire spread: burn probability

Burn probability (PB) is the conditional probability that given a small fire somewhere in the landscape the triggered wildfire would burn a given pixel.

Estimating PB is challenging as the spread of wildfire to a given pixel is a complicated process affected by many factors such as the type of vegetation (fuel), weather conditions, and land topology. These factors, in turn, consist of several key parameters such as the flammability of fuel, vertical arrangement of fuel, moisture content of fuel, wind speed and direction, relative humidity, and the transition between the surface fire (fire spreading on the land) and the crown fire (fire spread on the top of the trees). Furthermore, other parameters such as the oriantion of fire (downhill or uphill) matter in fire spread. Preisler et al. (2004) employed logistic regression using nearly the same parameters as they used to predict PI (see Section 2.1) to predict the probability of a small fire becoming a large fire (in an area greater than 0.04 ha), equivalent to the probability of burning (PB).

PB can also be estimated as the relative frequency of burning where stochastic (or Monte Carlo) wildfire simulation models are being run thousands of times, counting the number of times a certain pixel is burnt (Scott et al., 2013). Having the probability of a small fire (or PI) and the conditional probability of a large fire given a small fire (or PB), the unconditional probability of a wildfire can be estimated as:

(3)

Models developed for wildfire spread simulation include empirical, semi-empirical, and physical models (Pastor et al., 2003). Some of these models such as FARSITE[[1]](#footnote-1) (Finney, 1998) and BehavePlus (Andrews, 2013) need detailed spatial information on topography, fuels, and weather conditions which is not readily available for many locations of interest. A comprehensive review of wildfire simulation models can be found in Papadopoulos and Pavlidou (2010).

In the present study, to foresee whether an ignition (a small fire) would become a wildfire, a simplistic forest-fire model (Drossel and Schwabl, 1992) is used. The model developed by Drossel and Schwabl (1992) consists of the following steps:

* considering the fuelscape as a grid, each cell can have three states: “empty”, “occupied by a tree”, and “a burning tree”,
* fire from a burning tree can spread with a probability of θ to other trees (if any) in its Moore neighborhood (i.e., at most eight other trees),
* a tree can ignite with a probability of σ even if no other tree in its neighborhood is on fire,
* an empty cell can be filled with a probability of λ with a tree (usually considered if time between two sequential fires would be long enough to allow for growing new plantation).

## 2.3 Fire intensity

Compared to other wildfire parameters, fire intensity contains as much information about a fire’s behaviour as can be presented via a single number (van Wagner, 1977). Fire line intensity is the rate of heat release per unit time per unit length of fire front (kJ/s.m or kW/m), regardless of its depth. Fire intensity (I), also known as Byram’s fire line intensity or frontal fire intensity, can be calculated as (Byram, 1959):

(4)

where H (kJ/kg) is the fuel low heat of combustion, w (kg/m2) is the weight of fuel consumed per unit area in the flaming zone, and r (m/s) is the fire spread rate perpendicular to the fireline. H is equal to the high heat of combustion minus heat losses from radiation, incomplete combustion, and fuel moisture. Compared to the other parameters in Byram’s fire intensity, H varies much less from fuel to fuel and can thus be considered as a constant. Investigating previous studies, Alexander (1982) suggests a basic value of 18700 kJ/kg for the low heat of combustion of fuels in wildfires.

Values of w and r, in particular, can significantly vary for different fuels. A grass fire may travel at a rate of r = 5 km/h whereas fire in a dry eucalypti forest may travel at a rate of r = 1 km/h, even capable of throwing embers up to 1 km ahead of the fire (Cheney, 1990). As a result, the fire intensity of wildfires can vary approximately from 15 to 100,000 kW/m (Byram, 1959). Nevertheless, fire intensities rarely exceed 50,000 kW/m and for the most of crown fires lie in the range of 10,000-30,000 kW/m (Alexander, 1982). Fire intensity can also be calculated based on the flame length, L(m), (Byram, 1959):

(5)

Flame length (L) is the distance between the tip of the flame and the ground midway in the zone of active combustion whereas flame depth (D) is the ground distance between the leading and rear edges of the solid flaming zone (Alexander, 1982). Fire length, fire height, and fire depth have been denoted in Figure 2. At very low wind speeds on level terrain, flame length and flame height would coincide. Equation (5) has been developed for surface fires, and in order to be applied to crown fires, one-half of the mean canopy height should be added to L (Byram, 1959). A thorough review of fire intensity-fire length relationships for different types of fuel can be found in Alexander and Cruz (2012).

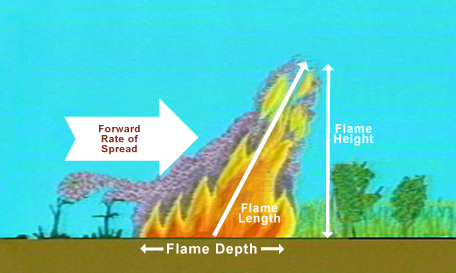


Figure 2. Flame characteristics (Utah State University website).

Based on the flame length, fire intensity can also be classified into six classes as reported in Table 1 (Scott et al., 2013). Such classification can be used to make a rough estimate of the fire intensity based on the visualization of the flame length.

Table 1. Flame length range associated with six standard fire intensity classes.

|  |  |
| --- | --- |
| Fire intensity class | Flame length (m) |
| Class 1 | 0.0 - 0.6 |
| Class 2 | 0.6 - 1.2 |
| Class 3 | 1.2 - 1.8 |
| Class 4 | 1.8 - 2.4 |
| Class 5 | 2.4 - 3.7 |
| Class 6a | 3.7 - 15 |
| Class 6b | > 15 |

Having the flame depth, the frontal fire intensity can be converted to area-fire or reaction intensity IR (kW/m2) (Alexander, 1982):

(6)

If the flame can be considered as a solid body (Butler and Cohen, 2000; Heymes et al., 2013), it can be modeled using Solid Flame Model (Mudan, 1987). As such, the amount of heat intensity (kW/m2) a receptor (e.g., human, or target equipment) at a distance of X from the flame’s ground centre (Figure 3) receives can be calculated as:

(7)



Figure 3. Flame as a tilted cylinder (Assael and Kakosimos, 2010).

where Fview is the view factor, which is the fraction of the emitted radiation received by the receptor; is the atmospheric transmissivity (i.e., the transmissivity of the layer of air or gas between the flame and the receptor) (Assael and Kakosimos, 2010). Having the values of flame length (L), flame depth (D), the angel of tilt (θ), and the receptor distance (X), the amount of Fview can be calculated using the relationships given by Moudan (1987) (see Appendix).

corresponds to the fraction of the thermal radiation received by the receptor (0.0 – 100%), taking into account the mitigation effect of atmospheric humidity, concentration of carbon dioxide, and the dissipation due to the distance. In the worst case scenario, leads to conservative results in determining safety zones (Heymes et al., 2013).

# Bayesian network

## 3.1. Bayesian network formalism

Bayesian network (BN) is a graphical tool for reasoning under uncertainty (Pearl, 1988; Neapolitan, 2003). In a BN, random variables are depicted by nodes while the direct dependencies among the nodes are depicted as directed arcs. Satisfying the Markov condition, a BN factorizes the joint probability distribution of its variables as the product of the marginal and conditional probability distributions of the variables given their parents:

(8)

where Pa(Xi) is the parent set of the variable Xi.

A dynamic Bayesian network (DBN) is a replication of an ordinary BN over time intervals (in case of discrete DBN), that, compared to ordinary BN, facilitates explicit modeling of temporal changes of random variables. Dividing the timeline into a number of time intervals, DBN allows a node at a time slice to be conditionally dependent not only on its parents at the same time slice but also on its parents and even itself at previous time slices:

(9)

## 3.2. Modeling domino effects using dynamic Bayesian network

Khakzad (2015) developed a methodology based on DBN for modeling the most probable sequence of events given a primary event. Compared to a previous methodology based on conventional BN (Khakzad et al., 2013), the developed DBN takes into account all possible escalation scenarios, given a primary event, at each time step and chooses the one with the highest probability. This way, the likeliest sequence of events over time and their respective probabilities are determined.

Figure 4(a) displays a typical oil terminal comprising six oil atmospheric storage tanks. Given a primary fire (e.g., tank fire or pool fire) in one or more storage tanks, all possible fire propagation scenarios in the plant can be modeled as a DBN as depicted in Figure 4(b). To model the domino scenarios triggered by a tank fire at T1, for example, the state of the node T1 at the first time step (denoted by t = 0 in Figure 4(b)) is instantiated to “T1 = Fire” while the states of the other nodes at t = 0 are instantiated to “Safe”[[2]](#footnote-2). Based on the assigned marginal and conditional probabilities, the developed DBN computes unconditional probabilities of the storage tanks at each time slice. For the sake of exemplification, the conditional probabilities assigned to node T4 at the second time step, t = 1, are reported in Table 2.

(a) (b)

Figure 4. (a) A storage plant consisting of six oil storage tanks. The arcs denote the heat radiation intensities above a credible threshold in case of tank fires. (b) Modeling potential domino scenarios as a dynamic Bayesian network.

In Table 2, the probabilities P1, P5, and P15, known as escalation probabilities, can be calculated using a variety of techniques such as probit functions (Cozzani et al., 2006; Mingguang and Jiang, 2008; Landucci et al., 2009) which are based on the intensity of the escalation vector (in this case, the magnitude of heat radiation tank T4 receives from possible tank fires at T1 and T5) and type (e.g., whether T4 is atmospheric or pressurized) and size (e.g., volume of T4) of target vessels.

Table 2. Conditional probabilities assigned to node T4 at t = 1. The same conditional probabilities repeat for other sequential time steps.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  |  |  | T4 t = 1 | |
| T4 t = 0 | T1 t = 0 | T5 t = 0 | Fire | Safe |
| Fire | Fire | Fire | 1 | 0 |
| Fire | Fire | Safe | 1 | 0 |
| Fire | Safe | Fire | 1 | 0 |
| Fire | Safe | Safe | 1 | 0 |
| Safe | Fire | Fire | P15 | 1 - P15 |
| Safe | Fire | Safe | P1 | 1 - P1 |
| Safe | Safe | Fire | P5 | 1 - P5 |
| Safe | Safe | Safe | 0 | 1 |

In the present study, we use probit functions developed by Landucci et al. (2009) to calculate the escalation probabilities of atmospheric and pressurized vessels under the impact of external fires:

For pressurized vessels: (10)

For atmospheric vessels: (11)

where ttf (s) is the time to failure of the target vessel; Q (kW/m2) is the received heat radiation; V (m3) is the target vessel’s volume. Having the ttf, the vessel’s probit models can be used to estimate the failure probability of the vessel as:

(12)

(13)

where Y is the probit value; Pr is the failure probability of the target vessel; ɸ(.) is the cumulative standard normal distribution.

It should be noted that the foregoing relationships are valid only if the amount of heat radiation received by a target vessel is higher than thresholds of 15 kW/m2 and 45 kW/m2 for atmospheric and pressurized vessels, respectively. For instance, in Figure 4(a), it has been assumed that among possible tank fires at the storage tanks, only the magnitudes of heat radiation T4 receives from tank fires at T1 and T5 are above the threshold (≥ 15 kW/m2); this is why in the DBN in Figure 4(b) there are arcs from T1 and T5 to T4.

# Application

## 4.1. Case study

For illustration purposes, consider the oil storage plant (oil terminal) in Figure 5 which is adjacent to woods from the south and east sides of the plant. The terminal consists of eight storage tanks of oil (atmospheric floating-roof tanks), with three types of storage tanks: tanks 1-3 with a diameter of 50 m, height of 12.2 m, and volume of 23,500 m3; tanks 4-7 with a diameter of 37 m, height of 12.2 m, and volume of 12,900 m3; and tank 8 with a diameter of 24 m, height of 12.2 m, and volume of 5,400 m3.

For illustrative purposes and availability of wildfire data only, it has been assumed that the plant is located in Alberta Province in Canada. The approximate location of the plant has been denoted in Figures 6 and 8 with arrows. The prevailing wind direction and speed have been obtained as south-to-north and 5 m/s, respectively, from the regional weather station on October 17, 2017. The direction of the prevailing wind has been denoted by yellow arrows in Figure 5.



Figure 5. An oil terminal consisting of eight atmospheric floating-roof tanks of oil. The direction of wildfire spread (wind direction) has been denoted by arrows.

## 4.2. Wildfire ignition probability

The ignition probabilities for Alberta Province were obtained from Alberta Wildfire, a website administrated by Alberta Agriculture and Forestry, updated on a daily basis. The website also provides daily data and information on drought code, fine fuel moisture code, head fire intensity, rate of spread, biuldup index, crown fraction burned, and precipitation for the current day as well as next-day forecast.

Figure 6 depicts the ignition probabilities (PI) for October 17, 2017, determined in seven categories. Considering the demonstrative location of the oil terminal on the map (at the tip of the black arrow) and adjacent areas, a PI = 0.65 was considered in this study.



Figure 6. Wildfire ignition probability in Alberta, Canada, per October 17, 2017. The approaximate location of the chemical plant has been marked with an arrow (Alberta Wildfire)

## 4.3. Wildfire burn probability

Considering σ = λ = 0 and θ = 0.5 for illustrative purposes (see Section 2.2), a Javascript programme[[3]](#footnote-3) (Figure 7) based on the forest-fire model of Drossel and Schwabl (1992) was coupled with Monte Carlo simulation to estimate the likelihood of random small fires (ignitions) evolving as a wildfire reaching to the oil terminal. The ignition points were randomly selected across the entire landscape.

The oil terminal in Figure 5 was assumed to be located at the north side of the landscape in Figure 7(a). Accordingly, given a random small fire in the south of the landscape (Figure 7(b)), if the wildfire reaches the trees at the north side of the landscape (Figure 7(c)), the oil terminal would presumably be exposed to the wildfire. The burn probability of the oil terminal (the probability of the wildfire burning the pixels at the north of the landscape) can thus roughly be estimated as:

(14)

where N is the total number of Monte Carlo simulations (the total number of random ignitions) while n is the total number of simulations where an ignition turned out as a wildfire and reached the north side of the landscape. Considering 5000 Monte Carlo simulations, a PB of 0.63 was calculated.

(a) (b) (c)

Figure 7. Wildfire spread in a hypothetical landscape. (a) a random ignition occurs in the landscape, (b) the small fire escalates to a wildfire, (c) the wildfire reaches the oil facility northern the landscape.

## 4.4. Wildfire fire intensity

Similar to PI, the fire intensity information was obtained from the Alberta Wildfire website for October 17, 2017 (Figure 8). Fire intensities have been presented in the form of standard fire intensity classes (see Table 1) rather than numeric values in kW/m. Considering the location of the oil terminal, the fire intensity class 5 was chosen, corresponding to a flame length of 3.7 m according to Table 1.

Having the maximum flame length as L = 3.7 m, the frontal fire intensity was calculated using Equation (5) as I = 4466 kW/m. Assuming a flame depth of D = 5.0 m, area fire intensity immediately at the fire line was calculated using Equation (6) as IR = 893 kW/m2. Considering a wind speed of uw = 5 m/s in the direction of fire spread (Figure 5) and approximately equal distances of tanks 3 and 6 from the centre of the fire as X = 15 m, a view factor of Fview = 0.024 was calculated (see Appendix). Using Equation (7), the magnitude of the heat radiation received tanks 3 and 6 at a distance of 15 m from the head fire (in the direction of wind) would be around IR-15 = 21.8 kW/m2.

As pointed out by Scott et al. (2013), “for the same fire environment, wildfire intensity is greatest at the head and declines quickly along the flanks and rear where the flame front is oriented across or against the heading direction”. As such, tanks 3 and 6, which are both exposed to the heading fire are expected to receive the maximum amount of fire intensity, that is, IR-15 = 21.8 kw/m2 whereas tank 1, which is exposed to the flanking fire, would receive less heat radiation.



Figure 8. Wildfire intensity in Alberta, Canada, per October 17, 2017. The approximate location of the chemical plant has been marked with an arrow (Alberta Wildfire)

The reduced amount of heat radiation tank 1 receives from the wildfire can be calculated by modifying the view factor. In this regard, assuming that the flame is not tilted towards tank 1 (i.e., no change in the direction of wind), the modified flame length (L’) and tilt angle (θ’) to be used in the calculation of the view factor of tank 1 (see Appendix) could be calculated as L’ = h = L. Cos(θ) and θ’ = 0. This results in a view factor of Fview = 0.008 and heat intensity of 7 kW/m2 which is way below the damage threshold of 15 kW/m2 for atmospheric tanks. As a result, tank 1 would not seem to be impacted by the wildfire of the given intensity.

Given the heat intensities tanks 3 and 6 receive from the wildfire, that is, 21.8 kW/m2, the respective damage probabilities can subsequently be calculated using Equations (11)-(13) as Pw3 = 0.87 and Pw6 = 0.72. The subscript w denote the damage probability due to the direct impact of wildfire. Due to possible damage inflicted by the wildfire, tank fires are considered as the most likely consequence at tanks 3 and 6.

## 4.5. Domino effect modeling

Assuming that wildfire-induced tank fires at tanks 3 and 6 can trigger more tank fires at the other storage tanks via domino effect scenarios, the amounts of heat radiation each storage tank would receive from a tank fire at a neighboring storage tank have been calculated using consequence assessment software ALOHA as presented in Table 3.

Table 3. Heat radiation intensity (kW/m2) tank Tj receives from a tank fire at tank Ti. The values less than 15 kW/m2 have not been presented.

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Ti | Tj |  |  |  |  |  |  |  |
| 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
| 1 |  | 20 |  |  |  |  |  |  |
| 2 | 20 |  | 15 | 15 |  |  |  |  |
| 3 |  | 15 |  |  |  |  |  |  |
| 4 |  |  |  |  | 20 |  |  | 15 |
| 5 |  |  |  | 20 |  |  | 15 |  |
| 6 |  |  |  |  |  |  | 20 |  |
| 7 |  |  |  |  | 15 | 20 |  | 20 |
| 8 |  |  |  |  |  |  |  |  |

Considering possible wildfire-induced tank fires at tanks 3 and 6 as the primary events which can trigger a domino effect in the oil terminal, the DBN methodology explained in Section 3 (Khakzad, 2015) was used to model all domino scenarios (fire propagation through the plant). The fire escalation probabilities for the first 60-min exposure of the oil terminal to the wildfire have been reported in Table 4 assuming that at the time of exposure t = 0 all the tanks are in the safe mode.

As can be seen from Table 4, the escalation probabilities of tanks 3 and 6 at t =20 min are due to the heat intensity of the wildfire (bold numbers). The escalation probabilities of all the tanks, including tanks 3 and 6, in the next time steps, i.e., t = 40 and 60 min, are due to possible domino effect scenarios triggered by the wildfire. For illustrative purposes, a time interval of 20 min has been chosen in the modeling of the fire propagation using the DBN. As can be seen from Table 4, the escalation probabilities at t = 20 min are the probabilities of wildfire-induced tank fires at tanks 1, 3, and 6. As time passes by, the escalation probabilities gradually increase due to the effect of possible domino scenarios. The temporal contribution of the storage tanks to the wildfire-induced domino scenario has been schematized in Figure 9, with the most likely sequence of events as fires at tanks {3, 6} → {2, 7} → {1, 8, 4, 5}.

Table 4. Fire escalation probabilities of the storage tanks within the first 60 minutes of being exposed to the wildfire.

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| t (min) | Storage tank | | | | | | | |
| 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
| 0 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| 20 | 0.00 | 0.00 | **0.87** | 0.00 | 0.00 | **0.72** | 0.00 | 0.00 |
| 40 | 0.00 | 0.56 | 0.98 | 0.00 | 0.00 | 0.92 | 0.48 | 0.00 |
| 60 | 0.46 | 0.83 | 1.00 | 0.24 | 0.21 | 0.98 | 0.78 | 0.25 |

t = 0 min t = 20 min

t = 40 min t = 60 min



Figure 9. Temporal escalation of fires given the wildfire. The wind direction is south to north.

Having the ignition probability of PI = 0.65 (Section 4.2), conditional burn probability of PB = 0.63 (Section 4.3), and the conditional escalation probabilities (PE) in Table 4, marginal (unconditional) wildfire-induced escalation probabilities of the storage tanks can be calculated as:

(15)

For instance, the marginal escalation probability of tank 1 at t = 60 min would be P(T160 = Fire) = 0.65×0.63×0.46=0.19.

## 4.6. Risk assessment and management

The risk of wildfires at process plants is not limited merely to the direct structural damage of process equipment and loss of assets. Revenue losses, locally, regionally and nationally, incurred by business disruptions due to plants shut downs either as safety precautions or because of process equipment damage could be much larger.

During the Fort McMurray wildfires in 2016, major oil producers were forced to cease their operations for safety precautions and staff evacuation. For more than two weeks oil sands operations were shut down, leading to a reduction of 1 million barrels of oil each day. The loss of revenue due to a total loss of 14 million barrels of oil in production was estimated around $760M (The Globe and Mail). Therefore, calculating the risk simply based on immediate impact of wildfires (e.g., damage to process equipment) and setting risk management strategies based on such calculation not only would be too simplistic but misleading.

Nevertheless, the risk of structural damage to the process plants contribute to the total risk and need to be taken into account as for setting protective measures and keeping operations running. Furthermore, reducing the vulnerability of process plants to wildfires would increase the availability of the plants by reducing maintenance and repair downtime. In the present study, knowing the wildfire-driven escalation probabilities of the storage tanks as the only type of process equipment at the oil terminal, the risk of structural damage can be calculated as:

(16)

where Pi is the wildfire-related escalation probability of the i-th storage tank calculated using Equation (15), and Ci is the cost of the i-th tank in monetary units. Considering only the approximate cost of the storage tanks, and not their contents, as $1.6M for T1-T3, $1.2M for T4-T7, and $0.8M for T8 ([www.Matche.com](http://www.Matche.com)), the risk of damage to the storage tanks after one hour of being exposed to the wildfire can be estimated as $2.67M.

The risk of structural damage can be reduced via different strategies, such as increasing the safety distance between the process plant and the forest by deforestation of the adjacent land to bare mineral soil (ENFORM, 2012), reducing the flammable inventory of the storage tanks, fireproofing of exposed storage tanks, artificial river, and fire trench[[4]](#footnote-4).

Cost-benefit analysis is usually employed to determine the optimal risk management strategy among available alternatives. For this purpose, the cost of each strategy is totaled with the amount of residual risk (residual risk is the amount of risk after the implementation of the risk management strategy), and the strategy with the least total amount can be selected as the optimal strategy. In the present study, to exemplify an application of cost-benefit analysis, we consider the fireproofing of T3 and T6 due to their largets contribution to the initiation and escalation of wildfire-related domino effect (see the probabilities in Table 4 at t =20 min and 40 min).

The fireproofing cost of the storage tanks were calculated based on the external surface of each storage tank (i.e., lateral area plus the top area) while assuming a cost of $430/m2 for fireproofing (the material plus the labor). As such, the fireproofing costs of the most critical storage tanks, that is, tanks 3 and 6, are estimated around $1.72M and $1.07M, respectively. Assuming that the fireproofing of a storage tank would protect it from the wildfire heat for at least one hour, the escalation probabilities of the storage tanks along with the amount of (residual) risk were calculated for the following plans using the DBN approach:

* no tank is fireproofed: cost of fireproofing = $0.0; residual risk of the plant = $2.67M;
* T3 is fireproofed: cost of fireproofing = $1.72M; residual risk of the plant = $1.05M;
* T6 is fireproofed: cost of fireproofing = $1.07M; residual risk of the plant = $1.52M;
* both T3 and T6 are fireproofed: cost of fireproofing = $2.79M; residual risk of the plant = $0.0.

The total amount of fireproofing cost and residual risk for each fireproofing plan has been depicted in Figure 10, indicating the fireproofing of T6 as the optimal risk management plan. As can be seen, despite the fact that the fireproofing of both T3 and T6 would lower the risk of wildfire to zero, its higher cost compensates for the zero residual risk and thus rules it out as an optimal plan.

Figure 10. Cost-benefit analysis of fireproofing.

## 4.7. Discussion

In the present study, we developed a dynamic risk assessment framework to assess the impact of wildfires on oil facilities, mainly by integrating the available tools and online real-time databases. Using the daily-updated information and forecasts about the ignition probability and wildfire intensity in the developed framework facilitates both the assessment of the same day’s and the prediction of the next day’s impact (risk) of wildfires on process plants operating in wildland.

During wildfires, oil facilities can be threaten by either airborne embers or radiant heat. The threat of airborne embers is greater than the threat of radiant heat since the airborne embers can travel with a favorable wind for several kilometers ahead of the fire front and land around tank openings or enter the vents. Quantifying the risk of airborne embers is very challenging since it depends on a number of random parameters (the trajectory of embers, the accumulation of embers near critical spots, etc) the prediction of which is subject to high uncertainty. Nevertheless, simple measures such as use of cone shaped tank tops, turning the vent openings downward, and keeping the storage area free of spilled flammable chemicals and vegetation can effectively mitigate the risk of airborne embers (ENFORM, 2012).

The focus of the present work, however, has been on the risk of wildfires’ radiant heat, which despite being easier to quantify based on current techniques and available databases, lacks in the available directives and guidelines. For instance, the FireSmart®, a Canadian field guide for protecting oil facilities against wildfires (ENFORM, 2012), identifies a rule of thumb minimum safety distance of 30m for the structures and a safety distance of 3m for propane tanks as the only type of process vessels from forest vegetation. However, Heymes et al. (2013) showed that even a small fire of 2m high and 5m long is able to increase the internal pressure of pressurized tanks and eventually lead to a BLEVE (boiling liquid evaporating vapor explosion) and a subsequent fireball.

In the absence of methodologies and guidelines for quantitative impact assessment of wildfires on process plants, the dynamic risk assessment framework proposed in the present study can be employed for determination of safety distances between the critical unites and the forest from one hand and between the critical units themselves to prevent domino scenarios from the other hand.

In the case of existing facilities, in which the safety distances between the units cannot easily be changed, the developed methodology can be used to forecast the risk of wildfires on a daily basis and take appropriate precautionary risk mitigation measures. These measures may be either temporary such as the installation of fire walls in order to protect exposed units (e.g., T3 and T6 in the present study) or lowering the chemical inventory of the exposed units to reduce the likelihood of domino effects, or may be permanent such as fireproofing of the critical units (though not so practicable in the wake of an imminent wildfire).

In the present study, a number of random variables were used to quantify the impact of wildfires on oil facilities. Some of these variables such as ignition probability, PI, (Figure 6) and head fire intensity, I, (Figure 8), which are updated daily and available online, directly contribute to the calculated risk and are hence of paramount importance.

Other parameters such as wind direction and speed, obtainable online or from weather stations, may change much more rapidly and over much shorter time intervals (e.g., a few minutes). Figure 11 shows the fire escalation probabilities of the storage tanks exposed to the same wildfire as Figure 9 but with a wind blowing from the east to the west. In this case, tank 1 is the only storage tank directly impacted by the wildfire’s heat radiation. After 60 minutes of being exposed to the wildfire, the fire at tank 1 would at most escalate to tank 2, resulting in a much less severe domino effect compared to the one in Figure 9.

Another important variable worth paying more attention is the estimation of burn probability (PB). In the present work, for illustrative purposes only, we employed a simplistic fire spread modeling with solely one influential parameter, that is, the probability of fire spread from a burning tree to its adjacent non-burning trees, θ (Figure 7). Using the same approach as Section 4.3 yet with a different amount of θ = 0.4, a negligible burn probability of PB = 0.09 was calculated (compare with PB = 0.63 resulted from θ = 0.5 in Section 4.3). Disregarding the oversimplicity of the employed fire spread model, it can be deduced that a slight variation in the amount of θ seems to have a notable impact on the calculated risk, emphasizing the sensitivity of the analysis to this parameter.

t = 0 min t = 20 min

t = 40 min t = 60 min



Figure 11. Temporal escalation of fires given the wildfire. The wind direction is east to west.

# Conclusions

The increasing number of wildfires due to climate change from one hand and an increasing growth in the number of oil exploration and production plants in the wilderness from the other hand have exposed both the forests and oil facilities to the risk of wildfires. In the absence of guidelines and methodologies for quantitative impact assessment of wildfires on oil facilities, in the present study, we have developed a dynamic risk assessment framework by integrating available techniques and online databases.

The developed methodology uses daily updated maps of ignition probability and fire intensity, both available online for most wildlands, along with wildfire spread software to predict the probability and the magnitude of radiant heat an oil facility would be exposed to due to a potential wildfire. Having such information, the available techniques for domino effect analysis can be used to investigate the possibility of wildfire-induced domino scenarios in the facility.

The methodology can be used to identify safety distances both between the process units and the forest vegetation and between the process units themselves, especially in the design phase of oil facilities in wildland. For existing facilities, likewise, the methodology can assist facility owners in identification of critical process units and the facility vulnerability so that protective measures can be devised. The proposed methodology is modular, consisting of techniques and tools for estimation of wildfire’s ignition probability, burn probability, fire intensity, as well as domino scenario probabilities; as such, one may enhance its accuracy by replacing the current modules with more sophisticated ones.

# Appendix

Fview can be calculated as a function of vertical Fv and horizontal Fh view factors as (Mudan, 1987; Assael and Kakosimos, 2010):

where:

;

;

The angle of tilt, θ, can be calculated as a function of wind speed uw as (Pritchard and Binding, 1992):

where Fr is the Froud number , and Re is the Reynolds number , both non-dimensional numbers. and are, respectively, the density (~ 1.21 kg/m3) and viscosity (~ 16.7 μ Pa s) of air; g is gravitational acceleration (~ 9.81 m/s2).

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1. FARSITE is available from <https://www.firelab.org/project/farsite>. [↑](#footnote-ref-1)
2. In the present study, the storage tanks are considered to have two states, namely “Fire” and “Safe”. [↑](#footnote-ref-2)
3. The programme is available from <http://www.shodor.org/interactivate/activities/Fire/>. [↑](#footnote-ref-3)
4. <http://www.bbc.co.uk/newsbeat/article/41608281/wildfires-why-they-start-and-how-they-can-be-stopped> [↑](#footnote-ref-4)