Development of a Fire-Induced Flashover Probability Index (FIFPI) for Eskom Transmission Lines

P Frost[1], H Vosloo[2], J Meeuwis[3]

[1]CSIR Meraka Institute, Pretoria, South Africa - pfrost@csir.co.za
[2]ESKOM TSI, Rivonia, Johannesburg - Hein.Vosloo@eskom.co.za
[3]University of Johannesburg, Department of Geography, Environmental Management and Energy Studies - junem@uj.ac.za

Abstract— The need for a fire-induced flashover probability index (FIFPI) for Eskom's transmission lines (South Africa) became evident soon after the installation the Advanced Fire Information System (AFIS) in 2004. Thousands of wildfires were detected by satellites close to transmission lines, but only a small percentage (4%) of these fires caused a flashover. Historical flashover data was compared to satellite fire information as well as air temperature, relative humidity, wind speed and wind direction within a logistic regression analysis to develop a flashover prediction model. The FIFPI model was able to predict problem fires with a misclassification cost of only 3.87%. The aim of this study was to develop a prediction model with the ability to accurately predict fire-induced flashover occurrences on Eskom transmission lines in order to reduce the large amount of false alarms (SMS and email messages) produced annually by AFIS.

Keywords: Flashovers, Transmission lines, MODIS, Numerical Weather Forecast models, Probability Index, Logistic regression, Wind, air temperature, relative humidity.

I. INTRODUCTION

During the 2004 fire season, South Africa's largest power company Eskom, implemented a satellite based fire information for the first time to help combat flashovers caused by wildfires underneath transmission lines. The quality of electricity supply through transmission lines are severely affected (in the form of line faults) by natural phenomena such as, bird streamers, lightning, fires and pollution. Flashovers cause very short interruptions in the supply of power and these in turn have major financial implication to customers with continuous process factories.

Eskom operates 28 000 km of high voltage transmission lines (132kV to 765kV) and is South Africa's national electricity utility. Electricity is generated predominantly by means of coal-fired power stations and one nuclear station with three hydro peaking stations. This constitutes 95% of the electricity of Africa (Anon 2004). The rights-of-way (ROW or servitudes) of these power lines cover large areas and traverse a number of biomes, ranging from arid vegetation through grasslands and savanna, to tropical vegetation.

The Council for Scientific and Industrial Research (CSIR) in collaboration with Eskom developed the Advanced Fire Information System (AFIS) with the main focus on the prediction, detection and assessment of wildfires in South Africa. The system combines fire detection information from the TERRA and AQUA MODIS (Moderate Resolution Imaging Spectro Radiometer) polar orbiting satellite sensors with the Meteosat Second Generation (MSG) geostationary satellite sensor from Eumetsat. As soon as a fire is detected within 3 km of a transmission line, a cell phone text message or email alert is automatically generated and sent to the relevant line manager as well as Eskom control centre.

Because of its dielectric properties, air acts as an isolation medium between live conductors and the ground below it.

During a fire, the properties of the air change as smoke particles fill the space between the ground and transmission line which could result in an electrical discharge or flashover to occur. The mechanism active during a fire-induced flashover of a power line is highly dynamic and complex and authors explain the phenomenon in different terms (Sukhnandan and Hoch 2002). In order to prevent the spread of fires underneath transmission lines early fire detection information is required to pinpoint the location and possibly provide additional info on the temperature and size. In the past Eskom line managers were dependant on information from local residents about fire occurrences and locations

The problem with fire-induced flashovers is not entirely unique to South Africa – countries such as the U.S.A., Australia and Mexico also struggle with flashovers caused by fires (Primen, 2001). The AFIS system has become a useful tool for the early detection of fires close to Eskom transmission lines. The ability to send SMS and email messages to the relevant person as soon as a fire is detected is one of the biggest advantages of the system (Frost *et al*. 2007). The problem, however, remains that thousands of fires are detected in the proximity of transmission lines annually, but only a small percentage of those fires cause a fire-induced flashover on the transmission lines (Vosloo, 2005). Studies have indicated that an average of 2% to 4% of all fires close to Eskom transmission lines cause a flashover (Vosloo, 2005). In AFIS this equates to thousands of fire alert messages sent to Eskom transmission line managers annually of fires close to transmission lines that never lead to flashovers. The ability to predict the flashover danger that a fire will pose underneath an Eskom transmission line based on forecasted weather and environmental conditions will enable the prioritisation of AFIS alert messages by providing an indication of the flashover potential as part of the alert message. This in turn will help Eskom transmission line managers to first react to the fire alerts with the highest flashover potential, hopefully resulting in a quicker fire suppression which will lead to less fire-induced flashovers.

Aicher (1949) has shown that atmospheric conditions play an important role in the triggering of a fire-induced flashover. The aim of this research is to analyse atmospheric (air temperature, relative humidity, wind speed and wind direction) conditions present around a transmission line during a fire-induced flashover in order to derive a flashover prediction model based on these key indicators. One aspect that seems to be very important is atmospheric conditions. The probability of a flashover under high Fire Danger Index (FDI) conditions is much higher than under low FDI conditions as demonstrated by Vosloo, (2005). This current research entails the development of a prediction model and testing of various environmental parameters including air temperature, relative humidity, wind speed and direction to determine which of these variables or combination of variables contribute most to fire-induced flashover events.

II. METHODOLOGY

The development of a fire-induced flashover prediction model required the adoption of various image processing and data analysis techniques to deal with the variety of data sources that ranged from satellite imagery and GIS map layers to numerical weather forecasts. A variety of data sets were acquired for both the training of the prediction model as well as the validation of the results. With the MODIS active fire product as base layer, weather forecast variables served as input to the predictor data set of the model, while flashover statistics for 2007 provided the target data set within the logistic regression analysis.

A. Target variable

The main inputs for the development of the target variable as illustrated in Figure 1, were the MODIS active fire data, a shape file of the Eskom transmission grid and historical fire-induced flashover point records for 2007. In order to develop the target variable for the prediction model, two GIS functions were applied to extract MODIS active fire pixels close to Eskom transmission lines. The "buffer" function in ArcMap was used to create a 3 km buffer around all transmission lines in the study area. MODIS active fire pixels that fell within these buffer zones were extracted with the "clip" function and a new data set was created containing only the selected MODIS active fire pixels close to the transmission lines.

A *Python®* script was written to test and correlate the proximity and date of each MODIS active fire (in buffer zone) in relation to historical flashover occurrences. A buffer of 3 km was created around all historical flashover points for 2007. This 3 km radius was chosen to ensure that only the 1 km² MODIS fire pixels related to the flashover would be classified and not other fires in the vicinity that had nothing to do with the flashover. The 3 km radius also made provision for fires that were burning towards the line. Grass fires can spread at a rate of 1.7 km h^{-1} (Cheney and Sullivan, 2008). MODIS fires that were detected within a radius of 3 km of a flashover point and that occurred on the same day as the flashover were classified as a "True" flashover and were assumed to be the fires that caused the fire-induced flashover. Fires that fell outside the 3 km flashover point buffers or that were on a different date from a flashover event were classified as a "False" flashover and were assumed not to be the cause of a flashover.
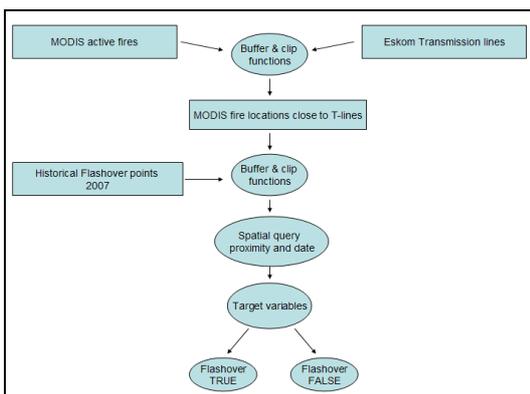
Figure 1. Development of target variables

B. Predictor variable

The main inputs for the development of the predictor variables were the MODIS active fire data, a shape file of the Eskom transmission grid and four primary input data sets (air temperature, relative humidity, wind speed and wind direction). In order to develop the predictor variables for the prediction model, two GIS functions were applied to extract MODIS active

fire pixels close to Eskom transmission lines. The "buffer" function in ArcMap was used to create a 3 km buffer around all transmission lines in the study area. MODIS active fire pixels that fell within these buffer zones were extracted with the "clip" function and a new data set was created containing only the selected MODIS active fires pixels close to the transmission lines.

C. MODIS fire detection

MODIS active fire satellite products are produced daily by the MODIS Direct Broadcast (DB) reception and processing systems located at the Satellite Application Centre (SAC) at Hartbeesthoek as well as the CSIR Meraka Institute in Pretoria. The collection 5 version of the MODIS fire detection algorithm (Giglio *et al.* 2003) produce daily active fire locations that feeds in to the Advanced Fire Information System (AFIS). An ASCII file is created after each satellite overpass from the Terra and Aqua satellites, including the following parameters, latitude and longitude of each fire, the time and the date of each fire location, the brightness temperature in Kelvin, the satellite ID and a confidence factor.

D. Numerical weather forecasting

Numerical meteorological forecast models (Marchuk, 1974) of the atmosphere are run daily and form the basis for routine weather forecasts provided by National Weather Services around the globe. In 2006 the South African Weather Service (SAWS) implemented the Unified model (SAWS, 2006) from the UK Met office. The model makes use of a horizontal resolution of 12 km and consists of 38 vertical layers (Ndabambi and Poolman, 2007).

The MODIS active fire data set was used as reference data source during the extraction of the numerical weather forecast data for every fire point. The following numerical weather forecast parameters were extracted for each of the MODIS fire pixel locations from the SAWS database:

- Air Temperature (2 m above land surface).
- Relative Humidity (2 m above land surface).
- Wind Vectors (The geostrophic wind approximations are broken into its two horizontal components.

The parameters were 14:00 pm (SAST) forecasts, predicted at 08:00 am (SAST) daily. The time difference between the 14:00 pm (SAST) forecast data and the MODIS active fire data were never more than an hour and thirty minutes. The U and V wind vectors were converted to wind speed and direction.

E. Logistic Regression analysis

Logistic regression (LR) is part of a category of statistical models called *generalised linear models* and allows one to predict a discrete outcome from a set of variables that may be continuous, discrete, dichotomous, or a mix of any of these. LR does not involve decision trees and is especially effective as a predictive analysis tool on non-linear data sets (Perlich *et al.* 2003). The algorithm for logistic regression is

$$y = \frac{bo}{(1 + b1 * \exp(b2 * X))} \qquad (1)$$

where *y* is the predicted value of the dependent variable, *x* is the independent variable, and *b* is the regression coefficient (i.e. the logit).

Model prediction accuracies of each of the predictor variable combinations in Table 1 were calculated based on three statistical tests. These included the cross validated relative cost, misclassification cost and the Receiver Operating Characteristics (ROC) value for the learning and validation data sets (Perlich et al. 2003).

Table 1.   Model predictions for different variable combinations

Variable	Cross Val Cost	Misclass (%) (Learning data)	ROC	Misclass (%) (Validation data)
T,RH,WS, WD	0.07	1.01	0.98	3.87
WS, RH,WD	0.10	2.50	0.98	5.70
WS, RH, T	0.07	1.01	0.98	4.45
WS, RH	0.13	3.50	0.98	7.50

T = Temperature, RH = Relative humidity, WS = Wind speed, WD = Wind direction

The results were focused on the target class, "True" flashovers. The misclassification error on the validation data set (Table 1) illustrated the true capability of each of the predictor variable combinations to predict a fire-induced flashover. Of the 2248 MODIS fire pixels tested in the logistic regression, 10% (224) of the pixels were left out of the model for validation purposes. The 10% validation data was thus a fully independent data set on which the misclassification error (validation data) in the last column was calculated. By comparing the results in Table 1 for the different variable combinations, the combination of air temperature, relative humidity, wind speed and wind direction provided the lowest misclassification error on the validation data set of 3.87%, while recording a low cross validation error of only 0.07%. The second best combination was the wind speed, relative humidity and air temperature variables which scored a misclassification error on the validation data set of 4.45% while also recording a cross validation error of 0.07%. The third best combination was the wind speed, relative humidity and wind direction group that showed a misclassification error on the validation data of 5.87% and a cross validation error of 0.10%. Lastly the wind speed and relative humidity combination showed a misclassification cost of 7.5% and the highest cross validation error of 0.13%. The Receiver Operator Characteristics (ROC) analysis for all the variable combinations showed a very high model accuracy of 0.98%, indicating a strong ability of predicting "True" flashover events for all the variable combinations

The results confirm that the variable combination of air temperature, relative humidity, wind speed and wind direction provides the most accurate fire-induced flashover predictions and implies that each of them contribute something unique to the models prediction capabilities

The relative importance test provided an analysis of the sensitivity of each of the variables in the logistic regression and assigned a relative importance (%) to each. Figure 2 illustrates the results from the relative importance test with the predictor variables on the Y axis and the relative importance (%) on the X axis. Wind direction was assigned the highest relative importance (primary splitter) by the LR analysis, followed by wind speed with an 80% importance. Relative humidity scored a 50% importance while air temperature was the lowest of the four variables, with a 20% relative importance.

The results from the logistic regression importance test indicate that wind direction is strongly correlated to the "True" flashover target category. Together with wind speed the two variables seem to outweigh the importance of air temperature and relative humidity. Wind direction is a much more complex variable compared to the other three variables. A 0 degree angle does not simply relate to a low flashover probability or a 360 degree angle to a high flashover probability. The non-linear nature of the LR might be better for describing the relationship between wind direction and fire-induced flashovers
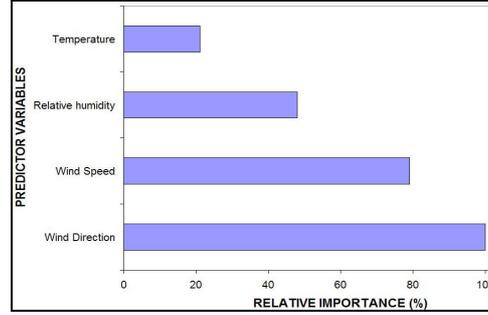
Figure 2.   Relative Importance test on predictor variables

A.   Development of the Fire-induced Flashover Probability Index (FIFPI)

Based on the results obtained from the evaluation of the different models the LR was used to calculate the fire-induced flashover prediction model with air temperature, relative humidity, wind speed and wind direction as the main predictor variables. The logistic model formula computed the probability P of a "True" flashover based on the predictor variables. The logistic model formula (Sherrod, 2003) was calculated as:

$$P = \frac{1}{(1 + \exp(-(Bo + B1.X1 + B2.X2 + ... + Bt.Xt)))} \quad (2)$$

Where β_o is a constant and β_i are coefficients of the predictor variables. The computed value, P, is a probability in the range 0 to 1. The exp() function is e raised to a power.

A maximum likelihood analysis was performed which provided the probability coefficients (parameters) for each of the predictor variables, which enabled the calculation of the FIFPI according to the logistic model formulae:

$$FIFPI = \frac{1}{(1 + \exp(-(196 + 6.24 * RH + 0.0505 * T + 0.557 * WD - 0.909 * WS)))}$$

Where RH describes the relative humidity in %, T the air temperature in degree Celsius, WD the wind direction in degrees from North and WS the wind speed in m s^{-1}.

B.   Validation of the FIFPI model against existing Fire Danger Indices

The FIFPI model prediction capability was tested against the derived fire danger index variables. This data set included three variations of the Lowveld Fire Danger Index (LFDI) currently being used by Eskom, and the McArthur Grassland Fire Danger Index (MK 4) from Australia. A LR model was used to validate the FIFPI model against the LFDI and MK 4 models by calculating the variable importance as well as a confusion

matrix. These tests indicated the significance and contribution of each of the models to the prediction of a "True" flashover.

Table 2 illustrates the relative importance of the different models to predicting a fire-induced flashover. The FIFPI achieved a 100% relative importance, followed by the Australian MK 4 model with 85% importance. The LFDI 2 and LFDI 3 models scored lower importance values of 56% and 54%, while the LFDI 1 model scored a very low 12%.

Table 2: Relative Importance between FIFPI and Fire Danger Indices

Prediction models	Relative importance (%)
FIFPI	100
MK 4	85
FDI 3	56
FDI 2	54
FDI 1	12

A multiple regression analysis was performed to determine the correlation between the different models as well as the relationship with the flashover (target) data. Correlation is a measure of the association between two variables (FIFPI and FDI's), indicating if the value of one variable changes reliably in response to changes in the value of the other variable. The correlation coefficient can range from 0 to 1.0, where 0 indicates a low correlation and 1 a very strong correlation.

The FIFPI model as illustrated in Table 3, scored a 0.98 correlation with the "True" flashover target data, followed by a 0.80 correlation between the WK 4 model and "True" flashover data. The LFDI 2 and LFDI 3 models had a 0.64 correlation with the "True" flashover data, while the LFDI 1 only achieved a 0.38 correlation. The WK 4 model also correlated well with the FIFPI with 0.84.

Table 3: Correlation Matrix

	FIFPI	FDI 1	FDI 2	FDI 3	WK 4
FIFPI	1.0	0.40	0.67	0.67	0.84
FDI 1	0.40	1.0	0.85	0.84	0.39
FDI 2	0.67	0.85	1.0	0.99	0.78
FDI 3	0.67	0.84	0.99	1.0	0.77
WK 4	0.84	0.40	0.78	0.77	1.0
Flashovers	**0.98**	**0.38**	**0.64**	**0.64**	**0.80**

IV. CONCLUSION

This study has shown that modeled weather forecast data and satellite based fire products can be used to provide predictions of fire-induced flashovers underneath Eskom transmission lines. The FIFPI was able to correctly predict 98.9% of the flashovers in the validation data set using the LR model. During the assessment each of the variables contributed uniquely to the predictive capabilities of the model as was evident in the rise of the misclassification cost with the removal of any of the four variables.

Wind direction and wind speed was found to be the most important variables causing sharp increases in flashover probabilities, as soon as north westerly winds with wind speeds above 4 m s^{-1} were reached. While wind direction was previously seen as only an indicator of other meteorological factors, the study has shown it to also be a unique predictor of fire related flashovers. By including wind direction in the predictive model, the misclassification cost of the flashover prediction model decreased from 4.45% (wind speed, relative humidity and temperature) to 3.87% (wind direction, wind speed, relative humidity and temperature).

The validation study comparing the flashover prediction capabilities of the FIFPI with a number of existing fire danger indices demonstrated the effectiveness and the model to provide improved prediction of dangerous fire weather conditions. The three Lowveld models (LFDI) were unable to provide consistent accurate predictions. The MK 4 model provided the second best prediction capability which could be attributed to the fact that the model is also a LOG function similar to the FIFPI. Linear models such as the Lowveld FDI's seem to have limited capabilities for flashover prediction as demonstrated in this study

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