Transformer Lifetime Prediction

EE292K : Intelligent Energy Projects
Christian Osorio, Nandan Sawant

1. Problem statement

The costs of blackouts can be astronomical. The Department of Energy estimates the total cost of the August 2003 blackout of the Northeastern United States and Canada to be about $6 billion[1]. Because of this, improving the reliability of the electrical grid is of paramount economic concern. It is important to know the condition of the grid and its components to make the expected performance quantifiable, and to make risks and costs predictable and controllable. Today, as our ability to monitor the state of the power grid and its components increases, it is possible to make maintenance effective, efficient and timely, which may allow us to postpone investments in a justified way and permit controlled overloading. Moreover, it enables us to justify the asset management policy to stakeholders such as clients, shareholders and regulators.

Our focus will be on scheduling the maintenance of these components based on the probability of failure of individual components, and how these components affect the system as a whole. One of the key components in the grid, in terms of both reliability and investment, is the power transformer. The reliability of transformers is a prime concern to grid operators. This analysis will predict the transformer reliability and the associated costs based on relevant degradation mechanisms.

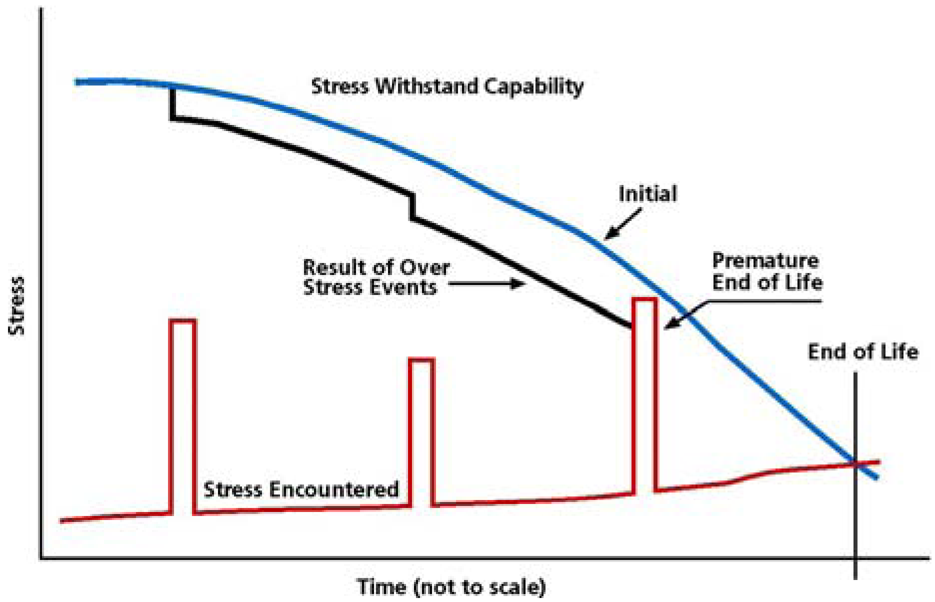
2. Introduction

Tranformer Failure Modes
There are several ways in which a transformer can fail. Transformer failure can usually be attributed to the failure of a component. These failures can occur in the tap changer, bushings, windings, core, or the tank and dielectric fluid. The can also be a failure for other reasons such as temperature[9]. Because of the prevalence of power transformers in modern society, the failure modes of power transformers have been well studied. There are well accepted models for modeling the degradation of the quality of the paper winding insulation of transformers, as well as for modeling the health of the transformer bushings and tap changers [10, 11, 12].

Extreme Value Theory
Extreme value theory is a branch of statistics dealing with the extreme deviations from the median of probability distributions. It seeks to assess the probability of events that are more extreme than any observed prior. Extreme value analysis is widely used in many disciplines, ranging from structural engineering, finance, earth sciences, traffic prediction, geological engineering, etc. For example, it might be used in the field of hydrology to estimate the value an unusually large flooding event, such as the 100-year flood. Historical data on loss severities in insurance are often modelled with a variety of heavy-tailed distributions. Fitting can be carried out with standard software and it is common practice to fit a number of models to a given dataset and to select the best fitting ones according to goodness-of-fit criteria. [3][4]

Modeling in Industry

Transformer lifetime, in industry, is generally modeled as an ideal model perturbed by results of over-stress events. In this study, we adapt this model for our purposes.



[6]

3. Solution

The goal of this project is to create an algorithm for predicting the probability of failure of one of transformer components. We base our method on the assumption that we would have detailed data on the life of the transformer so far via some sort of sensor measurements. This sensor data would provide historical data with which we could build a probability distribution of deviations from the expected behavior. Using this distribution, we would then try to predict when the transformer is likely to fail. We also assume that these sensors would give us knowledge of the current state of the transformer.

In order to predict the probability of failure of a transformer, we need to be able to model common problems with transformers. Our initial focus was on transformer insulation paper degradation. A first order model of paper degradation in transformers in presented in works by Emsley and Lundgard [10, 11]. This model served as the basis for our analysis.

$$\frac{dDP(t)}{dt} = -k(t)\,[DP(t)]^2,$$

$$DP(t) = \frac{DP(t_0)}{1 + DP(t_0)\int_{t_0}^{t} k(\tau)\ d\tau},$$

$$k(t) = A\exp\left(-\frac{E_a}{R_g\ T(t)}\right),$$

Because there is no publicly available data on the health history of transformers, we had to generate this data ourselves. In this way, this project is more of a verification of our method rather than an application to real data. We assume that the deviations from the norm would follow an extreme value distribution. We generate a vector of deviations, and apply these to the model to generate a health history for the transformer.

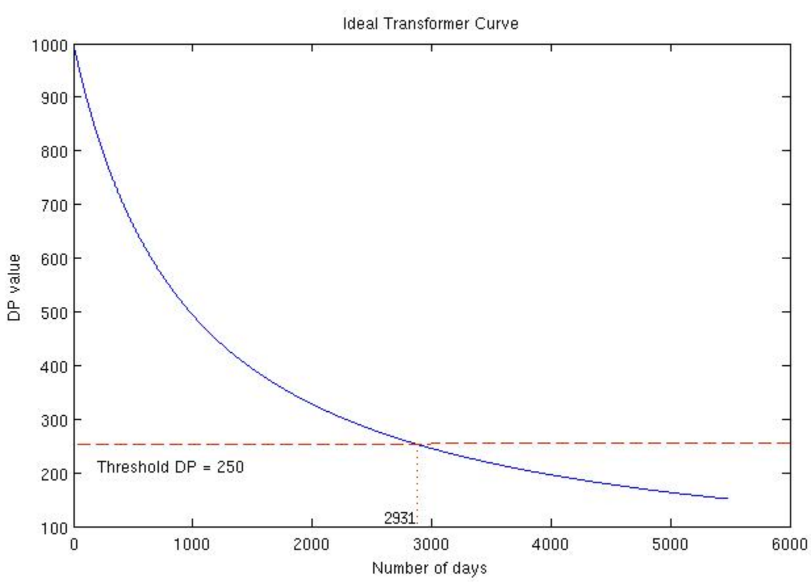
The parameter which reflects the overall "health" of the insulation paper is the degree of polymerization (DP). In order to model this, we start with the model presented by Emsley.

At each time step, we take the expected DP value at the next time step and subtract a deviation generated from a generalized extreme value distribution. The distribution causes increased loss of DP at each time step. This new value is located in the model, and the next time-step is taken from that point. The process is repeated until the transformer DP reaches the point of failure. In this way, we model a history of the transformer life.

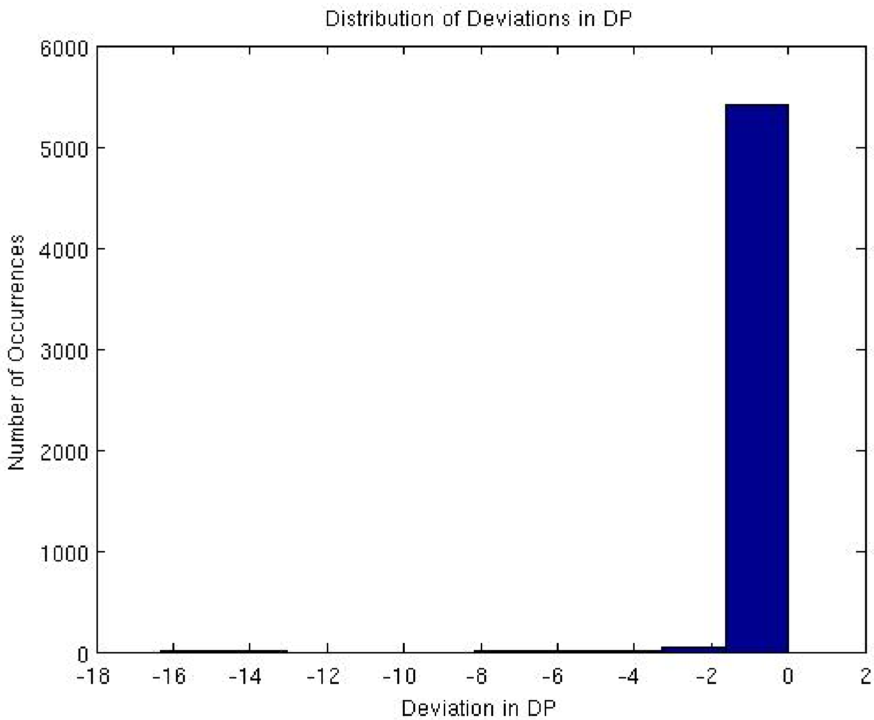
At any time step, we can predict the probability of failure of the transformer in some set amount of time-steps. We do this by fitting the deviations from the model to a generalized extreme value probability density function. We then run a monte carlo simulation using this distribution across a set time period and check whether the transformer fails or not. The number of failures divided by the number of trials gives the probability of failure.

4. Analysis and Simulations

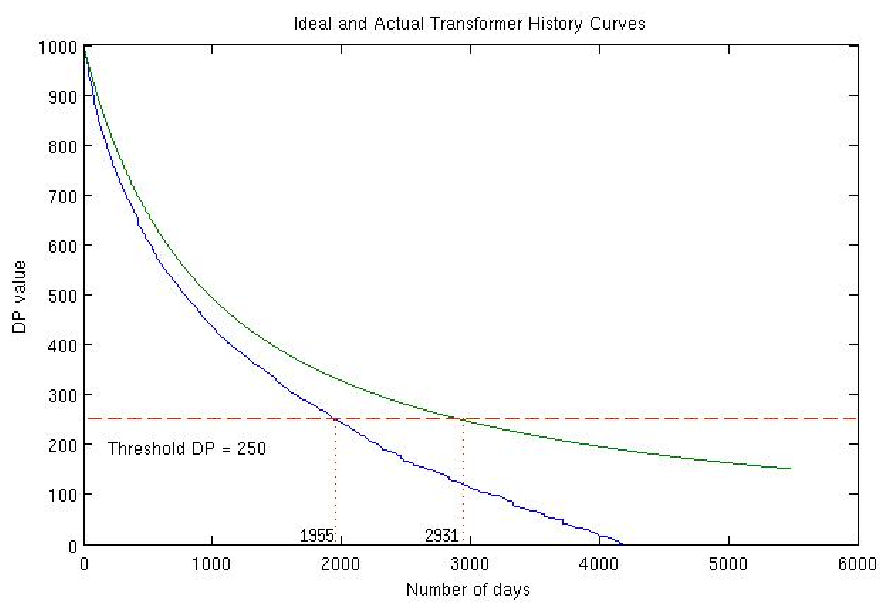
The first step of the simulation is to generate the transformer history. Next, we predict the probability of transformer failure. First, we simulate the ideal transformer based on the model. The DP degradation curve for an ideal transformer is shown below. We assume that the initial value of DP is 1000. The threshold DP below which the transformer ceases to function is assumed to be 250. 1 day is treated as 1 time step. As can be seen from the curve, an ideal transformer, with these parameter settings, lasts for about 2931 days.



The second step is to generate a deviation from expected values using an extreme value distribution at each time step. We use a generalized pareto distribution as our extreme value distribution, with mean very close to 0 and a very high spread.

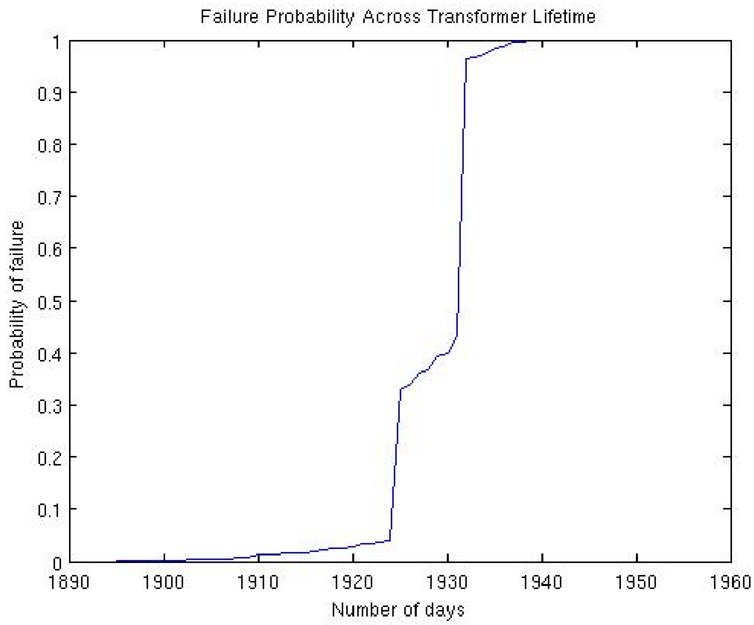


Third step is to generate a transformer history curve, which is nothing but the transformer's ideal curve perturbed by deviations at each step generated in step 2. The figure below shows the transformer history curve. One can note that expected lifetime of the transformer has decreased to 1955 days because of the deviations from the model.



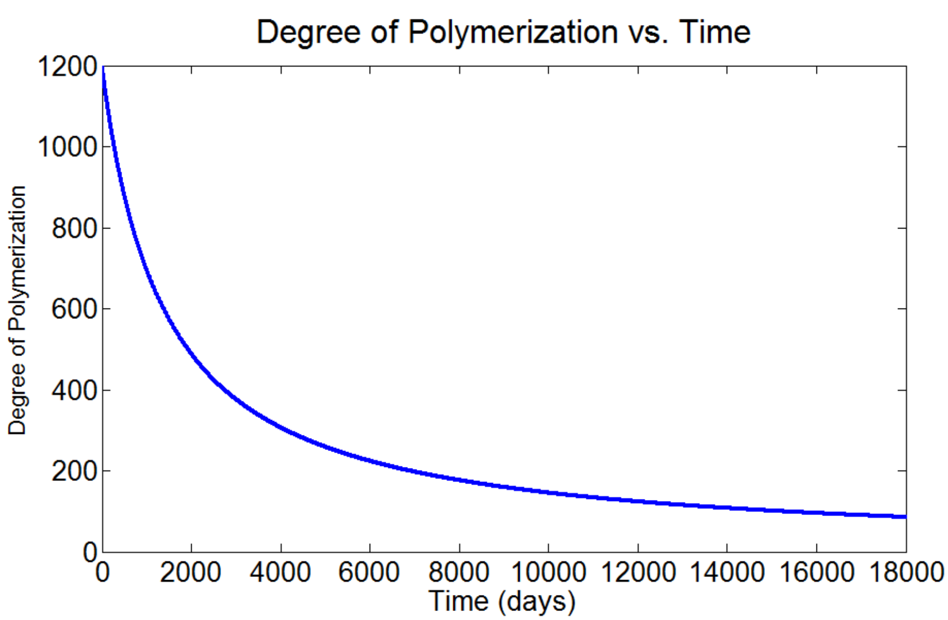
This ends the first part of the simulation. We use this transformer history curve and try to predict expected lifetime of the transformer.

We compare the history curve with the ideal curve to extract the deviations from the expected behavior. Next, we fit this data to a generalized pareto distribution to get the parameters for the GPD. We use this distribution in a Monte-Carlo simulation to calculate the probability of the transformer failing.

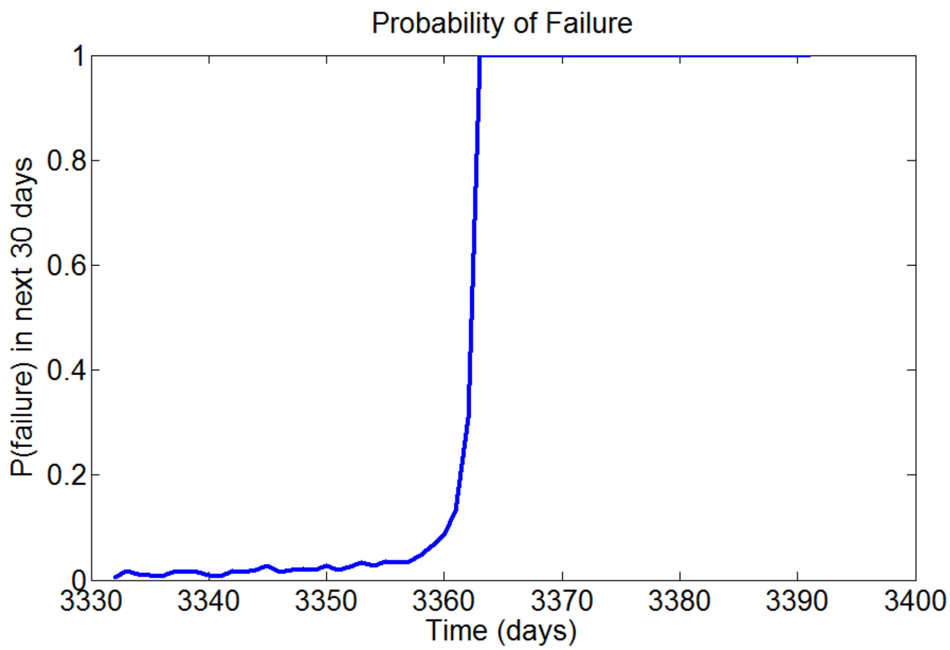


The above probabilities were calculated as the probability of failure within the next 10 days. The probability of failure starts very close to zero, and rises to 100% 10 days before the "actual" failure on day 1955.

The following figures show results from a separate simulation using similar settings. For this simulation, the curve is very smooth as there were no major detrimental events.



The probability of failure was calculated for failing within the next 30 days. We see that 30 days before the actual failure, the probability of failure is 100% as expected.



It is important to note that occasionally, the failure of a transformer will have an extremely low probability just before it fails. This occurs when a large deviation from the expected behavior occurs towards the end of the lifetime of the transformer. This would correspond to a large detrimental event. These extremely unlikely events pose a problem for predicting failures.

5. Future work

Thus far, we have only explored the probability of failure of a single transformer due to a single failure mode. Our next step in this project would be to include more degradation mechanisms that are relevant to the transformer lifetime. Currently our analysis includes modeling of only paper degradation process. The next step would be to model the probability of failure of tap changers, as these most often lead to transformer failures[9].

We hope that analyzing additional failure modes would be a rather straightforward process that could be based on the work that we've already done. It may be the case that the different failure modes are correlated, and this adds a complication to the problem. Our planned approach to this problem is to find some common parameter between the models. For example, the DP calculation is heavily dependent on temperature as is transformer bushing lifetime. By extracting the temperature from the DP simulations, we hope to be able to properly model the correlation between the two failure modes.

Another goal of this project is to apply our method to actual data. Using actual data will allow us to better define the model. For example, our use of the extreme value distribution is a guess. By using real transformer data, we can fit the appropriate distribution to the data while keeping our method the same.

After adding more dimensions of failure, we would like to add the costs of failure to our analysis to aid with decision making in terms of replacement and maintenance. To associate a cost with the failure of a transformer would allow us to decide whether a transformer is a candidate for maintenance, replacement, or whether it is appropriate to let the transformer run to the end of its life.

The truly powerful part of this study would be to expand the analysis to multiple transformers. Because power grids are built to handle N-1 contingencies, the cost of failure of a single transformer would likely be of no real concern to a utility company. If multiple transformers were to fail, however, the costs could be severe. Multiple component failure can cause widespread outages and grid instability. Analyzing the probability of failure of multiple transformers and the costs associated with these events is the ultimate goal of this project.

6. References

1. The Economic Impacts of the August 2003 Blackout, Electricity Consumers Resource Council, February 9, 2004

2. Prediction of remaining life of power transformers based on left truncated and right censored lifetime data, Yili Hong, William Q. Meeker, and James D. McCalley, Ann. Appl. Stat. Volume 3, Number 2 (2009), 857-879

3. Extreme Value Theory as a Risk Management Tool, Paul Embrechts, Sidney I. Resnick and Gennady Samorodnitsky, North American Actuarial Journal, Volume 3, Number 2, April 1999

4. The Peaks over Thresholds Method for Estimating High Quantiles of Loss Distributions, Alexander J. McNeil & Thomas Saladin

5. Anomaly Detection: A survey, Varun Chandola, Arindam Banerjee and Vipin Kumar, ACM Comput. Surv. 41,3, Article 15 (July 2009)

6. Grid Analytics - T&D Power Equipment Diagnosis/Prognosis thru Smart Grid Technologies,
Alex Rojas, GE

7. Power Transformer Reliability Modeling - Arjan Schijndel

8. Validation of reliability forecasting for power transformers - Arjan van Schijndel, Jos M. Wetzer, and Peter A.A.F. Wouters (2008)

9. A statistical approach to processing power transformer failure data - R. Jongen, et. al., Cired 19th International Conference on Electricity Distribution, Paper 546, May 2007.

10. Review of chemical indicators of degradation of cellulosic electrical paper insulation in oil-filled transformers- A.M. Emsley and G.C. Stevens , IEE Proc.-Sci. Meas. Technol. Vol. 141, No. 5, September 1994

11. Ageing of oil-impregnated paper in power transformers- Lars E. Lundgaard, Walker Hansen, et al., IEEE PWRD Dec. 2002

12. Advanced on-site diagnosis of transformer on-load tap changer, Jur J. Erbrink, Edward Gulski, et al. , IEEE 2008

Appendix - Simulation Codes

CreateTransformer.m

```
clear all;
close all;

%% Set the parameters for the transformer

% The activation energy
Ea = 111*10^3; %J/mol

% Process Constant
A = 2*10^+8; %h-1

% Gas Costant
Rg = 8.314;

%Temperature (As a function of time. Assumed constant)
T = 370; %K, 98 deg C

% Reaction rate
k = A*exp(-Ea/(Rg*T)); %h-1
k = 24*k; %d-1

% Original DP value (Degree of Polymerization)
DP0 = 1000;

% Threshold DP value below which transformer ceases to function
DPc = 250;

%% Create the ideal transformer

% Start of history
t0 = 1;

% End of history
tm = 15*365; % Arbitrarily chosen as 15 years since average transformer life with above parameters was aobserved to about 10-12 years

% Generate the curve
DP(t0) = DP0;
for t=t0+1:tm
    DP(t) = DP(t0)/(1+DP(t0)*k*(t-t0));

    if DP(t) < DPc && DP(t-1) >= DPc
        disp(sprintf('Ideal transformer would last for %d days or %d years',t, t/365));
    end
end

% figure, plot(t0:tm,DP);
% title('Ideal Transformer Curve');
% xlabel('Number of days');
% ylabel('DP value');

%% Create a transformer history

% Set parameters for Extreme Value Distribution
sp0 = -3; % shape parameter
sig0 = 0.05;
mu0 = 0;

% Generate deviations for each time-step
for i=t0:tm
    Dev0(i) = gevrnd(sp0, sig0, mu0);
end

figure, hist(Dev0);
```

```
% Generate the curve by introducing deviations to the original curve
DPa(t0) = DP0;
for t=t0+1:tm
    DPa(t) = DPa(t-1)/(1+DPa(t-1)*k*1);

    DPa(t) = max( DPa(t) + min(Dev0(t),0), 0);

    if DPa(t) < DPc && DPa(t-1) >= DPc
        disp(sprintf('Non-ideal transformer would last for %d days or %d years',t, t/365));
        TL = t;
    end
end

figure, plot(t0:tm, DPa, t0:tm, DP);
title('Ideal and Actual Transformer History Curve');
xlabel('Number of days');
ylabel('DP value');
```

PredictFailure.m

```
%% Compute the probability that transformer will fail in next m days

% Prediction days
m = 10;

% Today
%today = TL-5m:TL;
Tw = 25;

for today=TL-Tw:TL
    today

tic;
%% Compute the distribution of deviations based on history

for t=t0+1:today
    ind = find(DP<DPa(t-1),1);
    Dev(t-1) = DPa(t) - DP(ind);
end

%figure, hist(Dev);
paramhat = gevfit(Dev);
sp = paramhat(1); sig = paramhat(2); mu = paramhat(3);

disp(sprintf('Curve fit successful ! sp = %d scale = %d mu = %d ',sp, sig, mu));

%% Run the simulation for next m days

% Number of iterations
numit = 10000;

itcount = 0;
for it=1:numit
    currentDP = DPa(today);
    for tn=1:m
        ind = find(DP<currentDP,1);
        currentDP = max( DP(ind) + min(gevrnd(sp,sig,mu),0),0);
        if currentDP < DPc
            itcount = itcount + 1;
            break;
        end
    end
end

pf = itcount/numit;
disp(sprintf('Probability of failure on day %d is %d', today, pf));
toc;
```

```
pfv(today) = pf;
end

figure, plot(TL-Tw:TL,pfv(TL-Tw:TL));
title('Failure Probability Across Transformer Lifetime');
xlabel('Number of days');
ylabel('Probability of failure');
```