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Dynamic Line Rating in Power Systems

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Dynamic Line Rating in Power Systems

A Thesis submitted in partial satisfaction
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in

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by

Junjie Liu

March 2017

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ABSTRACT OF THE THESIS

Dynamic Line Rating in Power Systems

by

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It is necessary for power operators to determine the capacity constraint of transmission lines to ensure the safety requirement, this process is also called line rating. There are several factors that would affect maximum rating, such as weather and conductor thermal conditions. Compared with existing static conservative line rating, dynamic line rating (DLR) is given to determine the capacity based on real time conditions, thus usually the operators are able to obtain more potential available capacity without exceeding safety margin. Conductor temperature is a significant feature in DLR processing, while measurements from sensors are expensive and inaccurate. Thus this thesis proposes a multi-factor model to calculate conductor temperature with high load current using parameter estimation.

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1. INTRODUCTION

1.1 Transmission line measurement background

It is always the most significant requirement that power utilities need to monitor the real time characteristics of the transmission lines. One implementation of the real time data, which is also the most important one, is safety concern. Power operators set maximum power capacity restriction, which is also called line rating in order to limit the load current, maintaining acceptable line clearance and conductor temperature to protect the transmission line conductor and also the public safety. In the past decades, power operators were able to measure the line current and bus voltage, now they have capability to measure other real time data, such as conductor and ambient temperature, wind speed and direction, solar heat, sag and line tension. In fact, these data could also be useful to increase the efficiency of the power transmission.

1.2 Line Rating Overview

The first concept which needs to be explained is rating. The rating of a transmission line is defined as the amount of current that can be carried by a conductor without exceeding its maximum allowable conductor temperature (MACT) or maximum sag. [5]

Sag is the transmission lines clearance against the ground. Operators must ensure that the energized conductor does not sag dangerously close to the public and also to protect the integrity of the conductor itself. [5]

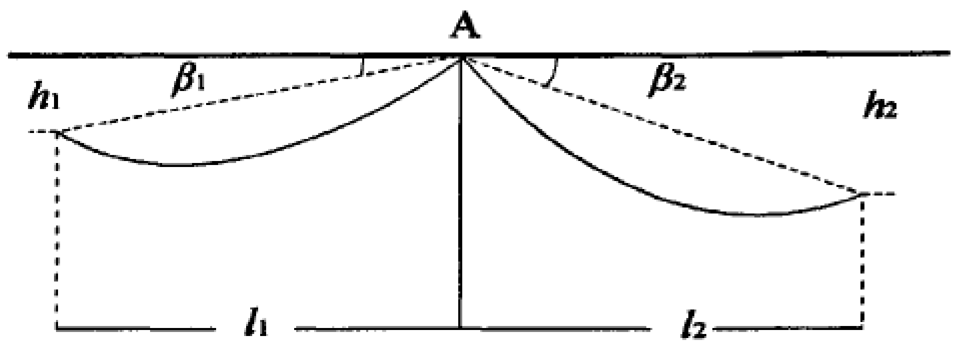

Fig.1. Strain sections with different heights

The way to calculate sag is simple, research [4] has been made to figure out the formula between sag and tension. The maximum sag along the line is:

$$S = \frac{\omega \cdot l^2}{8 \cdot \sigma_0' \cdot \cos\beta}$$

Where ω is conductor weight per unit length (N/m), σ_0' is the measured horizontal tension (N), l is the span length (m).

Power operators set maximum power transmission capacity restriction based on the thermal safety limit of the conductor. In the past decades, thermal ratings are under the worst conservative weather assumption, which is high ambient temperature, low wind speed and high solar radiation in order to prevent conductor being damaged. The rating does not vary with real time weather conditions or time, therefore it is called static line rating (SLR). The assumption for SLR in USA is: the wind speed is 0.61m/s, ambient temperature is 37℃ and MACT is 90℃. In fact the probability of this conservative weather conditions is very little, around 0.02% [2], which means in most of the time the potential capacity of the line has been wasted because of the static rating.

Dynamic Line Rating (DLR) technology enables power operators to change the maximum power capacity limit dynamically based on the real time weather conditions, rather than fixed assumption, thus it is usually higher than the static rating. Compared with other ways to increase capacity, DLR is able to install to the original system without changing the existing transmission line structure, and it is easy to implement and maintain. DLR could save million dollars if 1% of the transmission lines were implemented with DLR technology. [4] So it makes DLR system possible exploiting the potential line capacity and improving the asset utilization efficiency.

DLR is a very updated technology. U.S. Department of Energy has made a technical topical report [12] to explain the details of DLR. Overview of different DLR methods can be found in paper [1]. There is also a DLR system application in research [13].

2. DYNAMIC LINE RATING TECHNOLOGY

2.1 Heat balance equation

Temperature is the most significant safety factor that the power operator should concern if changing the capacity limit. Thus it is necessary to discuss about heat balance equation before explaining what exactly DLR technology is:

Steady-state equation:

$$I^2R(T_C) + Q_S = Q_R + Q_C$$

Where $R(T_C)$ (Ω/m) is the AC resistance at temperature T_C , it is determined by conductor itself. Q_S is the heat gain from solar radiation (W/m), determined by material absorptivity. Q_R is the radiation heat loss (W/m), determined by material emissivity. Q_C is the convection heat loss (W/m), determined by wind speed and direction.

Transient equation:

$$I^2R(T_C) + Q_S = MC_P\frac{dT_C}{dt} + Q_R + Q_C$$

Where M is the mass per unit length conductor (Kg), C_P is the heat capacity $(J/(Kg\ ℃))$. These two are both determined by conductor itself.

2.2 Rating procedure

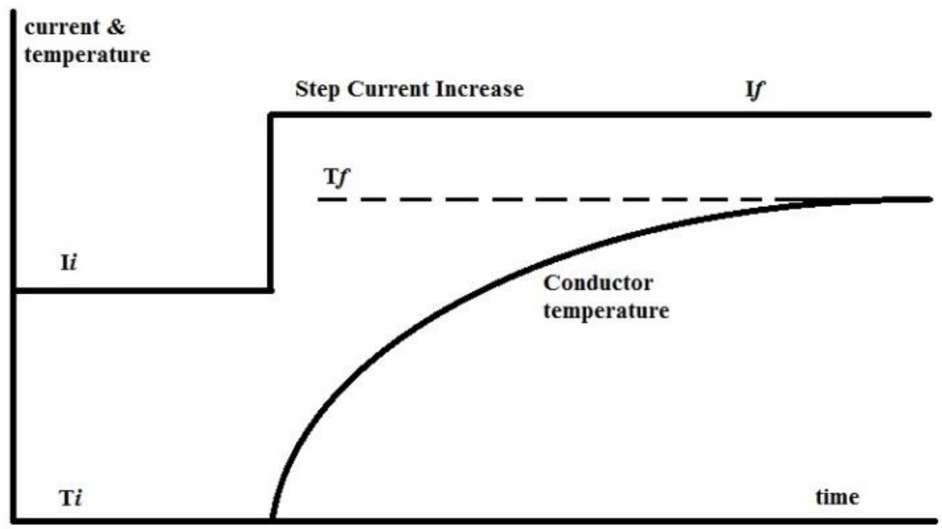

Fig.2. Transient heat balance equation

DLR determines the real time maximum allowable transmission capacity, which is also the rating. There are two values need to be preset and initialized. One is the time interval t, which is called the unit current-monitoring time period, usually 5-10 minutes, the other one is the final temperature T, which is the maximum allowable thermal limit preset by the operator. The Figure 3 shows the procedure of the transient rating calculation.

The condition is that all the weather data have been measured. I_i is still the initial current, and there are three possible end current values I_1, I_2 and I_3. A step current increase occurs from I_i to I_1, I_2 or I_3, all the end current values can be simulated by the heat equation.

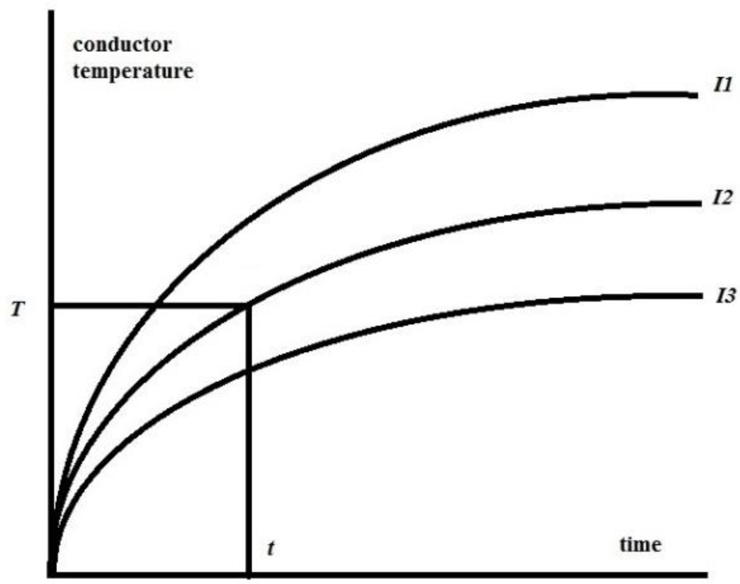

Fig.3. Current (rating) calculation

It happens that among all the end current curves, the conductor temperature exactly reaches thermal limit T on the I_2 curve after the time period t, thus current value I_2 is the maximum allowable rating under all the threshold conditions above. The related unknown parameters in the heat equation such as radiation heat loss can be calculated by IEEE standard 738-2012. [4][6]

The Figure 4 shows one comparison example between DLR and SLR. Apparently, DLR is able to overcome transmission “bottleneck” based on real time weather conditions when the operator receives the power peak demand so that improve the efficiency.

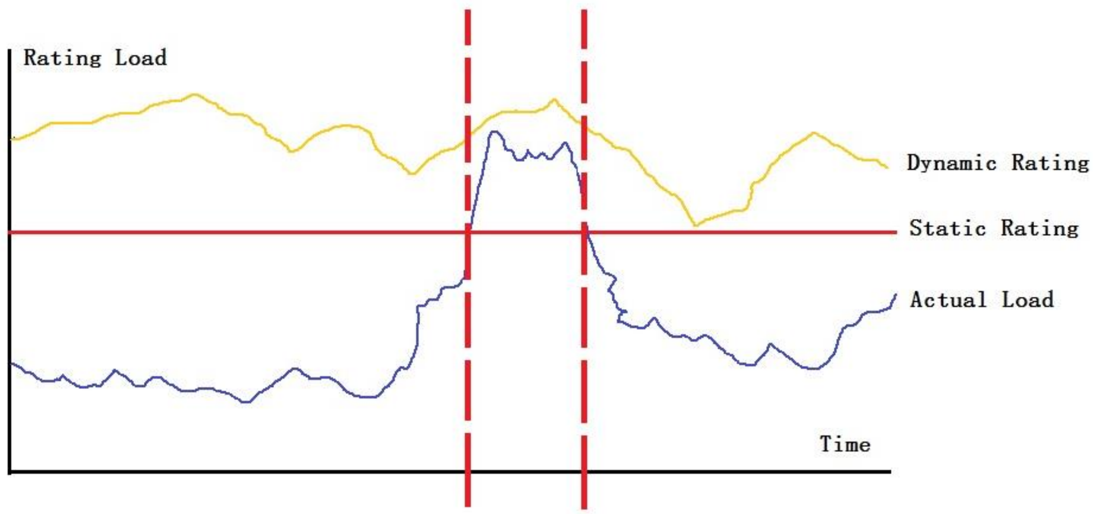

Fig.4. Example of load profile comparison between different rating methods. If without DLR, the event within red dotted lines will be reported as a congestion violation

3. PARAMETER ESTIMATION

3.1 Conductor average temperature measurement problem

Based on all the discussion above, conductor temperature is the critical factor that affects dynamic rating. However it is a severe problem for power operators to consider that how conductor temperature should be determined. It is possible to measure the temperature using thermal sensors; but the truth is the data from the sensors are point data, which means the measurements are particularly the temperature values from the points where the sensors are located, not the average temperature alone the transmission line. This temperature distribution character is due to the geographical and ambient differences of the strain sections. In order to obtain the real time average temperature, two methods have been proposed to solve this problem.

3.2 State Change Equation method

One of these two methods is the State Change Equation (SCE).The SCE is given by:

$$\sigma_n - \frac{l_r^2 g_n^2 E cos^3 \beta_r}{24\sigma_n^2} K_n = \sigma_m - \frac{l_r^2 g_m^2 E cos^3 \beta_r}{24\sigma_m^2} K_m - \alpha E(t_n - t_m) cos\beta_r$$

Where K is the relative load coefficient:

$$K_m = 1 + \left(\frac{2\lambda cos\beta}{l}\right)^2 (\frac{g_{0m}}{g_m} - 1)(3 + 2\frac{\lambda cos\beta}{l}\frac{g_{0m}}{g_m} - 4\frac{\lambda cos\beta}{l})$$

Where there are two states of the conductor m and n , σ is the tension, l is the span length, g is the external load, β is the height difference angle, E is the elastic coefficient, t is the temperature, α is the dilatation coefficient.

The equation above provides a method to calculate the dynamic average temperature, however it has a critical shortcoming. If the ambient temperature is much lower than the conductor temperature, and the conductor temperature is not far or close to MACT, most of the coefficients in the equation will change with uncertain rate, and it is not convenient at all for operators to identify all the transmission line coefficients before every rating procedure, in fact the operators always use empirical coefficient values to calculate approximate temperature. Thus there would be significant amount of error if this method was implemented in high current load cases.

3.2 Tension method

Another way to obtain the temperature is to estimate the relationship between tension and temperature and find out the fitting curve to predict temperature. The estimation model is proposed as: [8]

$$t = 91.26929 - 2.6593F - 3.01958 \times 10^{-7}F^2 + c$$

While this method provide more accurate and easier way to calculate the temperature, the fatal disadvantage is that most of the well performance points of the training set which are close to the fitting curve are within the range of 12 ℃~32 ℃. Another shortcoming is that this method only takes account into the tension factor, without paying attention to the load current. These disadvantages make it the same limitation as SCE method above, which is that it is infeasible in high current cases.

3.3 Multi-factor estimation model

Time	Ambient temperature (℃)	Solar radiation temperature (℃)	Humidity	Wind speed (m/s)	Wind direction (degree)	Load current (A)	Average temperature (℃)	Sag (m)	Tension (N)
2008-12-22 17:00:01	16.8	16.8	28	3.33	77	192	29.7973	5.780988	14939
2008-12-22 18:00:01	15.6	15.6	30	3.761	60	182	28.70677	5.66087	15252
2008-12-22 19:00:01	14.4	14.4	33	3.142	66	200	28.42824	5.624454	15350
2008-12-22 20:00:01	13.4	13.4	34	3.552	69	190	28.31793	5.609713	15390
2008-12-22 21:00:01	12.4	12.4	37	2.573	72	180	27.83067	5.542185	15576
2008-12-22 22:00:10	11.4	11.4	38	3.768	98	190	27.61488	5.510834	15664
2008-12-22 23:00:01	10.7	10.7	41	3.174	53	132	27.29778	5.462642	15801
2008-12-23 0:00:01	10.3	10.3	42	3.601	63	174	27.08503	5.428727	15899
2008-12-23 1:00:01	9.9	9.9	45	2.767	47	101	27.00363	5.415347	15938
2008-12-23 2:00:01	9.4	9.4	44	3.198	67	98	26.80729	5.382164	16036
2008-12-23 3:00:01	9	9	43	3.483	45	95	26.80729	5.382257	16036
2008-12-23 4:00:01	8.7	8.7	42	3.531	61	92	26.90399	5.399149	15987

Fig.5. Example of data set from China Southern Power Grid

In order to indicate the dynamic capacity rating limit, we need to use real time data from the sensors. Here we have 2-year, over 16000 monitoring data sets from one particular transmission line in China Southern Power Grid with the help of two professors from Shanghai Jiaotong University. In this data set, the measurements are ambient temperature, conductor temperature, tension, load current, wind speed, wind direction, solar radiation, humidity, sag and capacity. The resolution is one measurement per hour.

First of all we did a factor selection research to find out the most significant parameter which could change the power capacity significantly. Here we can do this by controlling variables. Specifically the way is to set one initial value of interested parameter, fix other parameters, and make this parameter change in a certain range, then see how much the capacity rating would change.

Below are the results. Detail solution will just be discussed in ambient temperature because all the other parameters go with the same solutions.

Factor #1 Ambient temperature

Initial value: 30℃, make 2℃ fluctuation, fix other conditions, check the capacity under ambient temperature equals 32℃ and 28℃ respectively. Below is the algorithm example that how we do variable controlling in Matlab coding.

As figure 4 shows, the data in our Marlab code is saved as matrix form. Columns are different parameters, and rows are different time resolution. Now we would like to pick some rows from the original data matrix to build a new matrix. The parameter values in the first column (which is the ambient temperature) in the new matrix are just 28, 30 and 32, and all the other parameters in other rest columns stay similar or the same. So by this new matrix we are able to indicate that if ambient temperature changes from 30 to either 28 or 32, how the capacity would change.

Here we make a more precise instruction using the 28-30 ambient temperature example. Firstly we find all the rows with value 28 and 30 in the first column from the original data matrix, and put these rows into two matrix respectively. Then combine these new two data matrix head-to-tail, just like the left matrix in figure 6.

	Ambient temperature	Wind speed
1	28	3.33
2	28	3.78
3	30	3.56
4	30	3.34
5	30	3.78

SORT →

	Ambient temperature	Wind speed
1	28	3.33
4	30	3.34
3	30	3.56
2	28	3.78
5	30	3.78

Fig.6. Example of controlling variable in data matrix

Next step is to sort the wind speed column, just as the right matrix shows in figure 6, and now we have a new matrix with a sorted second column. Search the same or similar wind speed values in the second column, just as the row 1 and 4, row 2 and 5 in dark color, and now we obtain two groups of data which have same wind speed, but different ambient temperature, so the wind speed factor has been fixed. Pick all the groups and build a new matrix, continue the iteration to the parameter in the third column and so on. By the end of iterations, we are able to obtain a controlled variable data matrix.

Below are the controlled variable data groups we found. In conclusion, 2℃ fluctuation in ambient temperature will make around 5% capacity change. The rest work of other factors is the same.

	Ambient temperature	capacity	Capacity change
1	30	1193.40	+10.31%
	32	1070.50	
2	30	765.93	+6.79%
	32	713.92	
3	30	931.58	-0.9%
	28	940.77	
4	30	816.26	-0.2%
	28	814.49	

Table.1. Capacity factor selection result for ambient temperature

Factor #2 Wind speed and direction

Initial wind speed: 2.5 m/s, make an increase of 2.1m/sec. the result is:

Wind speed	Wind direction	capacity	Capacity change
2.5	179	708.06	
4.6	179	881.90	+19%
4.6	85	1076.70	+18%(2.5), +34%(4.6)

Table.2. Capacity factor selection result for wind speed and direction

Factor #3 Humidity

Humidity	capacity	Capacity change
27	392.29	+6.44%
100	419.99	

Table.3. Capacity factor selection result for humidity

There are few cases about changing solar radiation in the data set, neither the cases that the conductor temperature reaches the MACT, so here we reference the solar radiation and MACT results from research [4].

Solar radiation

Cloud shadowing will just cause few percent capacity changes

Total eclipse will increase +18% capacity

MACT

Initial value: 70℃

+10℃（80℃） increase of MACT will bring 20% more capacity

+20℃(90℃) increase of MACT will bring 35% more capacity

To conclude above, ambient temperature and humidity is not able to make over 10% capacity changes with large amount of changes itself. It is hard to change the solar condition, and solar radiation could make few capacity changes either. Hence besides tension and load current, the significant factor that we would like to consider in the model are wind speed and wind direction.

Thus it is possible to propose a better approach to obtain the conductor temperature in high current case. Based on the previous feature selection study, we know that the temperature can be simulated as a function of the following parameters:

$$T = f(F, I, v, \theta)$$

Where T is the conductor temperature, F is the tension, v is the wind speed and θ is the wind direction against transmission line.

Getting inspired by all the work done before, we are able to propose a new multi-factor estimation model:

$$T = af(F) + bf(I) + cf(v) + df(\theta) + m$$

Where a, b, c, d, m are all unknown weight coefficients we need to determine.

Here we have another concern. Wind speed and wind direction could be much significantly correlated with conductor temperature if we combine these two parameters together as one parameter because they are from the same weather condition:

So the model might be in this form:

$$T = af(F) + bf(I) + hf(v,\theta) + m$$

It will be verified in next section.

3.4 Parameter correlation

Before starting estimate the model, it is necessary to consider the parameter correlations between temperature and tension, current, wind speed, wind direction respectively.

In order to consider the correlation, we pick up 616 data points from the data set as the training set. The time interval of these points is around June, and within two weeks. The reason of this rule is that DLR is a dynamic technology, the estimation model made by these training set should not be long-period data. Another reason is about our case assumption. June is not the highest-temperature month but always has high power load due to the upcoming summer cooling, which means the load current would be high enough to match the case of the estimation model.

Plot all the parameter versus conductor temperature, we have the following scatter diagrams. From the figure we could easily find an interesting phenomenon. It seems that conductor temperature is extremely related to tension.

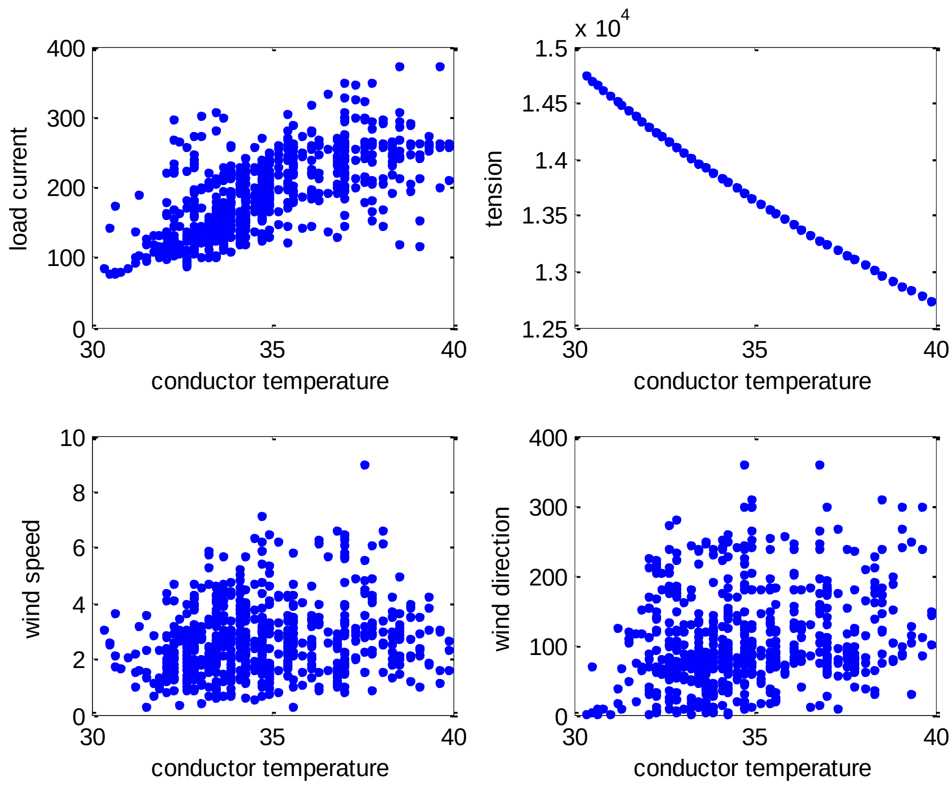

Fig.7. Scatter diagrams of 616 chosen data points between conductor temperature versus other parameters

In fact the value of correlation is also very high (close to 0.9). In order to find out the reason of this high correlation value, we plot all 16000 data set of tension versus conductor temperature.

We are able to see that the tension will be either 0 or no sense if the temperature is not within this interval. The result is the same in tension-based model which we discussed in the previous section. In that model most of the well performed data points are within the range of 12℃~32℃, and the ambient temperature is close to the conductor temperature.

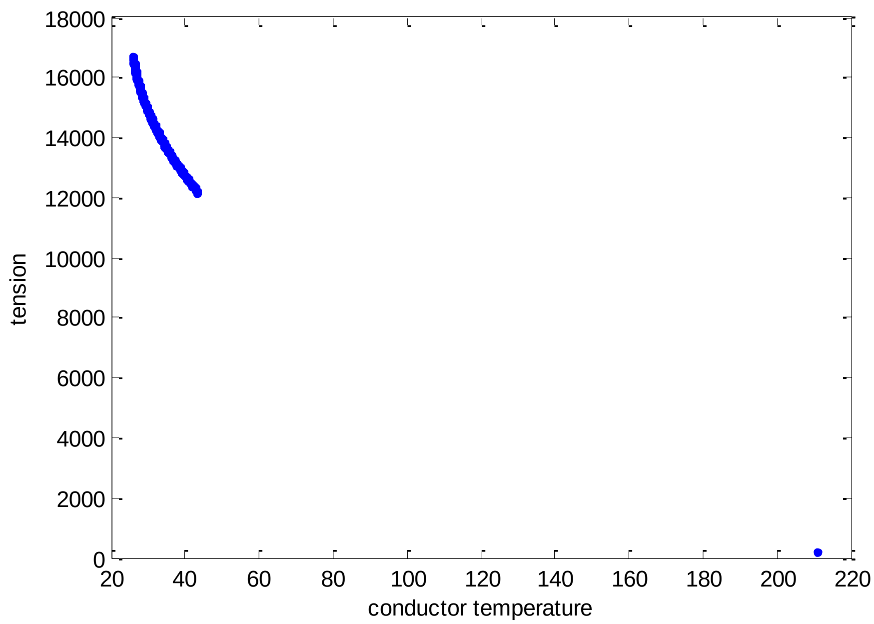

Fig.8. Scatter diagram of all 16000 data points between tension versus conductor temperature

One possible reason is that tension sensor does not provide well performance measurements when the conductor temperature stays high, the other reason is that high temperature changes the physical properties of the transmission lines so that affect the tension.

Going back to the correlation discussion, here we show the calculated correlation values of different parameters versus conductor temperature respectively.

Parameter	correlation
Load current	0.6477
Wind speed	0.2322
Wind direction	0.1818

Table.4. Correlations of different parameters versus conductor temperature

The load current basically satisfies the common physic knowledge background which is that current has a second order relationship with temperature, and the points

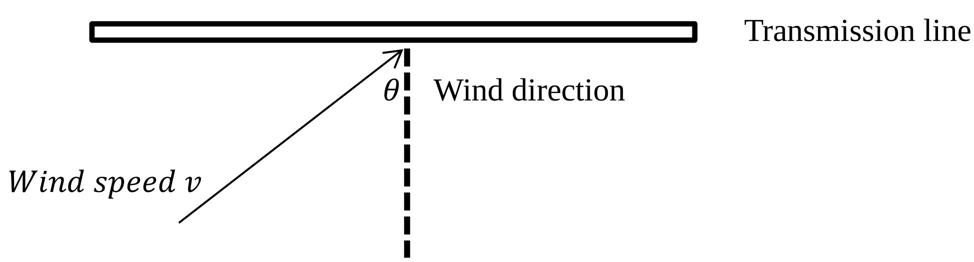

Fig.9. 2-D example of new combined wind condition parameter model

look similar to the quadratic curve more or less. However wind speed and wind direction is far from expectation. Here we combine these two parameters as one new parameter $w = v \cdot \cos\theta$.

We consider the wind speed as amplitude, use this trigonometric function to represent the combined parameter. If we consider the wind as fluid, the cooling effect would be maximum if the wind direction is 90 degree. This satisfies the monotony of cosine function. Hence the next step is to plot this combined parameter scatter diagram.

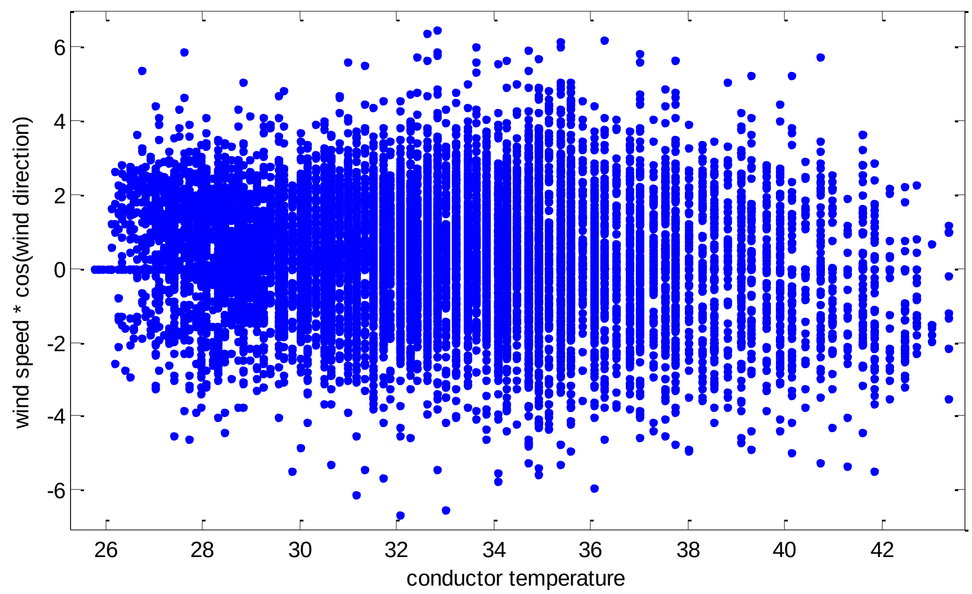

Fig.10. Scatter diagram of combined parameter versus conductor temperature

The result is that the general trend is almost a straight line, which means that it could hardly to find any correlation between combined parameter w and conductor parameter, which means we should give up this new parameter concern. Thus it is necessary to pre-process the data points in order to improve correlation. The main method is to use least square variance distance to remove the noise points.

3.5 Data pre-processing

To remove the noise point, firstly it is necessary to find out the fitting curve between load current and conductor temperature.

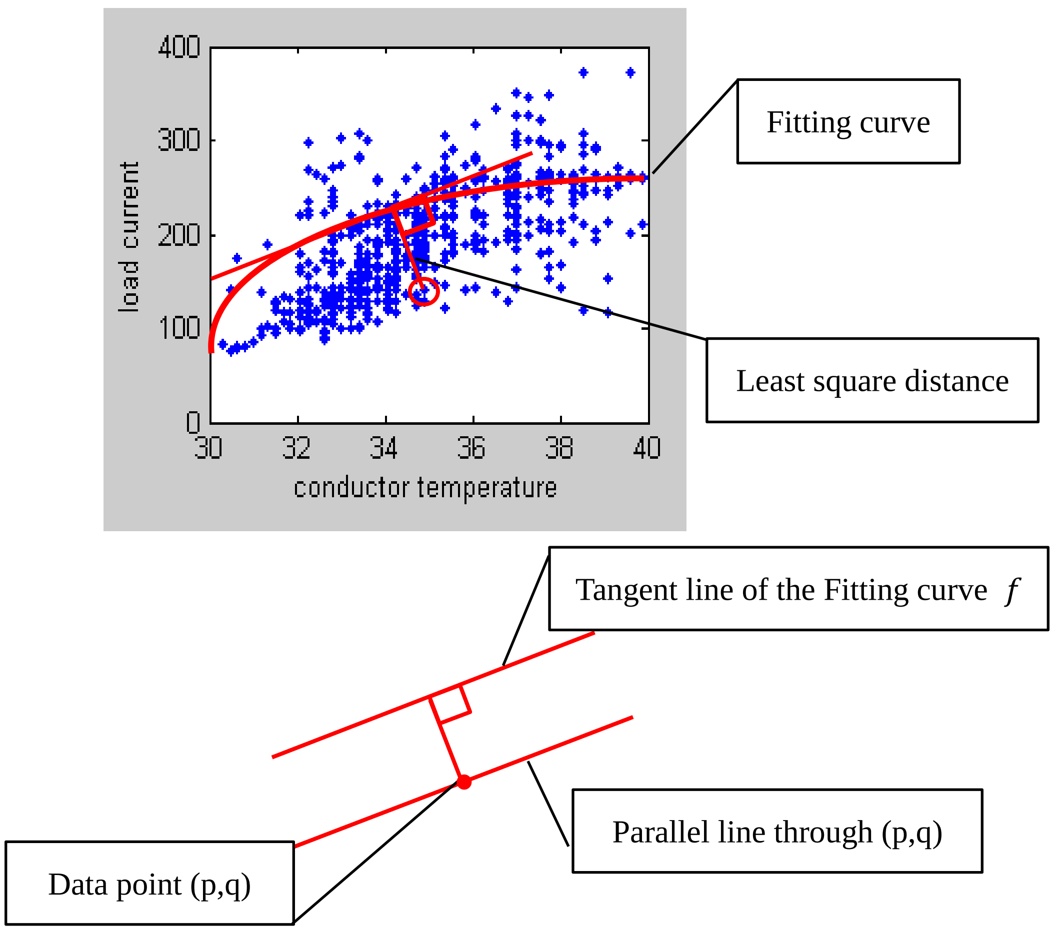

Fig.11. Least square distance from a data point to the fitting curve

Once the fitting curve is obtained, we calculate the least square distance of every data point as variance. Then set up a distance threshold, all the data points with distance beyond that threshold would be removed.

The least square distance can be formulated as optimization problem:

$$minimize\ distance^2 = (x-p)^2 + (y-q)^2$$

$$subject\ to\ (x,y) \in fitting\ curve\ f$$

$$(p,q) \in\ the\ data\ set$$

In order to obtain the minimum value of the distance, take the derivative of the $distance^2$ function and make it equal to 0, we have:

$$\frac{dG}{dx} = \frac{d(distance^2)}{dx} = 2(x-p) + 2(y-q) \cdot \frac{df}{dx} = 0$$

The slope of the tangent line is the derivative of the fitting curve $\frac{df}{dx}$, solve the equation above then we will obtain the point (x_0, y_0) on the fitting curve which has the minimum distance with the data point (p,q), hence the minimum distance would be:

$$minimum\ distance^2 = (x_0 - p)^2 + (y_0 - q)^2$$

The fitting curve can be achieved by subsets of the load current data set. Another way is to use this itself to estimate the fitting curve since the percentage of the noise data is not very high. Here we use the former approach. The fitting curve f is:

$$f \to T = 27.4195 + 0.0383I - 2.049 \times 10^{-5} I^2$$

And the derivative is:

$$\frac{dT}{dI} = -4.089 \times 10^{-5} I + 0.0383$$

Plot the distribution of the distance so that we could have better knowledge about the variance. Set the threshold as 1.38, hence all the data points with least square distance greater than 1.38 will be removed.

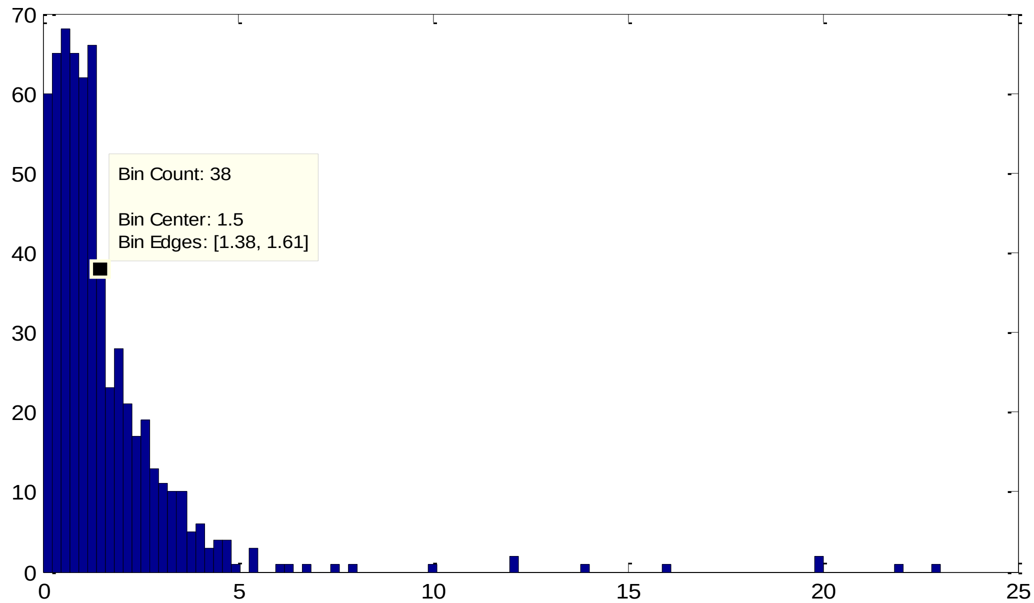

Fig.12. Least square distance distribution. The x-axle is distance and the y-axle is the amount count

The amount of rest points is 386. Now most of the noise points have been removed, and we will verify it with one more correlation calculation. Plot the updated clean data points as scatter diagram.

Parameter	Updated correlation	Previous correlation
Load current	0.7673	0.6477
Wind speed	0.3569	0.2322
Wind direction	0.2021	0.1818

Table.5. Correlation comparison before and after noise processing

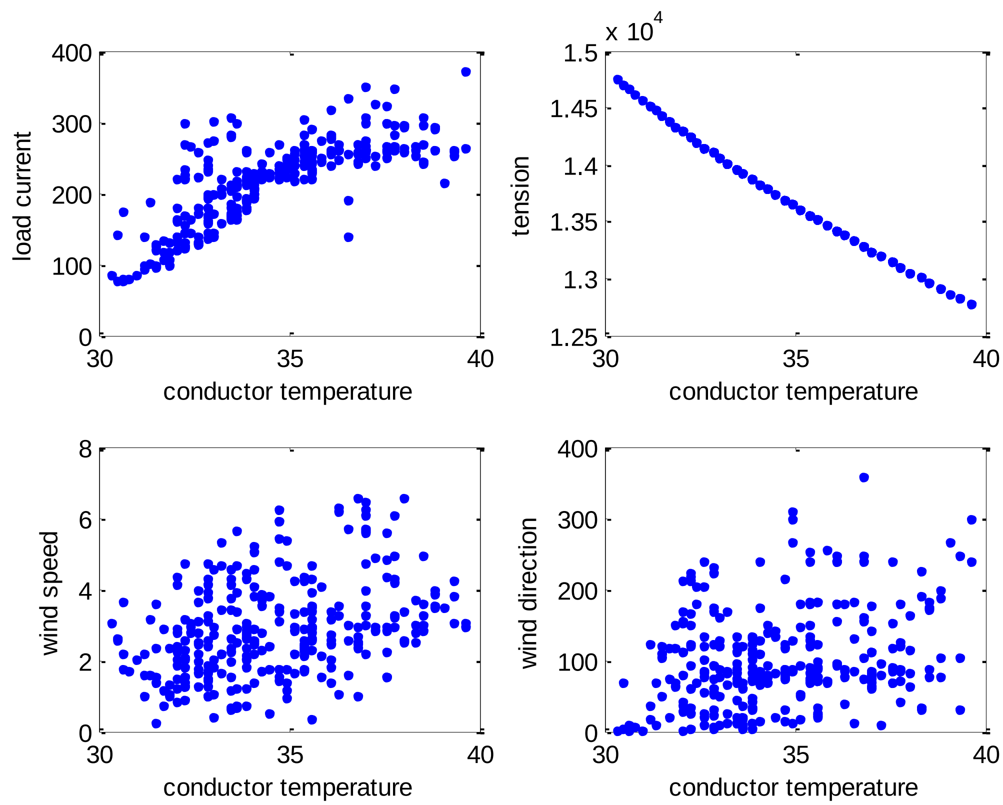

Fig.13. Scatter diagrams of clean data after removing noise points

From the figure we could have a conclusion that all the correlations have been increased. We neglect the wind direction factor since the correlation of it is below 0.3. The correlation of wind speed is also not significant, but not negligible, thus we formulize it as linear model because it will have least effect on the multi-factor model. As to the tension factor, the correlation is extraordinarily close to 1, which means it has significant possibilities to have a linear model.

As to the parameter wind speed and direction, in the factor selection section, both of these two factors have shown significant effect on the capacity, but we obtain the contrary result in correlation analysis. The possible explanation is that during factor selection we just simply consider two parameters, which are conductor temperature versus wind speed. But in the model estimation we compare conductor temperature with four different parameters, which might cause these parameters to affect each other in one equation. Another possibility is that the wind speed would also affect correlation and model estimation result in terms of affecting tension.

To sum up, load current has a quadratic relation, both tension and wind speed is identified as linear model, wind direction is negligible. The final estimation model we would like to propose is: $T = aF + b_1 I^2 + b_2 I + cv + m$

3.6 Overfitting and underfitting analysis

In the proposed multi-factor model, we set load current as second order and tension as linear. While there are some concerns claiming that the model should be general form in order to cover all the possibilities:

$$T = \sum_{i=1}^{n} a_i F^i + \sum_{i=1}^{n} b_i I^i + \sum_{i=1}^{n} c_i v^i + \sum_{i=1}^{n} d_i \theta^i + m$$

The reason we do not propose general model is the principle of Occam's razor in machine learning. It is possible to obtain an incorrect overfitting curve if considering very complex estimation model with similar qualification, and a underfitting curve if considering very simple model.

$$T = a_1 F^2 + a_2 F + b_1 I^2 + b_2 I + cv + m \ (overfitting)$$

$$T = aF + b_2 I + cv + m \ (underfitting)$$

If the model is underfitting, the error will increase with same test set; if overfitting, firstly it will show less error with same test set, but the error will increase if we change a new test set. We will qualify all the concerned possible models below in section 3.8 using this test set error analysis:

3.7 Parameter estimation

Least square estimation certainly should be the best method to obtain this estimation model. Rewrite and formalize the model:

$$T = [F \quad I^2 \quad I \quad v \quad 1]\begin{bmatrix} a \\ b_1 \\ b_2 \\ c \\ m \end{bmatrix} + error$$

In Matlab function `'lsqlin'` is able to solve the least square estimation problem and give back the parameter matrix result. The result is:

$$a = -0.0049, b_1 = 1.9466 \times 10^{-5}, b_2 = -0.0095, c = 0.0168, m = 102.9485$$

$$T = 102.9485 - 0.0049F + 1.9466 \times 10^{-5} I^2 - 0.0095I + 0.0168v$$

Another way is based on data statistics, substitute into the training set and find out the fitting curve. In Matlab we are able to solve this model using function `'regress'`. By this way we can also evaluate the correlation coefficient of the obtained fitting curve. The correlation coefficient of this estimation model is nearly 1, which means the regression is extraordinary. Both of these two ways turn out to show the same result.

3.8 Evaluation

In order to verify that the proposed new multi-factor model performs better in high load current case, we could verify the accuracy of the conductor temperature calculations comparing with other methods.

In this verification part we use the same test set from China Southern Power Grid data set to compare the qualification among new model and these following models respectively:

1. Previous SCE and tension methods
2. Underfitting model (remove the second order section of load current)
3. Overfitting model (add a second order section of tension)
4. Model trained by data with noise
5. Model trained by all 16000 data set

In order to show better comparison result, we define negative error rate, which means the conductor temperature calculation is higher than the true temperature measurements.

1. Previous SCE and tension methods

	Ambient temperature (℃)	Load current (A)	Tension (N)	Measured conductor temperature (℃)	State change equation method		Tension method		Multi-factor model	
					Calculated temperature (℃)	error (%)	Calculated temperature (℃)	error (%)	Calculated temperature (℃)	error (%)
1	29.1	259.17	14680	31.58	31.35	0.72	30.57	3.21	29.86	5.44
2	28.8	196.4	14814	30.32	31.08	2.45	30.1	0.74	29.24	3.55
3	28.6	196.4	15085	29.52	30.53	3.32	29.21	1.05	27.92	5.43
4	28.1	225.41	14905	29.73	30.9	3.77	29.79	-0.19	28.76	3.26
5	28.3	220.13	14997	29.62	30.71	3.56	29.49	0.44	28.32	4.41
6	28.2	213.1	14905	29.58	30.9	4.25	29.79	-0.69	28.77	2.73
7	31.6	544.88	13867	39.59	33.01	19.93	33.9	14.39	35.60	10.07
8	31.5	543.12	14183	39.31	32.37	21.45	32.51	17.3	34.03	13.42
9	31.6	519.21	13733	38.87	33.29	16.77	34.53	11.18	35.97	7.46
10	31.3	500.22	14004	38.26	32.73	16.88	33.28	13.01	34.45	9.96
11	31.7	434.46	13550	37.61	33.66	11.72	35.42	5.83	36.10	4.01
12	31.9	519.91	13958	38.59	32.83	17.54	33.49	13.22	34.88	9.62
13	32.1	539.6	13958	39.48	32.83	20.28	33.49	15.19	35.10	11.10
14	32	541.54	13912	38.69	32.92	17.53	33.69	12.92	35.34	8.65
15	32.2	541.19	14092	39.05	32.55	19.95	32.9	15.76	34.46	11.76
16	32.4	597.23	13775	40.84	33.2	23.01	34.33	15.95	36.72	10.09
17	32.3	497.23	13821	39.1	33.11	18.1	34.11	12.76	35.31	9.68
18	32.5	501.1	13733	39.01	33.29	17.2	34.53	11.51	35.78	8.27
19	32.2	502.51	14046	37.59	32.65	15.15	33.1	11.97	34.26	8.85
20	32	503.91	14004	37.37	32.73	14.17	33.28	10.95	34.48	7.72
21	32	500.92	14046	37.22	32.65	14.02	33.1	11.09	34.25	7.98
22	31.7	494.77	14275	36.58	32.18	13.69	32.13	12.19	33.07	9.61
23	31.7	493.89	14229	36.81	32.27	14.05	32.32	12.21	33.28	9.58
24	31.3	474.9	14546	35.34	31.63	11.75	31.06	12.12	31.55	10.72
25	29.8	468.57	14680	33.94	31.35	8.23	30.57	9.93	30.84	9.14

Table.6. Temperature calculation error analysis compared with tension and SCE method

From the table we are able to indicate that the proposed multi-factor model has similar error percentage as the other two methods when the ambient temperature is close to the conductor temperature.

In the figure the dot points are close to each other when the temperature difference is small. However, as the conductor temperature rises up and becomes far from ambient

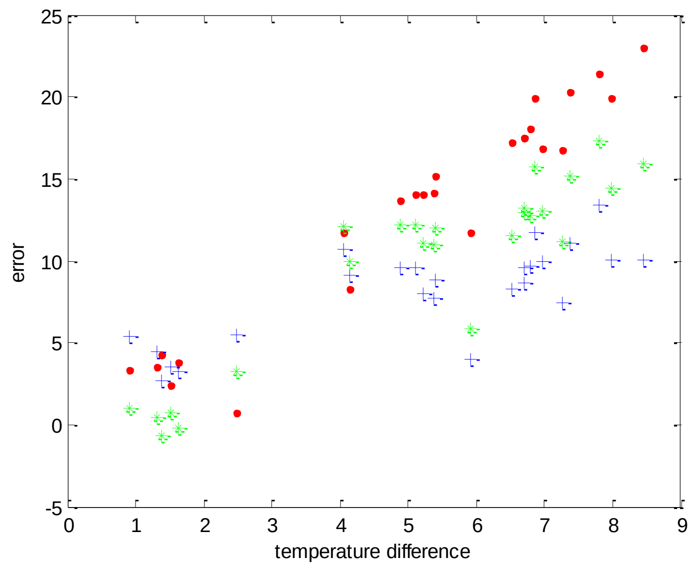

Fig.14. Scatter diagrams to show the comparison of error rate. The x-axle is conductor temperature minus ambient temperature, and the y-axle is the error rate. Red dots refer to SCE method, green dots refer to tension method, blue dots refer to the proposed model

temperature, which means the temperature difference keeps increasing, the updated multi-factor model has remarkably better performance, especially from row 10 to row 20. So the conclusion is multi-factor model performs better in high load current case.

2. Underfitting model (remove the second order section of load current) and Overfitting model (add a second order section of tension)

Recall the overfitting and underfitting analysis in section 3.6, now we are able to do the qualification. First step is to inspect underfitting, remove the second order of the load current, the new model is:

$$T = 102.0945 - 0.0049F - 0.0013I + 0.0071v$$

Then second step is to inspect overfitting, add a second order of the tension, the new model is:

$$T = 215.178 + 6.11 \times 10^{-7}F^2 - 0.021F - 1.01 \times 10^{-13}I^2$$
$$+4.63 \times 10^{-11}I - 7.72 \times 10^{-11}v$$

Use the same test set, the comparison result is shown below. Obviously the error rate of underfitting model increases significantly with the same test set, but the overfitting model stays similar, sometimes even has better error performance.

The reason of this better performance has been explained in previous section. If a model is overfitting, it will show little error when being tested by the test set which is similar to its training set.

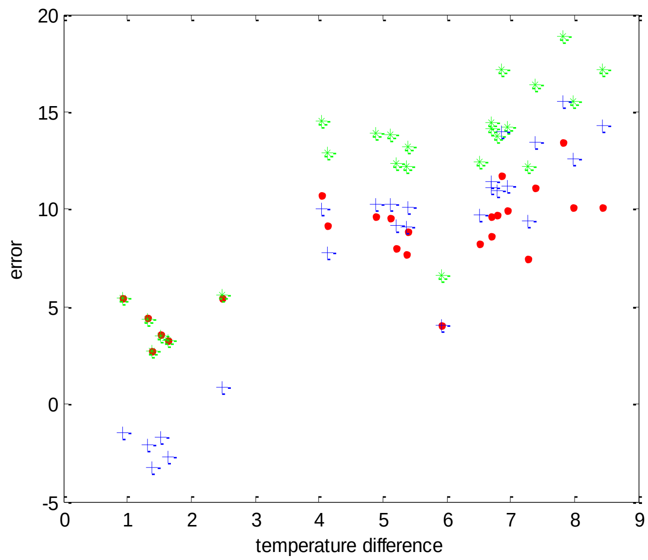

Fig.15. Scatter diagrams to show the comparison of error rate. The x-axle is conductor temperature minus ambient temperature, and the y-axle is the error rate. Red dots refer to proposed model, green dots refer to underfitting model, blue dots refer to overfitting model

Because overfitting model is the best fitting curve of one specific training set, and it is certain that it will give us perfect result if the test set is similar to the training set. In the meanwhile this property provides us an approach to identify whether a model is overfitting or not.

The approach is to test the model with several completely different test sets. If the model shows well performance in one test set, and bad performance in other ones, then it is an overfitting model.

Multi-factor model		remove second order of load current		add second order of tension	
Calculated temperature (℃)	error (%)	Calculated temperature (℃)	error (%)	Calculated temperature (℃)	error (%)
29.86	5.44	29.83	5.56	31.30	0.88
29.24	3.55	29.25	3.53	30.84	−1.70
27.92	5.43	27.92	5.41	29.96	−1.50
28.76	3.26	28.77	3.24	30.53	−2.70
28.32	4.41	28.32	4.38	30.24	−2.08
28.77	2.73	28.78	2.69	30.53	−3.22
35.60	10.07	33.44	15.54	34.59	12.62
34.03	13.42	31.89	18.87	33.22	15.50
35.97	7.46	34.13	12.20	35.21	9.41
34.45	9.96	32.82	14.21	33.98	11.18
36.10	4.01	35.13	6.58	36.10	4.03
34.88	9.62	33.02	14.42	34.18	11.42
35.10	11.10	33.00	16.42	34.18	13.41
35.34	8.65	33.22	14.13	34.39	11.12
34.46	11.76	32.34	17.18	33.60	13.95
36.72	10.09	33.82	17.19	35.02	14.26
35.31	9.68	33.73	13.75	34.80	10.99
35.78	8.27	34.15	12.45	35.21	9.73
34.26	8.85	32.62	13.23	33.80	10.09
34.48	7.72	32.82	12.18	33.98	9.07
34.25	7.98	32.62	12.36	33.80	9.19
33.07	9.61	31.50	13.88	32.84	10.22
33.28	9.58	31.73	13.80	33.03	10.28
31.55	10.72	30.20	14.54	31.79	10.05
30.84	9.14	29.55	12.92	31.30	7.77

Table.7. Temperature calculation error analysis compared with overfitting and underfitting models using same previous test set

3. Overfitting model (add a second order section of tension) with different test set

Based on above, to continue qualification, use another subset of data as a new test set to verify the model one more time.

	Ambient temperature (℃)	Load current (A)	Tension (N)	Measured conductor temperature (℃)	Multi-factor model		add second order of tension	
					Calculated temperature (℃)	error (%)	Calculated temperature (℃)	error (%)
1	29.3	222	13243	37.00	36.91	0.26	37.67	−1.79
2	29.7	196	13469	35.82	35.84	−0.03	36.50	−1.88
3	30.4	168	13008	38.30	38.16	0.35	38.95	−1.70
4	30.9	176	13420	36.08	36.12	−0.13	36.75	−1.86
5	30.7	218	12832	39.31	38.93	0.98	39.95	−1.63
6	32.5	230	12871	39.08	38.73	0.91	39.73	−1.65
7	32.6	232	13243	37.00	36.90	0.28	37.67	−1.79
8	32.4	222	13381	36.28	36.23	0.12	36.95	−1.85
9	32.3	171	13557	35.38	35.46	−0.23	36.06	−1.92
10	31.4	218	13743	34.48	34.46	0.05	35.17	−2.00
11	29.9	208	13792	34.25	34.23	0.04	34.94	−2.02
12	29.3	198	13831	34.07	34.06	0.02	34.76	−2.03
13	28.7	184	13880	33.84	33.85	−0.02	34.53	−2.05
14	28.7	154	13929	33.62	33.70	−0.23	34.31	−2.07
15	28.3	138	14018	33.22	33.32	−0.30	33.92	−2.11
16	27.9	126	14067	33.00	33.13	−0.39	33.71	−2.13
17	27.2	118	14106	32.84	32.98	−0.44	33.54	−2.15
18	26.9	112	14155	32.63	32.77	−0.44	33.33	−2.17
19	26.4	110	14243	32.26	32.35	−0.28	32.97	−2.21
20	26	108	14243	32.26	32.36	−0.31	32.97	−2.21
21	25.8	106	14243	32.26	32.37	−0.35	32.97	−2.21
22	26.2	118	14018	33.22	33.41	−0.58	33.92	−2.11
23	26.6	164	13831	34.07	34.14	−0.23	34.76	−2.03
24	27.6	220	13606	35.14	35.13	0.02	35.82	−1.94
25	28.4	240	13420	36.08	36.03	0.12	36.75	−1.86

Table.8. Temperature calculation error analysis compared with overfitting models using a different test set

It is obvious that after using the new test set, the model with adding second order section of tension remains higher error rate compared with proposed model. It verifies that the model is overfitting if adding a second order section of tension in the original model.

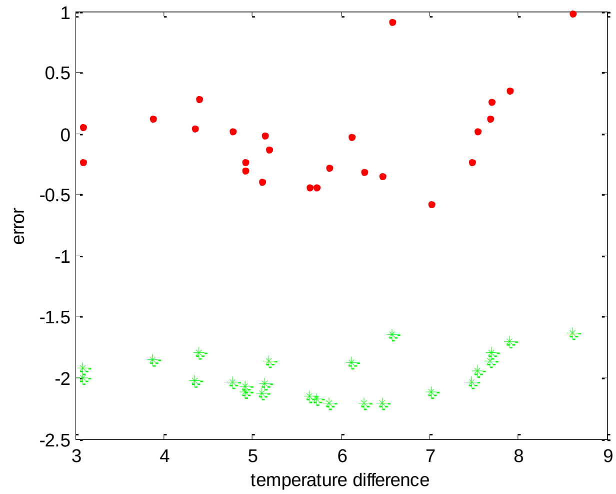

Fig.16. Scatter diagrams to show the comparison of error rate. The x-axle is conductor temperature minus ambient temperature, and the y-axle is the error rate. Red dots refer to proposed model, green dots refer to overfitting model

4. Model trained by data with noise

Next qualification is to compare the model trained by the data before removing noise points and the model trained by the clean data after removing noise points. The result satisfies our expectation. The model trained by clean data has better performance.

	Ambient temperature (℃)	Load current (A)	Tension (N)	Measured conductor temperature	Multi-factor model (clean data)		Multi-factor model (data with noise)	
					Calculated temperature (℃)	error (%)	Calculated temperature (℃)	error (%)
1	29.3	222	13243	37.00	36.91	0.26	37.16	−0.41
2	29.7	196	13469	35.82	35.84	−0.03	36.05	−0.64
3	30.4	168	13008	38.30	38.16	0.35	38.34	−0.10
4	30.9	176	13420	36.08	36.12	−0.13	36.31	−0.64
5	30.7	218	12832	39.31	38.93	0.98	39.17	0.36
6	32.5	230	12871	39.08	38.73	0.91	38.98	0.26
7	32.6	232	13243	37.00	36.90	0.28	37.16	−0.42
8	32.4	222	13381	36.28	36.23	0.12	36.48	−0.56
9	32.3	171	13557	35.38	35.46	−0.23	35.64	−0.73
10	31.4	218	13743	34.48	34.46	0.05	34.71	−0.66
11	29.9	208	13792	34.25	34.23	0.04	34.47	−0.64
12	29.3	198	13831	34.07	34.06	0.02	34.28	−0.62
13	28.7	184	13880	33.84	33.85	−0.02	34.05	−0.61
14	28.7	154	13929	33.62	33.70	−0.23	33.84	−0.67
15	28.3	138	14018	33.22	33.32	−0.30	33.44	−0.65
16	27.9	126	14067	33.00	33.13	−0.39	33.22	−0.66
17	27.2	118	14106	32.84	32.98	−0.44	33.05	−0.65
18	26.9	112	14155	32.63	32.77	−0.44	32.83	−0.61
19	26.4	110	14243	32.26	32.35	−0.28	32.40	−0.44
20	26	108	14243	32.26	32.36	−0.31	32.41	−0.46
21	25.8	106	14243	32.26	32.37	−0.35	32.41	−0.48
22	26.2	118	14018	33.22	33.41	−0.58	33.48	−0.79
23	26.6	164	13831	34.07	34.14	−0.23	34.31	−0.71
24	27.6	220	13606	35.14	35.13	0.02	35.38	−0.68
25	28.4	240	13420	36.08	36.03	0.12	36.30	−0.62

Table.9. Temperature calculation error analysis compared with noise data model

5. Model trained by all 16000 data set

Last qualification is to compare the multi-factor model trained by 380 clean data points with the general model trained by whole data set (16000 data points)

	Ambient temperature (℃)	Load current (A)	Tension (N)	Measured conductor temperature (℃)	Multi-factor model		general model	
					Calculated temperature (℃)	error (%)	Calculated temperature (℃)	error (%)
1	29. 1	259. 17	14680	31. 58	29. 86	5. 44	29. 86	5. 46
2	28. 8	196. 4	14814	30. 32	29. 24	3. 55	29. 21	3. 67
3	28. 6	196. 4	15085	29. 52	27. 92	5. 43	28. 02	5. 09
4	28. 1	225. 41	14905	29. 73	28. 76	3. 26	28. 81	3. 08
5	28. 3	220. 13	14997	29. 62	28. 32	4. 41	28. 41	4. 10
6	32. 5	230	12871	39. 08	38. 73	0. 91	37. 77	3. 36
7	32. 6	232	13243	37. 00	36. 90	0. 28	36. 13	2. 36
8	32. 4	222	13381	36. 28	36. 23	0. 12	35. 52	2. 09
9	32. 3	171	13557	35. 38	35. 46	−0. 23	34. 76	1. 75
10	31. 4	218	13743	34. 48	34. 46	0. 05	33. 92	1. 61
11	29. 9	208	13792	34. 25	34. 23	0. 04	33. 70	1. 59
12	29. 3	198	13831	34. 07	34. 06	0. 02	33. 53	1. 56
13	28. 7	184	13880	33. 84	33. 85	−0. 02	33. 33	1. 51
14	28. 7	154	13929	33. 62	33. 70	−0. 23	33. 16	1. 36
15	28. 3	138	14018	33. 22	33. 32	−0. 30	32. 81	1. 24
16	27. 9	126	14067	33. 00	33. 13	−0. 39	32. 63	1. 13
17	27. 2	118	14106	32. 84	32. 98	−0. 44	32. 49	1. 06
18	26. 9	112	14155	32. 63	32. 77	−0. 44	32. 30	1. 01
19	26. 4	110	14243	32. 26	32. 35	−0. 28	31. 92	1. 06
20	26	108	14243	32. 26	32. 36	−0. 31	31. 93	1. 03
21	25. 8	106	14243	32. 26	32. 37	−0. 35	31. 93	1. 00
22	26. 2	118	14018	33. 22	33. 41	−0. 58	32. 88	1. 03
23	26. 6	164	13831	34. 07	34. 14	−0. 23	33. 57	1. 45
24	27. 6	220	13606	35. 14	35. 13	0. 02	34. 53	1. 75
25	28. 4	240	13420	36. 08	36. 03	0. 12	35. 36	1. 97

Table.10. Temperature calculation error analysis compared with general data model trained by 16000 data sets

The model trained by all 16000 data set is a general model that fits the general condition. The comparison result proves it by showing that the general model has similar and even better error performance when the conductor temperature is not far away from

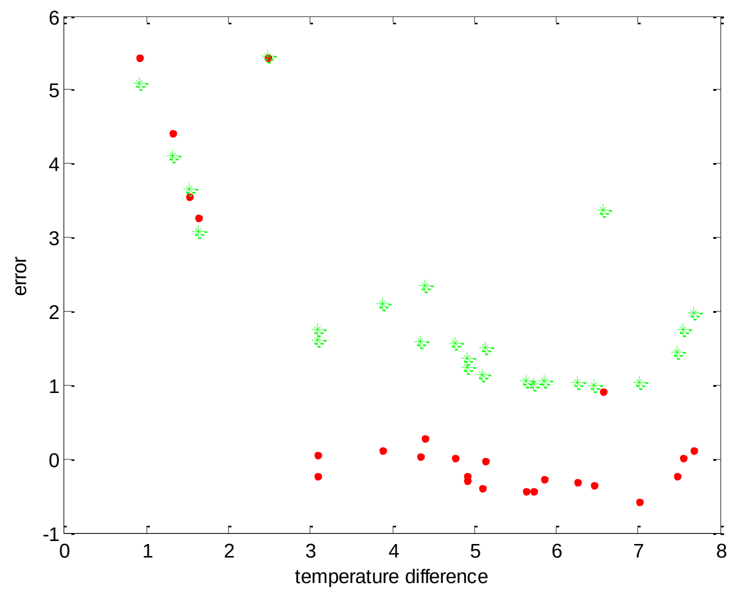

Fig.17. Scatter diagrams to show the comparison of error rate. The x-axle is conductor temperature minus ambient temperature, and the y-axle is the error rate. Red dots refer to proposed model, green dots refer to general model

the ambient temperature (the rows above the fifth row in table 10). However within the high temperature difference interval, the proposed model still shows less error rate.

To summarize the qualification section, we are able to indicate that:

1. Compared with existing SCE and tension method, the proposed model has better conductor temperature calculation result in the case that the load current is high and the conductor temperature is much higher than the ambient temperature.

2. The possible model which removes the second order section of load current is underfitting.

3. The possible model which adds the second order section of tension is overfitting.

4. The possible model trained by data with noise shows worse conductor temperature calculation performance.

5. The possible model trained by all 16000 data sets shows better conductor temperature calculation performance in general case, but worse in our particular assumption, which is the load current is high and the conductor temperature is much higher than the ambient temperature.

Based on all above, the proposed multi-factor model is able to provide more accurate conductor temperature calculation with high load current.

4. IMPLEMENTATION IN DLR

4.1 Capacity calculation

The value of conductor temperature is needed in the calculation of maximum power capacity, so we are able to implement the model proposed above in the DLR procedure. IEEE Standard 738 indicates the method to calculate the power capacity of transmission lines using the heat balance equation. Recall the heat balance equation:

$$I^2R(T_C) + Q_S = Q_R + Q_C$$

The equivalent problem of calculating maximum capacity is to identify the maximum allowable current since the voltage in power grid stays constant. Thus if we set MACT as 90℃, the maximum power capacity is:

$$I_{max} = \sqrt{\frac{Q_R + Q_C - Q_S}{R(90℃)}}$$

Q_R is the radiation heat loss (W/m), the calculation is:

$$Q_R = \pi D \varepsilon \sigma [(T_c + 273)^4 - (T_a + 273)^4]$$

Where D is the diameter of the conductor line, ε is heat dissipation coefficient, usually around 0.4 to 0.6, σ is constant 5.67×10^{-8}.

Q_S is the heat gain from solar radiation (W/m), the calculation is:

$$Q_S = \alpha q_s \sin\theta A'$$

Where α is heat absorption coefficient, usually it is equal to heat dissipation coefficient ε, around 0.4 to 0.6, q_s is solar radiation, θ is solar incident angle, A' is the projection area of conductor line. In order to make full use of sensor measurements, research [4] indicates another model to calculate Q_S using real time data:

$$Q_S = 10 \times \alpha D[25.631 \times (T_c - T_a) + 10.192v - 28.797]$$

Where v is wind speed, T_c is conductor temperature, T_a is ambient temperature.

$R(T_C)$ is the AC resistance at temperature T_C (Ω/m), the calculation is:

$$R(T_C) = \left[\frac{R(75) - R(25)}{75 - 25}\right] \times (T_C - 25) + R(25)$$

Since $R(25)$ and $R(75)$ are needed in this method, the International Electrotechnical Commission (IEC) proposed another method to calculate AC resistance:

$$R(T_C) = (1 + k)R_d$$

$$R_d = R_{20}[1 + \alpha_{20}(T_C - 20)]$$

Where R_d is DC resistance, α_{20} is constant 0.00403, k is skin effect coefficient 0.0025.

Q_c is the convection heat loss (W/m), there are great amount of methods to calculate Q_c, here we use heat transfer coefficient method. The heat transfer coefficient $h(t)$ indicates the comprehensive effect made by ambient temperature and wind conditions. The calculation is:

$$Q_c = h(t)(T_c - T_a)$$

Hence the rating calculation procedure is:

$$h(t) = \frac{I^2 R(T_C) + Q_s - Q_r}{T_c - T_a}$$

$$h_{90}(t) \approx h(t)$$

$$I_{max} = \sqrt{\frac{h_{90}(t)(90 - T_a) + Q_R - Q_S}{R(90℃)}}$$

I_{max} is the maximum capacity limit that we would like to calculate. The changing rate $\Delta h(t)/h(t)$ is only 0.4% while the conductor temperature changes from 30 to 90, thus we approximate $h_{90}(t)$ as $h(t)$.

4.2 Load profile and cost optimization

In optimization technique, a better optimal solution will be obtained if expanding the feasible set. If we consider the power generation as an optimization problem, capacity limit is one of the problem restriction, then increasing maximum capacity is a method to expand feasible set. DLR makes the power line more efficient by adding up capacity limit, thus it is able to provide lower power generation cost in the optimization problem.

Figure 18 shows the graph representation of power grid. [11] It has 5 transmission lines, 3 generators and 2 loads. Based on this representation we are able to formulize the generation optimization problem as following.

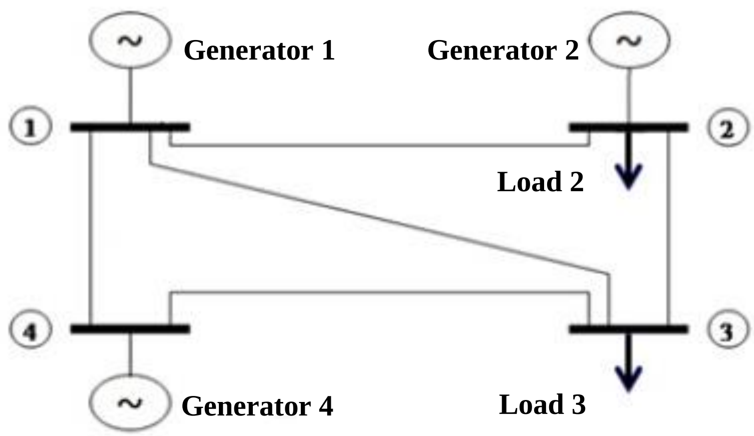

Fig.18. Power grid graph representation

$$\min_{P1g,P2g,P4g} cost(P1g) + cost(P2g) + cost(P4g)$$

$$subject\ to \qquad P1g \in (P1min, P1max)$$

$$P2g \in (P2min, P2max)$$

$$P4g \in (P4min, P4max)$$

$$P1g + P2g + P4g\ (power\ supply) = P2l + P3l\ (power\ load)$$

$$P13 \le C_{max}\ (power\ flow\ constraint)$$

The last restriction is the maximum power flow limit, which is namely capacity limit of transmission line 1-3. Our implementation method is to firstly calculate the static rating using worst conservative weather condition, and then the dynamic rating based on real time conditions. After obtaining both generation costs, compare the results and verify whether the generation cost will decrease or not.

	Ambient temperature (℃)	Wind speed (m/s)	Wind direction (degree)	Tension (N)	conductor temperature (℃)	Load current (A)	Calculated rating (A)
2009-06-19 0:00:01	30.8	2.295	129	13557	35.38	304	978.12
2009-06-19 1:00:01	30.5	1.739	298	13655	34.90	246	933.29
2009-06-19 2:00:01	30.2	1.781	13	13655	34.90	238	778.49
2009-06-19 3:00:01	29.8	1.758	216	13694	34.71	228	890.69
2009-06-19 4:00:01	29.7	1.455	87	13694	34.71	220	928.45
2009-06-19 5:00:01	29.5	1.159	81	13694	34.71	218	879.83
2009-06-19 6:00:01	29.5	1.691	180	13694	34.71	214	676.51
2009-06-19 7:00:01	29.6	1.254	298	13655	34.90	212	851.47
2009-06-19 8:00:01	30.6	1.573	60	13243	37.00	300	866.80
2009-06-19 9:00:21	32.2	2.12	163	12969	38.52	372	746.56
2009-06-19 10:00:01	32.3	2.183	185	12420	41.83	384	642.56
2009-06-19 11:00:01	33.6	2.552	237	12695	40.12	386	899.12
2009-06-19 12:00:01	34.8	1.892	205	12420	41.83	264	711.45
2009-06-19 13:00:01	36.2	2.073	299	12459	41.58	320	830.37
2009-06-19 14:00:01	35.6	1.524	179	12234	43.03	372	519.80
2009-06-19 15:00:01	35.8	2.351	298	12420	41.83	378	878.39
2009-06-19 16:00:01	36.1	1.976	266	12646	40.42	380	876.20
2009-06-19 17:00:01	35.3	3.073	238	12783	39.60	372	980.89
2009-06-19 18:00:01	34.3	2.51	358	13283	36.79	255	703.92
2009-06-19 19:00:01	33.2	3.17	179	13420	36.08	282	755.13
2009-06-19 20:00:01	31.9	3.392	182	13518	35.58	290	787.93
2009-06-19 21:00:21	31.6	2.715	95	13420	36.08	281	1053.50
2009-06-19 22:00:21	31.2	3.149	89	13518	35.58	262	1107.23
2009-06-19 23:00:01	31.1	2.116	72	13469	35.82	244	981.22

Table.11. 24-hour data and rating analysis

Assume the worst weather condition is that wind speed is 0.6 m/s, ambient temperature is 37℃, MACT is 90℃. We pick up a set of 24-hour data on June to calculate and analyze the rating. The calculated static rating is 422.75A.

From the figure it is obvious that DLR provides more capacity rather than holding static rating limit as SLR. Two peaks appear around 10am and 4pm, the capacity limit indeed has been added up at 12pm, however at 2pm the maximum allowable capacity drops instead of increasing as expectation.

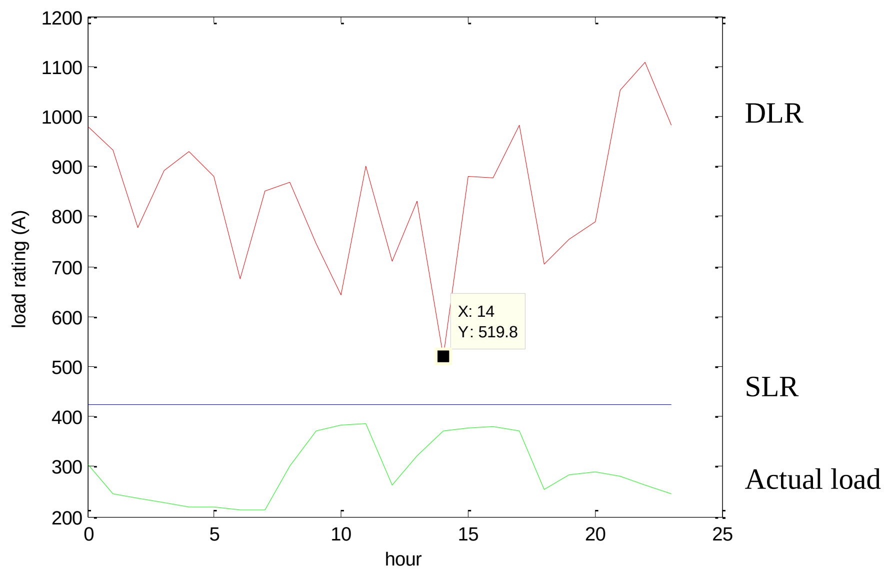

Fig.19. 24-hour load and rating profile. Two peaks appear around 10am and 4pm

We are able to find the reason in Table 11. The weather condition at 14:00 could not satisfy the assumption for better capacity, the wind speed is low, ambient temperature and conductor temperature is high. This also verifies that DLR only provides more potential available capacity without exceeding safety margin.

The generation cost function is formulized as:

$$cost(P1g) = 561 + 792P1g + 15.62P1g^2, 0.5\, p.u. \leq P1g \leq 6\, p.u.$$

$$cost(P2g) = 310 + 785P2g + 19.4P2g^2, 0.5\, p.u. \leq P1g \leq 4\, p.u.$$

$$cost(P4g) = 78 + 797P4g + 48.2P4g^2, 0.5\, p.u. \leq P1g \leq 6\, p.u.$$

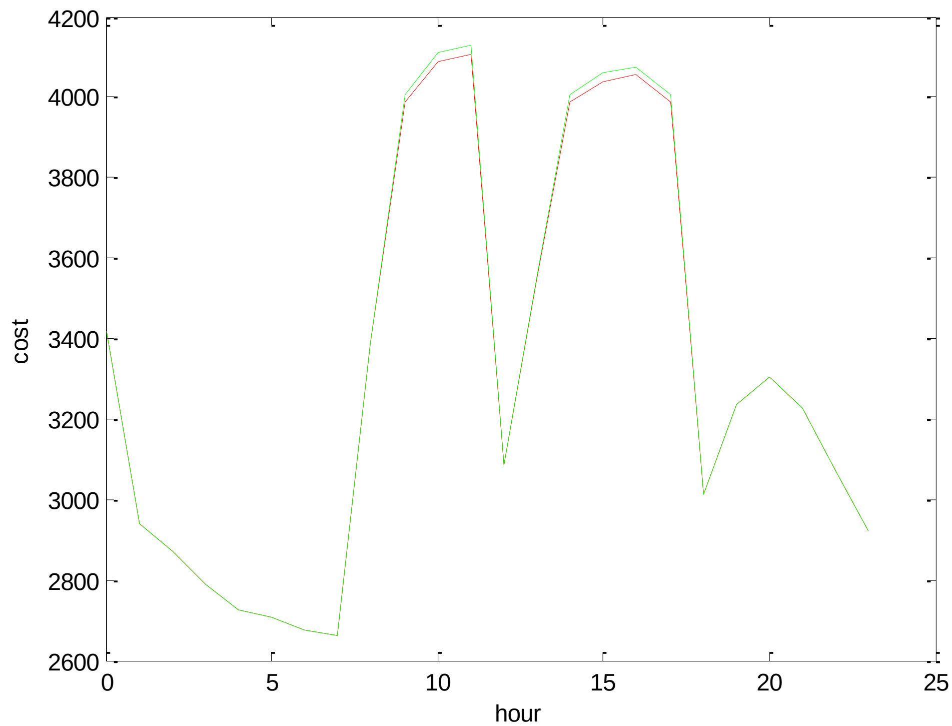

Fig.20. 24-hour generation cost between DLR and SLR. Red curve refers to cost of DLR and green curve refers to SLR. There is almost no cost difference during low power demand period, such as 0:00 to 6:00.

To normalize the problem, we define per-unit ($p.u.$) as the unit of power. The base for per-unit is $V_{base} = 220kV, I_{base} = 200A, S_{base} = 44MVA$. In Matlab we use CVX to solve this optimization problem.

From the figure we know that during two peak load period (around 10:00 and 15:00), the generation cost of DLR is lower than SLR, this satisfies the expectation that expanding the capacity restriction brings us better optimal solution. There is almost no cost difference during low power demand period, such as 0:00 to 6:00. The possible reason is that the original capacity limit could sufficiently satisfy the power economic dispatch so that increasing maximum capacity is not able to bring cost changes.

5. CONCLUSION

To ensure both the thermal limit of conductor and public safety, power operators need to set up maximum transmission capacity. Since the voltage of most power grid stays constant, the equivalent problem is to set up maximum current, this process is also called line rating. There are several factors that would affect maximum rating, such as weather and conductor thermal conditions. The existing rating method is to determine a static capacity limit based on the assumption that all the worst conditions happened at the same time. In fact the probability of this worst case is almost 0, thus the potential capacity of the transmission line has been wasted because of the conservative assumption. In order to obtain more potential available capacity without exceeding safety margin, dynamic line rating (DLR) is proposed to determine the capacity based on real time conditions, thus usually the dynamic capacity limit is much higher than the static line rating.

Conductor temperature is one of the most significant factors in DLR processing. However real time measurements from sensors are point data which are inaccurate, and it improves great amount of cost to implement sensors on every line. Thus this thesis proposes a model to calculate conductor temperature correlated with wind speed, wind direction, load current and tension. These parameters are chosen based on data pre-processing, correlation analysis and feature selection. The final conductor temperature calculation model is obtained by parameter estimation, the load current is in quadratic form and the rest of parameters have linear relations. In the evaluation section we qualify the proposed model with other possible and existing models, the result shows that our model has less error and better calculation performance in the assumption that the load current is high, which means the ambient temperature is much lower than the conductor temperature.

The value of conductor temperature is needed in capacity calculation, thus we implement the proposed multi-factor model to calculate the conductor temperature in order to obtain the dynamic line rating. The result of load profile shows that DLR is able to provide more potential available capacity, especially during high load period. However sometimes the DLR is close to SLR since the ambient conditions could not support such high load current. After applying DLR in generation cost optimization problem, the result is that during high power demand period, the operators are able to obtain better optimal minimum cost due to the increase of the maximum allowable power flow capacity. To summarize, DLR enhances the efficiency of the transmission, and brings more economic power dispatch.

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