Risk informed design modification of dynamic thermal rating system

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Abstract: Future grids will be operated much closer to their security limits due to the ever increasing power demands and the restrictions on land and space to build more transmission corridors. As one of the many smart grid technologies, the dynamic thermal rating (DTR) system of transmission lines offers the solution to increase line current capacity without infringing the conductor’s maximum operating temperature. Hence, it has emerged as a popular solution for the aforementioned challenges. Owing to that, there is a strong interest of this technology. For this reason, this study presents a systematic framework for assessing the reliability and the risk of a DTR system. The research was carried out in two parts and is able to optimise the risk and the reliability (cost) of the DTR system. In addition, a weather estimation model is proposed to estimate the weather data when the DTR sensors are not functional. This is contrary to the existing literature which suggests that conservative assumptions be made. The results show that the proposed weather estimation model avoids overestimation of the DTR system risk.

Nomenclature

- $Q_c$: convection heat loss at weather region $i$ (W/m)
- $Q_r$: radiated heat loss at weather region $i$ (W/m)
- $Q_s$: solar heat gain at weather region $i$ (W/m)
- $T_{at}$: conductor temperature at weather region $i$ (°C)
- $T_{at}$: ambient temperature at weather region $i$ (°C)
- $V_{w}$: wind speed at weather region $i$ (m/s)
- $\phi$: wind angle at weather region $i$ (degree)
- $\beta$: solar angle at weather region $i$ (degree)
- $I$: transmission line ampacity ($A$)
- $R_{AC}$: conductor AC resistance at $T_{ac}$ ($\Omega/m$)
- $P_{DTR}$: up-state probability of DTR system
- $RS$: remaining strength of conductor (%) (lbs)
- $RAI$: remaining strength of aluminium strands (%) (lbs)
- $STR_A$: initial strength of aluminium strands (lbs)
- $STR_ST$: initial strength of steel core (lbs)
- $STR_T$: initial strength of conductor (lbs)
- $t$: elapsed time (hour)
- $\alpha_L$: number of aluminium/steel strand aluminium/steel strand diameter (m)
- $\alpha_L$: rated strength of aluminium/steel strand (lbs)
- $LC_P$: loss of load probability due to DTR system failure
- $EENS$: annual energy not served
- $Risk_{DTR}$: total risk of network with DTR system
- $Risk_{NoDTR}$: total risk of network without DTR system
- $Impacts_{load}$: impact of loadloss
- $Impacts_{anneal}$: impact of line annealing
- $Cost_{loadloss}$: cost of loadloss
- $Cost_{anneal}$: cost of line annealing
- $LC$: load curtailment at bus $i$ (MW)
- $LB$: load bus
- $PG$: generated power at bus $i$ (MW)
- $P_{min}$: minimum generated power at bus $i$ (MW)
- $P_{max}$: maximum generated power at bus $i$ (MW)
- $G$: generator bus
- $PD$: power demand at bus $i$ (MW)
- $\theta$: bus voltage angle
- $Y_{x}$: reactance of line connecting bus $i$ to bus $j$
- $\forall i \in LB$: set of all load buses
- $\forall i \in GB$: set of all generator buses
- $\forall i \in B$: set of all buses
- $\forall i \in B$: set of all connected buses to bus $i$

1. Introduction

The static thermal rating (STR) of an overhead line is a rating that has been determined using the worst set of ambient weather conditions that can be expected during a particular season [1-3]. This effectively yield a seasonal thermal rating (SSTR), typically higher in winter months [1]. There are two disadvantages to these rating methods. First, they underestimate the line rating for the majority of time when wind speeds are higher or temperatures are lower than the assumed conditions. Second, a low probability, the actual weather conditions might turn out worst than the conservative assumptions. Should this be the case there is a risk of overloading the lines. The dynamic thermal rating (DTR) uses real-time meteorological data to compute transmission line ratings [3-6]. As it uses live weather conditions, it eliminates some of the problems that result from the use of the STR and SSTR techniques [7]. The usage of DTR is also supported by works that have clearly demonstrated the actual weather conditions are most of the time more desirable than the conservative assumptions [8-10]. It has been shown that a DTR system is able to usually increase transmission line capacity by 10-30% with improvement of 50% being possible in windy areas [7, 11]. The installation cost of a DTR system is cheap when compared to major physical line upgrades and uses sensors that are commonplace [12-14]. A DTR system therefore offers an ability to delay new line investments, increase electrical transmission reliability and offer increased options in faulted network conditions.

The formation of IEEE Standard 738, for the calculation of overhead line steady-state and dynamic heat balance based on the meteorological conditions, is a testament to the importance of DTR technology [15]. Hence, several studies related to DTR have been undertaken. One study showed that the application of the DTR system for a power network enables evaluation of the conductor ageing process for better transmission line management
2 Overview of DTR system integrity assessment framework

An overview of the proposed methodology is given in Fig. 1. The process is divided into two parts. The first part of the methodology conducts a reliability assessment of DTR system and attempts to explore as many design options as possible. The design options are referred to as various non-functional redundancies. In the second part, the risk assessments of DTR system are conducted. The risk of DTR system is evaluated by examining its impact on the IEEE 24-bus reliability test network (RTN). Owing to the many combinations of DTR system and power network component statuses, the state space is explored using the Monte Carlo (MC) method. If any particular DTR sensors are not functional, the missing weather data is estimated using the multiple-linear regression (MLR) weather estimation model. Subsequently, the line rating values are evaluated based on the IEEE Standard 738. On the contrary, the DTR sensors are normal and the line ratings are determined without the need of weather estimation. To determine the impact of DTR system on the RTN, DC-OPF was performed. During which, the expected energy not served (ENS) and line annealing properties are recorded and they represent the average risk of DTR system. Part 2 is repeated until all the DTR system designs have been assessed. Finally, the most suitable design is suggested (or selected) based on the optimisation among the risk values and the reliabilities of all the designs.

3 Assessing DTR system reliability

3.1 Reliability model

A transmission line that is spread across n weather regions can be assumed to require n monitoring stations. In any weather region, it is assumed that the weather conditions remain constant. Air temperature is fairly constant over large areas and can generally be given by local meteorological data centres. The solar radiation angle and level have relatively small impact in the calculation of line ratings and the assumptions given by the IEEE Standard 738 can therefore be used [21]. Hence, in our DTR system model, each station has only wind speed and wind angle sensors. Note that in the initial design each DTR sensor has a redundancy. These sensors can either be functional or non-functional. In the functional state, the sensor is operating normally and delivers an accurate measurement. In the non-functional state, the sensor is either damaged or is not operating. During mal-operation, the measurements are inaccurate. The reliability of the whole DTR system is determined using the reliability of the sensors. This is done through the use of the event tree analysis (ETA) as shown in Fig. 2 due to its fast computation and versatility [22]. Initially, the statuses of all the respective sensors are consolidated using the majority vote system. It works by validating the sensor values through comparisons with its redundant measurement values. The voting system is used as it has proven to be effective in various fields of nuclear and power engineering where sensing activities are required [23–27]. This process produces the statuses (up or down) of the wind speed and wind angle sensing abilities. Both of the sensing abilities need to be in the up-state in order to yield a normal operating monitoring...
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relationship between variables (weather data) that are related in a non-deterministic way by using the least-squared estimation (LSE) technique [34]. Generally, it takes on the form as shown in (7)

\[ y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_p x_p \]  

(7)

Relating the equation back to this paper, \( y \) are the missing wind speed/angle values of a particular weather region known as the response region and \( (x_1, x_2, \ldots, x_p) \) are the available wind speed/angle data in a region known as the regressor regions and are used to predict \( y \). All the regressor regions were selected based on a high correlation of weather data with the response region. This selection process is illustrated in the results section. Finally, \( \beta \) is the coefficient of regression that is obtained by solving the simplified parallel LSE equations as shown in (7a) [see (7a)]

\[ \text{The value } k \text{ is the size of the sampled weather data.} \]

### 4.4 Risk evaluation model

Risk is defined as the product between the impact of an event and the probability of that event to occur [31]. The impacts that are considered in this paper are loss of load and line annealing. Loss of load is induced by the failure of DTR system and during low DTR ratings under high loading conditions. Line annealing is due to line over-rating. The total risk of the DTR system is given by both events and is stated as in (8)

\[ \text{Risk}_{\text{DTR}} = \text{LOL}_{\text{DTR}} \times \text{Impact}_{\text{LOL}} + \text{AP} \times \text{Impact}_{\text{AP}} \]  

(8)

AP is the probability of a line to experience annealing.

The impact of loadloss is the product between the EENS and the cost per megawatt hour (MWh) stated in (8a)

\[ \text{Impact}_{\text{LOL}} = \text{EENS} \times \text{Cost}_{\text{LOL}} \]  

(8a)

The impact of line annealing is the product between the loss of tensile strength (LoTS) due to annealing and the cost of line annealing, stated in (8b)

\[ \text{Impact}_{\text{AP}} = \text{LoTS} \times \text{Cost}_{\text{AP}} \]  

(8b)

LoTS is expressed as a percentage of its initial strength and is determined using the Harvey model stated as in (9) [35]

\[ \text{LoTS} = 100 - \text{RS} \]  

(9)

\[ \sum_{i=1}^{k} y_i = \beta_0 + \beta_1 \sum_{i=1}^{k} x_{i1} + \beta_2 \sum_{i=1}^{k} x_{i2} + \cdots + \beta_p \sum_{i=1}^{k} x_{ip} \]  

\[ \sum_{i=1}^{k} y_{i1} = \beta_0 \sum_{i=1}^{k} x_{i1} + \beta_1 \sum_{i=1}^{k} x_{i2} + \cdots + \beta_{p-1} \sum_{i=1}^{k} x_{ip} \]  

\[ \vdots \]  

\[ \sum_{i=1}^{k} y_{ip} = \beta_0 \sum_{i=1}^{k} x_{i1} + \beta_1 \sum_{i=1}^{k} x_{i2} + \cdots + \beta_{p-1} \sum_{i=1}^{k} x_{ip} \]  

(7a)

\[ \text{RS AI} = \left\{ \begin{array}{ll}
-0.2475 + 134e^{-0.000125y_j - 0.000000133y_j^2} & \text{if } (-0.2475 + 134) < 100, \\
100, & \text{otherwise}
\end{array} \right. \]  

(8b)

**Fig. 3** Percentage improvement in system EENS

\[ \text{where} \]

\[ \text{RS} = \text{RS AI} \times \frac{\text{STR AL}}{\text{STR E}} + 100 \times \frac{\text{STR ST}}{\text{STR E}} \times 1.09 \]  

(9a)

\[ \text{(see (9b))} \]

\[ \text{STR} = \text{STR AL} + \text{STR ST} = \frac{1}{4} \left( \sigma_{AL} \cdot d_{AL} + \sigma_{ST} \cdot d_{ST} - S_{AL} \right) \]  

(9c)

### 5 Numerical results and discussion

#### 5.1 Description of the test system

The reliability data and the number of DTR sensors in a base case DTR system design are shown in Table 1. It shows that the initial design has two wind speeds and two wind angle sensors. The risk of the DTR system was assessed in the IEEE 24-bus RTN. The line between bus 7 and bus 8 of the RTN was selected for the DTR system application as it displayed the highest EENS improvement after uprating as shown in Fig. 3. This line is also known as the DTR line. Furthermore, 20 years hourly historical weather data of wind speed, wind angle and air temperature were obtained from the British Atmospheric Data Centre website [36]. The weather data were sampled from 25 weather regions spaced ~5 miles apart and they are assumed to spread along the DTR line. Hence, the proposed DTR model has 25 monitoring stations. Owing to the high reliability of the RTN, the generation sources and loading levels were increased five-fold in order to highlight the effect of having various designs of the DTR system.

Moreover, an aluminium conductor steel reinforced (ACSR) Lapwinding conductor was assumed for the DTR line and it has diameter of 28.1 mm. The line was also assumed to be a straight
Table 2  RRW analysis on monitoring station and DTR system reliability

<table>
<thead>
<tr>
<th>Cases</th>
<th>Monitoring station</th>
<th>DTR system</th>
</tr>
</thead>
<tbody>
<tr>
<td>base case</td>
<td>0.9572</td>
<td>0.9352</td>
</tr>
<tr>
<td>perfect wind speed sensors</td>
<td>0.9791 (+2.2%)</td>
<td>0.9790 (+2.1%)</td>
</tr>
<tr>
<td>perfect wind angle sensors</td>
<td>0.9794 (+2.5%)</td>
<td>0.9796 (+2.3%)</td>
</tr>
</tbody>
</table>

5.2 Reliability assessment of DTR system

Using the proposed reliability model, the reliability of the monitoring station in each region and the DTR system were calculated as 0.9572 and 0.3352, respectively. To explore other designs, RRW and WRM were performed to determine the critical components of the DTR system. The results for RRW and WRM are shown in Table 2 and Fig. 4, respectively. In Table 2, the results show that wind speed and wind angle sensors are equally critical in the reliability of the DTR system. In Fig. 4, the reliability of the monitoring station and the DTR system responds in the same manner when the reliability of the wind speed and wind angle sensors was varied individually. The variation was made by multiplying the failure rate of the sensors according to the scale that is shown in this figure. It was observed that the results from Table 2 and Fig. 4 agree with each other and all design works should be performed on both types of sensors. Consequently, the three following designs were considered for wind speed and wind angle sensors:

Design (A): Add redundancy.
Design (B): Reduce failure rates on top of option A.
Design (C): Reduce failure rates and shorten repair times on top of option A.

The effects of exploring Design A are shown in Fig. 5. It shows that the reliability of the monitoring station increased by 4.4% from 0.9572 to 0.9993 when the number of sensors was increased from 2 to 3. However, the DTR system shows an improvement in its reliability from 0.3352 to 0.9826. Redundancy enhancements achieved through the use of more than three sensors were insignificant due to saturation of reliabilities as they approached toward the perfect state. Beyond this point, an even number of sensors provided lower reliability than odd number of sensors. The reason is because the majority vote system requires an even number configuration to have more functional sensors than odd number configuration in order to have normal sensing abilities. For example, a three- and four-sensor design requires 67 and 75% of functional sensors, respectively, in order to yield a normal sensing ability. This shows that the number of redundancy is not always directly proportional to the DTR system reliability. From the perspective of a DTR system planner, cost can be saved by not investing in the wrong number of DTR sensors. Designs B and C were explored and their responses are shown in Fig. 6. During the analyses, failure and repair rates of wind speed and wind angle sensors were scaled with factors of 1–0.02. As expected, Design C is superior to Design B.

5.3 Robustness of weather estimation model

In this section, the robustness of the proposed MLR model is demonstrated. First, the set-up of the model is described. The correlations of wind speed and wind angle among the 25 regions were determined and it was found that wind speed generally has higher correlation among the regions than wind angle. Hence, the correlation levels of 95 and 90% were selected to qualify a candidate region as a wind speed and wind angle regressor region, respectively. The qualified pairs of regressor and response regions are shown in Table 3. Although a higher correlation level was needed to qualify as wind speed regressor region, the member in this group is significantly more than that of wind angle. In each region, weather data from at least one regressor region is needed to estimate the missing wind speed or wind angle. If all sensors in all the regressor regions are unavailable, the weather data cannot be estimated and STR would be assumed.
Table 3 Wind speed, wind angle regressor and response region pairs

<table>
<thead>
<tr>
<th>Regions</th>
<th>Wind speed regressor regions</th>
<th>Wind angle regressor regions</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>2.3, 4.5, 6.6</td>
<td>2.3</td>
</tr>
<tr>
<td>2</td>
<td>1.2, 4.5, 6.6</td>
<td>1.3</td>
</tr>
<tr>
<td>3</td>
<td>1.2, 4.5, 6.7</td>
<td>1.2, 5.6</td>
</tr>
<tr>
<td>4</td>
<td>1.2, 3.9, 6.5</td>
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<tr>
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<td>6.8, 9.9</td>
</tr>
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<td>6.5, 8.9</td>
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<tr>
<td>9</td>
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<td>6.7, 9.7</td>
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<td>5.6, 8, 10.12, 15.16</td>
<td>9.1, 12.12</td>
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<td>9.1, 12.12</td>
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<td>19</td>
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<td>19.21, 22.25</td>
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<tr>
<td>25</td>
<td>20, 21, 22, 23, 24</td>
<td>23, 24</td>
</tr>
</tbody>
</table>

There are two types of regressions in the proposed MLR weather estimation model – complete and incomplete. The former is defined as the case in which weather data in all the regressor regions are available. Incomplete regression is the case where weather data from at least one but not all the regression regions are missing (sensor in non-functional state). Weather estimations of the following three scenarios were investigated for their accuracy in all regions:

Scenario (1): Wind speed estimation.
Scenario (2): Wind angle estimation.
Scenario (3): Wind speed and wind angle estimations.

To ensure that the results in each scenario are fully representative of the MLR model performance, all the combinations of cases in each scenario were exhausted. For complete regressions, there are 25 possible combinations of cases in each scenario. Incomplete regressions have 24,206, 398 and 443,492 numbers of cases in each scenario, respectively. The estimated weather data were used to calculate the estimated line ratings and the differences from actual line rating values (calculated from actual weather data) were determined. The findings of all cases of the same scenario and regression type were consolidated. The results of complete and incomplete regressions are shown as the boxplot in Fig. 7a and b, respectively.

Fig. 7a shows that complete regression of Scenario 1 yields negligible percentage differences between the estimated and actual line ratings. Complete regression of Scenario 2 produces a slightly higher percentage difference due to the lower correlation of wind angle among the regions. The percentage differences are between −0.8 and 0.6%. A positive value indicates that the estimated line ratings are higher than the real ratings and vice versa. Owing to the negligible effects of Scenario 1, the results of Scenario 2 and 3 are similar. As transmission assets are expensive and sensitive toward thermal overload, the line ratings estimated in Scenarios 2 and 3 should be reduced by at least 6% to avoid over-rating. In this paper, a slightly conservative value of 1% was adopted. Line ratings estimated from Scenario 1 do not require reduction due to negligible differences from real line ratings.

Similarly, Figs. 7b shows that the percentage differences in the line ratings are higher in Scenario 2 than in Scenario 1. Hence, estimation errors of wind speed have only little influence in Scenario 3. As expected, incomplete regression yields a higher percentage difference than complete regression across all the scenarios.

For the same security reasons as mentioned previously, estimated line ratings obtained through incomplete regression in Scenarios 1, 2 and 3 should be reduced by at least 0.6%, 4.5% and 5.32%, respectively. In this paper, we adopted the slightly more conservative values of 1%, 3% and 6%, respectively.

Both of the results demonstrated that accurate MLR weather estimation models were constructed by considering only the strong correlations of wind speed and wind angle among the weather

![Boxplot of percentage differences between estimated and actual line ratings for scenarios 1, 2 and 3](image_url)

Table 4 Average VOLL for various conditions

<table>
<thead>
<tr>
<th>Average interruption cost of 1 h, £/MWh</th>
<th>Winter</th>
<th>Summer</th>
</tr>
</thead>
<tbody>
<tr>
<td>Peak (3-9 pm)</td>
<td>6495.09</td>
<td>6268.81</td>
</tr>
<tr>
<td>Off peak</td>
<td>6252.70</td>
<td>5727.02</td>
</tr>
<tr>
<td>Weekends</td>
<td>5624.43</td>
<td>5178.49</td>
</tr>
</tbody>
</table>

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5.4 Risk assessment of DTR system

All the DTR system designs suggested in Section 6.2 were subjected to risk assessment. For comparison, their risk values were determined with and without the use of the proposed MLR model. Moreover, the risk of a base case DTR system and a DTR system with its sensor reliability reduced by ten-fold (indicated as less DTR) were examined as well.

During the risk assessment, the average values of loadloss (Vol.Lt) as shown in Table 4 were used. These values were taken from the report of the Royal Academy of Engineering for the UK Prime Minister’s Council of Science and Technology [37]. For the cost of annealing, conductor replacement is considered necessary for every 100% of conductor annealing. Using the data sheet published by the Southwire company [38], an ACSR Lapwedge conductor, the conductor of choice for our DTR line, is weighted at 5972.7 lbs/km and is priced at $1.31/lb. Given a 75 km DTR line as stated in the RTN, the total weight of the conductor was calculated as 440 lbs (rounded value) and the price of replacing the conductor was valued at 797,060/100% annealing.

Finally, by using (8) and (9), the risks are calculated and are shown in Table 5. In all the scenarios, the risks of loadloss without weather estimation are higher than when weather is estimated. In the former case, when the DTR sensors are not functional, the line ratings revert to STR and waste huge current carrying capacity that lead to more loadloss than the latter case. Moreover, actual line ratings are sometimes lower than the STR and lead to more cases of conductor overrating and higher risk of annealing. Overall, the results clearly indicate that the proposed MLR model avoids overestimating the DTR system risk.

Owing to the accuracy of the MLR weather estimation model, its avoiding line annealing in all the scenarios except for the ‘less DTR’ scenario. Line annealing persists in this scenario as its sensors have very low reliability and are prone to failure. In some cases, weather cannot be estimated due to the loss of all regressor sensors subsequently forcing the STR to be accepted. Hence, the risk of annealing is not due to the inaccuracy of the MLR model. Rather, it is the result of unreliable DTR sensors.

Finally, optimisation between the reliability and the risk of all the DTR system designs was performed and the results are as shown in Fig. 8. Note that reliability is expressed in the form of a ratio by comparing other designs with the ‘base case’ DTR system, which also represents the scale of DTR system costs. Moreover, two types of risk values are displayed in this figure – one for the case with MLR weather estimation and the other without. Moreover, shown in this figure are the intersections between the reliability line and risk lines that indicate the optimum DTR system reliability. The results show that the optimum DTR system reliability is lower when it is equipped with the MLR weather estimation function. These results concur with Table 5 that the proposed weather estimation model avoids overestimating the risk of the DTR system. In other words, given the same load level, the use of an MLR weather estimation function can accommodate a less reliable DTR system while lowering its risk impact. Note that the optimum DTR system designs have reliability values that are not exactly the same as those that are presented in Fig. 8 due to the smoothing of the lines during plotting. Hence, the next available choice was suggested as the optimum design. In the case where MLR weather estimation was used, the ‘base case’ design was found to be the optimum whereas ‘Design A’ is the optimum for the case without MLR weather estimation.

6 Conclusions

One of the main concerns of DTR system deployment is to ensure it operates properly at all times with minimal risk to the power network. To address this, this paper presented a framework that assesses the integrity (reliability and risk) of a DTR system. As a bottom line, three contributions are concluded from the presented works.

First, a framework that assesses the reliability and risk of DTR system was proposed. Part 1 of the framework explores various DTR system designs and evaluates their reliabilities. In Part 2, the risk values of all the designs are assessed. Then, the optimum DTR system design is selected based on the optimisation between the risk and reliability values.

Second, this paper proposed an MLR weather estimation model, as reverting to STR during DTR sensor failures was found to overestimate the risks of the DTR system. The weather estimation model was proven to be accurate and can estimate line ratings close to the actual values. This allows more loads to be served and reduces line overloading occurrence. It is also robust against the loss of multiple weather data. As a result of this model, a less reliable DTR system can be used while lowering its risk to the power network.

Finally, the analyses of DTR system reliability pointed out that having more DTR sensor redundancies is not necessarily better for the reliability of the DTR system. In particular, when the majority

<table>
<thead>
<tr>
<th>Scenarios</th>
<th>With weather estimation model</th>
<th>Without weather estimation model</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Risk of loadloss, GE/year</td>
<td>Risk of annealing, kW/year</td>
</tr>
<tr>
<td>base case</td>
<td>1.9605</td>
<td>0</td>
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<td>less DTR</td>
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<td>1.0261</td>
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Table 5: Risk of various DTR system design options

Fig. 8 Reliability and risk curve of DTR system with and without MLR weather estimation function

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