Temperature Sensitive Load Modelling for Dynamic Thermal Ratings in Distribution Network Overhead Lines

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***Abstract*—Real-Time and Dynamic Thermal Ratings have been discussed in the literature as potential methods to increase network headroom, typically to allow the connection of distributed generators, mitigating the need for network reinforcement. The work presented in this paper considers the effectiveness of these techniques in terms of possible consumer connections as opposed to generation. A generalized temperature sensitive load modelling procedure is presented in order to derive representative demand group time-series profiles, and as such model the possible connections across the entire seasonal cycle. The procedure has been tested against real-world data taken from a rural 20kV feeder in the North of England detailing the period October 2013 – October 2014. This work was carried out as part of the LCNF funded Customer-Led Network Revolution (CLNR) smart grid project.**

***Keywords*—Power systems, Power system management, Smart grids, Transmission Lines**

I. Introduction

The current carrying capacity of power system components such as such as Overhead Lines (OHLs), Power Transformers (PTRs) and Underground Cables (UGCs) can be determined as a function of the cooling and heating elements of each component's heat balance equation [1]. For the purposes of rating these components for their use in the power system, typically a set of worst-case meteorological conditions are utilized [2, 3], in combination with a particular temperature limit. In the case of OHLs, this temperature limit is referred to as the Circuit Rated Temperature (CRT). If this temperature is exceeded for a given period of time, the line will sag to a point where the minimum required ground clearance is no longer maintained. The technique of Real-Time and Dynamic Thermal ratings (RTTRs and DTRs respectively) aims to exploit the difference between these worst-case conditions and those which are observed in real-time, whilst ensuring that the same risk of exceeding the CRT is maintained in order to preserve the required level of ground clearance [4]. Since the chosen worst-case conditions are often highly pessimistic, often

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increases in component capacities can be observed [5-9], providing additional network headroom. In addition to contributing to the low carbon transition, unlocking this latent headroom has a number of additional advantages. The utilization of pre-existing network equipment is increased, and as such this can minimize the need for high-cost capital reinforcement. The solution can be deployed in an area to defer a reinforcement, planned for some point in the future, to mitigate either financial or regulatory pressures. A significant factor in deploying this technique is that it can be retrofitted to existing networks rapidly. This allows for deployment as and when network congestion or constraints arise. The system can be installed as a potential problem emerges and either validate the necessity for reinforcement or be redeployed elsewhere if the issue does not develop in the manner which was previously estimated. It is within this final domain which this paper aims to contribute.

As has been documented at length, the requirement for increasing network capacity largely comes as a result of the 'transition pathways' to an 80% reduction in UK CO_2 emissions [10]. The electrification of heat and transport, the increased penetration of renewable generation sources and the decommissioning of existing generation plant combine to provide significant challenges to the operation and planning of these networks. Whilst the increased growth in large scale renewable generation is somewhat predictable, due to finite fossil fuel resources, the accommodation of both generation and LCTs on the demand side comes however, with significant uncertainty as to the magnitude of the required network headroom. The Future Energy Scenarios (FES) published by National Grid [11], show considerable variability in UK energy usage from the present day to 2035 and beyond, dependent upon the particular 'transition path' followed by the UK as a whole.

Whilst RTTRs and DTRs have previously been demonstrated as a means for facilitating new renewable generation connections typically concerning OHLs [12-15], relatively few have considered the potential to provide additional headroom to the demand-side [7, 16]. Those who have considered the demand-side often use randomized loading profiles [7], load duration curves [16], or loads based on a probability of overloading for modelling purposes [17]. This paper provides archival value by considering the mutual correlation between the effect of meteorological conditions on the capacity of the asset and the effect of these conditions on the electrical demand through the use of a time-series profile based approach.

Both the RTTR and DTR represent different formulations of the heat balance equation of the particular component under analysis. The RTTR presents a closed-form solution which determines the maximum possible loading capacity of a component at a particular point in time such that the OHL would reach its CRT after application of the load. The DTR represents the inverse case whereby OHL loading is provided as a step-change input to the equations and utilizes a first-order differential equation to determine the resultant operating temperature of the asset which may be above or below the CRT.

In previous literature concerning generation connections, typically the RTTR formulation of the heat balance equation has been utilized. In this paper we will use the DTR formulation for the following reasons. Whilst the RTTR gives information as to the maximum possible loading at a particular point in time these ratings do not provide useful information as to the possible number of consumer connections since at each time step a new RTTR is calculated which could be significantly different from the previous rating. Thus could result in significant fluctuations in the potential customer connections over time. By utilizing the DTR formulation, after an estimate of the new circuit loading as a result of the new consumer connections is made, this can be provided as an input to the model and the resultant circuit temperature derived. Where the derived circuit temperatures are found to exceed the CRT, there are two possible options. Firstly the customer numbers, or the mix of customers which have been introduced could be altered, or secondly, network ancillary services such as the charging / discharging of Electrical Energy Storage devices (EES), or Demand Side Response (DSR) could be used, in order to remove the CRT violation by reducing the overall circuit loading. By maintaining the CRT at, or below the presently used value, the risk of conductor ground clearance violations remains the same, even though the circuit loading itself is likely to be far greater than under current network operation.

The use of the DTR method also means that the loading results can be directly compared against those from the currently used and somewhat similar planning standard which governs OHLs in the UK, Engineering Recommendation P27 [2]. The structure of this paper is as follows.

Section II outlines the rationale for the steps taken in this evaluation, including a description of the DTR formulation of the OHLs heat balance equation and the requirements of the load modelling approach to provide inputs to the DTR.

In order to provide generalized demand inputs to the DTR model Section III firstly presents a clustering study of customer types within real-network electrical demand groups. The result of this study is a set of generic customer mixes representative of typical distribution network demand connections. This section also presents the temperature sensitive, MV feeder load synthesis method which provide inputs to the DTR OHL model.

As discussed previously, there is the potential to increase the natural number of consumer connections through the use of network ancillary services. Section IV presents a zonal method, used to categorize the nature of these services.

Section V presents the rationale for selection of the MV case study location. Section VI details the resultant number of possible consumer connections for each of the representative demand groups and outlines the expected number of CRT violations through the use of the current seasonal ratings and the DTR, in addition to the expected energy not served in each of the scenarios. These sections are followed by a description of potential future work and the overall conclusions of the paper.

II. Background

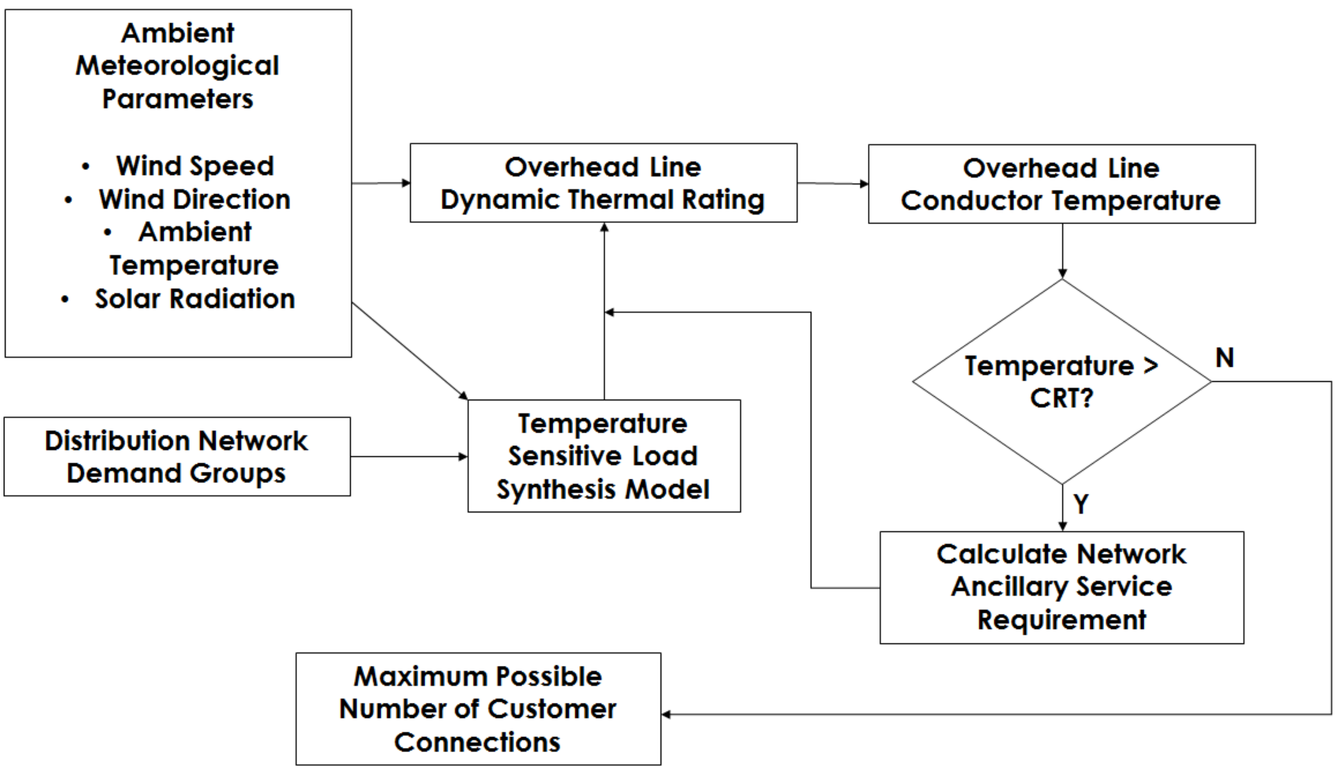

Figure 1 – Block diagram of the information and model input/output flows presented in this paper

Figure 1 shows a flow chart of the main components presented within this research. Ambient meteorological parameters provide inputs to both the OHL DTR and the temperature sensitive load modelling. The clustering algorithm provides the consumer mixtures for each of the distribution network demand groups which are then modelled and provide inputs to the DTR model. The output from the DTR is the conductor's temperature as a result of load model inputs and these conductor temperatures are then compared against the relevant CRT. Where the CRT is violated due to the combination of load modelling and ambient parameters, the necessary network ancillary services in order to remove the violation are derived.

A. Real-Time and Dynamic Thermal Ratings

As discussed previously, the current carrying capacities of OHLs are affected by the meteorological conditions surrounding them. The DTR formulation of the heat balance equation of the OHL is shown in (1) and follows the dynamic formulation of the CIGRE OHL model found in [1].

$$I^2R = Q_c + Q_r - Q_s + mC_p \cdot \frac{dT}{dt} \tag{1}$$

Where, I is the line current, R is the conductor AC resistance, and Q_c , Q_r and Q_s are the convective cooling, radiative cooling and heating due to solar radiation respectively. The $mC_p \cdot \frac{dT}{dt}$ term refers to the thermal response of the conductor over time, m refers to mass of the conductor and C_p the specific heat.

This equation is then simply rearranged in order to determine the dT value as a result of a step change in input current. Values of line current will be derived using the method presented within this paper and provide the inputs to rearranged implementation of the DTR model shown in (1). The cumulative values of dT are then monitored over time in order to observe any potential violations of the CRT. Where a CRT violation occurs as a result of the conductor loading, this can be reduced based on a step decrease, and the resultant change in conductor temperature derived. This process can be iteratively performed until the conductor temperature returns to below the CRT value. By carrying out this process, the network ancillary service requirement to ensure non-violation of the CRT can be determined.

B. Electrical Demand Modelling

In order to credibly evaluate the capabilities of DTRs for load accommodation, this paper will model loading scenarios which are based on recently observed actual network loads. A factor in the decision to model additional present network consumers as opposed to those with LCTs is the speed at which DTR technologies can be deployed on active networks. In almost any location where network reinforcement is being considered to provide thermal headroom, it is likely that DTR equipment could operational long before planning or investment plans have been finalized, and at a considerable reduction in capital cost. If the decision is taken to reinforce at a later date, the original instrumentation can be re-deployed and put to use again.

As opposed to generation growth, demand increases can also be considered as somewhat uncontrolled and potentially somewhat invisible to the network operator. Visibility of the actual network capacity is therefore a crucial factor in ensuring that the network can cope with these increased demand levels [18], whether due to LCT growth or other factors. Conservative, deterministic methods which limit network capacity and minimise the number of customer connections are likely to the subject of significant review in the transition to the smart grid as evidenced in the current review of the UK distribution network planning standard [19].

C. Ancillary Network Services

Since both the DTR of the OHL and the load profile have a temporal function, there are likely to be periods for which the DTR may be unable to support a particular set of connected customers. These events may be limited at present but are likely to increase in frequency in future as a result of natural load growth. By comparing the resultant DTR and feeder load profiles, not only can the probability of such deficit periods be calculated, but also the power and energy requirements of ancillary services from sources such as DSR [20] or Electrical Energy Storage (EES) can be estimated in order to maintain the same levels of network risk as currently required in P27.

Whilst such services can clearly provide benefits to the electrical network, a series of aims have been outlined against which each scenario is mindful:

- Maximize the number of consumer connections
- Maximize the duration for which they can be connected
- Minimize the number of periods at which customers must be curtailed
- Minimize the magnitude and duration of any necessary curtailment

D. Case Study

In order to provide a critical evaluation a heavily sheltered OHL site has been chosen, one which is highly likely to represent the ‘worst-case’ conditions along the length of the line. This monitoring site is one of four installed as part of the Customer-Led Network Revolution (CLNR) Project [21] and consists of a section of rural 20kV OHL. Whilst the majority of the load increase previously discussed will occur within the low-voltage (LV) network, there is the potential for thermal ‘pinch points’ to occur on the upstream MV network with the additional constraint of N-1 compliance.

III. MEDIUM-VOLTAGE FEEDER LOAD SYNTHESIS

As noted in the introduction to this paper, previous work has not considered the conjunction of time-series demand modelling in conjunction with DTRs. An additional challenge is presented by the need to model grouped electrical demands at the Medium-Voltage level of the distribution system. The relationship between electricity demand and ambient meteorological parameters such as air temperature has been well documented [22-24], however a significant factor in these analyses is the modelling of electrical demands at either the national [23, 24] or individual consumer levels [25] in isolation. At the national level, the response of measured electrical demand to ambient temperature has often been simplified to a linear or second order polynomial model whilst highly detailed models of individual consumers, such as [25], take into account thermal comfort and efficiencies in conjunction with external air temperature. Based on the assumption that a suitable load synthesis method can be developed, the subsequent question to be posed is as to which groups of demands within the MV system should be simulated.

This section firstly presents the result of a clustering analysis carried out to determine the most likely electrical load groups within distribution networks based on their consumer composition. These then form the groups which will be synthesized using the proposed temperature sensitive load model.

A. Load group composition clustering

For the purposes of this clustering exercise, information on the composition of load groups connected at various voltage levels within the distribution network were supplied by UK DNO Northern Powergrid. These compositions refer to the relative percentages of consumers is each Elexon class. Elexon governs the balancing of supply and demand in the UK and classifies each electrical consumer from 1-8. For each of these classes a series of after diversity demand (ADD) profiles exists [26, 27] which will be used during the load synthesis phase of this work.

The widely used K-means++ and Hierarchical clustering algorithms [28] were used to cluster the group composition data and two approaches were tested when considering the levels at which to cluster the data. The first approach involves clustering data from all voltage levels together, hereby referred to as the ‘top-down’ approach; the second relates to clustering of the composition data at each voltage level individually. The accuracy of these top down and bottom up clusters was tested using a series of widely known criteria. For the Hierarchical clustering method, the Euclidean distance metric was used along with both the Ward and Average linkage methods. For each of the methods, the maximum number of specified clusters was set to 25.

B. Accuracy criteria

Each clustering method is likely to result in slightly differing clustering partitions. In order to assess the results of such algorithms, a number of accuracy criteria metrics exist [29]. Five of these criteria have been calculated for the clusters derived using both the top down and bottom up approaches.

1) Mean Index Accuracy (MIA)

The Mean index Adequacy (MIA) is the average value of the distances between the members of a cluster and its generated centroid. The MIA is calculated as:

$$MIA = \sqrt{\frac{1}{K}\sum_{k=1}^{K} d^2(c^{(k)}, C^{(k)})} \tag{2}$$

Where *d* represents the Euclidean distance, *c* denotes the derived cluster centroids, *C* represents the members of the found cluster *k* and *K* is the total number of clusters.

2) Similarity Matrix Indicator (SMI)

The SMI as defined in [30] is a function of the distance between centroids of derived clusters. It is calculated as follows, where $i, j = 1 \cdots K$.

$$SMI = \max_{i>j}\left\{\left(1 - \frac{1}{\ln[d(c^{(i)}, c^{(j)})]}\right)^{-1}\right\} \tag{3}$$

3) Average Silhouette and Global Silhouette Coefficients (AvgSC and GSC)

The silhouette coefficient represents the level of appropriateness with which a cluster member has been categorized. Here, the average and global silhouette coefficients as in [28] have been used, whereby values closer to 1 represent that the cluster members have been appropriately assigned and tend towards -1 where poor clustering has occurred.

4) Within Cluster between Cluster Ratio (WCBCR)

The WCBCR represents the ratio between the within cluster errors, i.e. the distances between the clusters members' and its representative centroid and the distances between the overall cluster centroids. The WCBCR can be calculated as a function of the MIA as follows [29]:

$$WCBCR = K \cdot MIA(K)^2 \left(\sum_{1 \le i \le j} d^2\left(c^{(i)}, c^{(j)}\right)\right)^{-1} \tag{4}$$

As the adequacy of the derived clusters increases, the values returned by each of the accuracy criteria tend towards a minima. This is with the exception of the SC and GSC which tend towards a maxima. With an increasing number of clusters however comes greater computational time and an increasingly large set of representative load feeders. In order to minimise the total number of representative feeders whilst maintaining a suitable level of dissimilarity between the feeders a ‘knee-method’ has been used in line with previous work [31] to determine the point at which the accuracy criteria values no longer decrease at a significant rate. A number of methods exist for determination of the knee point but in this work, the ‘Kneedle’ method [32] has been used, which has shown improved accuracy over techniques such as the L-method. Each of the criteria are then shown for the number of clusters at that point.

C. Representative Distribution Network Cluster Group Results

Table I – Clustering Algorithm Results for all Data Aggregation Levels

	Clustering Method	AvgSC	GSC	SMI	MIA	WCBCR
LV Feeder	1	0.5303	0.6184	1.7385	0.5665	0.2120
	2	0.5138	0.4876	1.8524	0.3317	0.0690
	3	0.5707	0.5524	1.2745	0.4143	0.0668
LV Substation	1	0.5160	0.6042	1.7256	0.5665	0.2536
	2	0.5390	0.4767	1.7730	0.3612	0.0824
	3	0.6637	0.6007	1.3584	0.3262	0.0524
MV Feeder	1	0.9092	0.8981	2.5467	0.3575	0.1568
	2	0.9092	0.8981	2.5467	0.1330	0.0217
	3	0.9092	0.8981	2.5467	0.1330	0.0217
All Data	1	0.5376	0.6068	1.7434	0.5891	0.2583
	2	0.4551	0.5141	1.9718	0.3410	0.0858
	3	0.5717	0.5515	1.3925	0.4009	0.0678

Table I shows the results of each of the clustering algorithms for both data aggregation approaches, here, ‘Clustering Method’ refers to the clustering algorithm used where 1, 2 and 3 are kmeans++, hierarchical with ward linkage and hierarchical with average linkage respectively. A scorecard type mechanism was used to decide upon the overall chosen clustering algorithm with points awarded for the minimum or maximum criteria value where appropriate. The Hierarchical clustering method with average linkage was found to score the highest overall. This clustering method was therefore used when determining the final chosen representative load group composition clusters.

Table II – Adequacy Criteria for Chosen Clustering Algorithm in each of the Test Cases

Assessment Metric	*LV Feeder*	*LV Substation*	*MV Feeder*	*All Data*
AvgSC	0.4354	0.5708	0.5353	0.5717
GSC	0.5097	0.7026	0.5066	0.5514
SMI	1.2745	1.3584	2.5467	1.3925
MIA	0.3657	0.3117	0.2534	0.4009
WCBCR	0.0521	0.0479	0.0788	0.0678

In order to test the overall accuracy of each of the derived cluster sets, each of the derived sets was used to classify data from the alternate aggregation levels, apart from the case of the clusters previously derived for all data. This was in order to remove any bias due to having previously clustered the data at the same level. A k-nearest neighbour search was used to classify the data using the appropriate centroids.

Table II shows the accuracy criteria calculated for each of the possible combinations. The centroids formed at the LV substation level have the highest adequacy for both the GSC and WCBCR criteria. The AvgSC value is the second highest and the SMI value is the second lowest. As discussed previously the WCBCR has been detailed as more accurate than the MIA and since overall the LV substation centroids perform well across all the possible data combination these centroids have been used. The resultant load groups which will be used to determine the capacity of RTTR for load accommodation are shown in Table III.

Table III – Clustering Results – Percentage Elexon Class per Representative Load Group

Elexon Class	1 (%)	2 (%)	3 (%)	4 (%)	5 (%)	6 (%)	7 (%)	8 (%)
Group 1	0.0	0.0	33.3	0.0	0.0	66.7	0.0	0.0
Group 2	16.4	0.0	6.9	0.0	43.7	23.0	0.0	10.0
Group 3	18.5	64.1	13.0	3.7	0.2	0.4	0.0	0.1
Group 4	73.4	14.5	8.6	2.5	0.5	0.2	0.2	0.1

Group 5	20.2	0.1	68.3	7.2	1.7	1.7	0.5	0.3
Group 6	0.0	7.6	0.0	80.4	3.7	0.0	0.0	8.3

D. MV Feeder Load Synthesis modelling

The overall premise for the load synthesis model presented in this paper has two main components. At each point in time, each k^{th} class of consumer (i.e. residential or industrial), can be thought of as contributing to the overall demand of group i (Li), as a function of both their expected real power demands (P_k) and the number of consumers in each class. This contribution can be expressed either as raw value, or can be normalised against the group demand and therefore expressed as a percentage. The normalised demand profiles will be referred to as $P_{k_{norm}}$. It is this normalisation which allows for the model to generalise for customer combinations not found within the training dataset. In addition to these demand contributions, each class also has associated with it a particular sensitivity to ambient temperature. The correlation model presented here attempts to determine this sensitivity to allow for derivation of the overall load groups' sensitivity.

Whilst the work presented in this paper utilizes data gathered as part of a UK project and therefore uses UK ADD profiles, similar profiles from non UK sources could be used to populate the method detailed in this paper such as in [33] or synthetically generated profiles from a method such as in [34, 35].

The Elexon ADD profiles discussed previously have been derived for each customer type, based on a series of 10 year average temperature values. While in practice, these conditions do not represent the actual ambient temperature values of the available testing datasets, some degree of temperature sensitivity is inherently present within these profiles as a result of the overall influence of seasonality. In order to account for the temperature variations between the 10 year average profiles and the real-time ambient conditions, a series of coefficients have been derived in order to enable modification of the original Elexon ADD profiles to take this into account.

As part of the CLNR project carried out in the North of England a series of monitoring points were installed to measure various parameters such as customer group demands from multiple electrical substations and substation feeders. In addition to the monitoring of demands, this project also installed a series of OHL monitoring sensors, data from which will be used within this paper as part of the overall DTR modelling procedure.

A selection of 11 customer groups has been taken from the available data sources. These constitute profiles from customers located at Secondary substations (LV/MV) and from direct MV feeder monitoring at Primary substations. These monitoring points also represent a wide variety of customer compositions, with high concentrations of Industrial and Commercial customers, Economy 7 customers and typical residential customers. Since the OHL monitoring equipment from the case study site is located on the 20kV network and some of the measured demand data comes from the LV network, firstly a step must be taken to ensure all data is comparable. Knowledge of the transformer tap ratio and an estimation of the transformer losses on load allow us to make all data appear as if it were connected directly to the 20kV MV network.

As a preliminary modelling step, for each of the CLNR load groups a demand profile is synthesized by calculating the product of the Elexon ADD profiles for each class and the number in each class. The difference between this synthesized profile and the real measured data is then calculated. A series of scatter plots have then been generated where the difference between the real and synthesized data is shown as a function of ambient air temperature. In these scatter plots the ambient temperature values are normalized to the maximum observed UK air temperature to date (38.5ºC) [36]. Figure 1 shows a set of example scatter plots of this initial synthesis error against normalized air temperature for a randomly chosen half hourly period.

As can be seen in Figure 2 a linear relationship can be fitted to the data and as a result the gradient and y-intercept parameters can be derived, in addition to the overall correlation coefficient between electrical demand and air temperature. Whilst there is the potential that for individual cases a linear model does not provide a best fit to the relationship, a linear modelling approach has been selected due to its relatively good performance and simple implementation across the entire dataset. Further work could consider the trade-off between increasing accuracy through implementation of more complex approaches. The derived parameters will serve as the values to be generated by the TSCs. After derivation, the resultant estimates of the gradient and y-intercept parameters can be used to modify the original Elexon ADD profiles and thus derive a more accurate estimation of the overall load group profile.

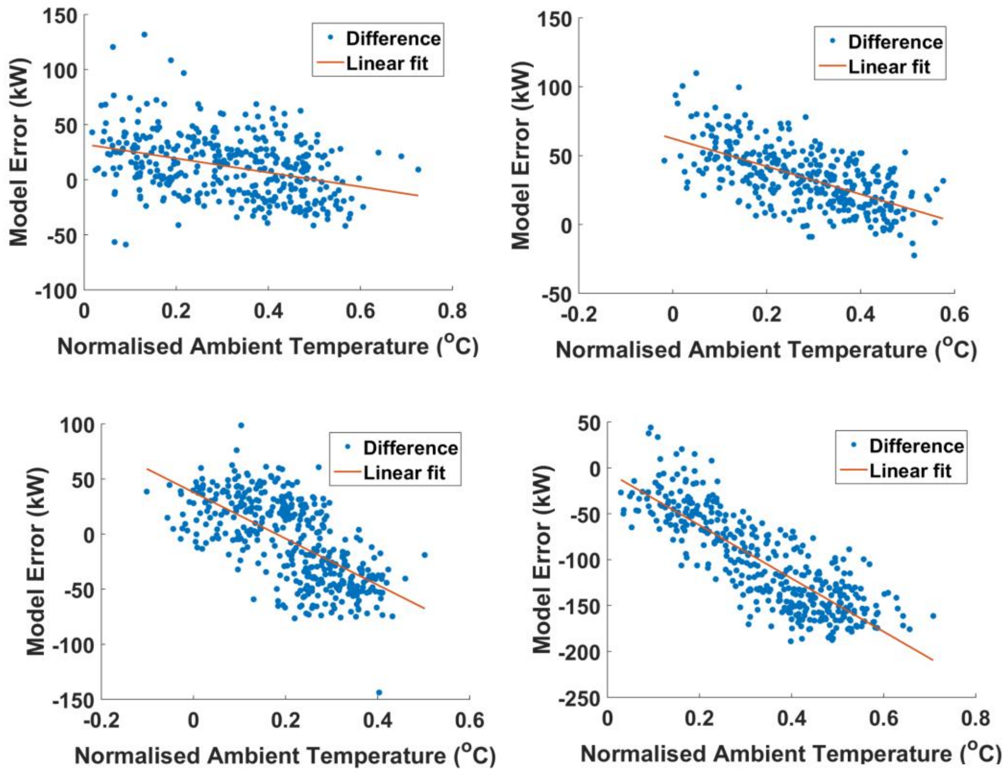

Figure 2 – ADD Model error and linear fit

Following the derivation of these original, unmodified group profiles, two selections must be made regarding the structure of the model and its inputs. Firstly, a selection must be made as to the normalization method discussed previously. Secondly, the overall number of model inputs must be selected, for example whether or not the number of consumers in each class should be included as model inputs.

Options for normalization include normalizing against either the overall group maximum demand regardless of time, as a function of the overall group demand at that particular point in time, or as a function of some subgroup demand, such as the total domestic (L_{Dom}) or Industrial and Commercial ($L_{I\&C}$) load. As part of the overall model testing, one of these candidates will be selected as the most appropriate (see Table IV).

Table IV –Proposed Normalisation Method Options

Normalization Candidate	Method
A	$\frac{P_k(t)}{L_{i_{max}}}$
B	$\frac{P_k(t)}{L_{i_{Dom_{max}}}}$

C	$\frac{P_k(t)}{L_i(t)}$
D	$\frac{P_k(t)}{L_{i_{Dom}}(t)}$

Where k is the class of consumer, P_k is the total real power demand for the number of consumers of class k within the overall load group (N_k), t is the half hourly period (1-48) and L_{Dom} is the total demand profile from domestic consumers within the group, derived as shown in (1) where K_{Dom} is the total number of domestic consumer classes and n is the total number of half-hourly data sample points:

$$L_{i_{Dom}} = \sum_{k=1}^{K_{Dom}} P_{k_{1\cdots n}} \tag{1}$$

In methods B and D the component of group demand L_{Dom} has been isolated from the overall group demand. There is no corresponding isolation of the demand from industrial and commercial customers $L_{I\&C}$ for two reasons. Firstly due to the relative percentage of industrial consumers in each of the test load groups there was insufficient data in order to accurately determine the required model outputs. Secondly, the temperature sensitivity of industrial and commercial loads has been discussed as being lower than that of domestic loads [37]. Therefore the choice not to model these consumers directly as being significantly temperature and therefore correlation sensitive was deemed appropriate.

The proposed model will provide a series TSCs which can be used in conjunction with the selected normalisation format in order to derive the overall group load-temperature correlation (C). In addition to the normalised consumer class profiles a number of additional model inputs were considered. A value was proposed which takes into account the ratio between the domestic and non-domestic loads (R) at a point in time. This is calculated as follows (2):

$$R_k(t) = \frac{P_k(t)}{L_{I\&C}(t)} \tag{2}$$

Where $L_{I\&C}$ is the total demand profile from Industrial and Commercial consumers within the group derived as shown in (3) and $K_{I\&C}$ is the total number of Industrial and Commercial consumer classes:

$$L_{I\&C} = \sum_{k=1}^{K_{I\&C}} P_{k_{1\cdots n}} \tag{3}$$

The final proposed model inputs proposed are the number of domestic consumers within each class (N_k), and the total number of domestic consumers ($\sum N_k$). Both ordinary and weighted least squares type models were considered in order to derive the TSC values. Weights (w) were considered as functions of the derived load-temperature correlation *p_values*. These values refer to the ability to reject a null hypothesis of correlation. If the *p_value* falls below a particular threshold, the null hypothesis can be rejected and a correlation is said to be present between the two variables. In order to provide weights to the least-squares algorithm, the value of $1 - p\_value$ was used. As per the selection of a suitable normalisation method, during the testing phase a suitable model structure will also be selected. The least-squares algorithm is solved in the usual manner, with firstly the formation of the correlation vector C and the weight vector W:

$$C = [c\ (1), c(2) \cdots\ c(n)]^T \tag{4}$$

$$W = [w\ (1), w(2) \cdots\ w(n)]^T \tag{5}$$

The format of the input rows of the matrix H, h_j will be determined during the testing section of this paper. The proposed structures for the rows of H are shown in Table V:

$$H = [h_1, h_2 \cdots\ l_n]^T \tag{6}$$

Table V - Proposed Model Structures

Correlation Model	Method
1	$h_j^T = \left[P_{k_{norm}}, \cdots, P_{K_{Dom_{norm}}}\right]$
2	$h_j^T = \left[P_{k_{norm}}, \cdots, P_{K_{Dom_{norm}}}, N_k, \cdots, N_{K_{Dom}}\right]$
3	$h_j^T = \left[P_{k_{norm}}, \cdots, P_{K_{Dom_{norm}}} \sum_{k=1}^{K_{Dom}} N_k\right]$
4	$h_j^T = \left[P_{k_{norm}}, \cdots, P_{K_{Dom_{norm}}}, R_k, R_{K_{Dom}}\right]$

$$C = H \cdot TSC \tag{7}$$

$$TSC = (H^T H)^{-1} H^T C \tag{8}$$

$$TSC_{weighted} = (H^T W H)^{-1} H^T W C \tag{9}$$

In order to test each of the potential model configurations, i.e. Normalization method A with Model Structure 2, Leave-One out Cross Validation was performed across each of the 11 test datasets from the CLNR project. Error was minimized across the testing datasets through the use of Normalization method D and overall model structure 3 utilizing the weighted least squares approach, and therefore this was selected as the modelling procedure to derive the final DTR inputs.

Considering the overall error of the approach, the original Elexon ADD profiles do not provide an estimation of their error for modelling purposes. Throughout the modelling procedure presented here, testing has been performed to ensure that the overall chosen modelling structure leads to the minimum error in the test synthesized profiles, however for the purposes of providing inputs to the DTR, the resultant synthesized MV feeder load profiles have been used directly.

The rationale for this approach is two-fold. Whilst errors in the synthesized profiles could potentially result in under or over-estimation of the final number of customers capable of being supplied by the DTR, the purpose of this paper is to demonstrate the overall capabilities of DTRs for load accommodation and to present the generalized method. In addition, since the final feeder load profiles have been synthesized for generalized demand groups, the actual error of these profiles is unknown. As such, development of a method which takes this into account was considered as out of scope for the research presented in this paper.

After selection of the appropriate modelling structure from the CLNR test cases, example profiles for each of the six generalized demand groups have been derived for a theoretical range of customer numbers. These profiles then act as inputs to the dynamic implementation of the CIGRE method [1] in order to derive values of the resultant conductor temperature. The zonal method outlined in section V has been used to determine the number of customers capable of being supplied with varying degrees of support from either DSR or EES. For comparison, the total number of customers able to be connected under the present P27 standard have also been calculated.

It should be noted that the load synthesis method presented here is inherently data driven and can therefore only take into account those temperature sensitivities which have been observed as a result of the gathered dataset. The accuracy of this approach will likely decrease over time given changes in natural environmental conditions. Whilst considered as out of scope for this particular research, an extension would be to consider the future impact of various climate scenarios on grouped demands, and the resultant correlation with OHL capacities.

IV. Load-DTR excursion analysis

The critical limiting factor when considering the capacity of OHLs is the effect of conductor temperature on line sag. Ground clearances must be maintained above a safe working limit. To that end, the CRT value of the OHL circuit is pre-defined and based on the approach taken in ER P27 [2]. The seasonal static ratings found in P27 are designed such that if they were to be observed on the network as continuous current values, there is a risk that for one 6 minute period per year the conductor safe working temperature will be exceeded. Clearly in present network loading scenarios, and taking into account the need for N-1 security, such constant current loading does not occur in practice. However, with the rise of peak shaving [38] as a network technique it is possible that such flatter load profiles will be observed more often than previous.

As a baseline comparison, the present maximum circuit loading values have been used to determine the initial number of customers capable of being connected for each load group. A key enabler of using DTRs to accommodate additional load is the mutual development of ancillary network services as a network control technique. In order for the service power and energy requirement to be credible, the decision has been taken to limit the maximum duration of a required response to a period of 4 hours. The duration limit is designed to be cognizant of the four hour tariff period in the wider CLNR project, and represents the typical duration of network peak demand (4pm to 8pm) in the UK. Any form of DSR which is required to last for longer than 4 hours was deemed to be represent an unfeasible number of additional customer connections.

For the purposes of evaluation, in addition to the level of risk which has been previously defined, a zonal method has been developed, in which differing numbers of additional customers are possible dependent upon the level of action which is required to be taken to mitigate a possible thermal overload of the conductor. Within this zonal system, an excursion is defined as a 5 minute period where the conductor temperature exceeds the circuit rated temperature which is currently in the case study network set to 50^{o}C. These zones are as follows:

- Zone A – possibly multiple excursions of 5 minutes (or less, however the resolution of the data is at 5 minute intervals) but limited in duration to one data sampling period.
- Zone B – consecutive excursions from 10 minutes up to the maximum DSR duration limit (in this case 4 hours)
- Zone C – consecutive excursions greater than 4 hours

By definition the excursions in Zone A require no form of corrective action, since after one data sampling point at this resolution, the conductor temperature returns below the circuit rated temperature. This was therefore viewed as equivalent to the level of risk as given in P27 which allows for one 5 minute exceedance of the conductor rated temperature per rating period. Zone B requires a form of DSR to mitigate against excessive conductor heating, up to the maximum possible duration. This response could come in a number of forms, for example discharging of energy storage devices in addition to load control. It is also not necessary for the service to come from one source alone, nor does it have to be from the same source for the entirety of the required duration. Figure 3 shows an example of a conductor temperatures being maintained within the circuit rated temperature limit through the use of DSR. As discussed previously, ensuring that the CRT is not violated ensures that the risk of a conductor thermal overload is maintained at, or below the level of risk implemented by the current network planning standard for OHLs in the UK.

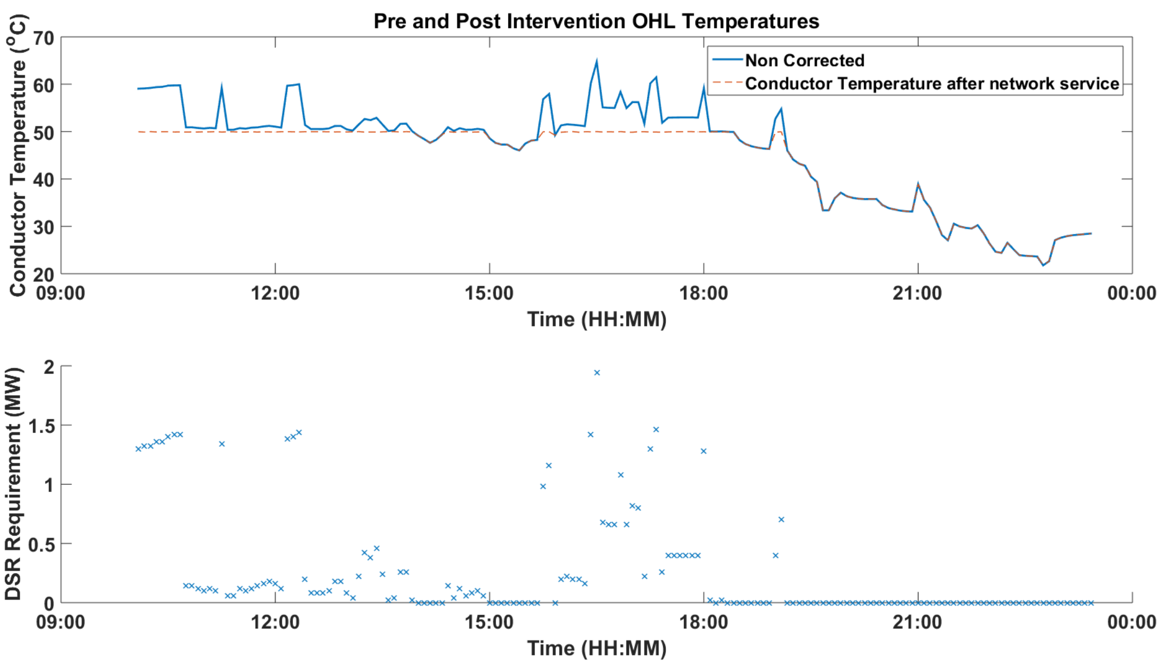

Figure 3 – Example of a maintaining the OHL circuit temperature limit through the use of DSR

V. CASE STUDY

As part of the CLNR project, four sites were initially chosen for installation of OHL monitoring equipment, with two sheltered and two non-sheltered sites. Sheltering refers to the level of obstructions surrounding the site, such as trees, foliage and buildings. The OHL construction at each of four sites is a 0.1in^2 diameter conductor of stranded copper and the CRT is 50^{o}C. Each site consists of a weather station, measuring wind speed, wind direction, ambient temperature and solar radiation. In addition, a current clamp located on the line provides measurements of average line current and surface temperature at five minute intervals. The real-time measurements of line current and conductor temperature were used to validate an offline model of the conductor's thermal behaviour, similar to the method presented in [39]. The presently implemented nameplate ratings for the sections of overhead line considered in this paper are shown in Table VI. The ratings are seasonal, and are defined for the following groups of months:

Table VI – P27 Seasonal Conductor Ratings

P27 Rating Period	Rating (A)
Summer – May, June, July, August	237
Spring / Autumn – March, April, September, October, November	275
Winter – January, February, December	296

It is important to note that the ratings shown in Table VI are valid for the entire length of the overhead line, whereas the calculated DTRs are valid only for the spans either side of the installed monitoring equipment. This is important since a rating downstream cannot be exploited if an upstream constraint exists, assuming that there is a uniform load drop from the primary substation to the remote MV feeder end, and that the system is primarily for accommodating demand. Where embedded generation (EG) is concerned, the problem becomes more complex. The location of the EG, its expected output profile and its electrical and geographical location on the feeder are all of crucial importance.

Measurement at all points along the length of the line is clearly preferred to provide maximum system visibility, however the cost of such a solution is likely to be very high. The minimum number of sensors required to provide adequate system visibility with an acceptable level of risk for decision making is clearly the answer. Deriving such sensor locations is however, a non-trivial exercise. When defining a particular set of spans for monitoring it is important that such sites provide year-round visibility, and that shifting weather patterns do not require additional monitoring. Sensitivity analyses

[39] have shown that the meteorological variable with the largest impact upon an overhead line's rating is wind speed closely followed by ambient temperature.

In order to carry out a sufficiently critical evaluation of increased circuit capacities, it was necessary to ensure that the available uplift was derived from the most limiting location of the available monitoring sites.

In order to study was carried out similar to that found in [3] to determine the distribution of ambient temperature values at low wind speeds. The site with the highest average wind speed at times of low wind speed (here defined as < 1m/s) was chosen as the critical site. Figure 4 shows the empirical cumulative distribution functions of these data.

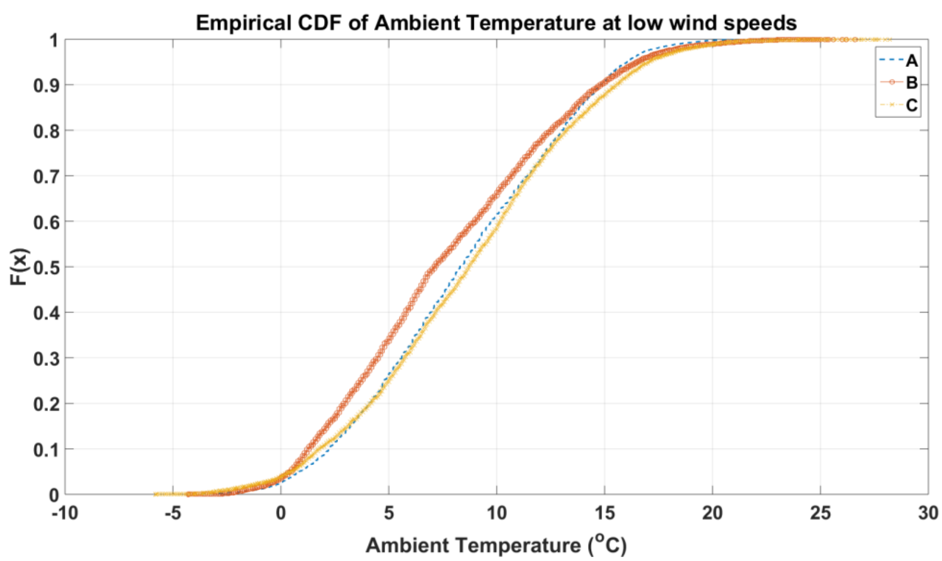

Figure 4 – Empirical CDF of Ambient Temperatures at low wind speed values

Site C has the highest average, and maximum temperature coincident with low wind speeds and was therefore selected as the 'critical span' in this study.

A. Wider implications from the Case Study site

The overhead line within the case study area gives a typical representation of rural MV overhead networks within the UK. Smart Grid Forum has defined a series of representative network types on which various smart solutions should be evaluated. It is felt that the work in this paper can directly feed into such evaluations.

VI. Results

In order to critically evaluate the potential for DTRs to support various loading scenarios, temperature sensitive load model presented in Section III-D has been used to simulate representative feeder load profiles for each of the six generic customer groups outlined in Section III-C across a range of total group members. Each of these profiles was then used as an input to the OHL DTR model in combination with the measured meteorological conditions taken from the chosen case study site.

A. Customer Connections

Table VII – Number of Customers Capable of Being Connected using both the Existing P27 Standard and the Zonal DTR Method

Group	Present P27 standard	Zone A	Zone B
1	200	150	250
2	250	150	250
3	2450	2500	3500
4	3950	3450	4750
5	1200	900	1300
6	600	450	650

Potential customer connections have been evaluated in three categories. In the first, the group demand profiles were evaluated against the presently implemented circuit ratings as shown in Table VI. In this evaluation, the maximum number of possible customer connections relates to the total group number for which there are no violations of the seasonal circuit rating, across each of the seasons. This does not directly relate to the concept of continuous circuit ratings. Simply, the maximum group demand observed as a function of typical cyclic loading must be lower than the seasonal rating in each period.

The same group demand profiles are then evaluated using the DTR method and the number of connections which relate to the requirements of both Zone A and B excursions outlined previously.

Table VII shows the number of customers capable of being connected with the available levels of support. Whilst those connections which could be categorized as being within Zone A are somewhat similar to the present circuit rating procedure it is noted that in almost all cases there are differences between the number of customers capable of being supported, and that in many cases the number supported by the DTR is lower than those from the present rating system.

This point will be discussed in greater detail within Section VI-B. For demand group 3, use of the DTR method allows for the connection of an additional 50 customers beyond the presently enforced seasonal ratings, whilst if suitable network ancillary services were to be made available, increases in customer connections, without the need for line upgrades are possible in 5 of the 6 loading scenarios.

In order to determine the upper limit for customer connections in Zone B, in each case where a conductor temperature has been calculated which exceeds the circuit rated temperature, a load reduction has been calculated which would bring the conductor temperature back to within the allowable limits. Figure 4 shows an example of the average and 99th percentiles of the required network service in the Winter period for demand group 4 in order to ensure that the circuit rated temperature is not exceeded. The use of the DTR method as opposed to the present static rating system allows for derivation of these values directly.

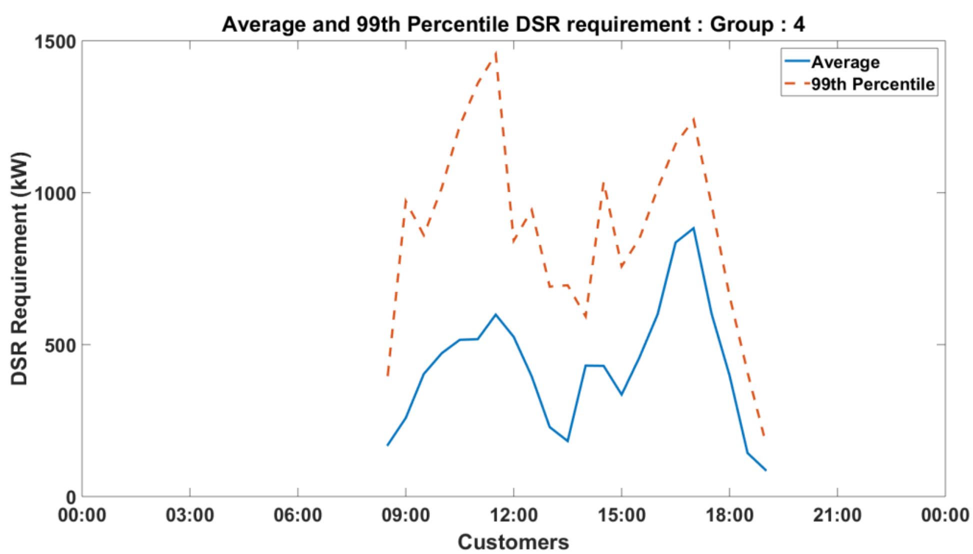

Figure 5 – DSR Requirement for Group 4 in the Winter period

B. EENS and CRT Limit Violations Analysis

In previous work, two techniques have often been used in order to evaluate those periods for which the use of RTTRs alone cannot provide sufficient network headroom for load connections. These are the Loss of Load Expectation (LOLE) and the Expected Energy not Supplied (EENS) [7, 16]. Since this paper is concerned with the use of DTRs as opposed to RTTRs, an additional assessment metric in the form of the number of CRT violation periods, and their resultant probability have also been calculated in addition to the EENS.

Table VIII – EENS and CRT violations analysis for each of the Generic Loading Conditions for both DTR and P27

	EENS		CRT Violations		CRT Violation Probability	
Scenario	P27	DTR	P27	DTR	P27	DTR
1	0	0.7833	28	0	1.4617x10-4	0
2	0	6.7850	310	0	0.0016	0
3	0	0	0	0	0	0
4	0	3.12	154	0	5.4921x10-4	0
5	0	11.2217	485	0	0.0025	0
6	0	3.4150	125	0	6.5253x10-4	0

Table VIII presents an evaluation of the differences in circuit characteristics between the customer groups capable of being supported using the present seasonal ratings and the same customer numbers when using the DTR method to rate the OHL. The results show that when using the DTR method with the seasonal rating customer numbers, there are in some cases, a large number of CRT violations. For single-circuit supply distribution-system OHLs, as in this case of the case study site in this paper, the risk of a CRT violation as termed in this paper is deemed to be 0.001% [3], analogous to one five minute period per rating season, or 3 per year. In the case of demand group 5, the number of customers theoretically capable of being supported by the current seasonal ratings would result in an EENS value of 11.2217 MWh and a risk of CRT violation of 0.253%.

This is likely to be as a result of the present seasonal ratings and their associated meteorological conditions not adequately taking into account the risk of CRT violations at the critically sheltered test site chosen for this evaluation. This result however is not entirely unexpected. In [7] on a number of occasions the RTTR was calculated as being below the seasonal rating for the given test site. If line loading values were to be increased to the point where they exceed the RTTR, but remain below the seasonal rating as is effectively the case within this paper it would be likely that the conductor would experience an increased number of CRT violations during these periods. The methods presented in this paper allow for estimation of these CRT violations due to derivation of conductor temperatures using the DTR method as opposed to the RTTR.

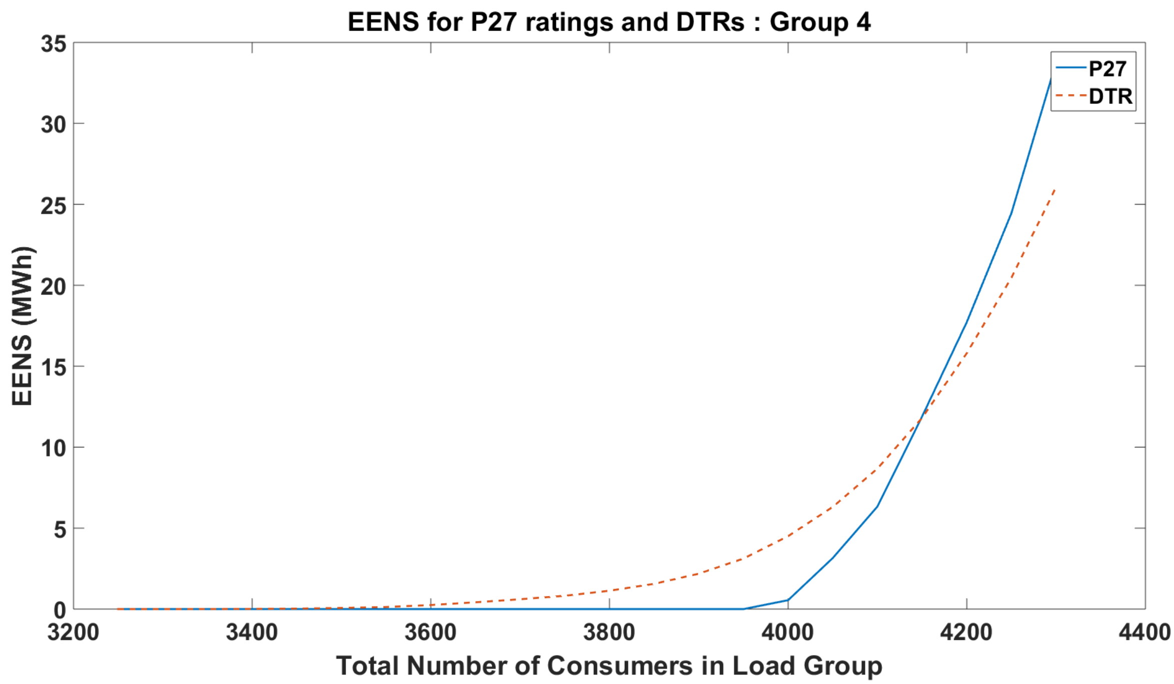

Figure 6 – EENS for Group 4 Loads at the case study location using both DTR and the presently implemented OHL ratings

Figure 6 shows expected EENS values for a range of customer numbers in the Group 4 demand scenario. As can be seen, use of the DTR for this load group results in an increased EENS versus the seasonal rating method due to CRT violations, up to around 4100 customers. After this point, the DTR method presents reduced EENS values by comparison. Similar results were observed across each of the remaining demand groups.

VII. Future Work

Future work will consider the benefits of combining the knowledge derived in this paper with that of various forecasting techniques. The aim of this work would be to analyze if forecasting would allow for a reduction in the requirement for DSR under a real-time operation scenario as opposed to mainly network planning framework examined here.

VIII. Conclusions

This paper has shown that the use of DTRs exposes potentially increased risks when implementing the current UK seasonal line rating system. The use of the DTR not only accurately evaluates the actual expected CRT violations and probabilities, but can also identify the magnitude, duration and times of day at which network ancillary services are required, in order to mitigate where such excursions may exist. The impacts of these findings are such that this information can be of great importance when considering the scheduling of such services, from the network as a whole.

Clustering results have delivered a set of generalized load groups typically connected to UK distribution networks based on their Elexon class composition. A temperature sensitive feeder load profile synthesis method is also presented to allow for accurate evaluation of each of the potential future loading scenarios. The results have been evaluated at a good approximation of 'critical span' along the length of a rural OHL such that the results can be deemed to be a worst case scenario of the potential for increasing the number of possible customer connections. In addition to quantifying these connections in terms of both the EENS and CRT violation probabilities, the required budget from ancillary network services to mitigate conductor temperature limit violations is also derived as a results of the use of DTRs.

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