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Weather-Based Dynamic Thermal Rating Forecasting Application for Long Transmission Line of Nepalese Grid: A Case Study in Chameliya-Syaule-Attariya 132 kV Transmission Line

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Abstract
Overhead transmission line current carrying capacity is limited by its heat-bearing capacity. Different meteorological factors further limit the heat-carrying capacity. In the Traditional approach, the thermal current capacity of the overhead transmission line conductor is determined by using the worst meteorological condition of very low wind speed (about 0.5 m/s) and the highest possible ambient temperature (about 45-degree celsius). Also, the effect of air incidence angle and heat loss due to rainfall cooling is being neglected. Dynamic Thermal Rating (DTR) is the assessment of the capability of a conductor determined by measured and forecasted weather data at real-time basis. The existing transmission system assets can be operated more efficiently maintaining the thermal line security level. This study provides a scheme for probabilistic DTR forecasting by incorporating issues such as forecasting uncertainties, and topological factors along the long transmission line, etc. For long transmission lines, there will be a high voltage drop in the transmission line after implementing DTR. A regression model is designed for forecasting the weather in real-time and system voltage drop is analyzed for both of the cases of static and dynamic line rating. Minimum span thermal capacity is determined among all critical spans using forecasted weather data to estimate the real-time DTR of the transmission line. Numerical testing for this scheme is performed and analyzed on one of the longest transmission line segments connecting Chameliya Hydropower Station with Attariya Grid Station of the Integrated Nepalese Power System (INPS).

Keywords
Dynamic thermal rating, voltage stability, transmission line, DTR model, INPS, Static Thermal Rating

1. Introduction

The interconnection between generation and load is achieved through transmission line conductors. An overhead transmission line is facing new challenges of under-utilization of line assets which consequently affects planning, operation, and control actions. With reference to St. Clair Curve, the capacity of a transmission line is limited by thermal limits, voltage limits, and system stability limits [1]. The actual thermal capacity of the line conductor is the maximum amperes that can be sent through the wire preventing damage from the heating loss [2] maintaining permissible sag and clearances. Thermal transmission capacity is affected by the temperature effect on sag clearances along the line spans caused by weather fluctuations which are time and space-dependent [3]. The current carrying capacity is different for different conductors and is affected by various local meteorological conditions. Traditionally, transmission capability is determined by using unfavorable weather conditions (very high surrounding air temperature along with lower wind velocity) [4]. Such a traditional approach leads to the decreased utilization of the transmission assets as such worst-case weather situations may not appear frequently during its life span [5]. For the grids with higher penetration of distributed energy generators, there will be generation curtailment because of limited line thermal capability [6]. The Dynamic Thermal Rating (DTR) technology of computing dynamic rating of transmission line by real-time monitoring of environmental parameter maximizes the ampacity of conductor and hence increased utilization of existing assets [5]. Using forthwith weather data in line thermal capability estimation enhances the performance and operating efficiency of existing system assets. DTR can be estimated by solving the heat loss/gain equation for the overhead line conductor [7] considering heat loss such as convection cooling, radiation cooling, and precipitation cooling as well as heat gains such as solar heat gain and electrical loss in the conductor. The heat transfer is governed by weather factors such as wind velocity, available solar radiation, and surrounding air temperature [1], parameters which is varying frequently with time and location. With enhanced penetration of renewable energy resources, transmission systems need to be operated more flexibly with increased capability leading to network reinforcement [8]. Constructing a new line in the restructured competitive electricity market is not an economically feasible way for congestion management for transmission utilities due to the unavailability of a right of way. Transmission line congestion, as well as increment of margin under contingencies, can be achieved using the DTR approach [9]. DTR implementation enhances line capability, enhances system reliability, helps in congestion management, supports wind power integration [3], and improves the tolerance limit of the lines during the N-1 line emergency [10]. DTR techniques also prevent earlier aging of the conductor occurred when the actual surrounding conditions are much worst as compared to selected weather conditions [11]. Dealing with errors that exist in weather data measurement, and unpredictable changes in weather conditions maximum thermal rating with greater reliability can be achieved [10].

2. Scope of DTR in Nepalese Grid

There is increasing penetration of distributed renewable energy resources as well as small hydro generators located far away from load centers increasing congestion in the Integrated Nepalese Power System (INPS). The need for flexibility in transmission system operation is increasing day by day due to renewable integration, the aging of transmission facilities, and load growth. As the construction of new lines is not feasible for the utilities here because of cost, time, space, and land constraints, the DTR approach is the most appropriate solution. DTR approach helps transmission system operators of INPS in congestion management by utilization of real-time weather factors and actual ampacity forecasting. Appropriate DTR forecasting with the integration of the day-ahead market provides more economical benefits for transmission utilities.

Nepal Electricity Authority (NEA) is facing load curtailment problems mainly in major populated cities during winter peaks. There is major transmission and generation outage problem caused by short time overloading of some critical transmission lines of INPS. Some of our transmission lines are not capable of handling power flow in the case of contingencies as they are already being operated in an overloaded condition. Also, the government of Nepal aims to achieve universal access to electricity and electricity-based cooking by 2030. With the widespread application of electric clean cooking and electrical vehicles, the existing transmission and distribution assets of INPS will be overloaded leading utility towards expensive short time investments. Using old and conservative techniques of Static Thermal Rating (STR) leads utility to construct new transmission lines soon as existing assets are not optimally utilized. Implementing DTR in INPS will provide a higher line ampacity and thus helps in congestion mitigation and decreased re-dispatching of generators when there is system congestion arrived due to line ampacity limits. The additionally available transmission line capability may help in improved system planning and enhanced system operation. DTR installation on lines leads to decreased congestion management costs and hence the risk of load curtailment.

3. Methodology

3.1 Previous Study

Many research works have been done based on the DTR optimization of the transmission line. The study in [4] presents a novel dynamic thermal capacity estimation model for power lines considering precipitation. In [5], the conductor thermal capability forecaster based on real-time weather conditions is developed. A study in [9] presents a methodology based on the weighted least squares technique for the determination of ambient temperature in all of the ruling spans of the transmission line using direct and indirect monitoring. In [8], the study is carried out to analyze the feasibility of DTR and its integration in dispatch optimization reducing transmission line capability forecasting errors. A heteroscedastic auto-regressive model for probabilistic DTR forecasting based on real meteorological conditions for overhead lines is presented in [12]. The analysis of the reliability impacts of using the dynamic line rating on the electrical power system network is reviewed in [6]. Research carried out in [13] presents the novel dynamic line rating application and tripping scheme modeling uncertainties on measurement using fuzzy numbers which avoid tripping of generators caused due to traditional line rating. A study in [11] gives the applicability of DTR to enhance the thermal capability of long transmission lines which are not thermally constrained but limited by voltage stability. Studies in [14] describe an algorithm for estimating nonlinear parameters with Tabu search methodology for the determination of the application of DTR in a real power system network. A study in [15] presents a model of density forecasting for predicting the actual dynamic thermal capability of transmission lines considering real market requirements. In [1], a technique for estimating actual overhead line conductor current carrying capacity using load flow simulations and a DTR forecaster is presented.

Many studies are carried out to estimate dynamic line thermal rating using probabilistic approaches. Different weather factors are used in the weather model for future weather forecasting and impose difficulties and uncertainties. Also, not any studies carry the spatial features of transmission lines due to different geographical conditions along the line. A probabilistic approach such as Monte Carlo Sampling provides a similar result but needs a higher iteration level for complex long transmission networks resulting in high computational costs. Among various weather parameters, the impact level of each weather factor on line thermal rating will be evaluated in this research and selected according to the highest impact level. Weather uncertainties and spatial topology of TL will be captured using the regression model. A fast iterative truncated normal probability distribution of line thermal capacity is proposed for calculation with lower cost.

In the case of INPS, there is no such study carried out considering the dynamic nature of transmission line conductors incorporating weather uncertainties and geographical conditions. Many of the transmission lines in INPS are being used in overloaded conditions during evening peaks of daily load. Also, some other transmission lines connecting major city loads are being overloaded during seasonal peaks. A study on the capacity expansion of major transmission lines present in the Nepalese grid will be beneficial for transmission utilities from a techno-economic perspective. This study is intended to fulfill those research gaps in the Nepalese grid.

3.2 Impact of Weather on Thermal Capacity

As the topology of the transmission line is different for long-length transmission, the thermal capacity of the conductor varies with the varying weather condition. There is a large number of weather factors affecting the thermal rating. The major weather factor and its impact on different ACSR conductors are evaluated in this section. For the analysis of one particular weather factor, the remaining weather factor is set to their conventionally used value for static thermal rating as provided in [7].

For the identification of the weather factors with higher impact levels, the difference between the maximum and minimum line thermal capacity to minimum line thermal capacity by the varying value of weather factor is estimated and given by,

$$ImpactLevel = \frac{Max.Capacity - Min.Capacity}{Min.Capacity} * 100\% \tag{1}$$

1 represents the response of varying different weather factors on line thermal capability. Here steady-state thermal capability of 250 mm2 ACSR BEAR is evaluated. ACSR BEAR is one of the most commonly used conductors in 132 kV transmission lines of INPS and hence same is used in Chameliya-Syaule-Atatriya 132 kV Transmission Line. The percentage impact level of weather on the thermal capacity for ACSR BEAR is presented in 1. Here, the factors relative humidity and ambient pressure have a negligible impact on line thermal capability.

Table 1: % Weather Impact Level

Factors	Limit	Wind Velocity, V (m/s)				
		0.6	2	4	8	12
Ta	0-45	34.9	34.2	33.8	33.5	33.4
Φ	0-90	44.8	50.8	53.7	55.9	56.8
Qse	0-1100	10.7	6.2	4.2	2.8	2.2
Pr	0-1	18.8	11.7	8.9	8.1	8.3
RH	0-100	0.0	0.0	0.0	0.0	0.0
Pa	80-120	0.0	0.0	0.0	0.0	0.0

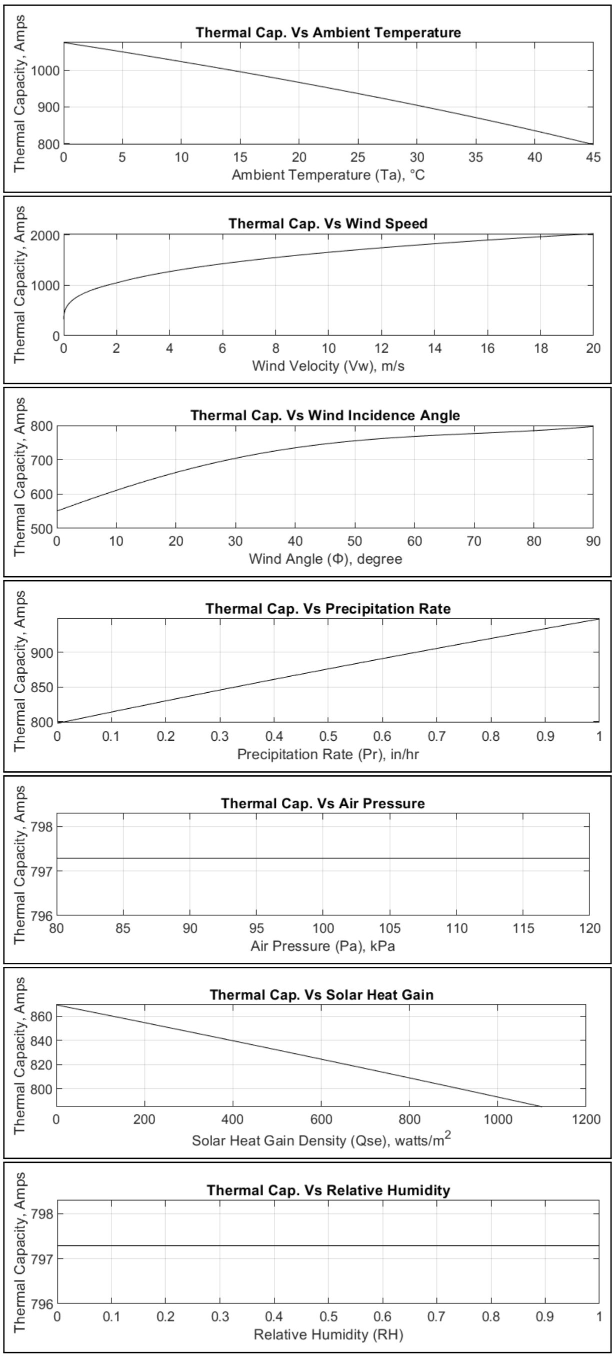

Figure 1: Thermal capacity with variations in weather factors

3.3 Regression Model of Weather Forecasting

The historical weather data along different selected span lengths of the overhead line is collected. Using the available historical weather data, a regression model is developed which estimates the future weather data with minimum forecasting errors. The regression equation for the day ahead weather forecasting is given by equation 2 similar in study [2].

Where the 'm' is the different weather factors under consideration i.e. ambient air temperature, wind velocity, wind incidence angle, and water precipitation rate; and 'k' is the targeted span location; β represents the coefficients of the regression equation; ε represents the error of regression model. Three geographic covariates i.e. latitude, longitude, and distance to the sea are used for better capture of spatial features.

$$W_{k,m}(t) = \beta_{k,m,0} + \left[\sum_{n_1=1}^{3} \beta_{k,m,n1} \times W_{k,m,n1}(t-24)\right] + \beta_{k,m,4} \times \omega'_{k,m}(t) + \left[\sum_{n_2=1}^{3} \beta_{k,m,4} + n_2 \times S_{n2}\right] + \varepsilon_{k,m}(t) \tag{2}$$

From the available historical weather data and future weather forecasting provided, regression coefficients of 2 can be estimated as per [16]. If the weather stations are not installed at or near the transmission lines, data from different weather agencies NASA Power Data Access and National Renewable Energy Laboratory (NREL) can be used as raw data for regression coefficient calculation. An organization like National Numerical Weather Predictions (NWP) provides the day ahead forecasted data which is used in our regression model for better capture of uncertainties. Since the weather along a long transmission line varies geographically as per its topological condition, the uncertainties in forecasting weather can be limited by using geographic covariates as modeled in the regression equation 2.

3.4 DTR Forecasting

The weather factors generally lie in a particular range except in the case of extreme weather conditions. Therefore, weather parameters are considered to have normal distribution along the transmission line segments. Here, the thermal capacity of a particular span of the transmission line is considered to have the truncated normal distribution. For the normally distributed random variable, the truncated normal distribution is defined as the probability distribution with bounded values (upper and lower extreme limits). In a truncated normal distribution, we generally choose a Probability Density Function (PDF) by specifying parameters mean (μ) and variance (σ^2) with truncation range (a, b). The span thermal capacity distribution Ik at any targeted span location 'k' is noted as I(μk, σk2, ak, bk).

Here, μk is the DTR mean, σk2 is the DTR variance, and outer limits of current are defined by bounding parameters ak and bk for that particular span. For calculation of the upper bounding limit, the lowest possible ambient air temperature, greatest measured wind velocity, rainfall rate, and right angles of wind incidence angle are considered. Similarly, for the calculation of the lower bounding limit, the highest surrounding temperature, least wind velocity, no rainfall rate, and parallel wind incidence angle to the conductor axis are considered. The probability density functions PDF and CDF of the truncated normal distribution can be derived similarly. By using the regression model, the mean and variance of selected weather parameters are evaluated and are used for the approximation of the DTR mean and DTR variance of span thermal capacity for a particular span selected by using the Taylor series. The DTR is then given by non-linear function f as:

$$I_k = \sqrt{\frac{Q_r + Q_c + Q_e - Q_s}{RT\,s}} \tag{3}$$

DTR with the low percentile can be evaluated and there will be a high probability that the actual thermal rating lies above the forecasted line thermal rating. Therefore, lower DTR percentiles (e.g. 2nd, 1st, and 0.1th of the forecasted DTR) have greater significance in ampacity forecasting.

4. Numerical Testing on INPS

Transmission lines of INPS show different seasonal behavior of load flow. During the dry season, major RoR projects of INPS will have less runoff resulting decrease in generation and there is increased power import from India. While during the wet season, there is excessive runoff available and an increase in generation capability which results in power export to the Indian grid. In general, there is the power flow from the mountain region to the Terai region and Indian grid during the wet season resulting in greater congestion on transmission lines connecting the generation end while during winter major transmission lines of the Terai region will have larger congestion as power is imported from Indian grid. The conclusion is that there is different loading pattern for different transmission line section at different seasons. For the proposed model numerical testing is provided on different transmission lines of INPS having seasonal and short-time peak overloading. The following section discusses the model efficiency against different types of transmission lines in different geographical conditions of Nepal.

4.1 Probabilistic Line DTR Forecasting of Chameliya-Syaule-Attariya TL

A 132-KV Chameliya-Syaule-Attariya transmission line of INPS from Balanch Hub Substation, Darchula to Attariya Grid Substation, Kailali, Nepal is investigated. The total line length is about 131 km connecting three substations with intermediate Syaule Substation. This transmission line connects the major far-western cities of Nepal having large load growth with generators of the different river basins of Darchula district. The transmission line construction cost for a small hydro project up to the load center at Attariya and Dhangadhi is not economically viable for both generators and utilities. Figure 4 shows the Google Earth image of the transmission line used for numerical testing.

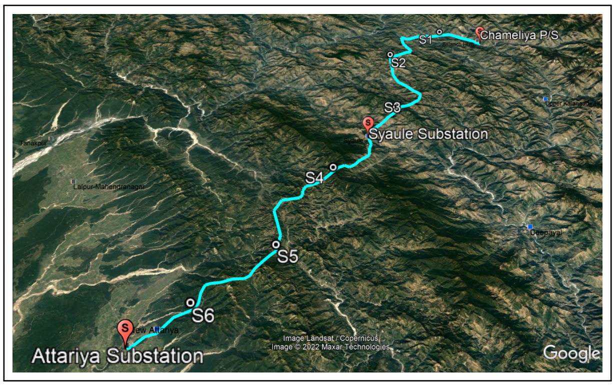

Figure 2: Layout of Chameliya-Syaule-Attariya A 132 kV transmission line, Nepal

As the weather sensors are not available along a line segment, historical data from organizations such as the National Renewable Energy Laboratory (NREL), NASA Power Data Access, and the Department of Meteorology, Nepal is used. For this numerical testing example past meteorological data from 2016 to 2019 are used for generating the regression equation, and data from the year 2020 is used for future weather prediction.

As represented in Figure 3, forecasted weather data approximately represents the actual weather data for different weather parameters. Also, individual weather parameter satisfies the two-sigma error range.

From the past weather data of the three closest weather station locations at a targeted span, a regression model gives the estimation of the weather condition for any of the days of the year 2020. Using these weather data as input for our DTR model, the dynamic thermal rating for that particular day can be estimated.

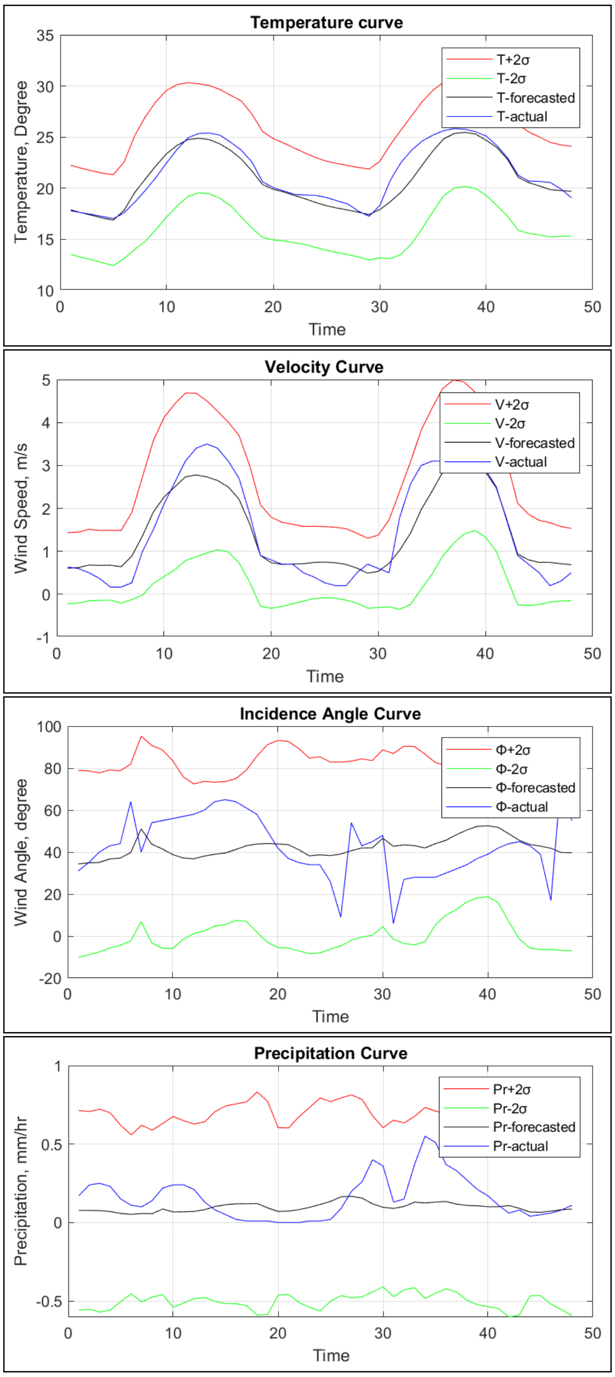

Figure 3: Weather predictions on June 5th and 6th, 2020, for Chameliya-Syaule-Attariya 132 kV transmission line

The actual line rating at that particular weather condition is calculated by using the exact measured weather parameters of the day while the forecasted dynamic rating is based on the weather data generated from the forecasting model of the regression equation. Using the mean and variance of weather data obtained from the regression model, the mean DTR also can be forecasted. The nature of mean DTR reflects a more accurate estimation of actual DTR as compared to the DTR forecasted using weather data from regression. The lower percentile such as the second and first percentile of forecasted DTR gives a more accurate estimation of the dynamic thermal rating.

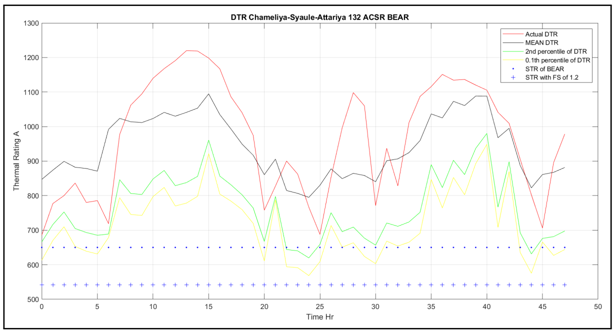

Figure 4: Comparison of actual and forecasted DTR percentiles estimated on June 5th – 6th, 2020 for Chameliya-Syaule-Attariya 132 kV Transmission Line

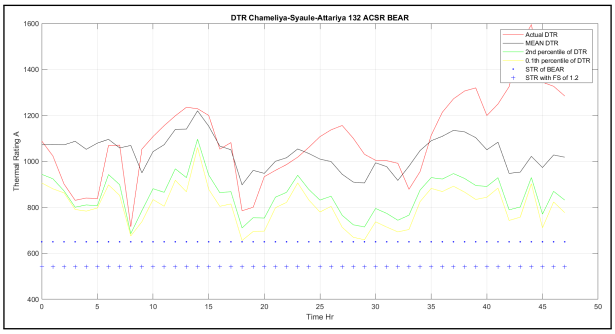

Figure 5: Comparison of actual and forecasted DTR percentiles estimated on February 5th – 6th, 2020 for Chameliya-Syaule-Attariya 132 kV Transmission Line

The two-day DTR forecasting for the 132 kV Chameliya-Syaule-Attariya transmission line on a summer day June 5th – 6th, 2020, and a winter day February 5th – 6th, 2020 are shown in the figure 4 and 5. The mean and lower percentiles of forecasted DTR are represented by different curves. It is noted that if accurate weather is achieved then more capacity can be generated as there is larger unused capacity available due to weather forecasting uncertainty.

4.2 Line Voltage Stability Assessment

The stability of the power system is the power system property that enables it to remain in a state of operating equilibrium under normal operating conditions and to regain an acceptable state of equilibrium after being subjected to a disturbance. Long transmission lines are limited by their voltage stability limit rather than their thermal limit. High line voltage drop leads to system voltage sag and hence system collapse. The line voltage drop depends on the current flowing through the transmission line conductor and its impedance. The per unit reactance of the transmission line depends on its Geometrical Mean Radius (GMR) and Geometrical Mean Distance (GMD) between phases which are supposed to be constant. Hence, the line voltage drop is dependent on line flow and its resistance. By implementing DTR, there will be increased line flow and hence increased voltage drop on the conductor. But in actual practice voltage drop is also dependent on the resistance of the conductor which is dependent on temperature and varies directly as per ambient temperature. Since we are increasing line current flow at the time of decreased ambient temperature and increased wind speed, there will be lower resistance of the conductor at that particular time. Therefore, there will not be such a significant increase in line voltage deviation by increased line flow at decreased ambient temperature and increased conductor cooling.

Let us consider Chameliya-Syaule-Attariya 132 KV transmission line for the numerical assessment. Chameliya-Syaule-Attariya is one of the longest transmission lines in INPS which can be a non-thermally limited line. It has a total length of 131 km connecting Chameliya HEP to Attariya Substation with intermediate Syaule Substation at 67 km far from Attariya grid substation.

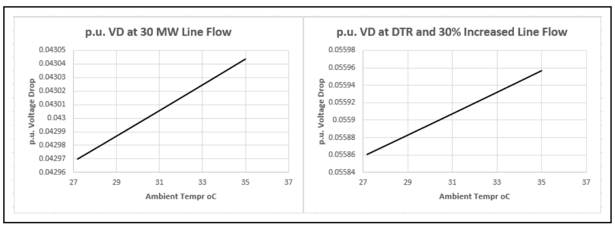

Figure 6: Temperature-Voltage Drop Relation for Chameliya-Attariya on 1st February 2020 with and without DTR

From the above analysis, for a cold winter day in February 2020, there is a maximum voltage drop of 0.04290227 p.u. on the Chameliya-Attariya 132 kV line with the existing flow and that of 0.055772951 p.u. when DTR with an additional 30% increased current. This is not such a significant increased line voltage drop against benefits taken from increased flow and DTR.

Results

From the initial assessment of DTR application in Chameliya-Attariya Transmission Line, the line thermal rating can approximately rise to 35% with a confidence level up to 98%. After implementing DTR in Chameliya-Syaule-Attariya line, about 30% of additional energy can be transmitted through the existing line annually. Therefore, there will be an enhanced utilization of existing assets leading utility to connect additional small power plants at different locations in Chameliya and nearer river basins.

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