A novel concept of dynamic line rating systems based on soft computing models

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***Abstract*— Due to the transformation of the electricity system, the system operators emphasize the maximum utilization of the existing network elements, such as transmission lines. Full utilization requires accurate tracking of the conductors' thermal behavior, which can also form the basis of the dynamic line rating (DLR) method. Due to these international trends, continuous monitoring of high-voltage transmission lines and developing resilience-increasing systems are becoming more common. The primary purpose of this paper is to demonstrate the operation and applicability limit of international DLR models and their conductor temperature tracking approach based on EU-funded international projects. The paper investigates two independent conductor thermal monitoring sensors and compares their measurements with the model results, highlighting key findings of the projects. A novel, neural network-based DLR concept is introduced based on the results presented, emphasizing its structure and operation steps. The advantages of the new concept in terms of conductor thermal tracking and power line rating are also presented in detail. One general novelty of the proposed concept is that it makes the transfer capacity calculation model operate independently from the line monitoring sensors over time. Thus, these devices can be dismantled or relocated to other spans or power lines based on the system operators' decisions. In this way, the novel concept has not only technological but also significant economic benefits.**

Keywords—power line, grid resilience, dynamic line rating, DLR, neural network, soft computing

I. Introduction

During the operation of the electricity system, the main goal is to maximize the utilization rate by always maximizing the power flow based on the set of limiting factors [1]-[3]. For most power lines, this limiting factor is the conductor's upper design temperature, which cannot be exceeded to avoid sag-clearance and annealing problems [4]-[6]. To maintain safe operation, transmission system operators have used static line rating or seasonal rating to determine the power lines' transfer capacity based on the worst-case combination of the environmental parameters [2][7]. However, these concepts no longer result in economic operation due to the electricity systems' trends in the recent decades [8]. One significant challenge of the electricity grid is the integration of the increased renewable energy sources resulting in intermittent power flow conditions [8]-[11]. These phenomena force the TSOs to track the thermal conditions of transmission lines more accurately. The economical and safe operation can only be ensured within these operating conditions if the power lines' transfer capacity limit is set dynamically and adapted to real-time weather and load conditions [9][12]. This method – the so-called dynamic line rating (DLR) – requires sensory monitoring of transmission lines and weather parameters around the phase conductors [7][9]. This paper presents a novel, soft-computing-based DLR concept that provides a more accurate conductor temperature calculation than the international models. Moreover, its DLR calculation can operate independently of sensory measurements over time.

II. Motivation

A. Existing DLR systems and approaches

The most common DLR models in the international literature are the CIGRE and IEEE [4]-[6]. These models approach the line rating issue through the conductor's thermal conditions [13]-[15]. Despite minor differences, their operation is similar under conservative circumstances [16]. In this paper, IEEE and CIGRE models are under the term "physical models", and those cases are presented where their outputs are close to each other.

The core of IEEE and CIGRE is that the conductor is in thermal equilibrium with its environment, so its temperature is affected by weather and load parameters [4][6]. Whether these environmental parameters change, the models distinguish between steady-state heat balance and transient state. The steady-state heat balance can be described with Equation (1), in which the individual cooling and heating factors, and thus the environmental parameters, are treated separately.

$$P_J + P_S + P_M + P_i = P_c + P_r + P_w \quad (1)$$

Where P_J is the Joule heating, P_S the solar heating, P_M the magnetic heating, P_i the corona heating, P_C the convective cooling, P_r the radiative cooling, and P_w the evaporative cooling. In the case of the transient state, the thermal equation is modified since the conductor can store heat that could increase its temperature, as seen in Equation (2).

$$Heat\ stored\ in\ conductor = Heat\ gain - Heat\ loss \quad (2)$$

Both IEEE and CIGRE models have formulas for conductor temperature tracking and line rating calculation, which are strongly related.

B. Experiences from international projects

Several international projects have compared line monitoring devices, conductor thermal behavior tracking, and dynamic line rating in recent years [12][13][17]-[19]. Given that the line rating of an observed transmission line is closely related to the conductor's thermal behavior, this paper focuses on conductor temperature tracking. This approach also makes it possible to compare the actual measurement results with the calculations by the physical models.

The data of two sensors (Sensor #1 and Sensor #2) operating on different measurement principles were used in the analysis. The technical parameters of the sensors are given in Table I.

TABLE I. Technical parameters of the applied sensors

Properties	Sensor #1	Sensor #2
Sensor placement	Phase conductor	Tower structure
Measured parameter	Conductor temperature	Conductor sag
Measuring unit	[°C]	[m]
Measuring uncertainty	±1°C (-20°C to 100°C)	±0.05 m (all circumstances)

Sensor #1 measures the conductor's surface temperature since that device is installed on the phase conductor, while Sensor #2 monitors the sag without any physical contact. Sensor #2 calculates the average temperature of the conductor with an accuracy of ±2 °C based on a CIGRE guideline [4].

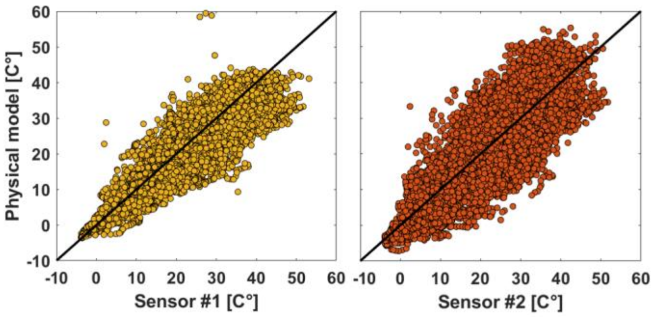

Fig. 1. Comparison of T_{cond} measurements with physical model calculation

In Fig. 1., the measured and calculated conductor temperature values are compared. On the x-axis, Sensor #1 and Sensor #2 records are shown, while on the y-axis, values calculated from the CIGRE model based on the weather station data are presented. Both sensors monitor the lower phase conductor of a single-circuit, 400 kV power line. It is clear from Fig.1. that the deviation is greater than the accuracy class of the sensors in many cases over six months.

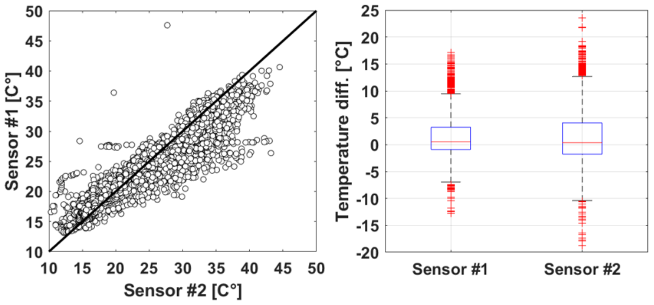

Fig. 2. a) Comparison of conductor temperature measurements by different sensors; b) Boxplots of temperature differences regarding sensor measurements and physical model calculations.

In Fig. 2 a), the scatter plot calculated from the measurements of the two sensors is presented. It is seen that a significant difference can be between the conductor surface and its average temperature. Fig. 2 b) shows box plots in the temperature differences calculated by the two sensors and the physical model. The mean values are around 0 °C; however, the standard deviation and variance exceed the sensors' technical specifications. Table II. shows the seasonal variation of standard deviations for a 400 kV transmission line.

TABLE II. The average standard deviation of the physical model from sensor measurements in all seasons, 400 kV power line

Season	Standard deviation Sens. #1 – Physical model	Standard deviation Sens. #2 – Physical model
Summer	5.20 °C	7.03 °C
Autumn	4.51 °C	5.96 °C
Winter	4.00 °C	5.23 °C
Spring	5.03 °C	6.74 °C

Table II. presents that the average conductor temperature calculated by the physical model can deviate by up to 5 °C from the surface temperature measured by Sensor #1 in the warmer summer month. This difference can exceed 7 °C by the average temperature measured by Sensor #2. This thermal deviation may also affect the DLR calculation.

The deviation shown plays a considerable role when, for some reason, sensory measurements are not available. Excellent examples are those cases when the line load is so low that a current transformer supply cannot be solved for sensor operation. A short case study is presented in Fig. 3.

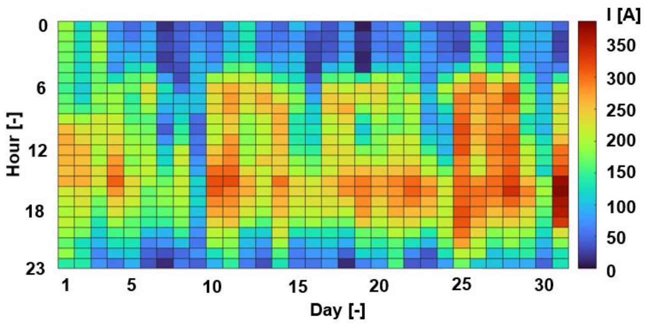

Fig. 3. Hourly line load distribution in a month

Fig. 3 shows an hourly breakdown of line load over a randomly chosen month. There are periods when the phase current does not reach the 65 A required for the current transformer to operate. In these cases, the sensor does not send data; thus, the conductor temperature is only available via different models' calculations. Suppose such a situation occurs on a colder day when the system operator wants to implement anti-icing on power lines. In that case, it is essential to have an accurate conductor temperature model.

C. Lessons learned from international projects

Based on the performed analysis, several important conclusions can be drawn.

- The measurement principles of the sensors determine what conductor temperature (surface or average) the device measure or calculate.

The surface and the average conductor temperature can differ significantly [4][5]. Contact sensors always measure the surface temperature at that point. However, the surface temperature is only essential for annealing problems as a potential local fault location. In those cases where the sag-clearance ratio forms boundary conditions, the average conductor temperature is the most critical parameter.

- There are circumstances when some of the line monitoring sensors cannot operate. In these cases, the accurate temperature calculation is favorable.

Conditions such as low-current may occur in the transmission line under which specific sensors (i.e., current-transformer supplied devices) do not operate. In these cases, the accuracy of the conductor temperature models is significantly enhanced.

- The conductor temperature calculated by the physical (IEEE and CIGRE) models may differ significantly from the measurement of the monitoring sensors.

This is consistent with other papers' findings and can be demonstrated for several transmission lines [4][9]. The discrepancy can be traced back to several reasons. First, the physical models deal separately with the heating and cooling effects on the conductor, which are difficult to combine into an empirical form. Second, the mentioned models contain negligence that may affect the computational results. Third, the input parameters required for IEEE and CIGRE models are often measured not directly in the conductor environment but where the weather station can be installed (on the legs of the steel tower). This does not guarantee that the conductor thermal ratio will be determined under the right conditions.

- There is a need for a new approach independent of the IEEE and CIGRE models that allows for more accurate and economic DLR calculations.

Given that the thermal conditions and line rating are closely related during the operation of the IEEE and CIGRE models, less accurate conductor temperature monitoring may also result in a less precise line rating. Therefore, more emphasis should be placed on calculating the thermal conditions of the conductor.

III. Introduction of the novel DLR concept

The novel concept presented in this paper needs to fulfill three criteria to ensure the economic operation of power lines; follow the conductor's thermal conditions well, provide safe and secure operation, and calculate line rating dynamically (DLR). Before introducing the concept, the conductor temperature tracking and the line rating calculation models are presented in detail. These models are firmly connected, and their operations form the basis of the novel concept described in the later chapters.

A. The conductor temperature model

When tracking the thermal conditions of the conductor, an obvious solution may be to use the measurements of the line monitoring sensors in terms of their accuracy, reliability, and resolution [20][21]. The more significant challenge is how to replace these costly devices in a way that does not significantly impair the accuracy of conductor temperature tracking. One good option can be the application of neural networks, which are used in other energy sector branches [22]-[25]. Neural networks are favorable because they are adaptive and can recognize patterns that can replace complex analytical relationships during training. Previous experience has shown that if a suitable training dataset is available, a neural network can calculate a conductor temperature with a more minor standard deviation than the IEEE or CIGRE models [21].

B. Parameter setting for the neural network

The proper functioning of neural networks requires a sufficient dataset to recognize patterns [26]. When choosing the network parameters correctly, the input and output combination is essential. In the present case, the input parameters are the environmental and load factors measured by the weather stations, while the output is the conductor temperature. However, based on experiences, it is a relevant question that surface and average conductor temperatures are different. A multivariate regression analysis was also performed for several transmission lines to determine which temperature is better explained by measured environmental parameters [27]. The result of a 220 kV single-circuit and a 400 kV double-circuit power line is presented in Table III.

TABLE III. Regression analysis of conductor temperature measurements

Parameter	220 kV power line		400 kV power line	
	Sensor#1	Sensor#2	Sensor#1	Sensor#2
Multiple R	0.91	0.87	0.98	0.94
Adjusted R Square	0.83	0.75	0.96	0.89
Standard Error	2.66	3.95	1.98	3.70
Observations	20799		19094	

Based on Table III., Sensor #1 has a lower determination coefficient and standard error for both power lines. This means that the applied weather parameters explain better the surface temperature than the average one in a simple, linear model. Then, it was investigated by a T-test which weather parameters are statistically relevant in a potential model. Comparing the P-value (at $\alpha = 0.05$) of each parameter, it was found that all the traditionally measured weather (ambient temperature, solar radiation, wind speed, wind direction) and load parameter (SCADA current) are relevant. Although the operation of a neural network differs from a single linear statistical model, these results form a reasonable basis for setting the network's parameters.

C. Applied network type and structure - experiences

Various neural networks can be used for each problem, including conductor temperature calculations [26]. This paper applies a cascade forward neural network with nearly 70 neurons in three regular and one.

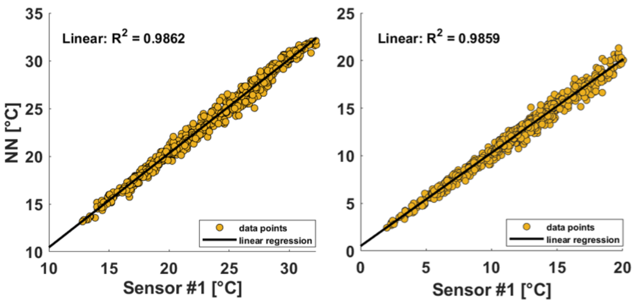

Fig. 4. Comparison of conductor temperature measurements of Sensor #1 to neural network model; a) Summer month; b) Winter month

The network requires five inputs, 4 of which are the already mentioned weather parameters, while the last one is the actual current extracted from the SCADA system. Neural network performance was measured by mean square error, and training was performed according to the LM method using a 12-month, quarter-hour data set. In Fig 4., data from Sensor #1 mounted on a European 110 kV transmission line were used in the evaluation. The scatter plot presents the neural network's performance after a one-year training period. The goodness of fitting is above 98% for the summer and winter.

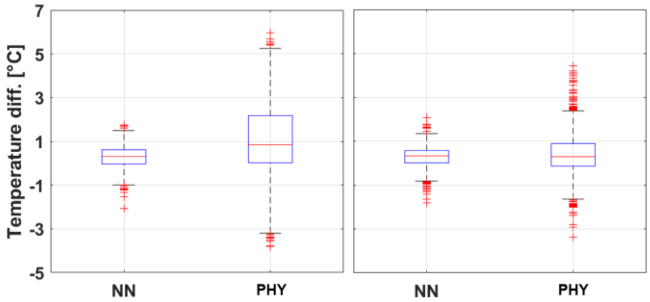

Fig. 5. Box plots of conductor temperature calculation deviation; a) Summer month; b) Winter month

In Fig. 5. the box plots of the neural network (NN) and physical model (PHY) are presented as output layers for the same periods. The mean value for the summer case is 0.30 °C, the 25th percentile is -0.03 °C, and the 75th percentile is 0.62 °C. The trends are the same for a colder period. This performance is close to the devices' accuracy range, resulting in a more accurate temperature calculation than the physical models.

D. *Line rating calculation model*

Assuming a transient state, the line rating for a given timestamp can also be calculated from the combination of the conductor temperature and the weather parameters using Equation (3) [4][5].

$$I^2 \cdot R = c \cdot m \cdot \frac{dT_{av}}{dt} - P_S - P_M + P_c + P_r \qquad (3)$$

Where c is the specific heat capacity of the conductor ($J \cdot kg^{-1} \cdot K^{-1}$) and m is the mass per unit length of the conductor ($kg \cdot m^{-1}$), dt is the applied period (s) and I is the line rating (A). When there is no steel core in the conductor, $P_M = 0$. In the case of the ACSR (aluminum steel reinforced conductors) [5]:

$$c \cdot m = c_a \cdot m_a + c_s \cdot m_s \qquad (4)$$

The subscripts a and s refer to the non-ferrous and ferrous sections of the conductor, respectively. In the conductor temperature change, the general aim is always to reach the upper thermal limit of the line. In this way, the so-called line rating is always adjusted to the changing environment resulting in a dynamic rating limit.

E. *The presentation of the novel concept*

Applying the presented models, a complex, novel concept can be built for a resilient, flexible system. The process diagram of the novel concept is shown in Fig. 6. The new concept starts similarly building up a traditional DLR system - line monitoring sensors and weather stations must be installed on the observed power line. These sensors can determine the conductor temperature with the accuracy described above. The main innovation of the concept is that the sensory conductor temperature measurement can be replaced using a neural network after a specific time. These sensor measurements function as a training dataset in the first year of the operation. The appropriate network learns to predict the proper conductor temperature for an input combination. Thus, after the training period (one year above the sensor calculation period), the sensor can be dismantled and freely transferred to other transmission line sections or another transmission line.

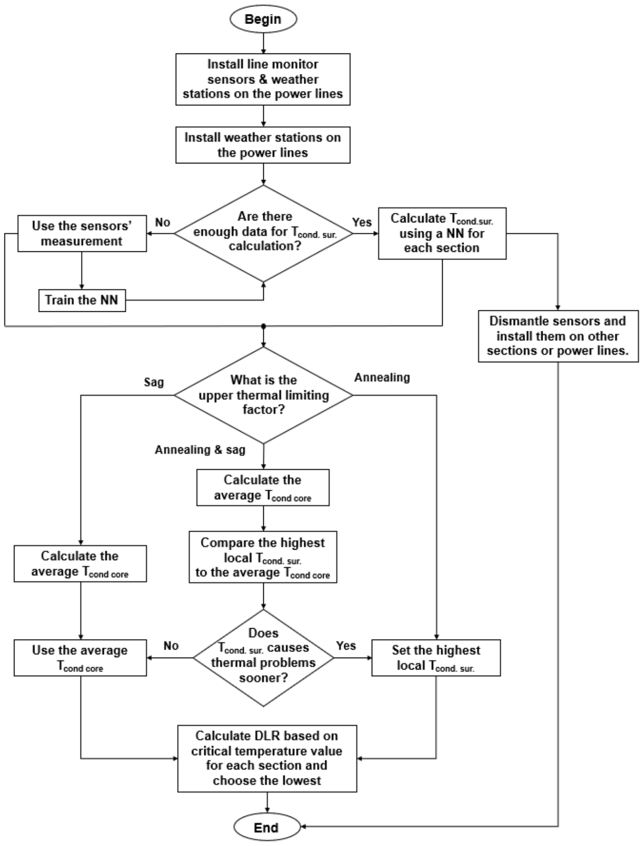

Fig. 6. The novel, soft computing based DLR concept's process diagram

Since the surface temperature of the conductor can be calculated with greater accuracy from the environmental parameters, the use of contact sensors is necessary. Thus, in the beginning, the sensor and later the neural network will also determine the surface conductor temperature. At this point, it is required to adjust to the limits of the operational conditions; in other words, whether sag-clearance or annealing causes a problem in the given case [4]. If sag-clearance conditions form the operation limit, the surface temperature needs to be converted to an average conductor temperature as it is closely related to sag [4][5]. For this purpose, the conductor surface measurements should be averaged and then the core temperature needs to be calculated using Equation (5) [5][28][29].

$$T_C - T_S = \frac{P_T}{2 \cdot \pi \cdot \lambda} \cdot \left[\frac{1}{2} - \frac{D_1^2}{D^2 - D_1^2} \cdot \left(ln \frac{D}{D_1}\right)\right] \qquad (5)$$

Where λ is the effective radial thermal conductivity ($W \cdot m^{-1} \cdot K^{-1}$), P_T the total heat gain per unit length ($W \cdot m^{-1}$), D the overall diameter of conductor (m) and D_1 the internal diameter of a steel core (m). Although the sag depends on the average conductor temperature, using the core temperature seems to be a good approximation in most cases.

In those cases where the conductor operates at a higher temperature (close to 100 °C), the annealing as a potential fault root can also occur. In these cases, the highest surface temperature should be used for line rating calculation instead of the average conductor temperature.

When both sag-clearance and annealing are limiting factors, both core and surface temperatures need to be calculated, and that one should be chosen which causes thermal problems sooner.

The line rating model can calculate the transfer capacity in real-time based on the calculated core temperature, surface temperature, or both. Choosing the lowest line rating calculated for each section, the transfer capacity can be extended to the whole power line. Thus, a safe and economic DLR system can be implemented.

F. Novelty, advantages, and application limits

The new concept has three significant advantages over previous approaches based on IEEE and CIGRE models. The first advantage is that neural networks allow a more accurate conductor temperature calculation than the physical models, thus making it easier to avoid problems due to possible thermal overloads. Using an appropriate amount of training data, the sensor measurements' accuracy range is possible via calculations.

The second significant benefit is that the new approach can reduce sag-clearance and annealing risk. The new concept considers that annealing is mainly related to the surface temperature while sagging is closely associated with the average conductor temperature.

The third great advantage of the developed concept (and the more accurate conductor temperature calculation) is that the system does not require sensory monitoring after training. The devices can be freely dismantled and relocated to other transmission sections or lines. This allows additional network elements to be economically integrated into DLR systems or a distributed sensor installation strategy on already selected transmission lines.

Regarding the application limitations, it is essential to mention that adequate training data is required for the neural network to function correctly. This also means that the sensors can only be relocated if they have been operating for at least one year. Nevertheless, the new concept allows for a significantly new approach from existing trends, resulting in more accurate and cost-effective DLR systems.

IV. Conclusion

Accurate tracking of the thermal conditions of transmission lines is key to a proper dynamic line rating system. When sensory observation cases are not provided, conductor temperature calculation models play a vital role. Several international projects have taken place and are currently underway to provide measurements of various line monitoring sensors. Based on the comparison of the measured conductor temperatures, the experience is that there may be a significant difference between the surface and average conductor temperature values. In addition, the analyses show that the physical models' calculations and the measured results are also inconsistent. Because of the close relationship between the thermal behavior of transmission lines and line rating, a new soft computing-based conductor temperature model based on accurate sensor measurements has been developed. Taking advantage of the neural network, the new conductor temperature tracking model has been incorporated into a concept that can significantly transform the operational practices of DLR systems. The three main advantages of the new concept are that it results in more accurate thermal monitoring than previous physical models, handles sag and annealing problems separately, and calculates line ratings after a specified time without sensory measurements. The new concept is technically and economically relevant, as the dismantled sensors can be relocated to other transmission line sections or even to new transmission lines.

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