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Transfer learning-based methodologies for Dynamic Thermal Rating of transmission lines☆

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ABSTRACT

Dynamic Thermal Rating (DTR) enhances grid flexibility by adapting line capabilities to weather conditions. For this purpose, DTR-based technologies require reliable and continuous measurement of the conductor temperature along the line route, which could hinder their wide-scale deployment due to the prohibitively high number of required sensors. Existing machine learning-based DTR methods infer conductor temperature from weather variables avoiding using complex and expensive measurement techniques, but their estimation accuracy greatly relies on the availability of a comprehensive set of measured data. To face these issues, this paper proposes the usage of transfer learning, a data-driven technique allowing the reduction of the number of sensors by transferring knowledge from a single calibrated source sensor to many target sensors. To the best of the author's knowledge, at the time of writing, the proposed approach is the first application of Transfer Learning in the domain of DTR which is validated on real transmission lines data. Experimental results from several real transmission lines equipped with self-organizing sensors-based DTR architecture show that transfer learning enhances the conductor temperature estimation reliability and accuracy of machine learning-based DTR techniques, suggesting the potential for practical applications, and reducing costs without losing accuracy for practitioners and system operators.

1. Introduction

The integration of renewable power generators (RPGs) in modern power systems brings environmental and social benefits such as reducing climate-changing emissions. However, their hosting capacity relies on the grid's ability to handle large power flows within strict line rating limits. Indeed, the uncertain generation profiles of RPGs can significantly perturb grid loading, inducing complex side effects. For instance, sudden wind speed increases in regions with many wind generators can congest lines, resulting in wind power generation curtailment. On the other hand, higher wind speeds can lower conductor temperature, raising overhead line capability. This extra capability is often neglected since systems operators adopt Static Thermal Rating (STR) policies, where line capabilities are assessed by considering worst-case weather conditions updated seasonally. This led to the development of Dynamic Thermal Rating (DTR) techniques, modeling dynamic conditions for line ampacity determination. Particularly, [1] shows the line ampacity estimated via DTR is 30% higher compared to STR (and remains 15% higher for more than 80% of the operating time). Hence, DTR is seen as a promising technology to enhance grid flexibility and RPG hosting capacity.

According to a recent comprehensive review [2], DTR technology could enable: (i) the estimation of the conductor temperature over time, (ii) the assessment of the load capability curve, and (iii) the prediction of the line ratings on several time horizons.

Particularly, several technologies and methodologies have been proposed in the literature for addressing task (i), which is recognized

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as the most critical process in DTR since its performance directly affects the accuracy and reliability of the computed thermal ratings. In particular, the conductor temperature of an overhead line (OHL) can be obtained through direct or indirect techniques. The former deploy conductor temperature sensors, whereas the latter employ analytic/data-driven-based estimation algorithms in the task of inferring the mapping between the conductor temperature and a set of easily measurable variables. Although direct methods are more accurate than indirect ones, the costs of the conductor temperature sensors, as far as the complexity of installing and maintaining these sensors, can hinder their widespread application in large-scale networks (more details are available in Section 2.2). These limitations have stimulated the research for data-driven-based indirect techniques, which aim at estimating the conductor temperature at specific line spans by processing the operation data (e.g. line current) and the weather variables measured along the OHL route (e.g. wind speed/direction).

Various techniques address the critical DTR process task (i) for developing effective DTR tools. Direct methods use sensors, while indirect ones employ estimation algorithms to relate conductor temperature to measurable variables. Direct methods are accurate but expensive and complex for large networks. Indirect methods estimate temperature using operational data and weather variables along the route, overcoming sensor limitations (details in Section 2.2). These limitations have stimulated the research for data-driven-based indirect techniques, which aim at estimating the conductor temperature at specific line spans by processing the operation data (e.g. line current) and the weather variables measured along the OHL route (e.g. wind speed/direction). In particular, data-driven algorithms emulate conductor temperature sensors by inferring the unknown mapping between measured variables (input) and conductor temperatures (output). Once this mapping is learned, sensors can be removed, and temperatures estimated using input data.

An alternative approach in indirect DTR tools uses data-driven techniques to enhance the accuracy of physical thermal models (e.g. IEEE standard [3]). Measured temperature profiles calibrate model parameters or improve accuracy through adaptive correction (e.g. grey-box modeling) [4]. Unfortunately, traditional machine learning-based DTR techniques require long-term installation of conductor temperature sensors to gather comprehensive data, often limited by economic factors. Hence, training a large number of local machine-learning models may be unfeasible due to the need to deploy a large number of conductor temperature sensors, whose availability is often constrained by economic issues.

To address this problem, this paper proposes transfer learning (TL) to enhance distributed DTR models using knowledge from a limited sensor dataset. Particularly, to the best of the authors' knowledge, this is the first TL application in this field. TL spreads trained model knowledge to uncalibrated models on various spans, identifying hidden relationships between distributed sensor data. This approach aims to reduce the required number of temperature sensors for accurate spatial temperature assessment. The expected benefits of using these techniques include: (i) improving the performance of data-driven models for DTR of transmission lines, particularly when the amount of data available for training the new model is limited or when the new task is related to the original task; (ii) reducing the costs associated with collecting data for machine learning-based DTR by potentially requiring fewer measured data to be collected and processed.

The proposed methods have been deployed for the DTR assessment of 11 spans of 7 transmission lines located in the south of Italy, which are frequently congested due to the widespread use of wind power generators. The analyzed lines are currently installed with a self-organizing sensors-based DTR architecture [5], equipped with weather stations measuring several environmental variables. Obviously, the indirect estimation of the sun irradiance is affected by strong uncertainties, which are mainly due to the sun position estimation errors and the approximation of the atmosphere reflectance properties [6]. Hence, the Authors' idea is to estimate the worst-case instances of these endogenous uncertainties by the proposed learning-based techniques. The effectiveness of this indirect estimation approach is confirmed by the good accuracy obtained during the experimental studies. Particularly, the proposed Parameter-based Transfer Learning approach offers potential cost savings by efficiently leveraging information from a source sensor, thereby reducing the need for extensive target sensor data collection and associated costs. Its superior predictive accuracy, evident when sufficient target data is available, can lead to better system maintenance scheduling, mitigating unexpected repairs and contributing to operational savings. Additionally, improved temperature predictions facilitate more efficient power transmission, reducing energy losses and enabling more cost-effective energy management. Moreover, the technique's adaptability across various sensors reduces the requirement for multiple, individual sensor models, minimizing development and tuning resources. Hence, the proposed approach presents a cost-effective, accurate solution for temperature estimation in power transmission systems.

The rest of the paper is organized as follows: Section 2 reviews the state-of-the-art to provide context for the proposed TL-based methodology, Section 3 discusses the proposed methodology of TL-based OHL conductor temperature estimation, while Sections 4 and 5 analyzes the case study and the conducted experiments, respectively. Finally, Section 6 presents the main conclusions.

2. Related works

2.1. Enabling technologies for DTR

The reliable temperature estimation along the line route by using direct/indirect methods is a crucial aspect in DTR-based tools [7]. Direct methods use sensing systems for conductor temperature, tension, or sag variation [8]. Sag variation monitors safe clearance at the maximum allowable temperature, while conductor tension helps estimate sag and average temperature via state change equation [9]. Strategies include vibration, inclination, and target monitoring [9–11]. These sensors provide localized data, suited for limited spans. To reliably estimate conductor thermal state, multiple sensors across the line route are essential [8,12,13].

Though direct methods measure key variables for line thermal ratings, sensor costs, and complexities limit large-scale use. This led to research on indirect DTR methods, estimating conductor temperature using mathematical models with easily measured variables. One promising approach uses synchrophasor data processing for average line temperature estimation [14]. While synchrophasor data is widely available, it estimates average temperature without ensuring maximum temperature compliance. Alternative methods estimate conductor temperature using a dynamic heat transfer model, leveraging line current and weather variables. Unlike synchrophasor-based methods, these estimate specific locations, typically critical spans with high conductor temperature.

Particularly, choosing between direct and indirect methods for DTR assessment involves a trade-off between accuracy and costs [7]. Indirect DTR tools using weather data have lower costs and their accuracy depends on adopted mathematical models. Distributed sensors offer higher accuracy but come with higher purchase, installation, and maintenance costs. Recent data-driven thermal modeling advancements improve the accuracy of indirect DTR tools, making them suitable for practical scenarios [15], motivating their deployment in this paper.

The optimization of transmission line ratings has been a key research focus in recent studies. The authors of [16,17] explored DLR forecasting methods like quantile regression, ensemble means, RNN, and CNN, suggesting ensemble forecasting is effective with low error rates. They proposed an algorithm to predict DLR, maintaining energy source balance. Moreover, the application of information and communication technology (ICT) has further enhanced the reliability and efficiency of the power grid as demonstrated by [18,19] through the employment of synchrophasor-based DTR and m integrity protection schemes (SIPS). Furthermore, [20] presented a data-driven method to assess real-time power system states. On the other hand, the authors of [21] addressed extreme weather risks with a multi-state model for resilient transmission systems against short-circuit faults. Furthermore, they also explored 5G-enabled switched fault current limiters (FCLs) for novel FCL allocation [22].

In light of these research contributions, transfer learning-based methodologies offer a promising direction for enhancing the efficiency and reliability of the dynamic thermal rating of transmission lines. Leveraging knowledge from a limited set of conductor temperature sensors, these methodologies could provide significant improvements in data-driven models for DTR, potentially reducing the need for data collection and thus the associated costs.

2.2. Indirect methods for DTR assessment

The authors of [23] used an Extended Kalman Filter-based dynamic state model to estimate conductor temperature considering uncertain weather variables which showed good performance in a controlled lab on a small conductor segment. [24] used a finite-element model for temperature estimation, challenging to apply in real-time. Furthermore, distributed field measurements and decentralized processing enabled the deployment of data-driven techniques for DTR assessment [15].

Particularly, data-driven algorithms learn the mapping between input weather/operating variables and conductor temperature, emulating sensor behavior. Post-training, sensors can be removed, and temperature estimated using input data alone. Methods can work independently (black-box) or combined with physical models (grey-box) for better accuracy. For example, data-driven models can fine-tune IEEE-standard-based thermal model parameters [3] to improve accuracy [25]. Grey-box models combine physical and data-driven approaches, reducing estimation errors [4], where hybrid methods show promise for digital twin development.

In all these applications, collecting a comprehensive data set of input/output observations is necessary to characterize the conductor's thermal behavior under different thermal exchange conditions. Consequently, many conductor temperature sensors should be installed on the monitored lines for long time periods, which could be a limiting issue for the large-scale deployment of data-driven DTR methods.

3. Transfer learning based conductor temperature estimation

TL [26] is a machine learning technique that leverages knowledge learned from one task to improve performance on a related but different task. It has been recently applied in the task of solving complex power system operation problems, such as load modeling [27], wind power forecasting [28–30], and dynamic security assessment [31,32]. Particularly, four categories are commonly used to classify TL-based approaches [26] such as (i) Instance-based transfer [33], which involves reusing labeled data from the source domain to improve the performance of a model in the target domain; (ii) Feature-based transfer [34], which involves finding an appropriate feature representation that reduces the difference between the source and target domains; (iii) Parameter-based transfer [35], which focuses on adapting the model parameters to better suit the target domain; (iv) Relational knowledge transfer [36], which involves building a mapping of relational knowledge between the source and target domains.

Another relevant classification of TL-based approaches is task adaptation, which refers to the transfer of knowledge from one task to another related task, and domain adaptation, which describes the transfer of knowledge from one domain to another related domain [37].

Particularly, this paper proposes the application of instance-based and parameter-based TL for DTR assessment considering the advantages linked to the TL deployment. Instance-based TL can increase the accuracy of thermal models by assigning higher weights to samples that are most relevant to the target task. With this approach, even when limited data is available, its informative content can be leveraged to improve the prediction of dynamic thermal behavior. Similarly, parameter-based TL can be an effective DTR solution by adapting an existing thermal model to new limited data. A pre-existing thermal model can be fine-tuned using the limited new data, leading to an improved model that can handle the dynamic thermal behavior. Hence, the proposed approaches belong to the domain adaptation category, as the knowledge is being transferred from one related domain to another.

3.1. Proposed methodology

Let us denote with $\mathcal{K}$ the set of spatial positions along a transmission line where the conductor temperature will be estimated. The term "spatial" implies that these points have a physical location along the transmission line route. The evolution of the conductor temperature y_k at a specific spatial location $k \in \mathcal{K}$ can be modeled by a first-order discrete-time thermal model f, such as those proposed in the IEEE 738 standard Appendix. This model maps the current value of the temperature at the kth position $y_k[i]$, the weather variables and the line current at time i to the next temperature value $y_k[i+1]$, where $\mathbf{x}_k[i]$ is the input vector containing the weather variables and the line current observable at the ith instant. Such a white-box model can be used to perform an iterative (or recursive) forecasting [38] returning the predicted one-step-ahead value $\hat{y}_k[i+1]$ based on the previous estimate. An iterative forecasting is required since, after the algorithm initialization, the actual value of the conductor temperature is unknown due to the absence of an installed sensor on the line when indirect methods are used.

An alternative to the white-box approach consists of adopting a statistical learning algorithm $\mathcal{A}$ to learn from data the mapping between current and future values. Once denoted with $\hat{f}_k$ the learned mapping, the black-box forecasting approach consists of iterating

$$\hat{y}_k[i+1] = \hat{f}_k(\hat{y}_k[i], \mathbf{x}_k[i], \alpha_k), \qquad k = 1, \ldots, |\mathcal{K}| \tag{1}$$

where $\alpha_k = \mathcal{A}(D_N)$ is a compact way to denote the model family, the hyperparameters and the parameters returned by the learning algorithm $\mathcal{A}$ on the basis of a training dataset D_N of size N.

It is common to set the problem of learning the input–output mapping $\hat{f}_k$ as a regression problem with M inputs and to adopt conventional machine learning algorithms (e.g. neural network, random forest, local learning) to learn the regression model from data [38]. This approach consists of first embedding the observed dataset in an input–output matrix format where the dataset $D_N = [\mathbf{X}_k, \mathbf{y}_k]$ is the concatenation of the input matrix $\mathbf{X}_k$ and the output vector $\mathbf{y}_k$. Given the nonparametric nature of the machine learning model, a training and test split procedure is typically adopted by the algorithm $\mathcal{A}$ to select the best set of hyperparameters (e.g. number of hidden nodes in a neural network). In the following, $\hat{y}_{test,t}$ indicates the portion of target data that is hold-out from the learning procedure to assess the performances of the model.

Although the use of machine learning-based techniques for estimating conductor temperature has shown promising results [4], their extensive application is limited by the large amount of data required to train an effective model.

The problem is exacerbated when the number of measured points $|\mathcal{K}|$ (and consequently of learned models) is large. To reduce the training data collection time (TDCT), the simultaneous installation of many temperature sensors will be necessary, which would negate the cost-effectiveness of indirect methods. Therefore, the challenge is to find strategies that can reduce the TDCT while maintaining a high level of accuracy.

A possible strategy for reducing the TDCT of machine learning models for conductor temperature estimation is by using Transfer Learning (TL). This involves defining two points in different transmission lines, called s (source) and t (target) ($s, t \in [1, \ldots, |\mathcal{K}|]$, $s \neq t$) when estimating the conductor temperature. Let us denote the number of collected data by the source and target hot spot with N_s and N_t, respectively, with $N_t \ll N_s$. In a traditional machine learning approach, two different models $\hat{f}_s$ and $\hat{f}_t$ would be built for the source and the target, respectively.

However, the limited number of collected data in the target dataset may not be sufficient to train an accurate $\hat{f}_t$ model. To overcome this issue, TL-based methods can be deployed to improve accuracy. This paper focuses on two specific TL strategies: instance-based and parameter-based. Instance-based TL is the process of transferring knowledge from a source domain to a target domain by reusing source instances in the target domain. This means that the learning algorithm $\mathcal{A}$ takes advantage of both the training sets D_{N_t}, D_{N_s} to learn the one-step-ahead target mapping parametrized by $\alpha_t = \mathcal{A}([D_{N_t}, D_{N_s}])$. Examples are Kernel Mean Matching [39], Nearest neighbor-based importance weighting [40], TrAdaBoost.R2 [41]. These approaches usually perform a weighting of the source data points to increase the similarity between the source and target distributions.

On the other hand, parameter-based TL is the process of transferring knowledge from a source domain to a target domain by reusing learned parameters from the source domain. The target learning process $\alpha_t = \mathcal{A}(D_{N_t})$ is either initialized or regularized by the set of parameters $\alpha_s = \mathcal{A}(D_{N_s})$. Examples include RegularTransferNN [42], TransferTreeClassifier [43], linear interpolation [44]. These methods are model specific: for example, RegularTransferNN trains a neural network on the target data using an objective function that is regularized by the Euclidean distance between the parameters of the source and target (i.e. the weights of the network). On the other hand, TransferTreeClassifier modifies a source Decision Tree on a target dataset, by adapting its shape and its parameters.

In order to cover the most widely applied categories in the TL-domain, the two approaches tested in this paper are TrAdaBoost.R2 and RegularTransferNN.

TrAdaBoost.R2 is an instance-based TL method that combines the strengths of AdaBoost [45] and a base model. Its main idea is to train a base model on the source data and then use a boosting approach (AdaBoost) to weight the instances from the source data based on their relevance to the target data. The weighted source instances are then used as additional information to train a base model on the target task data. On the other hand, RegularTransferNN is the parameter-based TL implementation adopted. It adapts the parameters of a pre-trained source neural network using a small amount of labeled target data to obtain a good target estimator.

3.2. Postprocessing

The data-driven models presented aim to predict the one-step-ahead sample by relying on the learned historical information. However, such a procedure does not necessarily account for the physical constraints guiding the conductor's thermal behavior (e.g. the maximum feasible temperature increment in a single time step, given the actual boundary conditions), resulting in potentially noisy predictions.

To mitigate this issue, a post-processing filtering step is applied to the predicted values $\hat{y}_{test,t}$. Several filtering approaches, conventionally applied in the domain of time series forecasting have been compared: moving averages, exponential moving averages, and weighted moving averages. Experimentation on a reduced sample of data showed that there were no significant differences among the tested approaches. We eventually selected a simple moving average filter (2) due to its simplicity and interpretability, while still providing an adequate level of noise reduction for the task at hand.

The filtered prediction $\hat{\hat{\mathbf{y}}}$ is computed as follows:

$$\hat{\hat{\mathbf{y}}}_{test,t}[i] = \frac{1}{M} \sum_{m=1}^{M} \hat{\mathbf{y}}_{test,t}[i-m], \tag{2}$$

where M is the number of previous samples considered in the smoothing process.

It is important to note that the application of the smoothing filter was not the critical factor enabling the Parameter-based Transfer Learning method to outperform the IEEE 738 standard. We performed preliminary experiments where the Parameter-based Transfer Learning method was applied without any post-processing. These experiments demonstrated that this method was still superior to the IEEE 738 standard, even in the absence of the moving average filter. The primary reason for employing the smoothing filter is to carry out noise reduction for improved consistency in the conductor temperature estimates.

4. Testing and validation methodologies

The validation of the proposed approach follows a conventional machine learning approach: the raw data (described in Section 4.1) is pre-processed in a suitable format for the subsequent learning process (presented in Section 4.2). Then, to ensure a fair and accurate comparison among the various TL methods, the data is split into training and testing set. A two-month dataset serves as the basis for the setup: the first month being used for training, while the second month is selected as test and transfer set to provide a consistent comparison of the results obtained from each method. Finally, the models under study (presented in Section 4.3) are trained on the available data, and their performance are validated according to the experimental setup described in Section 4.4. The following experimental setup is representative of a real-life operational situation where, due to economical constraints, the temperature measurement sensors can be only setup on the overhead lines for a limited amount of time on a limited amount of lines, therefore requiring the temperature estimations on novel lines, without the availability of sensors.

4.1. Data features

One of the distinctive features of this work is the employment of real-time data from a self-organizing sensors network for DTR composed of eleven computing nodes [6] installed at 4 m above ground [5]. Particularly, the demo area is located in a 150 kV grid in South Italy, and it was identified under Working Package 5 (WP5) of the "*Optimal-System mix of Flexibility Solutions for European electricity*" (OSMOSE) H2020 project [46]. This WP was led by Terna, the Italian TSO, and was focused on the role of Dynamic Thermal Rating Systems in enhancing flexibility services. The DTR systems, which were developed under this project, were installed on 11 spans of 7 power lines of a 150 kV grid and was adopted in the task of dynamically computing the load capability curves of seven high voltage overhead lines, which are frequently congested due to the large pervasion of generators in the served area. Unfortunately, further details about line installation are confidential information and cannot be shared.

The cooperative DTR sensors are deployed along the line route at 5 m from the ground and at distances ranging from 5 to 12 km, depending on the radio network coverage. Strategically placing these sensors along the line route is a complex issue, which has been addressed by the TSO considering the site orography. Each computing node includes a weather station, which measures air temperature [°C], wind speed [m/s], wind direction degrees, and sun irradiance [W/m]. Particularly, the time resolution of the data is 1 min and the collection period is two months, resulting in around 86 000 samples per sensor. The period of data acquisition is the period between September and November 2019.

The measurement of sun irradiance avoids the estimation of this quantity from the knowledge of shades, sun position, and atmosphere reflectance properties by using the equations reported in the IEEE 738 standard. Particularly, the distributed nodes have been equipped with sun irradiance sensors (please refer to [5,46] for further details), therefore the latter inputs have been neglected.

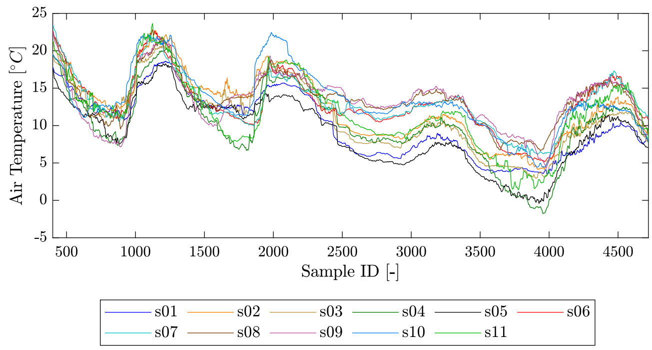

Fig. 1. Measured air temperature by each self-organizing sensor weather station.

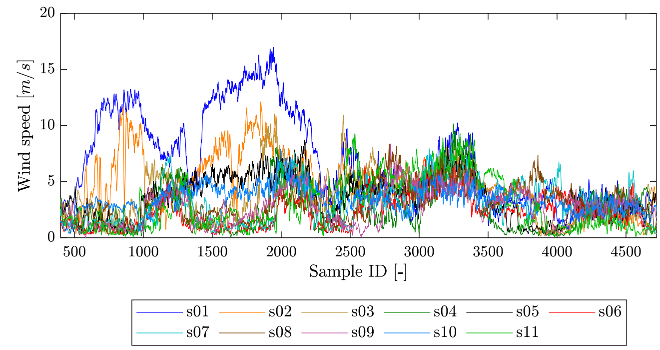

Fig. 2. Measured wind speed by each self-organizing sensor weather station.

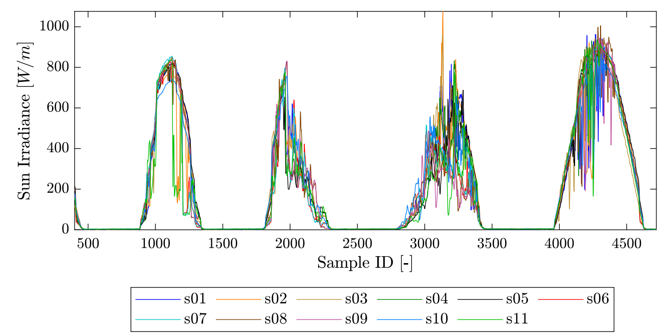

Fig. 3. Measured sun irradiance heat flow by each self-organizing sensor weather station.

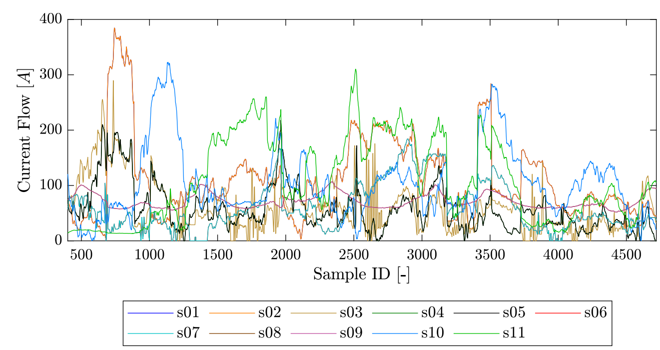

Fig. 4. Current flow for each line monitored by the corresponding self-organizing sensor weather station.

Moreover, the conductor temperature (the target variable to predict) is directly measured through a dedicated sensor, mounted around the conductor line.

It should be noted that the direct temperature sensors are primarily utilized for data collection to train the machine learning models and are not available during real-time operation. In this context, TL methods can offer an accurate and real-time alternative for estimating the conductor temperature without relying on the constant presence (and the corresponding economical cost) of the sensor.

While the raw data provides a comprehensive picture, further processing is necessary to accurately capture the actual environmental conditions at the conductor's height, which is roughly 30 meters above the ground. A wind shear model [47] is employed to adjust the measured variables, providing a more realistic representation of the environment surrounding the conductor.

The data acquired by the self-organizing sensor weather stations are broadcasted in real-time to a central server, where they are combined with the line current measurement for each ith sample and linked to the corresponding measured conductor temperature acquired from the Italian TSO Energy Management System. Hence, since this study uses the real operating conditions of the lines, simulations of the electrical system are not necessary.

The set of Figs. 1–4 shows the temporal profiles for some of the input variables of the addressed forecasting problem. Fig. 1 displays the air temperature evolution, a key factor influencing line conductor cooling. The trend indicates decreasing temperatures with similar patterns. However, an increasing spread between temperature profiles is observable from the end of the second observed day. Fig. 2 shows wind speed profiles, exhibiting considerable variability with no easily identifiable similar observed patterns. Sun irradiance heat flow (Fig. 3) shows the greatest pattern similarities across the self-organizing sensor weather stations. However, a detailed analysis reveals the variability of sun irradiance heat flow due to its dependence on local cloud coverage, which can rapidly change the measured heat flow. Fig. 4 presents the current flow for each line with a self-organizing sensor weather station installed. As observable, each line seems to have its own current profile.

The available data are gathered from the southern-east portion of the Italian HV transmission grid during the test of a real self-organizing sensors network DTR architecture [5], however, to preserve the integrity of the study and to respect confidentiality agreements, the exact locations of the self-organizing sensor weather stations used in this study are not disclosed.

4.2. Preprocessing

Before conducting the experiments, further pre-processing steps are applied to ensure their quality and integrity. The detection of abnormal behaviors in the data was performed through a combination of visual inspection and rule-based categorization, guided by expert knowledge. After the pre-processing phase, a limited number of data points (less than 100) were identified as affected by measurement error and removed from the data set. This extensive preprocessing process is performed to ensure an adequate data quality standard (especially concerning labeling accuracy and missing value removal) for the subsequent predictive steps. More precisely, transfer Learning methods, and in particular the Parameter-based Transfer methods, strongly benefit from accurate, well-labeled data from the target domain for effective training.

4.3. Analyzed methods

The *Parameter-Based Transfer* and *Instance-Based Transfer* methods presented in Section 3 are compared with multiple baselines: *Source Only*, *Target Only*, *Source and Target*, and *IEEE 738*.

Source Only is a method in which the model is trained only on data from the source task and then tested on data from the target task.

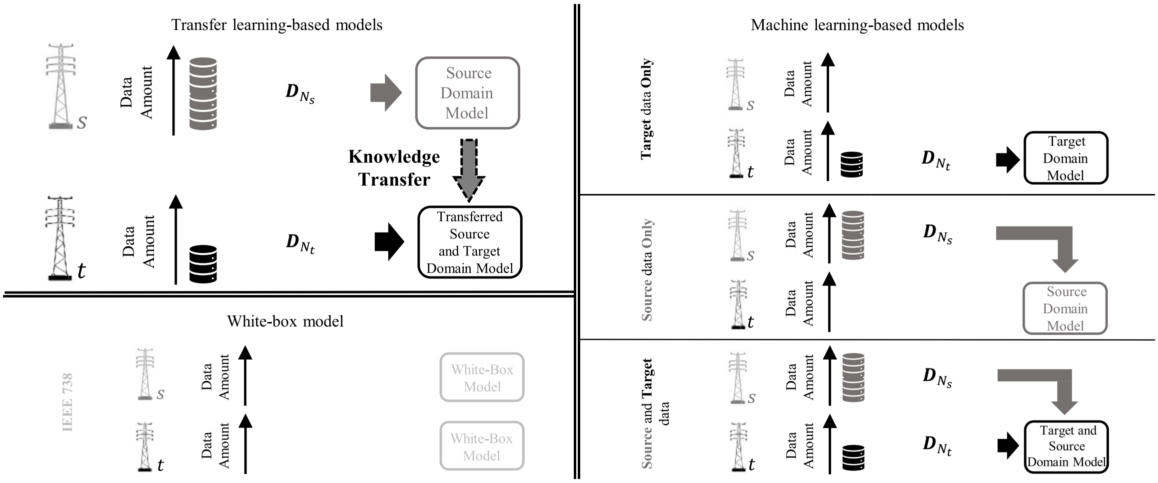

Fig. 5. Training data workflow per considered model. Grey and black-colored items correspond to the source and target DTR stations, respectively.

This method serves as a baseline to compare the performance of other methods and is based on the idea that a model trained on the source task data alone can provide a good representation of the target task. *Target Only* is a method in which the model is trained only on data from the target task. This method serves as a baseline to compare the performance of other methods and is based on the idea that a model trained on the target task data alone can provide a good representation of the target task.

Source and Target is a method in which the model is trained on data from both the source and target tasks, but no transfer of knowledge from the source task to the target task is attempted. This method serves as a baseline to compare the performance of other methods and is based on the idea that training a model on both source and target task data can provide an improved representation of the target task.

IEEE 738 is an estimation method for conductor temperature based on the thermal model proposed in the IEEE 738 standard. This method is used as a baseline for comparison with other methods, as it is a widely used industry standard for conductor temperature estimation.

The workflow of their training process is shown in Fig. 5. Particularly, this figure shows the amount of data used for target and source DTR stations and their path between the models. A null data amount means no training data are necessary (e.g. IEEE 738).

4.4. Experimental setup

This section outlines the experimental setup implemented for evaluating the proposed TL approach on sensor data.

4.4.1. Model parameters

The default regression model from the *Adapt* TL library [48] has been employed. It consists of a feed-forward neural network with an input layer of 5 units, corresponding to the measured variables (air temperature [°C], conductor current [A], wind speed [m/s], wind direction [°], and sun irradiance [W/m]), two hidden layers of 10 units each, and an output layer of a single neuron, representing the predicted actual conductor temperature [°C]. All the layers are fully connected.

The choice of activation function is critical in defining the model's ability to learn and generalize. For the hidden layers, we employed the Rectified Linear Unit (ReLU) activation function. The adoption of ReLU, which returns the input if it is positive and zero otherwise, can efficiently mitigate the vanishing gradient problem that can impede learning during the backpropagation phase. The output layer, designed to predict the actual conductor temperature, employs a linear activation function, typical in regression tasks.

The model is trained using the mean squared error (MSE) loss function and it has been used for both parameter-based and instance-based TL. In parameter-based TL, the weights of the model are fine-tuned on a new task using a small amount of labeled data from the new task, while in instance-based TL, copies of the model are trained on an iteratively re-weighted dataset that consists of both labeled data from the new task and labeled data from a related task.

Table 1
Main parameter settings of TL-based methods.

Target data available (days)	5, 10, 15, 20, 25
Corresponding percentage	17%, 33%, 50%, 66%, 83%
Test Set Size (days)	30
Number of Epochs	15
Batch Size	32
Number of Estimators for TrAdaBoost.R2	20
Moving Average Samples (M)	15

4.4.2. Experimental hyperparameters

In this experimental analysis, five main parameters have been considered: the number of available days from the target sensor data, the number of test days from the target sensor data, the number of epochs used during the model training process, the batch size used during the model training process, and the number of estimators used in the TrAdaBoost.R2 instance-based approach. These parameters and their respective values are summarized in Table 1. The batch size and number of epochs are determined based on a limited parameter tuning performed on a specific sensor pair. The number of estimators for the TrAdaBoost.R2 instance-based approach was set to the default value specified in [48].

Experiments are repeated for each sensor couple s, t (with $s \neq t$), to provide a comprehensive evaluation of the proposed TL approach, for a total of 110 couples. This approach provides valuable insights into the strengths and limitations of the TL methods across different sensor configurations.

The metric adopted is the root mean squared error (RMSE, (3)). In the equation, N_{test} indicates the size of the test set.

$$\text{RMSE} = \sqrt{\frac{1}{N_{test}} \sum_{i=1}^{N_{test}} \left(\hat{\mathbf{y}}_{test,t}[i] - \mathbf{y}_{test,t}[i] \right)^2} \tag{3}$$

5. Experimental results

The results presented in Fig. 6 and Tables 2, and 3 reveal that both Parameter-based Transfer and IEEE 738 methods exhibit relatively low root mean squared error (RMSE) values for all couples of the target sensor DTR stations. Particularly, the comparison between RMSE and MAE

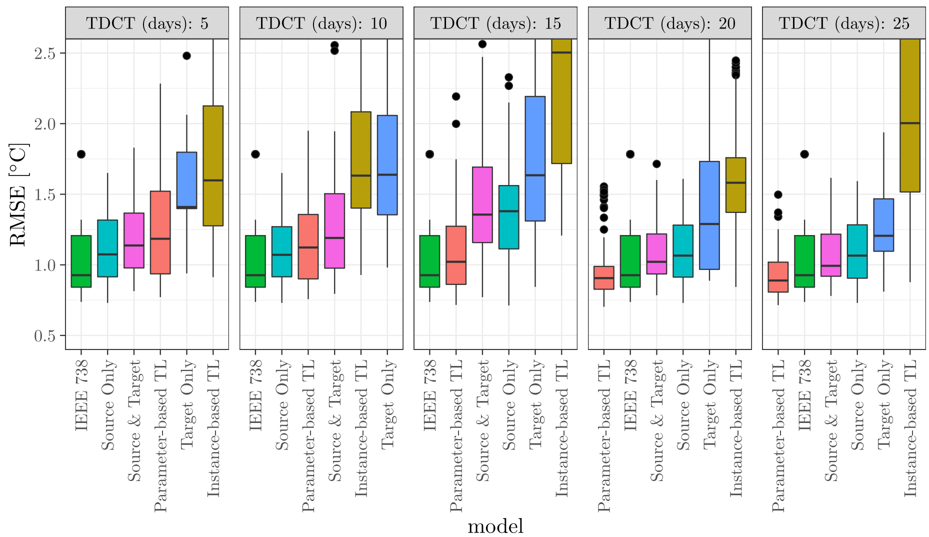

Fig. 6. Visualization of RMSE boxplot for each considered model across considered couple 'target' - 'source' DTR station. Each panel shows the results for a different amount of training data collection time (TDCT). In each panel, the methods are sorted by the median.

Table 2
Comparison of RMSE [°C] for the compared approaches.

Methods		Target data available d (days)				
		5	10	15	20	25
Parameter-based TL	μ	1.27	1.14	1.09	0.95	0.93
	σ	0.38	0.28	0.29	0.20	0.16
Instance-based TL	μ	1.74	1.71	2.88	1.62	2.16
	σ	0.64	0.47	1.27	0.34	0.90
Source Only	μ	1.13	1.11	1.38	1.11	1.11
	σ	0.24	0.23	0.36	0.23	0.23
Target Only	μ	1.74	1.78	1.78	1.35	1.28
	σ	0.77	0.65	0.63	0.41	0.28
Source & Target	μ	1.18	1.23	1.43	1.09	1.07
	σ	0.24	0.33	0.39	0.23	0.20
IEEE 738	μ			1.02		
	σ			0.30		

Table 3
Comparison of MAE [°C] for the compared approaches.

Methods		Target data available d (days)				
		5	10	15	20	25
Parameter-based TL	μ	0.98	0.85	0.81	0.67	0.66
	σ	0.94	0.81	0.82	0.70	0.69
Instance-based TL	μ	1.40	1.40	2.53	1.34	1.85
	σ	1.28	1.17	1.93	1.05	1.49
Source Only	μ	0.80	0.79	1.05	0.80	0.79
	σ	0.83	0.82	1.00	0.82	0.81
Target Only	μ	1.41	1.28	1.48	1.07	0.99
	σ	1.31	1.37	1.20	0.90	0.85
Source & Target	μ	0.83	0.91	0.99	0.76	0.74
	σ	0.83	0.89	1.08	0.77	0.75
IEEE 738	μ			0.72		
	σ			0.78		

tables seems to show model performance coherence by considering different metrics.

The Parameter-based Transfer method has an RMSE that is lower than the IEEE 738 method when the number of days available for the target sensor is sufficient ($d \geq 20$). The mean and standard deviation of the RMSE values for the former decrease as the number of target days increases, indicating that the available target data plays a significant role in enhancing the accuracy and stability of the TL-based method. Additionally, the Parameter-based Transfer method consistently outperforms the Instance-Based Transfer method and is competitive with respect to the Source Only and Target Only methods when the amount of target data is limited. The best performance is achieved using 20 and 25 available target days. It should be noted that, the advantage of the chosen Parameter-based technique is twofold: in both accuracy and computational time. In fact, Parameter-based TL only requires a single fitting of the model (to adapt the weights of the base model) whereas the chosen Instance-based technique requires multiple model fittings (as part of the boosting procedure, depending on a controllable hyperparameter).

On the other hand, the performance of the IEEE 738 method does not change with the number of target sensor days. Its mean RMSE is 1.02 and its standard deviation is 0.30, making it competitive with all the other data-driven approaches.

The non-transfer methods, *Source Only, Target Only, and Source & Target*, exhibit similar average performance. However, their behavior changes according to the amount of available target training data. As expected, Source Only is not affected by the amount of data, with only minor variations due to randomness in the training phase, while Target Only presents improved results with increasing data availability.

Source & Target follows this trend and reaches the performance of the IEEE 738 method when 20 days of target data are available and outperforms it with 25 days available. It emerges as a very promising method, considering its simplicity. It would also be possible to classify this method as a naive form of TL, which consists simply of exposing a model to information from both the source and target sensors.

The underperformance of the Instance-based Transfer method in our study can be attributed to multiple interrelated factors. Firstly, the varied and complex influences on the thermal behavior of electrical conductors may hinder the effective transfer of source instances to the target task. Secondly, the use of reverse boosting in conjunction with a neural network model might cause overfitting, potentially leading to the devaluation of key source instances. This devaluation could result in a selection of instances for the target sensor that do not accurately represent its real conditions, thereby generating unrealistic predictions.

Additionally, the differing statistical characteristics between source and target tasks are likely to have impacted the method's effectiveness. Each sensor's exposure to unique environmental and operational conditions can lead to distinct data distributions, which in turn, challenge the efficacy of directly transferring instances between tasks.

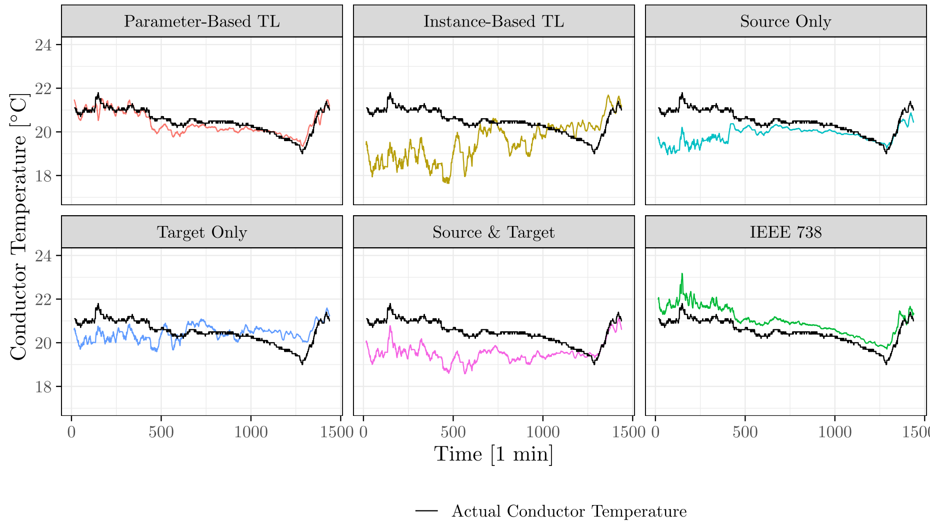

Fig. 7. Visualization of estimated and actual (black colored curve) conductor temperature profiles.

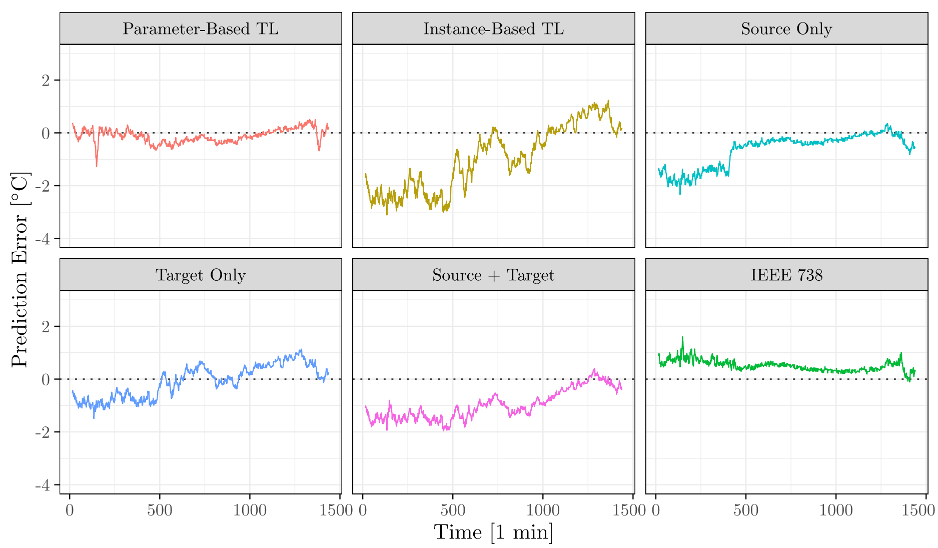

Fig. 8. Visualization of conductor temperature estimation error profiles.

Furthermore, the weighting system designed to signify the relevance of each instance to the target task may not provide meaningful information, considering the aforementioned factors. Instances with high weights might not necessarily contribute relevantly to the target task, adversely affecting performance. To address these issues, future research could focus on developing more refined strategies for instance weighting and selection, or explore methodologies that exhibit greater resilience to variations between domains.

Fig. 7 displays a comparison of the estimated conductor temperature profile of each model with the actual one (represented by the black curve) for an example reference time window. *Parameter-based TL* profiles are closer than those produced by *Instance-based TL*, which returns an unrealistic profile. It is interesting to note that the Parameter-based TL profile adheres more to the actual profile than non-TL-based data-driven methods and IEEE 738 standards. The superior quality of the *Parameter-based TL* method compared to other methodologies is more evident in Fig. 8, which shows the error profiles. It is noteworthy that the Parameter-based TL method does not show any bias, while IEEE 738 overestimates the conductor temperature in this time window.

In conclusion, the results of this study suggest that TL can be a valuable technique for reducing forecasting error when transferring knowledge from a source sensor to a target sensor. Among the different TL methods considered, the *Parameter-based* approach is the most effective in terms of reducing the RMSE. Moreover, the performance of this method can be further improved by making appropriate hyperparameters tuning. With the chosen TL-based model, the hyperparameters play a crucial role in the learning phase of the model, and their optimization can lead to improved accuracy and stability of the model.

In the context of the experiments conducted, it was observed that TL was able to effectively improve model performance when the amount of target data available surpassed 15 days. This finding highlights the importance of having a sufficient amount of target data when applying TL techniques to a specific problem. The results of these experiments suggest that having a greater amount of target data can contribute to the effectiveness of TL and that this threshold may vary based on the particular problem, model, and data in use. Statistical analyses were carried out to enhance the robustness of our study's findings. Upon

Table 4
Paired t-test (α = 0.05) to compare the mean of the "Parameter-based TL" approach against several other approaches. The alternative hypothesis is that the mean of "Parameter-based TL" is less than the mean of the other approaches. Results for 25 available target days.

Competitor	t-statistic	p-value	p-value $< \alpha$
Instance-based TL	−1.0e+01	4.0e−18	True
IEEE 738	−3.7e+00	1.7e−04	True
Source Only	−8.0e+00	6.0e−13	True
Target Only	−9.5e+00	3.2e−16	True
Source + Target	−5.8e+00	3.0e−08	True

rigorous statistical testing, it was shown that for 20 and 25 target days available, as shown in Table 4, the transfer learning (TL) methods statistically outperformed other methods, including the IEEE 738 standard, in predicting conductor temperature. However, while using less than 20 available target days, while TL methods did outperform the IEEE 738 standards, the difference was not statistically significant. This leads to an insightful observation: even in preliminary stages, TL algorithms can match or potentially surpass the performance benchmarks set by the long-standing IEEE 738 standards. Yet, the amount of available target data plays a crucial role. This highlights an opportunity for more meticulous optimization of the TL algorithms.

6. Conclusions

Dynamic Thermal Rating (DTR) technology enables the reliable exploitation of renewable energies by adapting the load capability of transmission lines to the actual weather and loading conditions. However, widespread DTR application is hindered by the need for numerous sensors required to reliably estimate the hot-spot line temperature (in case of direct and data-driven methods) or the usage of less reliable indirect estimation methods. Machine Learning (ML) techniques can be used enhance indirect methods but would require large amounts of sensor data for accurate training.

To address this challenge, this paper explored the potential for TL as a novel approach in DTR to improve the quality of the temperature estimation process, while limiting the number of required datapoints. The experimental results highlight the potential of TL in making the application of machine learning in DTR applications feasible. Future research will focus on two main directions. Firstly, this study focused on a specific transfer learning base model, therefore further analysis on role and impact on the results of the base model needs to be examined. Secondly, a comparative analysis with more complex based models as well as a deeper analysis of the trade-off between computational costs and predictive power could further support the application of TL in DTR.

Availability of data and code

The data used for this project is confidential and cannot be made available. However, the code used to generate the results is available through a GitHub repository at the following link: https://github.com/gmpal/DynamicThermalRating.

CRediT authorship contribution statement

Gian Marco Paldino: Writing – review & editing, Writing – original draft, Validation, Software, Methodology, Investigation. **Fabrizio De Caro:** Writing – review & editing, Writing – original draft, Validation, Software, Methodology, Formal analysis, Conceptualization. **Jacopo De Stefani:** Writing – review & editing, Writing – original draft, Methodology, Visualization, Formal analysis. **Alfredo Vaccaro:** Writing – review & editing, Writing – original draft, Supervision, Formal analysis, Data curation, Conceptualization. **Gianluca Bontempi:** Writing – review & editing, Writing – original draft, Supervision.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Gianluca Bontempi, Gian Marco Paldino reports financial support was provided by DigitalWallonia4.a. Gianluca Bontempi, Gian Marco Paldino reports equipment, drugs, or supplies was provided by Fonds de la Recherche Scientifique de Belgique (F.R.S.-FNRS).

Data availability

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Appendix. IEEE 738 standard

The IEEE 738 standard [3] calculates the relationship between bare overhead electrical conductor temperature and steady/time-varying electrical currents and weather conditions. The model's dynamic nature necessitates multiple applications over short time spans to assume parameter constancy due to input parameter fluctuations. The next-step estimation of the temperature is achieved by summing the previously estimated temperature T_0 with the change in conductor temperature dT_{avg} over the time interval dt. dT_{avg} is computed using the non-steady-state heat balance (A.1). The numerical integration of this equation over a time interval Δt leads to (A.2). It is important to note that this method does not require any training data: the conductor temperature is a time-varying quantity that depends on the current in the line, the weather conditions, the conductor characteristics as well as the starting temperature.

$$q_c + q_r + m \cdot C_p \cdot \frac{dT_{avg}}{dt} = q_s + I^2 \cdot R\left(T_{\text{avg}}\right) \tag{A.1}$$

$$\Delta T_{avg} = \frac{I^2 \cdot R\left(T_{avg}\right) + q_s - q_c - q_r}{mC_p} \Delta t \tag{A.2}$$

In (A.1) and (A.2), q_c [W/m] is the convection heat loss rate per unit length, q_r [W/m] is the radiated heat loss rate per unit length, mC_p [J/(m °C)] is the total heat capacity of conductor, T_{avg} [°C] is the average conductor temperature, q_s [W/m] is the heat gain rate from the sun, I [A] is the conductor current, $R(T_{avg})$ [Ω/m] is the AC resistance of conductor at temperature T_{avg}.

(1) can be rewritten using (A.2) as follows:

$$y_k[i+1] = y_k[i] + \frac{I^2 \cdot R(y_k[i]) + q_s - q_c - q_r}{mC_p} \Delta t \tag{A.3}$$

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