Adaptive soil model for real-time thermal rating of underground power cables

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Abstract: This study presents a validated adaptive method intended for real-time thermal rating (RTTR) of underground power cables. The accuracy of the RTTR algorithm, when producing emergency ratings or predictive calculations, strongly depends on the following parameters (which have large uncertainties): correct soil modelling, the proper determination of the soil properties and the accurate estimation of the ambient temperature. To remove the uncertainties, this study uses a novel approach to the modelling of the soil that allows the implementation of an extended Kalman filter to estimate robustly the properties of the soil and the ambient temperature in real-time with the data obtained from cable temperature sensors. These estimation techniques have been validated for several cable installations and the accuracy of emergency current calculations has been assessed by comparing the calculated results with finite element method simulations. In the context of smart grid applications, the possibility of adapting the estimation models in real time with the new obtained measurements is a key aspect to assure robustness and accuracy of the power system operation and control.

1 Introduction

Real-time thermal rating (RTTR) of underground power cables is becoming increasingly popular. The reason is that system operators need to push as much power as possible through the cables within safety limits to remain competitive. Nowadays, important cables are fitted with optical fibres (normally at the sheath/concentric wires layer) that can be used to measure the temperature distributed along the length of the cable. The purpose of the temperature measurement is to eliminate the uncertainties that exist in the values of the soil thermal resistivity, heat capacity of the soil and ambient temperature (soil temperature at burial depth). The data gathered by the temperature sensor together with better cable modelling is a relevant enhancement for smart grid applications, where the temperature of every conductor will be estimated accurately [1].

The thermal model of the cable itself can be made very precise because engineers know the construction materials and the dimensions of the different layers of the cable. In addition, the thermal properties of the cable layers do not change substantially during the lifetime of the cable. However, the resistivity of the soil normally ranges from 0.5 to 4 m·K/W depending on the type of soil and its moisture content [2]; heat capacity of the soil ranges from 400 to 1600 J/(kg K) [2], and the temperature can vary (at 1.2 m depth) up to 15°C [3] between winter and summer. Moreover, these parameters may have different values along the run of the cable because the terrain changes.

Designers and operators of cable systems can accurately compute the temperature of the conductor from the temperature at the external surface of the cable. This is normally straightforward, because precise and reliable models exist for the cable layers [2, 4–6]. However, if no measurement is available, in order to compute the thermal evolution of the cable, the surrounding soil has to be modelled. Usually, and unfortunately, there are large uncertainties in the soil data, which changes with region and season. Both the soil thermal resistivity and its temperature change along the run of the cable and with the weather conditions. For instance, wet soil is a better conductor of heat than dried-out soil. In addition, the moisture content of the soil around the cable depends on the current in the cable (moisture migration [7, 8]). Other sources of uncertainty include the burial depth, the density of the soil,

presence of neighbouring heat sources (e.g. steam pipes or other cables) and depth of the water table. Steady-state approaches to thermal rating [4, 6] have been long studied and are commonly used by power system operators. Nevertheless, this approach is highly conservative because frequently the conductor temperature is assumed to be at its normal operating temperature limit at the start of an emergency or the heat capacity margin is disregarded for short term rating calculations [9]. Also, usually conservative assumptions are made for the values of the thermal resistivity of the soil and ambient temperature.

To produce accurate emergency calculations and maximise the utilisation of cable systems, abundant research efforts have been made to enhance RTTR capabilities [7, 9–17]. The majority of published work on RTTR modelling successfully estimates the cable state (temperature of all its layers) when the temperature at an external layer of the cable is provided. Other research proposes offline inversion methods to estimate soil properties and show interest in data assimilation methods [8] for an easier online integration. Nevertheless, the authors of this paper have not found relevant published results in the real-time estimation of the properties of the soil using extended Kalman filtering techniques for underground cable systems. Thus in this paper, the authors introduce the implementation of an extended Kalman filter to enhance robustness and prediction capabilities of RTTR systems in scenarios where soil properties are unknown.

The development of a RTTR system for underground cables was first reported in 1979 [9]. The proposed cable monitoring and rating system uses measurements of conductor current and soil ambient temperature to estimate the present and future temperatures of the conductor. Such system presented already state estimation techniques but the soil was modelled as a single thermal node and soil properties were not estimated. More recent research on dynamic feeder rating systems [10] shows new capabilities of estimating the resistivity of the soil. In [10, 18], iterative techniques use steady-state equations to calculate soil parameters. These estimations are maintained constant for periods of 24 h. In [10], the thermal evolution of the soil is computed by means of equations that allow computing temperature rise as a function of time, losses, diffusivity and resistivity of the soil, using exponential integral functions, which are cumbersome.
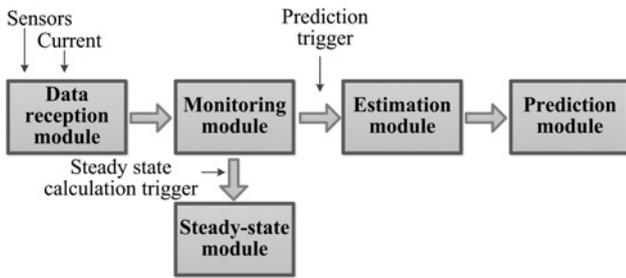
Fig. 1 *Block diagram of the RTTR presented in this paper estimation module uses the soil model and the extended Kalman filter to estimate the soil properties and produce predictive computations of the thermal status of the cable when the measurement of the fibre is not available*

As described below the differences between the method of [9] and our Kalman estimator are the facts that we introduce an extended Kalman estimator (non-linear) and we estimate the properties of the soil. On the other hand, the difference between the approach of this paper and Anders *et al.* [10] is that we use a thermal ladder to model the soil together with a Kalman filter and the soil properties are estimated recursively for each fibre measurement and for each time step. In [19, 20], other techniques are used to estimate the soil properties. However, the soil properties are calculated only once for a 7-day period.

Our paper presents a step forward in the direction of creating a robust, efficient and reliable RTTR by eliminating the limitations of the available techniques. It is important to mention that in the previous published work, recursive techniques for soil parameters are not used (when new data is available, reprocessing of all data has to be carried out). In this paper, none of the parameters are assumed constant since a complete transient model is available.

This paper uses a recently developed model of the soil that allows using well-known estimation techniques to compute the soil properties and the ambient temperature. This is based on an accurate physical discretisation of the soil, which enables building an extended thermal RC ladder. This technique was introduced in [18, 21], and was made optimal in [22] by finding the optimal discretisation and the optimal number of nodes to produce an accurate and fast model. The model is used to properly represent simultaneously the thermal dynamic equations of the cable and the soil in a single model. In this modelling context, the paper also introduces an extended Kalman filter that robustly and recursively estimates the state of the cable, soil properties and ambient temperature.

To the best of our knowledge, this is the first time that an extended, non-linear Kalman filter has been used to estimate successfully soil parameters in order to produce accurate emergency cable ratings for RTTR applications. The techniques of this paper have been extensively validated with finite element simulations.

2 Real-time thermal rating

There are two main functions that an RTTR system should perform: (i) compute the temperature of the conductor using as input data the measured temperature (at some location in the installation) and the

load current; and (ii) estimate (or predict) the future temperature of the conductor, from the initial state of the cable and soil, for the study of emergency situations.

2.1 Functional description

An RTTR system is intended to perform dynamic estimation of the cable rating or the conductor temperature based on real-time cable loading, temperature of the cable at some layer (by optical fibre measurements for example), ambient temperature measurements, and soil parameters. An accurate RTTR system should be able to estimate the steady-state (long-term) and the short-term ampacity based on the actual operating conditions of the monitored installation. Therefore usually a complete RTTR performs the following tasks: (i) monitoring of cable temperature; (ii) computation of cable ratings; (iii) estimation of soil parameters; and (iv) thermal predictive calculations [9–11].

2.2 Technical approach

The RTTR presented and developed in this paper is structured in five sub-modules: (i) data reception; (ii) monitoring module; (iii) steady-state module; (iv) estimation module; and (v) predictive module. The flow diagram is illustrated in Fig. 1. The first module receives the data from the temperature sensors and also the current that is circulating in the conductor. From experience, to perform a good estimation, historical data of at least the previous 150 h is needed. Thus, the collection of 168 h (one week) of data is recommended. However, the longer the historical data the more accurate the RTTR predictive calculations would be. The second module processes the measurements of the temperature sensors in the cable and using the models described in [2, 5, 6] computes the transient evolution of the temperature at the conductor of the cable. This module only uses the analogue electro-thermal circuit that corresponds to the cable model (see the left-hand side of Fig. 2). The third module offers capabilities of computing steady-state ratings also using standard formulae [5]. Finally, the estimation and predictive modules are capable of computing the soil properties and the ambient temperature in transient conditions to produce rating calculations when no fibre measurements are available. Since extensive literature is available in the three first modules [10, 11], this paper presents mostly the relevant improvements made here to the estimation of soil parameters and predictive calculations.

The accuracy of the RTTR greatly depends on the accuracy of the soil properties. RTTR systems do not normally have measurements of these properties; therefore they have to be estimated. To this end, we present an RTTR that uses the measurement of the temperature at the cable surface (or at any other layer) to estimate such properties by means of a Kalman filtering algorithm. Then the real-time information is fed to the other modules to update the model, and to produce accurate and up-to-date calculations.

3 Extended Kalman filter: estimation of soil parameters

In this section, a framework is presented to estimate the soil properties in real-time and transient conditions.
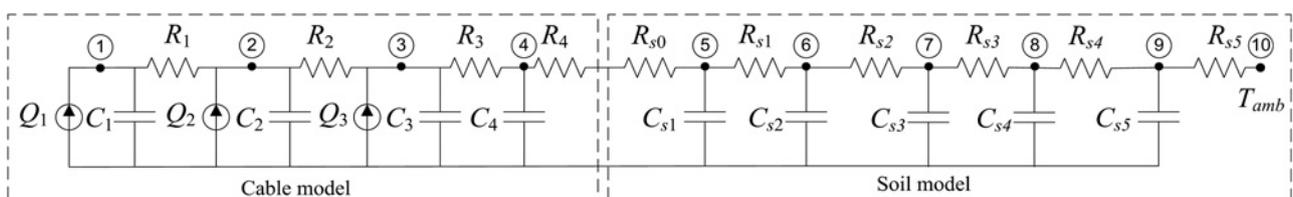
Fig. 2 *Ladder-type equivalent circuit for a cable of four layers and its surrounding soil that has been discretised into five layers*

To develop such framework, the ladder-type soil model presented in [22] is used. This model represents the thermal dynamic equations of the cable together with its surrounding soil. This extended model is illustrated in Fig. 2 for a particular example of a cable with four thermal nodes and a soil model of five nodes. The number of nodes needed to represent the cable is linked to its number of layers, and as it was discussed in [22], a model of five layers with an exponential layer distribution shows optimal results for all practical underground cable installations. This optimisation was carried out for a wide range of cable depths, soil properties, operation times, number of layers of the model and distribution of the layers of the model. Please see [22] for more details including a numerical example on how to construct such a model. The cable data is given in Fig. 8 in the Appendix. Phase voltage and current are the inputs to the model which calculates conductor, dielectric and sheath losses (Q sources in Fig. 2). These losses are connected at the appropriate nodes of the thermal ladder model. Resistances and capacitances of the cable are represented as R_1 to R_4 and C_1 to C_4. The RC ladder representing the soil is given by resistances from R_{s0} to R_{s5} and capacitances C_{s1} to C_{s5}.

Since this model allows for the representation of the cable and its surroundings in a compact thermal ladder equivalent and this complete model can be easily written in state space form, state estimators are the logical approach to solve this problem. Among the available state estimators, the Kalman filter is one that operates recursively on streams of noisy input data and produces a statistically optimal estimate of the underlying state [23]. This filter is especially useful for this application because Kalman estimators use a series of measurements observed over time, containing noise and other inaccuracies and can produce estimates of the states and other parameters that tend to be more precise than those based only on a single measurement. Moreover, Kalman filter implementations are easy to apply to systems that have closed state space formulations. In the RTTR of this paper, the objective is to produce the best estimate of the soil characteristics by using the temperature measurements delivered by the fibre and also the current that circulates through the cable. By processing this information and obtaining accurate soil parameters, the RTTR builds an adequate soil model and estimates correctly the conductor temperature when the fibre measurements are not available (predictive mode).

3.1 Implementation of the Kalman filter

Kalman filtering has been a subject of study since R.E. Kalman published his famous first paper on optimal filtering and prediction [24]. The Kalman filter is a well-studied and covered subject in most control and estimation books [25] and it is widely used in numerous applications. Examples include guidance, navigation and control of vehicles. It is also used in time series analysis such as signal processing [23, 25]. The Kalman algorithm works in two-steps, the prediction step and the update step. The prediction step advances the state of the system until the next scheduled observation and the update step incorporates such observation. If the observation is not available, multiple prediction steps can be taken and the update steps may be skipped. The Kalman filter is an efficient recursive filter that estimates the internal state of a linear dynamic system from a series of noisy measurements and together with the linear quadratic regulator, the Kalman filter solves the linear quadratic Gaussian control problem [25].

The first development of the Kalman filter [24] assumed that the underlying system is a linear dynamical system and that all error terms and measurements have a Gaussian distribution. Nevertheless, multiple extensions and generalisations have been developed. Particularly, the extended Kalman filter was developed to work also with non-linear systems [26–28]. Finally, if equations of the uncertain parameters of the system dynamics are added to the Kalman filter formulation, these parameters can also be estimated together with the state estimation that the Kalman filter delivers in its most basic form [29]. Since the development presented in this paper requires the capability of estimating soil parameters (principally the soil resistivity, heat capacity and ambient temperature), and in turn these parameters affect the system thermal dynamics, the extended Kalman filter with parameter estimation capabilities is the best choice.

The thermal equations of the cable together with the soil model that surrounds such cable allow writing the following state space equation

$$\dot{x} = Ax + Bu \tag{1}$$

where x represents the temperature of all layers of the cable and all layers of the discretised soil and u represents the losses: conductor, dielectric, sheath and armour of the cable. A and B are the state and input matrices, which are composed by the thermal ladder coefficients determined by the material and geometry of the cable and the soil.

Simple algebraic manipulation, leads to each component of the x vector to represent one of the thermal nodes in the thermal ladder. Hence, all the coefficients in A and B are proportional to $1/RC$ where R and C are, respectively, the thermal resistances and thermal capacitances of each particular thermal node shown in Fig. 2.

Since the RTTR application needs to estimate the ambient temperature, that is, the last temperature node in the thermal ladder and also the characteristics of the soil, (1) can be expanded with its corresponding parameter equations as follows [29]

$$\begin{bmatrix} \dot{x} \\ \dot{\theta} \end{bmatrix} = \begin{pmatrix} A & 0 \\ 0 & A_\theta \end{pmatrix} \begin{bmatrix} x \\ \theta \end{bmatrix} + \begin{pmatrix} B & 0 \\ 0 & 0 \end{pmatrix} \begin{bmatrix} u \\ 0 \end{bmatrix} + \begin{pmatrix} 0 & 0 \\ 0 & I \end{pmatrix} \begin{bmatrix} 0 \\ \theta_n \end{bmatrix} \tag{2}$$

where θ is the parameter to be estimated, A_θ is the matrix representing the parameter dynamics and θ_n is the noise parameter that allows the equation to evolve and move from the equilibrium point. The thermal parameters of the cable, R and C, are known. However, the parameters representing the soil, the values of R_s and C_s, depend on the resistivity and heat capacity of the soil. These parameters are uncertain; therefore they have to be estimated. As a consequence, the coefficients in the A matrix depend on θ and are no longer constant, but depend on the state vector $\begin{bmatrix} x \\ \theta \end{bmatrix}$. Then, (2) becomes a non-linear system and it has to be rewritten as

$$\begin{bmatrix} \dot{x} \\ \dot{\theta} \end{bmatrix} = f(x, \theta, u, \theta_n) \tag{3}$$

Moreover, since the coefficients in the A matrix are proportional to $1/RC$, the actual values of R and C of the soil cannot be estimated separately and one can only estimate a multiplying factor to $1/RC$. In this paper, such a factor is named α. Therefore θ is a vector composed by α and T_{amb} (soil ambient temperature).

The formulation in (3), with the extended state vector including the parameters to be estimated, enables the possibility of using the extended Kalman filter formulation on non-linear systems [23, 25, 27] for this particular application by updating the state variables and the filter variance at every time step.

3.2 Performance of the Kalman filter

The implementation described in the previous section has been carried out inside the RTTR engine. This permits to estimate both parameters, one parameter, or none of them depending on the degree of certainty. The latter situation would imply the estimation only of the thermal state of all the nodes. In the case when only one parameter is estimated, it is easy to understand that the Kalman filter delivers better results when the parameter to be estimated is T_{amb}. This is because, the uncertainty on α propagates in a large number of coefficients in the A matrix and the uncertainty on T_{amb} only represents uncertainty in one thermal node but not on the coefficients of the A matrix.

Kalman is a recursive filter that enhances its estimation as more measurements are provided. This behaviour can be observed in Fig. 3. This figure shows the time domain evolution of the estimated state and parameters of the Kalman filter for a situation of a trefoil cable buried in soil at a depth of 1 m with the fibre placed at the outer layer of the cable (variable 4) and with an ambient temperature of 20°C. Variables 1–4 represent the thermal nodes of the cable and variables 5–9 represent the thermal nodes of the soil model; see Fig 2. Finally, variable 10 represents the estimation of T_{amb}. The grey area represents the uncertainty of the estimation provided by the Kalman filter [25]. As it can be observed, the estimation is very accurate (nearly inexistent grey area) for the variables that are close to the measurement (variable 4). Nevertheless, if the thermal node is far away from the measurement, the uncertainty increases. Note, that the uncertainty on these thermal nodes decreases when more measurement samples are fed to the filter. For this particular case, after 150 h of data, the estimation of the filter obtains very accurate and the estimation of T_{amb} converges to the correct 20°C. This simulation was initialised with an ambient temperature of 14°C to show the evolution of the Kalman filter. In this example, a new data point is received from the fibre every 10 min. The more accurate the initial guess for the ambient temperature the faster the convergence and vice versa.

Since the Kalman algorithm is a recursive algorithm, the soil parameters do not need to be recalculated when new measurement data is available. It suffices to record the state of the Kalman filter, namely the value of the state vector x, parameter vector θ and uncertainty matrix [25], and when a new data sample is available, new parameters can be estimated with one simple iteration (and the old data does not need to be reprocessed). These parameters would be the optimal parameters considering all the previous information and the last sample. This recursive characteristic makes the Kalman technique very apt for an RTTR because it reduces the large computation burden for real time and smart grid applications.

3.3 Robustness analysis

A robustness analysis needs to be conducted to assess the feasibility of the RTTR algorithm presented in this paper. The analysis determines if the estimations delivered by the Kalman filter produce accurate results when using them for predictive calculations. To this end, the Kalman estimator has been tested in batches of 100 different situations. The statistical nature of each of these situations is described as follows:

(a) Generation of data:

1. Random ambient temperature is chosen with statistically uniform distribution between 10 and 30°C.
2. Random resistivity of the soil is chosen with statistically uniform distribution between 0.2 and 3 m·K/W.
3. Data is generated with these characteristics using finite element method (FEM) simulations and the information at the location of the fibre is recorded. Thermal data of 168 h is generated. FEM simulations are performed with the heat transfer module of COMSOL assuring that boundary conditions, mesh size and time step settings of the solver do not affect the final result. Also, the validity of the FEM simulation has been validated against the IEC results for the same case in steady state and transients.

(b) Kalman filter:

1. Random initialisation of α for the Kalman filter is chosen with statistical uniform distribution between 0.2 and 3. This intends to model the worst case scenarios in the knowledge of the resistivity of the soil because measurement of this quantity suffers of high uncertainty and it is not centred on its true value.
2. The ambient temperature for the Kalman filter is modelled with a normal distribution of standard deviation of 3°C around the real ambient temperature. This intends to model a worst case scenario on the measurement of the ambient temperature because in this normal distribution the errors could be as large as ± 9°C in the measurement of the ambient temperature. Such large errors are not expected in initial soil ambient temperature estimation.
3. The Kalman filter is run for 168 h of thermal data with the information of the current circulating in the cable and the temperature information of the fibre. The readings of the fibre are noisy measurements with an rms value of 0.5°.

(c) Prediction phase:

1. Predictive calculations are performed using the estimated parameters delivered by the Kalman filter in the previous phase.
2. Errors of the predictive calculations are computed in percent against the data generated in (a). The errors are computed as:
$\varepsilon(\%) = ((\Delta T_{FEM} - \Delta T_{pred})/\Delta T_{FEM}) \cdot 100$.
3. The error for each simulation is recorded. The FEM values of the properties of the soil and its estimated counterparts by the Kalman filter are also recorded.
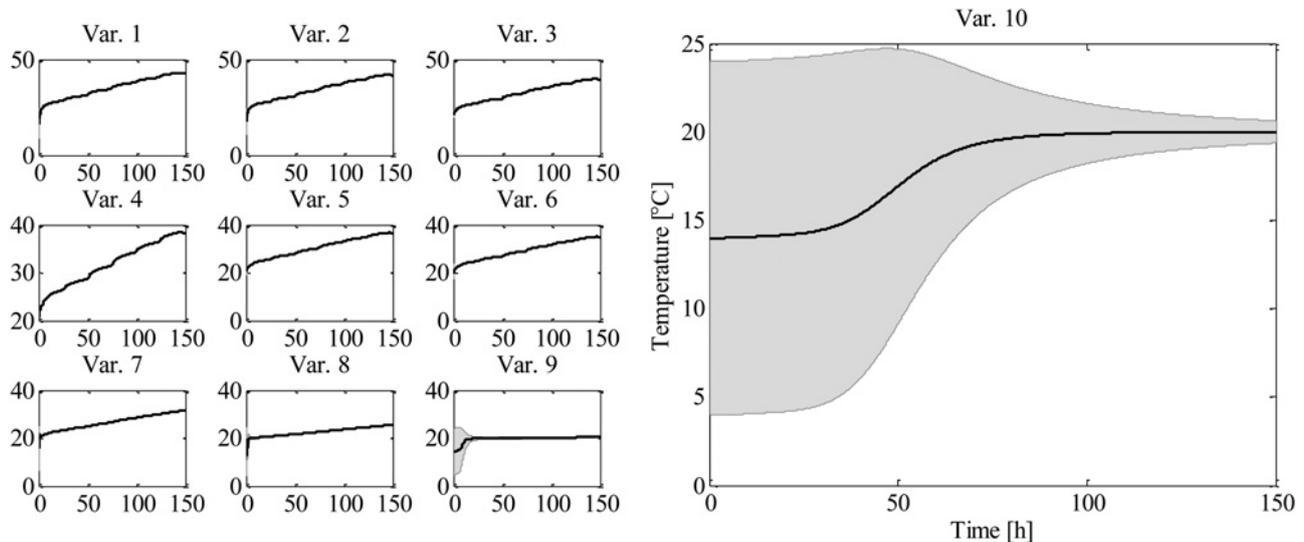

Fig. 3 *Evolution of all the thermal nodes in one simulation of the RTTR Kalman filter for a trefoil installation buried in soil at 1 m, Variables 1–4 represent the thermal nodes of the cable and variables 5–9 represent the thermal nodes of the 5-layer soil model, Finally, variable 10 represents the estimation of* T_{amb}*, The grey area represents the uncertainty of the estimation*
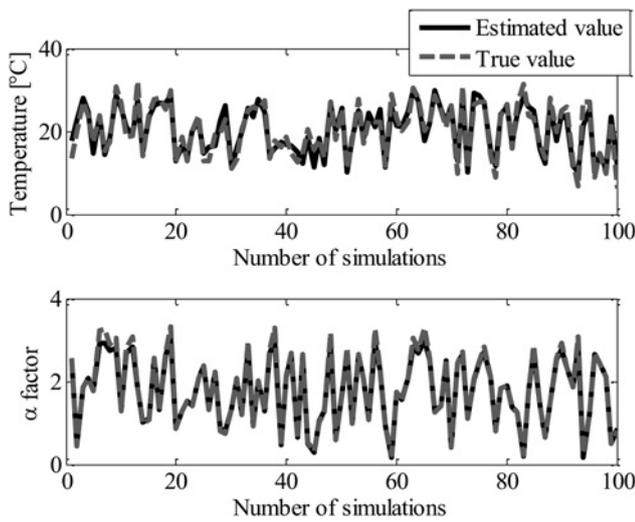
Fig. 4 *Estimated and FEM values of the ambient temperature and α in 100 different simulations where the true values (FEM values) of the ambient temperature are randomised between 10 and 30°C and the thermal resistivity of the soil is randomised between 0.2 and 3 m·K/W*

The results of this robustness analysis are shown in Figs. 4 and 5. From Fig. 4, one can observe that the estimated and FEM values of the ambient temperature (top plot) are very accurate for the great majority of cases. Similar results are obtained for the multiplying factor α of the resistivity of the soil (bottom plot). Note that each point in the plot is independent from each other. To obtain a point, 168 h of simulation are performed for a random set of ambient temperature and factor α. It is important to note that in a few instances the Kalman filter does not deliver a perfect estimation of the ambient temperature, which coincide with compensating errors in the estimation of α. This is explained because the Kalman filter tries to minimise the error of the model at the position of the fibre. In those situations, and since this is a non-linear system, there are multiple solutions and the Kalman filter may find one that does not correspond to the physical parameters. This could be solved with a large scale global minimisation algorithm, but normally these algorithms are very computational intensive and not convenient for real-time applications. Nevertheless, these cases are not an issue for the RTTR because as it can be seen in Fig. 5, the
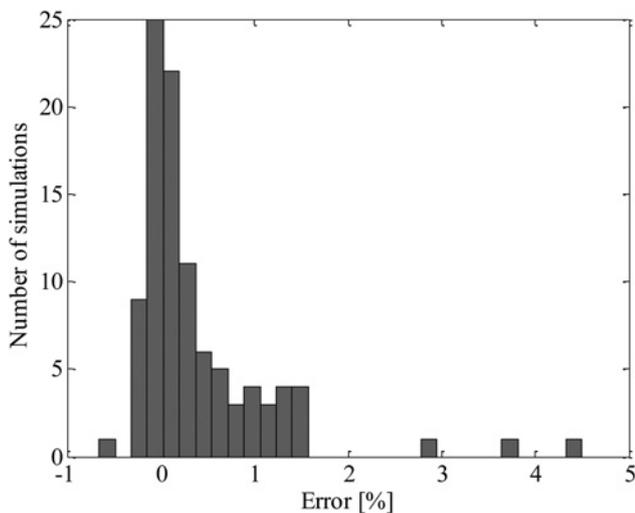
error is below 1.5% in 97% of the cases and in the worst case scenario the maximum error is of 4.5%. Fig. 5 shows the error distribution of the predictive calculation described in (c) in per cent for the 100 simulations of this analysis.

4 Results

In this section, the results of the RTTR are presented for two different installations: a trefoil cable buried in soil and two flat formations that run in parallel 1 m apart. For the sake of conciseness, we are presenting the results only for two installations, but similar validations have been performed for cables in tunnels, cables in troughs and cables in pipes.
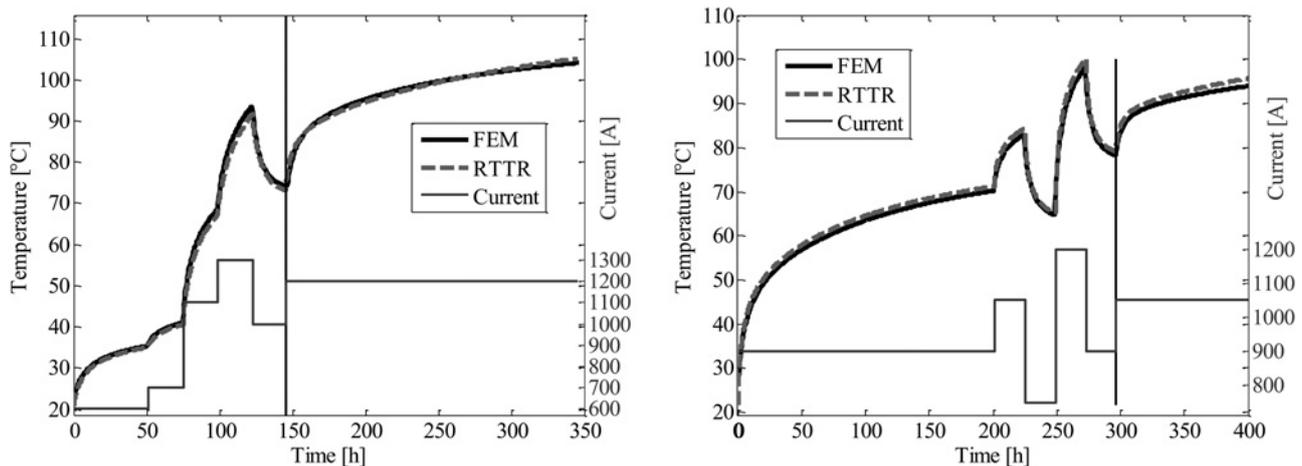
The validation procedure presented in this section consists in four steps: (i) generation of data from FEM simulations modelling the complete physics of the given installation; (ii) extraction of the temperature measurements at the fibre location from the FEM simulations, (iii) feed the RTTR engine with the fibre temperature; and (iv) produce estimated results with the RTTR and compare such results with those from FEM simulations.

4.1 Finite element simulations

4.1.1 Single trefoil cable buried in soil at 1 m: The first validation is conducted on a three-phase cable installation in trefoil formation buried in soil at 1 m depth. This installation can be observed in Fig. 7 (left) in the Appendix. This simulation involves a first period of 50 h with 600 A circulating in the conductor, followed by a pattern of 24 h steps of 700, 1100, 1300 and 1000 A. Finally, a predictive calculation of 200 h is performed at an emergency current of 1200 A. Fig. 6 (left) shows the comparison between the FEM results and the RTTR results and also the current shape. The vertical line in this figure shows the separation between the operation mode (fibre available) and the predictive mode (fibre not available). As it can be observed, the evolution of the temperature at the conductor of the cable is very well captured in the operation mode and also in the predictive mode, where the error is always smaller than 0.5°C. This proves the correct estimation of soil parameters. Particularly in this case, the soil ambient temperature is estimated to be 20.1°C (FEM value is 20°C) and the resistivity of the soil is estimated to be 0.89 m K/W (FEM value is 0.9 m K/W).

4.1.2 Two flat formations in parallel at 1 m: In this second case, the installation consists of two three-phase formations that run in parallel buried in soil at a depth of 1 m. The centres are 1 m apart; therefore induced heating between the formations is expected. This geometry can be observed in Fig. 7 (right) in the Appendix where the results of the simulation performed in FEM are shown.

In this case, the simulation starts with 200 h at 900 A followed by four 24 h steps at 1050, 750, 1200 and 900 A, respectively. Finally, 100 h at 1050 A. Fig. 6 (right) shows the thermal evolution of the temperature of the conductor of the cable for the FEM simulation and also for the RTTR simulation, as well as the current shape evolution. One can observe that the results from the RTTR are very accurate, both in the operation and the predictive regions. Particularly in this case, the soil ambient temperature is estimated to be 20.5°C (FEM value is 20°C) and the resistivity of the soil is estimated to be 0.92 m K/W (FEM value is 0.9 m K/W). Note that the estimated values and the FEM values are also very close in this case because the Kalman filter takes into account the mutual heating between the formations when estimating the parameters of the soil and the value of the ambient temperature. This feature is crucial because otherwise the Kalman filter would offset the estimated parameters trying to match a situation in the absence of mutual heating, which would lead to unrealistic estimated parameters. This allows obtaining predictive results of the temperature of the conductor that always match the FEM simulation within 0.5°C margin.

Fig. 5 *Distribution of the predictive error in per cent computed for the 100 simulations presented in Fig. 4*

Fig. 6 *(Left) Evolution of the temperature of the hottest conductor of a trefoil formation buried in soil at a depth of 1 m. (Right) Evolution of the temperature at the hottest conductor (the centre cable) in a flat formation that lies buried in soil at 1 m and runs parallel to a formation of the same characteristics, These installation can be observed in Fig. 7 in the Appendix, Temperature from FEM simulations is plotted in a solid black line and the output of the RTTR is plotted in a dashed line, Current is plotted in a thinner line*

5 Conclusions

This paper has presented important enhancements to the RTTR of underground cables. This paper introduces for the first time the use of the extended Kalman filtering techniques to process the temperature information at a particular location of the cable to estimate and update in real time the properties of the surrounding soil and the ambient temperature with a full transient model of the physics. Also, the feasibility of such implementation has been validated under realistic and varying conditions and the accuracy of the calculations has been assessed by comparing the calculated results with finite element simulations. Previous implemented methodologies in RTTR applications did not estimate the soil parameters recursively and in real time, thus they needed to reprocess all the data history every time new samples from the temperature sensors became available. This is a limiting factor in the context of smart grid applications when latencies become important.

A comprehensive set of robustness tests varying the soil properties and initial ambient temperature has been presented. Ninety-seven per cent of the calculations lie within a 1.5% error margin for different types of installations even under noisy measurements from the fibre. Accurate knowledge of soil thermal resistivity and ambient temperature is paramount because it enables the RTTR engine to calculate emergency ratings and temperature predictions based on the actual state of the cable.

The final purpose of this paper is to take advantage of the heat capacitance margin and the accurate knowledge of the soil properties to obtain precise short term emergency ratings. Better RTTR predictive systems, as the one presented in this paper, will permit the utilisation of cable systems to their maximum capabilities, integrate these systems in the future smart grid applications in order to better operate the grid and help defer costly capital investments.

6 Acknowledgments

7 References

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8   Appendix

This section shows the geometry of the two installations used in Section 4 to test the performance of the Kalman filter presented in this paper and also the model of the cable used in these tests. Fig. 7 presents the geometry of the installation used and Fig. 8 shows the construction details of the cable.
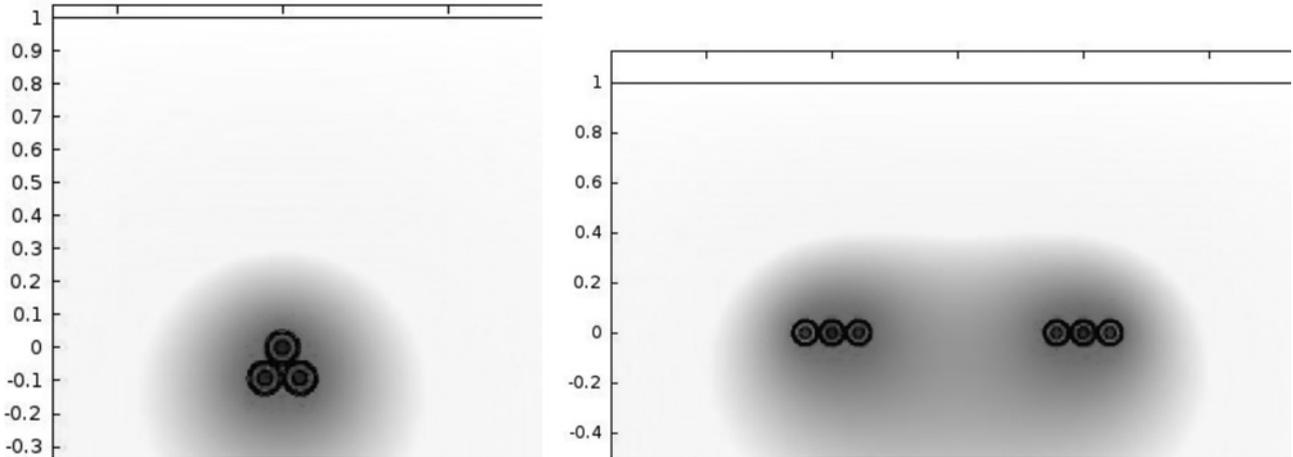
Fig. 7   *(Left) Thermal two-dimensional (2D) illustration of the temperature distribution of a trefoil cable installation buried in the soil at 1 m, This is the installation used in the first example of Section 4. (Right) Thermal 2D illustration of the temperature distribution of a two flat formations running in parallel buried in the soil at 1 m, This is the installation used in the second example of Section 4*
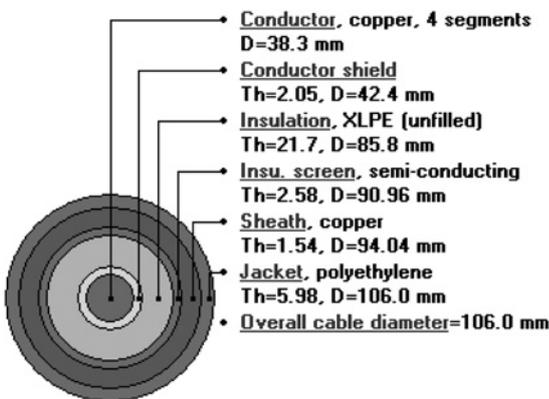
Fig. 8   *Model of the cable used as an example in this paper, The cable is a cable of six layers: copper conductor, screen, XLPE insulation, screen, copper sheath and PE jacket, As it is indicated in the IEC standards [5], this cable is modeled as a four node model as it is indicated in Fig. 2*