A COMPUTATIONAL APPROACH FOR ASSESSING COATING PERFORMANCE IN CATHODICALLY PROTECTED TRANSMISSION PIPELINES

Andres B Peratta, John M W Baynham, and Robert A. Adey
CM BEASY Ltd
Ashurst Lodge
Southampton, Hampshire, SO40 7AA

ABSTRACT

The paper presents an efficient and accurate 3D computational approach for assessing the quality of the coating of sub-surface underground transmission metallic pipelines under cathodic protection control. The CP system consists of a series of Impressed Current anode beds connected to the pipeline and distributed along its length. The computational approach addresses the problem of non-homogeneous electrolyte, by regarding the soil as a multi-layered region which may be thin in comparison with the characteristic length of the pipeline (typically tens of kilometres). The model considers the non linear electrode kinetics on the metal surfaces in the form of polarisation data and also considers the internal resistance of the pipeline and other electrical connections. The aim of the simulation is to predict the status of the coating in contact with the electrolyte, and to estimate the size and location of coating defects given a minimal number of field potential measurements taken from surveys.

Keywords: reverse simulation, cathodic protection system, CP, ICCP, impressed current, coating defects, BEM

INTRODUCTION

One of the most effective ways to control corrosion in metallic structures embedded in an electrolyte, such as the case of underground or subsea transmission pipelines, is by means of a combination of coating and cathodic protection (CP) systems. Field surveys such as the Direct Current Voltage Gradient (DCVG), and monitoring systems are aimed at different aspects of the assessment of the corrosion control system. Field measurements require skilled technicians, are often expensive and difficult to obtain. In addition, sections of the pipeline may not be accessible for the surveyors. In some instances the noise in the potential measurements can mask developing defects in the pipeline coating. Moreover, the interpretation of field data and its correlation to the performance level of the corrosion control system is not always straightforward.

The direct computational modelling of CP systems offers a variety of tools for processing the information collected from the field. The modelling complements and allows better interpretation of field measurements, as well as enabling the correlation against the CP design parameters and their impact on the observable magnitudes.

Broadly speaking, we distinguish two major divisions of simulation tools: forward and reverse. By forward simulation we mean the process of predicting field results, for example:
- ON and OFF potentials,
- potential gradients and currents fields in the soil, as well as
- overpotential and current density along the pipeline,

The forward modelling process requires that the CP design parameters are given as input data, such as for example:
- geometrical arrangement and material properties of pipelines and anodes,
- electrical resistivity distribution of the soil,
- type and location of the electrical connections between rectifiers, anodes and structure
- Coating breakdown factor along the pipeline

The forward simulation of CP systems by computational modelling has achieved a maturity in the past few years and is thus capable of producing reliable results for complex CP situations. This type of simulation is particularly useful at the design stage for the analysis of “what-if” case studies including the problems of interference with foreign CP systems or metallic structures.

On the other hand, the reverse simulation is aimed at discovering the input parameters which have caused a certain outcome in the results. From this point of view, optimisation problems can be regarded as a sub-category of reverse simulation problems.

Among other uses, reverse simulation is a particularly powerful approach for estimating the amount, size and location of localised coating failures along the pipeline as well as its uniform breakdown factor values, which are responsible for a certain pattern of ON and OFF potential measurements observed at ground level. Hence, the aim of this work is to present an efficient 3D reverse simulation capable of predicting the status of the coating in contact with the electrolyte, and to estimate the size and location of coating defects given a minimal number of field potential measurements taken from surveys.

Figure 1 illustrates the main concept behind the reverse simulation approach. The region within dashed lines represents the forward simulation with its inputs and outputs. The reverse simulation iterates several times on the forward simulation trying to find the best guess for the input parameters (coating quality) which produce a target outcome (electric currents and potentials in the electrolyte). The triangle “compare” evaluates the cost function \( g \) given by:
\[ g = \sum_{i=1}^{Np} w_{off} (\tilde{V}_{off_i} - V_{off}(x_i))^2 + w_{on} (\tilde{V}_{on_i} - V_{on}(x_i))^2 + w_j (\tilde{J}_i - j(x_i))^2 \]  

(1)

where the sum is done over all measurement points \( Np \) and \( \tilde{V}_{on} \), \( \tilde{V}_{off} \), \( V_{on} \) and \( V_{off} \) represents “on” and “off” potential experimental observations (with tilde) and simulation results (without tilde), respectively at point \( x_i \). \( J \) is current; while \( j \) indicates current density and \( w_{off} \), \( w_{on} \), and \( w_j \) are scale factors used to weight the different magnitudes involved in the cost.

This document is organised in the following way. The next two sections describe the forward modelling approach and provide pointers to the relevant literature involved in the method. Then, the reverse modelling approach is outlined. Afterwards, the effect of different properties of the coating on the observed pattern of overpotential are illustrated, following with a summary and conclusions at the end.

### FORWARD MODELLING OF CP SYSTEMS

The modelling of CP systems involves predicting the current and potential fields at any point in the electrolyte and at surfaces of electrodes. Under most common situations, this requires solving the steady state charge conservation equation in the electrolyte in 3D space given by:

\[ \nabla \cdot j = 0 , \quad x \in \Omega \]  

(2)

where 

\[ j = -\sigma(x) \nabla u(x) \]  

(3)

represents current density, \( \sigma \) is the electrolyte conductivity, \( u(x) \) is the potential field, \( \nabla \) is the 3D Laplace operator, and \( \Omega \) represents the integration domain (electrolyte).

Eqs. (2-3) can be solved together with the corresponding boundary conditions at \( \Gamma = \partial \Omega \) which are usually prescribed by imposing polarisation curves at the electrode surfaces, isolating conditions at ground level, and/or fixed potentials at any known equipotential surfaces in the electrolyte (if any).

The Boundary Element Method (BEM)\(^{1}\) has been widely used to solve Laplacian equations and in particular simulate cathodic protection systems for underground and offshore structures\(^{2,3,4}\). The most significant advantages of the method are first that the formulation is based on the fundamental solution of the leading partial differential operator in the governing equation, and second that it requires only mesh discretisation on the boundaries of the problem. The former aspect confers high accuracy, while the latter substantially simplifies the pre-processing stage of the model, since volume discretisation is not needed.

### THIN MULTI-LAYER ELECTROLYTE

The forward modelling of long transmission pipelines involves considering the soil as a thin layered electrolyte (See Figure 2), since the pipeline span (\( L \)) is much greater than the soil depth relevant for the modelling (\( h \)). In addition, the soil is generally stratified in one or many layers along the vertical (\( z \)) direction. This thin stratified integration domain is very difficult to solve with standard modelling techniques such as FEM or BEM. It often results in large computational models and places additional work on the user in generating the model data. Therefore, in order to be able to solve this type of integration domain without the need for extraordinarily high computational resources, a “multi-layer” BEM has been developed (ML-BEM).

The idea behind the ML-BEM is that the stratified nature of the medium is packaged into the corresponding Green’s function. In other words, the BEM is applied in the same way as in the case of the homogeneous electrolyte, except that the Green’s function for the homogeneous Laplace equation given by \( 1/(4\pi r) \) is replaced by the multi-layer Green’s function given by:

\[ G(x_i, x_j, m, n) = \frac{1}{4\pi \sigma_m} \sum_{k=1}^{N_{exp}} \alpha_{iml} \frac{1}{\|x_i - x_j + g_{ij}\|} \]  

(4)

where \( x \) denotes the 3D coordinates, the sub indices \( i \) and \( j \) stand for the source and field point,
respectively; \( m \) and \( l \) indicate the layer of the source and field points, respectively; \( \alpha_{ijml} \) is a weight coefficient and \( g_{ijml} \) denotes a displacement vector. The Green’s function written in this way can be regarded as the one produced by a weighted method of images.

The calculation of the weight and displacement vectors goes beyond the scope of this paper and can be derived from other references\(^5,6\). Finally, the Green’s function (4) replaces the \( 1/r \) kernel used for homogeneous regions, and the same BEM strategy can be employed.

The reverse simulation strategy is based on iterating over the forward simulation tool with the coating breakdown factor distribution until the cost function given by equation (1) achieves its minimum. The model of coating breakdown factor due to a number \( N_{def} \) of defects proposed in this work is given by:

\[
BF(s) = BF_0 + \sum_{k=1}^{N_{def}} BF_k \exp \left[ -\frac{(s-s_k)^2}{2D_k^2} \right]
\]

where \( s \) is the distance along the pipeline, \( BF(s) \) is the breakdown factor between 0 and 1, \( BF_0 \) is a uniform coating quality distributed along the pipeline, \( BF_k, s_k, \) and \( D_k \) are the damage size ratio, defect location and defect size length associated to \( k \)-th defect, respectively.

The reverse simulation follows a similar strategy to the one proposed in earlier publications\(^7\). Instead of defining coating resistance distribution, this work uses the coating breakdown factor. Therefore, \( BF_0, BF_k, s_k, \) and \( D_k \) define the \( 3N_{def} + 1 \) dimensional search space.

The search approach is based on an optimised Nelder-Mead (NM) also known as downhill-simplex algorithm\(^5,6\). The major advantages of the NM method are that it is simple and robust, it avoids the calculation of gradients (which would be very costly from a computational point of view), and can be used for a search space of large and variable dimensionality. However, the NM method is in principle unable to escape from local minima of the objective function, thus not being useful for reverse modelling of ICCP. However, when combined with other strategies such as Simulated Annealing (SA)\(^8,9,10\) this drawback can be overcome. This combination has been successfully implemented in earlier works\(^7\).

In this work the SA is replaced by a Kick-Off strategy. The idea is that when NM is trapped in a minimum (which might be a local one), the solution is kicked out to a new random point in the search space, and restarted. The strength of the kick is proportional to the distance travelled since the starting point. Then a new NM iteration starts. The iterations progress and all local minimum points found are compared, and at the end the lowest is chosen.
PRELIMINARY CASE STUDIES

Case Study 1
Before solving the fully reverse model, it is useful to explore as much as possible the effect of different types of localised coating defects on the potential distribution pattern observed at ground level. Such is the purpose of this case study. The model consists of a straight steel pipeline 10km long (with external diameter D=0.6m) buried 1m below ground level.

![Diagram of Case Study 1](image)

Figure 3: Case study 1: A 10 km long pipeline with 3 anodes and a coating defect (at x=5000m)

The CP system consists of 3 ICCP anodes as shown in Figure 3. The anodes are shifted 100m away from the pipeline in the $y$ direction.

The polarisation curve of bare steel exposed to the electrolyte is simplified as a linear function as shown in Figure 4. The over-potential of -700mV corresponds to zero current density.

![Linear polarisation curve](image)

Figure 4: Linear polarisation curve

In normal operation the coating is considered to have a breakdown factor of 0.1%, and the anodes operate at a constant current of 300mA each. The soil conductivity is considered to be 0.02 S/m.

Figure 5 shows the change of pattern in the signature due to local changes in the breakdown factor (BF) associated to a portion of 10m in the middle of the pipeline. The figure on the top shows the distribution of equi-potential lines at ground level under normal operational conditions, that is BF=0.001 (0.1%). The figure in the middle represents the distribution of equi-potential lines when the coating has BF= 0.1 (10%), while the picture at the bottom represents the extreme case of 10m of pipeline without coating.
Figure 5: Case study 1: Signature patterns due to different breakdown factors (BF) associated to a segment of 10m in the pipeline located in at x = 5000m. The vertical and longitudinal axis represent x and y dimensions in metres.

Figure 6 shows the value of over-potential measured along the pipeline in the case of different breakdown factors associated to the coating defect at x=5000m.
Figure 6: Case study 1: Over-potential along the pipeline for different breakdown factors associated to a defect located at x=5000m. (ICCP current fixed to 300mA).

The overall shift of over-potential apparent in Figure 6 results from the transfer of current from the regions with undamaged coating to the damaged section. The reduction of current density leads to a corresponding change of over-potential. Another distinctive effect of the defect on the over-potential profile is the pronounced “peak” of over-potential on the defect, which corresponds to reduced protection in that area.

Case study 2

Figure 7 shows a 16km length of pipeline, composed of 5 electrically connected subsections. At the connection joints between subsections there are four rectifiers delivering constant current to 4 anodes A1 to A4. The Table on the right hand side of the figure shows the xy coordinates of the anode in the ground. In the figure, Dz represents the vertical dimension of the anode, which extends down from the ground surface. Details of the pipeline are shown in Table 1. The total current delivered by the anodes is 60 Amps.

![Pipeline layout and relevant anode parameters](image)

**Table 1. Pipeline specifications**

<table>
<thead>
<tr>
<th>Anodes</th>
<th>x</th>
<th>y</th>
<th>Dz</th>
<th>diam</th>
</tr>
</thead>
<tbody>
<tr>
<td>A1</td>
<td>2000</td>
<td>-200</td>
<td>0–50</td>
<td>0.2</td>
</tr>
<tr>
<td>A2</td>
<td>5000</td>
<td>+200</td>
<td>0–50</td>
<td>0.2</td>
</tr>
<tr>
<td>A3</td>
<td>11000</td>
<td>-200</td>
<td>0–50</td>
<td>0.2</td>
</tr>
<tr>
<td>A4</td>
<td>14000</td>
<td>+200</td>
<td>0–50</td>
<td>0.2</td>
</tr>
</tbody>
</table>

The soil model consists of two layers, with depths and conductivity as shown in Table 2. The top of the
first layer and the bottom of the second layer are insulating. Note that models with this type of boundary conditions are not easily solved with standard techniques such as half space, or method of images\textsuperscript{1,11}.

<table>
<thead>
<tr>
<th>Layer</th>
<th>Zmin to Zmax</th>
<th>Conductivity [S/m]</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0 to -30m</td>
<td>0.02</td>
</tr>
<tr>
<td>2</td>
<td>-30m to -100m</td>
<td>0.007</td>
</tr>
</tbody>
</table>

Table 2 Soil properties (2 layer model)

Figure 8 shows the overpotential along the pipeline (which is almost the same as the OFF potential calculated above the pipeline at ground level) for different conditions of the pipeline. The red curve corresponds to a uniform breakdown factor BF\textsubscript{0} = 1 (100%, bare steel) for the whole structure. The green curve corresponds to the case of a uniformly partially damaged coating with BF\textsubscript{0} = 0.02 (2%). The black dotted curve corresponds to undamaged uniform coating characterised by uniform BF\textsubscript{0} = 0.01 (1%).

The solid black curve shows the pattern of results produced by 3 localised coating defects at 6000, 8000 and 1000m (with local breakdown factor BF\textsubscript{k} equal to 0.02 (2%), 1 (100%) and 1 (100%), respectively) on the pipeline which has an otherwise uniform breakdown factor of 1%. The length of each defect along the pipeline is 2m. It can be observed that the effect of the local damage on the overpotential is very localised, and that there is no observable general shift of over-potential. This is because in this case the change of current density is small at regions away from the damage.

Also note that the peak of each defect is at the same potential as the curve for corresponding value of uniformly damaged breakdown factor.

Figure 8: Case study 2: Comparison between different coating damages in the overpotential distribution along the pipeline.

RESULTS

In this section, the reverse modelling tool is tested with a simple model consisting of one pipeline and one anode. The conceptual model is shown in Figure 9. The pipeline section of interest is 1000m long, has 40cm of external diameter, and is buried 1m below ground level. It is protected by an anode 10m long at 20m apart from the pipeline. The total current delivered by the anode is constant and equal to 200 mA. The soil is highly saturated with sea water, and the conductivity is 0.5 S/m in the first layer from ground level to z=-50m and 0.05 S/m from z=-50 to z=-100m where non-conductive conditions are applied.
The problem consists in assessing the quality of the coating by interpreting measurements of ON potential at ground level along the pipeline. Field measurements are simulated with synthetic data of $\tilde{V}_{ON}$ potential plus added noise of ±10mV. This was obtained with a forward modelling considering a coating defect with the parameters shown in Table 3, under the column headed “SET DEFECT”. The column REVERSE MODELLING RESULTS are the best guess found by the reverse modelling tool. The search space in this case is 4-dimensional, and consists of the size, location, and local breakdown factor of the individual defect in addition to the uniform breakdown factor of the whole pipeline.

Figure 10 shows the comparison between the synthetic field measurements (red circles) and the solution found by the reverse modelling tool (green continuous line). The peak at $x = 0$ corresponds to the anode, whereas the peak at $x \sim 100$m ($s_k = 600$m) corresponds to the defect location.

Table 3. Comparison between set properties, and those found by the reverse modelling tool

<table>
<thead>
<tr>
<th>Property</th>
<th>SET DEFECT</th>
<th>REVERSE MODELLING RESULTS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Size ($D_k$)</td>
<td>8m</td>
<td>6m</td>
</tr>
<tr>
<td>Location ($s_k$)</td>
<td>600m</td>
<td>599m</td>
</tr>
<tr>
<td>Breakdown Factor ($B_{F_k}$)</td>
<td>0.8 (80%)</td>
<td>0.78 (78%)</td>
</tr>
<tr>
<td>Uniform breakdown factor $B_{F_0}$</td>
<td>0.06 (6%)</td>
<td>0.04 (4%)</td>
</tr>
</tbody>
</table>

Figure 11 shows the different trials of distribution of breakdown factor during the iterations in the reverse modelling. Initially, the prediction follows a random pattern, but when the defect location is about to be found, the convergence to the solution becomes faster.

Figure 10: Comparison between the solution of the reverse modelling tool and 40 field data points produced synthetically with the forward and additional 20mV noise peak to peak.
Figure 11: Breakdown factor distribution computed at steps 1, 2, 3, 10, 20 and 40 in the reverse modelling iterative scheme.

Figure 12 shows the cost function given by eq(1) with \( w_{off} = 0; w_{on} = 1 \) and \( w_J = 0 \) at different iteration steps of the calculation. A value of \( g = 1.8E-3 \) was obtained in 40 iterations.

Figure 12: Convergence history. Cost function given by eq(1) in function of the iteration step

The number of elements used to discretise the pipeline is 148; the reverse simulation took 40 steps to improve an initial configuration yielding a cost function value of 1.05, to the final configuration shown in Table 3 yielding 1E-3. The complete calculation took few seconds in a stand alone laptop personal computer.

CONCLUSIONS

A reverse modelling tool has been implemented and tested for detecting the location, size and strength of localised coating defects along metallic pipelines under ICCP control. The method iterates on existing forward model tools.
The outcome of the reverse modelling presented in this work is a set of parameters that describe the coating breakdown factor along the pipeline, such as size, strength, and location of localised defects, as well as a uniform breakdown factor for the coating. Therefore the dimension of the search space is \(3 \times N_{\text{def}} + 1\), where \(N_{\text{def}}\) is the number of defects expected to be detected.

The results presented in the last section demonstrate that the developed approach is effective and accurate in finding the location of an isolated coating defect. The error in predicting the size is comparable bigger.

The modified NS method improved in a way that is allowed to escape out of local minimum is proven to be a feasible approach for reverse modelling calculation in ICCP applied to coated metallic pipelines. It has been observed that there is a certain dependency of the search performance with the initial guess. This is not a desirable feature, and more research would need to be conducted in this direction.

The forward modelling is a useful to calculate the different patterns of potential at ground level produced by different features of the coating breakdown factor distribution. It may be possible to reduce the computational cost of the reverse modelling simulation by using this information, when the available field data is a two dimensional contour map of equipotential lines at ground level.

The methodology can be used to interpret survey data and to guide the type of data collected and its location thus significantly adding value to the data collected.

REFERENCES


