Metamodelling of the Electrical Conditions in Submerged Arc Furnaces

M. Sparta¹, D. Varagnolo², H. Martens²,³, and S.A. Halvorsen¹

¹NORCE Norwegian Research Centre AS, Norway, masp@norceresearch.no
²NTNU, Norway, damiano.varagnolo@ntnu.no
³Idletechs AS, Norway

Keywords: Finite Element Method, PLS regression, Multivariate metamodeling, Electrical Conditions, Submerged Arc Furnace

Abstract – Physic-based Finite Element Methods (FEM) models of submerged arc furnaces (SAF) are capable to accurately estimate the induced currents in the steel shell, the alternating current distributions in the material layers, and the active and reactive power densities within the furnace. However, a physics-based model is generally very demanding in terms of computational time and resources, and therefore difficult to employ during control operations and in fast prototyping. In this paper we analyze to which level one can obviate these inconveniences through metamodels that are grounded on physics-based modelling. We find that with properly tuned metamodels it is possible to establish: a) forward relationships, to effectively show the relative importance of each input parameters for a given output, b) inverse relationships, to infer the input parameters given a set of outputs.

We moreover show how to construct metamodels of the SAF electrical conditions that retain the same generalization capabilities as the original model, while being computationally lightweight.

INTRODUCTION

With the emerging of suitable simulation programs and computational capabilities there have been an increase of simulations and modeling attempts to investigate the electrical conditions of industrial Submerged Arc Furnaces (SAF). For example, a 3D Direct Current (DC) model was used to investigate current and power distribution for one point in time in the Alternate Current (AC) cycle (Dhainaut, 2004). Later, it was demonstrated that, as long as electromagnetic induction can be neglected, the results from two DC computations can be combined to find the condition for any point in time during an AC cycle or the time averaged power and current distribution (Halvorsen, Olsen and Fromreide, 2016). Other examples include a 3D computational fluid dynamic model to investigate the internal dynamics of an electrical furnace for smelting of Platinum Group Metal concentrates (Bezuidenhout, Eksteen and Bradshaw, 2009), the use of Maxwell’s equations in connection with a Finite Volume Method approach to model steel-making process (Toh et al., 2005) as well as a Multiphysics model (coupling thermodynamics, electrical condition, hydrodynamics, heat radiation and chemical reactions) for a SAF (Darmana et al., 2012).

More recently, it has been shown that physic-based models implemented in 3D Finite Element Method (FEM) simulations are capable to accurately estimate the induced currents in the steel shell, the alternating current distributions in the material layers, and the active and reactive power densities within the furnace (Herland, Sparta and Halvorsen, 2018), the effects of electrode shape, pitch circle diameter and frequency on the current distribution (Tesfahunegn et al., 2018, 2020).
The drawback of these physic-based models is that the solution of the underlying equations is very demanding in terms of computational time and resources. This makes it economically inconvenient to employ such simulations during control operations and in fast prototyping. To overcome this limitation we previously developed a procedure to derive metamodels based on physic-based FEM models of a SAF (Sparta et al., 2021). In this context a metamodel shall be intended as a surrogate of the original model that retains the same generalization capabilities as the original model, while being computationally lightweight, i.e., a statistical model of the input-output behavioral repertoire of the physics-based model. A multivariate metamodel of the FEM model can be realized in two modelling “directions”, classical (or direct, forward) and inverse (Tøndel and Martens, 2014). The direct multivariate metamodeling (DM) approximates the FEM model in its presumably causal direction. From a functional perspective it can be written as Outputs ≈ DM(Inputs). Here, the complicated mathematical relations encoded in the equations of the FEM are approximated by a statistical prediction model Outputs = f(Inputs, α) with a simpler structure f(.) of linear or non-linear type. Its predictive parameter set α is estimated statistically by applying a chosen multivariate regression method to a chosen set of simulation data [Inputs, Outputs]. Once parameters α have thus been estimated for the deterministic FEM, the metamodel may be used for uniquely predicting the outputs for new inputs via its metamodel*: Outputs(New)= DM(Inputs(New), α). A metamodel can be also realized in the opposite direction, Inputs ≈ IM(Outputs), where IM(.) represents the “inverse” multivariate metamodeling. Similarly to direct metamodelling, the indirect metamodelling approach relies on statistical methods to estimate the parameters β in a regression model Inputs=f(Outputs, β). This attempts to answer the question: “which set of inputs to the FEM model yields a given set of outputs?”. But we note that such information is normally not available to the FEM practitioners. We note that a FEM model may be non-injective, i.e. several different sets of FEM Inputs may give the same set of Outputs. Mechanistic models of this nature are in general called “mathematically sloppy” (Gutenkunst et al., 2007). Inverse metamodeling only works for non-sloppy mechanistic models. Otherwise it cannot give unique predictions of the model Inputs from chosen or measured values of the Outputs. If it is mathematically sloppy, the inverse regression modelling is imprecise, while the direct regression modelling may still be very precise, in the sense that there are many alternative parameter combinations, e.g. positioned along manifolds in the input space, that give more or less the same outputs (Tafintseva et al., 2014).

To obtain a direct or inverse metamodel, one needs to implement a physics-based model that gives a suitable representation of the system at hand, generating a set of Outputs as a function of a set of Inputs. With this model, a database of numerical experiments can be obtained by the help of cost-effective experimental design approaches. Following this paradigm, the extension of the database depends in primis on the dimension of the input space (model parameters, initial conditions, numerical control parameters etc). However, when possible, inherent symmetry of the model can be exploited to formally increase the size of the database without adding requirements on the computational complexity for generating the samples; alternatively, numerical constraints can be implemented in the procedure to determine data-based model coefficients that ensure proper physical behavior.

The final step consists in applying statistical analysis methods to devise a data-driven approximation of the physic-driven model. In our test, the direct metamodel demonstrated to be able to reproduce with high accuracy active and reactive powers, reactances, resistances and induced power. The inverse metamodel was able to predict with fair accuracy the input used to generate selected outputs but could not resolve the simulation of lifting an electrode.
To improve the performances and avoid these mis-detections, in this contribution we revisit the final step of the previously developed procedure and apply alternative improved statistical analysis tools.

To serve the purpose of the manuscript, i.e., to investigate how to metamodel SAFs, plus the capabilities and limits of such metamodels, we organized the text as follows: first, the metamodel procedure will be briefly presented, highlighting the difference with the original procedure. Subsequently, the statistical performance of the overall regression approach to metamodeling will be assessed using relevant study-cases.

**METAMODEL CONSTRUCTION**

In this section we review the steps necessary to metamodel a FEM model of electrical conditions of a SAF producing ferromanganese alloys.

**The FEM Model**

The considered FEM model is implemented in COMSOL v5.5 (COMSOL Inc., 2020) and is a direct derivation of a previously existing model originally developed to compute skin and proximity effects in large ferromanganese and ferrosilicon furnaces (Herland, Sparta and Halvorsen, 2018). The original model has been parametrized to investigate the effects of 12 input variables on the electrical conditions. The input set includes the conductivity of the charge and, for each electrode, the root mean square (rms) of the current, the height of the tip with respect to the metal bath the shape, and the conductivity of the coke beds. For a more detailed description of the FEM model and its implementation we refer to (Sparta et al., 2021).

Given the physical properties of the materials and their configurations, the model can predict currents distributions in the furnace and therefore active and reactive power for each domain (electrode, coke beds, metal, charge, steel shell, steel roof), plus all the corresponding ancillary quantities such as resistances and reactances (total and per electrode). For the sake of brevity these variables will be cumulatively referred to as the output of the model. Representative results obtainable with the model are shown in Figure 1, depicting induced power on the steel shell surface (left panel) and the power distribution on a cross section of the furnace (right panel).

![Figure 1: Induced power of the furnace shell surface, where electrodes and coke beds are shown for clarity (left). Power distribution in cross section of the furnace across two electrodes (right).](https://ssrn.com/abstract=3926715)
The FEM input → output database
The next step is to identify, by means of numerical experiments, how variations in the input influence the output of the model. This means that the need is to construct a database that captures this information. For this reason, for each of the input parameters, we considered 4 possible numerical values selected to span a reasonable range. For example, the rms current for one electrode was chosen in the set [127—138] kA. Even with this simple set up, the number of simulations grows exponentially with the number of input parameters: exploring all the combinations would require $4^{12}$ FEM calculations, clearly beyond typical computational capabilities. To limit the number of simulations while capturing the most feature of the combined effects of the inputs we adopted a design of experiment based on an optimized multi-level binary replacement (OMBR) design (Martens et al., 2010). This design gave 128 input combinations that were applied 5 times (with different variable orders) for a total of 640 simulations. At this stage, it is important to realize that the FEM has an inherent rotational symmetry of order 3 with respect to the central vertical axis. In practice, this allows to derive, without additional FEM simulations, 1280 additional input/output combinations leading to a database of 1920 entries (Sparta et al., 2021). This can be represented by an Input matrix (with dimensions 1920x12) and an Output matrix (with dimension 1920x40, where 40 is the number of output values collected for each simulation).

Surrogate modelling by linear regression
The approach outlined here attempt to replace the relation between matrix of variables $X$ (NxJ) and the matrix of observations $Y$ (NxK), using a linear model. In the simplest case, the linear model is written as:

$$Y = b_0 + XB + F$$

[1]

where $b_0$ and $B$ (with dimensions 1xK and JxK, respectively) are the coefficients of the affine map and $F$ (NxJ) is a residual matrix. For the task of finding the optimal affine map, a Partial Least Square Regression (PLSR) approach, relating the J $Y$-variables to the K $X$-variables, each variable rescaled to a variance of 1, via a reduced-rank subspace regression, was considered since, in comparison to other least squares algorithms (e.g, MLR) is more robust to noise, and it gives compact and interpretable subspace regression models under a wide range of collinearity conditions. The optimal subspace dimensionality of the linear PLSR model and hence the rank of regression coefficients $B$ was determined by leave-one-out cross-validation (Arlot and Celisse, 2010). For a recent review on PLS regression and its use in multivariate metamodeling we refer to (Abdi et al., 2013) and (Tøndel and Martens, 2014).

In the Direct Metamodel, the algorithm uses $X =$ Input and $Y =$ Output whereas $X =$ Output and $Y =$ Input is used when computing the Inverse Metamodel. In our previous work we demonstrated that the linear models obtained with the PLSR give excellent performances in the direct directions. In the inverse direction, the surrogate model gave fair results, but we have shown that it could not resolve an experiment in which one electrode was lifted while holding or the other input parameters constant.

In this paper we revisit the case employing more sophisticated techniques allowing more flexibility in the linear model. In the specific, here we use:

- The PLSR1 version of the algorithm: in other words, here a PLSR is constructed for each of the K output variables, compared to the previous PLSR2 approach where all output variables are addressed at once.

Electronic copy available at: https://ssrn.com/abstract=3926715
• The use of Interactions and Squared terms in the input space: Eq. 2 demonstrates how the X matrix is expanded. For a X matrix with J columns there are J(J-1) “Interaction” columns and J “Squared” columns, leading to a X^{IS} with J(J+1) columns.

\[
X^{IS} = \begin{bmatrix}
    x_1, x_2, ..., x_J, x_1 x_2, x_1 x_3, ..., x_{J-1} x_J, x_1^2, x_2^2, ..., x_J^2
\end{bmatrix}
\]

Even if the model \( Y = b_0 + X^{IS} B + F \) remains linear, this increase the flexibility of the regression model.

Finally, here we explored how constructing the underlying database in a tighter region around the relevant test cases improve the robustness of the metamodels and the reliability of the results.

### RESULTS AND DISCUSSION

For this analysis, we will focus on the result of a linear scan of a simulated electrode lifting, i.e., the case that was not captured by the previously available models. To this end, we collected 21 FEM simulations for which all the input parameters were constant except for the electrode tip position that varied in the range 1.0 - 1.5 m (Sample 1 to 21). Our earlier attempt to reconstruct such an input using the Inverse Metamodel on the output of the FEM simulations was able to identify the lifting of the electrode, but the rate of the lift was noticeably underestimated (2.5 cm/step). In fact, the position of the tips was overestimated in the first part of the scan and underestimated at higher values. The inverse metamodel compensated this error with a spurious decreasing trend in the conductivity of the coke bed as the electrode was lifted (for comparison, in the reference calculation the conductivity of the coke bed was fixed at 310 S/m). We suspect that the reason for this shortcoming is due to the sloppiness of the FEM model, i.e., the fact that certain combinations of the FEM inputs give more or less similar responses (i.e., FEM outputs). Under this condition, the resulting metamodel would be unable to properly resolve the original input combinations (Sparta et al., 2021).

Figure 2 reproduces our original results (IM1) together with results obtained using variation on the PLSR algorithm. With IM2, the regression addresses, at once, only 3 input parameters (Electrode tip position, coke bed conductivity and coke bed shape) pertaining to Electrode 1 at once, whereas in IM3 a specific PLSR is constructed for each variable (in agreement with the PLSR1 formulation). It should be noted that all three Inverse Metamodels share the same underlying database and information (X), but the predictions are different because the model is cross-validated and this procedure selects, in the different cases, different model rank.

In other words, cross-validation and rank selection is carried out for each variable in the PLSR1 algorithm and or cumulatively for an ensemble of variables (PLSR2) and this may lead to small variations in the performance of the models.

In this case, the optimization one achieves with dedicated PLSRs does not lead to an improvement of the performances of the metamodels: the results on the electrode tip position are almost indistinguishable (Figure 2, left panel) and a strong unfounded variation in the coke bed conductivity is predicted (Figure 2, right panel). The summary of the performance of the different inverse metamodels is given in Table I. Here, the error analysis (Min, Max, Root Mean Square Error (RMSE)) are shown together with the calculated slope of the linear scan for the position of the electrode tip and coke bed conductivity. As shown in Figure 2, the performances of IM1, IM2 and IM3 are almost indistinguishable, confirming that minor variations in the PLSR algorithm cannot address the shortcomings of the original inverse metamodel.
An alternative route to increase the flexibility of the model is to include interactions and squared effects into the model. The performances of metamodels exploiting such interactions and squared effects are investigated in Figure 3. Here, the improvement on the prediction of the electrode tip position is significant. Both IM4 (in which the database is supplemented with square terms) and IM5 (with the addition of square terms and all the interactions) are found to be in good agreement with the reference values (Figure 3, left panel). As for the conductivity of the coke bed (Figure 3, right panel), one can note that a decreasing trend remains; however, this trend is significantly improved compared to the results in Figure 2. This is confirmed by the numerical data in Table I. Compared to the original results the slope of the electrode tip variation per step doubles to 2.0 cm/step (ref. 2.5 cm/step), while the slope on the conductivity of the coke bed halves to -1.5 S/m/step (ref. 0.0 S/m/step).

Figure 2: Electrode tip position and conductivity of the coke bed in a linear scan. Values computed with Inverse Metamodels (IM) vs references. IM1, IM2 and IM3 are metamodels constructed with variation of the PLSR algorithm.

Figure 3: Electrode tip position and conductivity of the coke bed in a linear scan. Values computed with Inverse Metamodels (IM) vs references. IM4 and IM5 are metamodels for which the underlying database has been enriched with interactions and squared effects.
Interestingly, we notice that the square terms added to the database for IM4 carry the information and flexibility necessary to achieve the improvement. Further adding other interactions (IM5) does not improve the accuracy of the inverse metamodels in terms of absolute accuracy.

In our original publication, we noticed that the relatively simple strategy for generating database points led to a database for which certain output parameters stretched far outside the range of normal industrial operations. For example, the total active power of the furnace was found in the range [18.5 - 63.0] MW compared to the ca. 40 MW of the furnaces for which this model is devised (Sparta et al., 2021). While having a database that spans a large range is important to ensure broad applicability, this may also lead to metamodels that are skewed towards areas of little interest.

Here we explore how changing the parameters used in the definition of the underlying database modify the performances of the final metamodels. We are actively engaged in the definition of advanced strategies for the collection of sensible FEM datapoints, but for this test we utilize a pragmatic approach. A new database was constructed in the identical way as for the original one, the only difference being the range for the coke bed conductivity. In the new database we used [260 - 370] S/m whereas the original one spanned over [170 - 460] S/m. The net result is that the new database shows total active powers in the range [21.1 – 50.5] MW. The new database was used to construct two additional inverse metamodels: IM6, that uses only the FEM outputs, and IM7, that uses also interactions and squared terms as features. The results about comparing IM6 and IM7 shown in Figure 4. Both the electrode tip position and the coke bed conductivity are found to be relatively close to the reference. The performance of IM7 is particularly good both for the accuracy of the prediction of the electrode tip and the flatness of the coke bed conductivity during the scan. Although a small spurious decreasing trend in the coke bed conductivity is still present, these results show a great improvement over our original results as seen in the comparison offered in Table I.

![Figure 4](https://ssrn.com/abstract=3926715)

**Figure 4**: Electrode tip position and conductivity of the coke bed in a linear scan. Values computed with Inverse Metamodels (IM) vs references. IM6 and IM7 are metamodels for which the underlying database has been enriched with interactions and squared effects.
Table I: Performance indicators of the ability of different Inverse Metamodels to interpret the result of a linear scan in the electrode tip position.a

| Metamodelb | Electrode Tip Position | Conductivity of coke bed |
|------------|------------------------|--------------------------|
|            | Max (cm) | Min (cm) | RMSE (cm) | Slope (cm/step) | Max (S/m) | Min (S/m) | RMSE (S/m) | Slope (S/m/step) |
| IM1 (l)    | 23       | 0        | 13       | 1.0            | 73        | 8         | 47        | -3.3           |
| IM2 (l)    | 24       | 0        | 13       | 1.0            | 79        | 14        | 52        | -3.3           |
| IM3 (l)    | 24       | 0        | 13       | 1.0            | 71        | 6         | 45        | -3.3           |
| IM4 (ls)   | 5        | 0        | 3        | 2.0            | 39        | 4         | 25        | -1.8           |
| IM5 (lsi)  | 8        | 0        | 5        | 2.0            | 49        | 21        | 39        | -1.5           |
| IM6c (l)   | 11       | 0        | 6        | 1.7            | 27        | 8         | 19        | -1.0           |
| IM7c (lsi) | 4        | 2        | 3        | 2.4            | 26        | 14        | 20        | -0.6           |

a The reference value for the slope of the linear scan is 2.5 cm/step for the electrode tip position and 0.0 S/m/step for the coke bed conductivity. b The type of metamodel is specified in parenthesis, (l) only linear terms used, (ls) linear and square terms, (lsi) linear, square and interaction terms. c IM6 and IM7 are based on a database with a tighter range for the coke bed conductivity.

To sum up: We have demonstrated that
a. Variation in the algorithm defining the inverse metamodel (PLSR1 vs PLSR2) gives small variations in the results, but do not improve the performances
b. Inclusion of interactions and square effects can give substantial improvements in accuracy.
c. More robust and accurate inverse metamodels are obtained by reconstructing the underlying database to be more representative of the area of interest.
d. The positive effects described in b and c were found to be additive and the final inverse metamodel, constructed on the tighter database and employing interactions and squared terms, was able to accurately predict the progression of the tip position in an electrode lifting simulation.
e. In spite of the improvements, traces of the mathematical sloppiness that links electrode tip position and the conductivity in the coke bed remain. Even the final inverse metamodel predicts a spurious decreasing trend in the coke bed conductivity.

Potential benefits of metamodels for SAFs
The purpose of this manuscript is to investigate how to metamodel SAFs, including studying capabilities and limits of such modelling. We will, however, include a brief discussion of potential benefits:

The classical (or direct, forward) metamodel will reveal the influence of the input variables. The researchers will learn which parameters combine to supply a certain result and whether each relevant parameter has a strong, medium or weak influence. This insight can then be “translated” and used in communication with metallurgists and furnace operators. The metamodel can also be adapted with a suitable, user-friendly interface for rapid what-if studies. Appropriate case studies can then be developed and the metamodel can effectively be applied for hands-on exercises, similarly to how the company Elkem has utilized a comparatively simple stoichiometric model in their continued education for metallurgists (Halvorsen, 1995).

Electronic copy available at: https://ssrn.com/abstract=3926715
An inverse metamodel will apply output values to estimate input values for a complex FEM model. In our case, input values can be electrode tip positions, conductivity of the coke beds, parameters defining the shape and size of the coke beds, etc. If furnace measurements can supply sufficient, suitable output values, such metamodels can be applied to estimate the inner furnace conditions (input values) during operation. An initial study has revealed that available process data are not sufficient (Stråbø, 2020). Another study has shown that induced currents in the steel shell carry information on inner furnace conditions, and proposed methods for appropriate measurements (Halvorsen et al., 2021). Future work will concentrate on clarifying whether such and/or other additional measurements are sufficient for identification of inner conditions. Adapting suitable metamodels will be an integrated, essential part of such research.

CONCLUSIONS

As described above, we have recently devised a procedure to generate direct and inverse metamodels based on simulations by a far more complex physics-based FEM model. With this contribution, we have successfully shown how previous shortcomings in the inverse metamodels can be lifted through ad hoc tuning and improving of the metamodel construction, to obtain excellent agreements with the reference data.

ACKNOWLEDGEMENTS

This paper is published as part of the project Electrical Conditions and their Process Interactions in High Temperature Metallurgical Reactors, in short Electrical Conditions in Metal Processes (ElMet Project No.: 247791), with financial support from The Research Council of Norway and the companies Elkem and Eramet Norway.

REFERENCES

Abdi, H., Chin, W. W., Vinzi, V. E., Russolillo, G. and Trinchera, L. (eds) (2013) in New Perspectives in Partial Least Squares and Related Methods. New York: Springer-Verlag.

Arlot, S. and Celisse, A. (2010) ‘A survey of cross-validation procedures for model selection’, Statistics Surveys, 4, pp. 40–79. doi: 10/dk3ww4.

Bezuidenhout, J. J., Eksteen, J. and Bradshaw, S. (2009) ‘Computational Fluid Dynamic Modelling of an Electric Furnace Used in the Smelting of PGM Containing Concentrates’, Minerals Engineering, 22, pp. 995–1006. doi: 10/crh6qv.

COMSOL Inc. (2020) COMSOL Multiphysics. Available at: https://www.comsol.com/ (Accessed: 15 October 2020).

Darmana, D., Olsen, J. E., Tang, K. and Ringdal, E. (2012) ‘Modelling concept for submerged arc furnaces’, in Ninth International Conference on CFD in the Minerals and Process Industries. Melbourne, Australia: CSIRO. Available at: http://www.cfd.com.au/cfd_conf12/ (Accessed: 28 August 2020).

Dhainaut, M. (2004) ‘Simulation of the Electric Field in a Submerged Arc Furnace’, in Proc. of the Tenth Int. Ferroalloys Congress, INFACON X, pp. 605–613.

Gutenkunst, R. N., Waterfall, J. J., Casey, F. P., Brown, K. S., Myers, C. R. and Sethna, J. P. (2007) ‘Universally Sloppy Parameter Sensitivities in Systems Biology Models’, PLOS Computational Biology, 3(10), p. e189. doi: 10/cf6dfr.

Halvorsen, S. A. (1995) ‘Mathematical Modelling – An Integrated Part of Elkem’s Continued Education for Process Metallurgists’, in Proc. of the Seventh Int. Ferroalloys Congress, INFACON VII. Trondheim, Norway, pp. 729–738.

Halvorsen, S. A., Olsen, H. A. H. and Fromreide, M. (2016) ‘An Efficient Simulation Method for Current and Power distribution in 3-Phase Electrical Smelting Furnaces’, IFAC-PapersOnLine, 49, pp. 167–172.

Halvorsen, S. A., Sparta, M., Risinggård, V. K. and Fromreide, M. (2021) ‘Electrical Conditions in 3-phase Submerged Arc Furnaces: Learning from the ElMet project’, in Proc. of the Sixteenth Int. Ferroalloys Congress, INFACON XVI, p. Accepted.

Herland, E. V., Sparta, M. and Halvorsen, S. A. (2018) ‘3D models of proximity effects in large FeSi and FeMn furnaces’, J. South Afr. Inst. Min. Metall., 118, pp. 607–618. doi: 10/gdz8n8.

Martens, H., Måge, I., Tøndel, K., Isaeva, J., Hoy, M. and Sæbø, S. (2010) ‘Multi-level binary replacement (MBR) design for computer experiments in high-dimensional nonlinear systems’, J. Chemom., 24(11-12), pp. 748–756. doi: 10/b8gfn.
Sparta, M., Varagnolo, D., Stråbo, K., Halvorsen, S. A., Herland, E. V. and Martens, H. (2021) ‘Metamodelling of the electrical conditions in Submerged Arc Furnaces.’, Metall and Materi Trans B. doi: 10.1007/s11663-021-02089-7.

Stråbo, K. (2020) Metamodelling and inverse metamodelling electrical conditions in ferromanganese furnaces. Master Thesis. NTNU.

Tafintseva, V., Tøndel, K., Ponosov, A. and Martens, H. (2014) ‘Global structure of sloppiness in a nonlinear model’, Journal of Chemometrics, 28(8), pp. 645–655. doi: 10/f6dsjp.

Tesfahunegn, Y. A., Magnusson, T., Tangstad, M. and Saevarsdottir, G. (2018) ‘The Effect of Pitch Circle Diameter of Electrodes on Current Distributions in Submerged Arc Furnace’, in Proceeding of the 2018 IEEE MTT-S International Conference on Numerical Electromagnetic and Multiphysics Modeling and Optimization (NEMO), pp. 166–169. doi: 10/ghgptf.

Tesfahunegn, Y. A., Magnusson, T., Tangstad, M. and Saevarsdottir, G. (2020) ‘Comparative Study of AC and DC Solvers Based on Current and Power Distributions in a Submerged Arc Furnace’, Metallurgical and Materials Transactions B, 51, pp. 510–518.

Toh, T., Yamasaki, N., Seki, T. and Tanaka, J. (2005) ‘Magnetohydrodynamic simulation in steel making process by 3D finite element method’, in Proceeding of the 4th International Conference on CFD in the Minerals and Process Industries, SINTEF-NTNU.

Tøndel, K. and Martens, H. (2014) ‘Analyzing complex mathematical model behavior by partial least squares regression-based multivariate metamodeling’, WIREs Comput Stat, 6, pp. 440–475.

Manuel Sparta
Senior Scientist, NORCE Norwegian Research Centre

Manuel Sparta holds a Ph.D. in Computational Chemistry from the University of Bergen. Since 2016 he has been working as a researcher within mathematical modelling and simulation at NORCE (previously Teknova). He is engaged in the Multiphysics simulations of various production processes and modeling of electrical conditions and process interactions in high temperature metallurgical reactors.