Neural Network-based Surrogates of Gear Whine Noise for Uncertainty Propagation

Barbara Zaparoli Cunha, Christophe Droz, Abdelmalek Zine, Mohamed Ichchou, Stéphane Foulard

INSTITUTE OF FUNDAMENTAL TECHNOLOGICAL RESEARCH
AND COMMITTEE ON MECHANICS
POLISH ACADEMY OF SCIENCES

7th European Conference on Structural Control

Book of Abstracts and Selected Papers

Editors:

Jan Holnicki-Szulc, David Wagg and Łukasz Jankowski

Co-editors:

Bartłomiej Błachowski and Piotr Tauzowski

since 1993 IPPT PAN

WARSAW 2022

INSTITUTE OF FUNDAMENTAL TECHNOLOGICAL RESEARCH
AND COMMITTEE ON MECHANICS
POLISH ACADEMY OF SCIENCES

7th European Conference on Structural Control

Book of Abstracts and Selected Papers

Editors:
Jan Holnicki-Szulc
David Wagg
Łukasz Jankowski

Co-editors:
Bartłomiej Błachowski
Piotr Tauzowski

WARSZAWA 2022

ISBN 978-83-65550-37-8

Institute of Fundamental Technological Research PAN
02-106 Warszawa, ul. Pawińskiego 5B
www.ippt.pan.pl

Committee on Mechanics, Polish Academy of Sciences
02-106 Warszawa, ul. Pawińskiego 5B
kmech.pan.pl

Neural Network-based Surrogates of Gear Whine Noise for Uncertainty Propagation

B. Z. Cunha[1,2], C. Droz[3], A. Zine[4], M. Ichchou[1], and S. Foulard[2]

[1] *Laboratoire de Tribologie et Dynamique des Systèmes, École Centrale de Lyon, Écully, France.*
[2] *Compredict, Darmstadt, Germany.*
[3] *Univ. Gustave Eiffel, Inria, COSYS/SII, I4S team, Rennes, France.*
[4] *Institut Camille Jordan, École Centrale de Lyon, Écully, France.*

e-mail: barbara.zaparoli-cunha@ec-lyon.fr

1. Abstract

Noise, Vibration, and Harshness (NVH) performance is a key aspect to evaluate passengers' comfort in vehicles. At the gearbox level, the gear tooth profile deviations give rise to vibrations during the gear meshing process, which is the source of gear whine noise. Therefore, an NVH design should account for the uncertainties at the gear micro-geometry level, demanding several evaluations of the gearbox model. Our study introduces a gearbox surrogate model based on Neural Networks (NN) to create a fast and accurate copy of the static and dynamic gearbox simulations made in Romax software. An accurate surrogate model was built, enabling a reduction of uncertainty propagation analyses time by a factor of 380, compared with traditional modeling by Romax.

2. Introduction

Gear whine is a tonal and annoying noise that originates in the gear meshing process in gear transmissions. The main cause of gear whine is the Static Transmission Error (STE), which can be defined as the difference between the actual contact position of the output teeth and its theoretical position in a perfect conjugated contact [16] accounting for deviations from an involute profile due to profile modifications, manufacturing errors, misalignments, and elastic deflections [4]. The challenges to designing a silent gearbox increase in the cases of lightweight gearbox design, a crucial requisite to more sustainable vehicles [14], as lightweight gearboxes tend to be more flexible, leading to more misalignments, higher STE, and greater amplitudes of housing vibration, radiating more noise.

The proper evaluation of the whining noise includes the evaluation of the STE and, subsequently, the application of the STE as a source of excitation of the system to evaluate its dynamic behavior, which closely correlates with the whining noise [14]. Åkerblom [1] provided a review of the methodologies used to model the STE and the gear transmission dynamic analysis. Guo et al. [6] showed that the housing should be included in the system model, allowing to account for the coupling effects of it with the system and to quantify the housing vibration. Besides, the effect of manufacturing errors and other uncertainties in the gear teeth profile cannot be neglected, once the profile errors are the cause of the system excitation, and, therefore, micro-geometry uncertainty propagation must be performed even for tight tolerances [4].

To alleviate the computational burden of the numerous and costly evaluations involved in the uncertainty propagation of the static and dynamic analyses of the entire gearbox, this paper proposes to create a surrogate model based on Neural Networks (NN). The surrogate models or response surface methods are simple and efficient input-output maps of a more complex model with little loss of accuracy and are currently used to speed up many engineering problems [2, 13].

A surrogate model of the STE was developed by Park [11] using a parametric second-order regression to fit the model. However, Machine Learning (ML) methods usually have better generalization capabilities than parametric methods and can deliver better prediction results. This statement is supported by the results from the comparison of three different STE surrogates done by Korta and Mundo [8]. To the author's knowledge,

the development of a surrogate to predict dynamic responses of an entire fully-coupled gearbox system has not been achieved so far. By implementing an automatic integration of *Python* with the Romax software [12], this work will enable the creation of a novel NN-based surrogate model for the static and dynamic analysis of complete gear transmission. The present paper adds to the current state of the art as it analyzes a surrogate of a complete gearbox model, including housing and dynamic effects.

3. Construction of the Surrogate Model of the Gear Whine Analyses and Uncertainty Propagation Methodology

The first step in building a surrogate is to have a high-fidelity simulation model being used as the ground truth. Therefore, a complete model of gearbox with gears, shafts, bearings and housing was built in Romax software. The gear bodies are modeled as integral with the shafts using Timoshenko beam elements, while the bearings are modeled as [6x6] stiffness matrix by linearizing their behavior near the operational condition. The housing is modeled by a Finite Element (FE) model reduced with the Craig-Bampton method to decrease the computational cost of the simulations while still taking into account the dynamic behavior, which results in a fully-coupled system of the gearbox [7].

First, a static analysis of the system is performed on each load condition to evaluate the system elastic deflection, which includes bearing displacements and the deformations of the shafts, gears, and housing and results in the gear mesh misalignment. The FE-based model of the tooth contact provides the tooth compliance matrix $\boldsymbol{C}$, the mesh stiffness k and tooth deflection in relation to the input angular position θ [4]. The tooth compliance matrix accounts for tooth bending, root rotation and translation, Hertz deformation, and radial deformations. Then, STL can be evaluated simultaneously with the static load distribution in the contact line $\boldsymbol{p}$ for a given static force transmitted F, by solving:

$$\begin{cases} \boldsymbol{C}(\theta)\boldsymbol{p}(\theta) = STE(\theta) - \boldsymbol{e}(\theta) \\ \sum_i p_i(\theta) = F \end{cases} \tag{1}$$

where, $\boldsymbol{e}$ is the vector with the initial gap between the teeth at each discrete point, including the effects of the micro-geometric modifications, manufacturing errors, and gear mesh misalignment.

The STE displacement multiplied by the system compliance at the gear mesh location results in the force resulting from the transmission error. This force is then applied as the excitation source of the system in the dynamic analysis. In this paper, the dynamic system is modeled by a linear analysis with constant mesh stiffness approximated to its average value and it is solved in the frequency domain. The resulting frequency response functions (FRF) allow evaluating, e.g., the bearing forces and housing responses across the operating speed range.

Using the physics-driven gear transmission model, M pairs of input-outputs are sampled based on Latin Hypercube Sampling (LHS) to create a database of supporting points in the design space of interest. The LHS results in an informative database, with good space-filling properties and allows capturing the effects of the iterations among the variables. The *Python* routine integrated with Romax enables to perform the sampling by running the gear transmission model with the parameters defined by the LHS.

A fully-connected NN is used to create the surrogate model in this paper and it can be trained to predict all static and dynamic quantities of interest related to the gear whine at once. The inputs of a fully-connected NN are combined through a sequence of arithmetic operations that depend on the NN parameters called weights and biases. In supervised training, as in this paper, the NN outputs are compared with the reference outputs from the physical-driven model and an assessment of the error between them defines the NN loss function. The training process consists of optimizing the weights and biases of the NN to minimize the loss function. In order

to improve the NN performance and the optimization convergence, the inputs and outputs are scaled before training, in the data preprocessing stage.

The ML performance is evaluated in the remaining samples of the database, known as the test dataset. The workflow for the construction of the surrogate model is presented in Figure 1 and further details on the implementation of NN can be found at [5, 10]. Once trained, the surrogate model can predict the gearbox static and dynamic results with little loss of accuracy and with low computational cost.

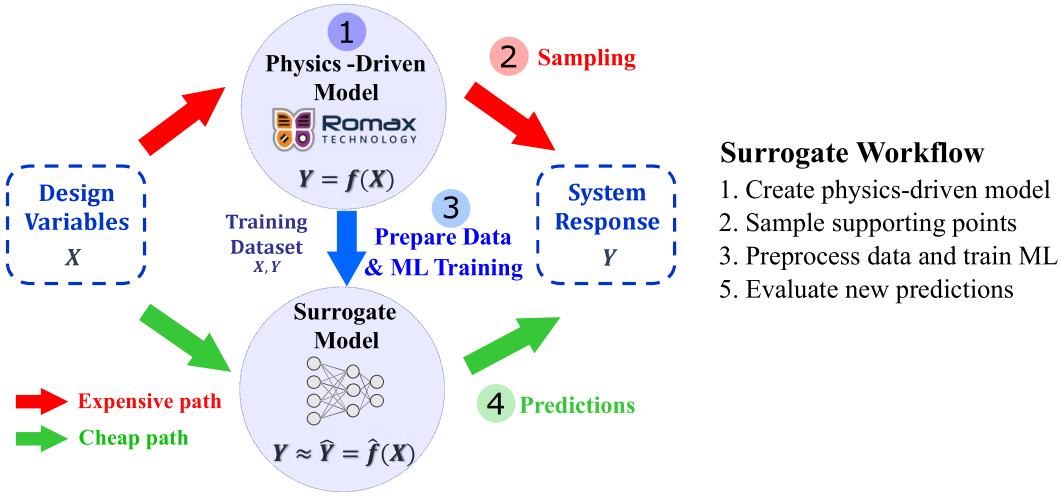


Figure 1: Workflow for the construction of the surrogate model of the gear transmission.

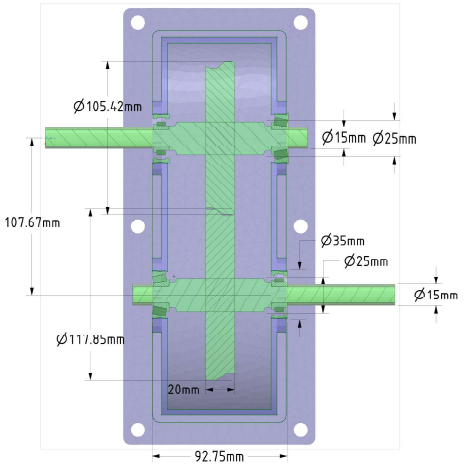
Hence, surrogate models are widely used in analyses that demand a large number of evaluations of the same function, as in uncertainty propagation analyses. These analyses provide the output uncertainties given the input uncertainties and are necessary to develop robust and reliable designs. Popular and accurate uncertainty propagation methods are based on Monte Carlo (MC) simulation methods [9], which generate random samples from the input statistical distribution and evaluate the deterministic response of each sample. The ensemble of all deterministic responses converges towards the stochastic response as the number of samples tends to infinity.

MC methods are convenient as they use the non-modified deterministic model, but are computationally costly as they demand numerous evaluations of this model. Thus, the joint use of MC with surrogates is advantageous and, therefore, largely used in the literature [3], as it enables fast evaluations of the deterministic model, optimized simultaneous evaluation of large sets of samples by using batch prediction and automatic parallelization of the solution.

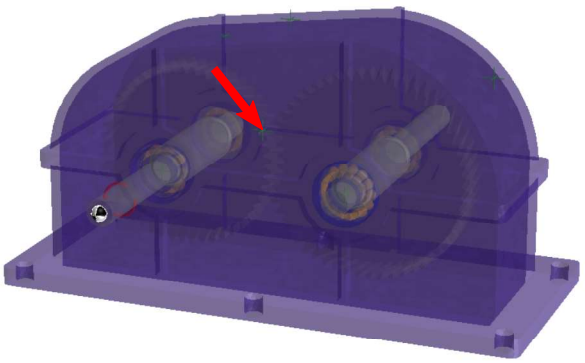
4. Gear Whine Static and Dynamic Uncertainty Propagation Results via the Surrogate Model

This section presents the results of the investigation of the use of the NN-based surrogate model to propagate the effects of micro-geometry errors on static and dynamic indicators of gear whine noise. The analyses were carried out using a single-stage gear transmission with helical gears with module equals two, face width of 20 mm and having 55 and 49 teeth in the wheel and pinion, respectively. Figure 2a shows the main dimensions of the gearbox used and Figure 2b shows the Romax model with the position where the housing acceleration was evaluated. The results were obtained for a load case with 50 Nm of input torque. All analyses were carried out using a desktop with 4 cores with $3.6GHz$ and an NVIDIA Quadro P400 GPU.

The gear micro-geometry parameters illustrated in Figure 3 were considered as inputs, namely the involute crowning C_α, the lead crowning C_β and lead slope $C_{H\beta}$, for both pinion and wheel teeth, implying a six-dimensional design space. Table 1 presents the design space of interest considered for the input variables, from where $M = 1000$ input-output pairs were sampled using the Latin hypercube sampling method with Romax, which took 1891.85 seconds. Any output of the high-fidelity model can be used to train the surrogate model.



(a) Top view of 2D drawing.



(b) Model in Romax with red arrow indicating the position where the housing acceleration was evaluated.

Figure 2: Single stage gear transmission.

Table 1: Design space of the gear teeth micro-geometry input variables. The ranges apply to both pinion and gear micro-geometries.

	$C_{H\alpha}$ $[\mu m]$	C_{β} $[\mu m]$	$C_{H\beta}$ $[\mu m]$
Lower Bound	0	0	-20
Upper Bound	15	15	20

In this paper, the peak-to-peak transmission error (PPTE) and the housing acceleration at the position indicated by the red arrow in Figure 2b were chosen as the static and dynamic indicators of the gear whine performance, respectively.

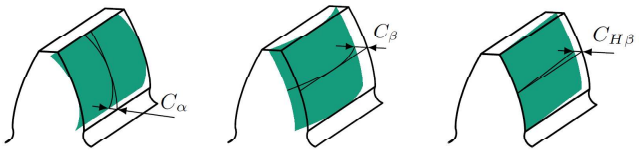


Figure 3: Gear tooth micro-geometry parameters used: involute crowning C_{α}, lead crowning C_{β} and lead slope $C_{H\beta}$. Source: [15].

4.1. NN-based Surrogate Accuracy

The surrogate model is based on a fully-connected NN with one input layer with six neurons, four hidden layers with 16 neurons each, and 101 neurons in the output layers, which correspond to the number of evaluated output results for each design, that is the PPTE and the housing acceleration evaluated at 100 different frequencies input shaft speed ranging from 0 to 4000 rpm, as illustrated in Figure 4. The neural units use the *sigmoid* function as activation function, excepted by the output layer that uses *softmax* function. The *Adam* optimizer is used to optimize the *mean squared error* during the NN training, which takes place in 3000 epochs with batches of 16 samples. The database was divided into 200 samples for the test database and 800 samples for the training dataset, from which 80 samples are used as the validation dataset.The inputs and the outputs were

scaled using respectively *StandardScaler* and *MinMaxScaler* from *scikit-learn* library and are fitted solely in the training dataset. The NN implementation was done with *Keras* library in *Python*.

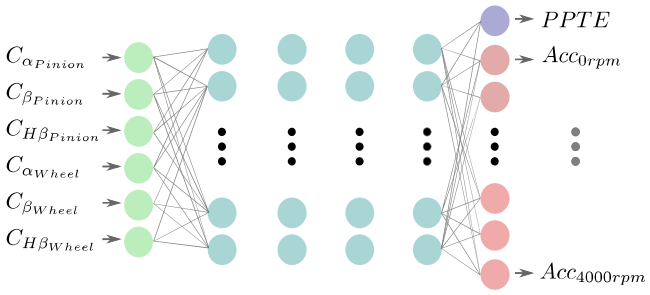
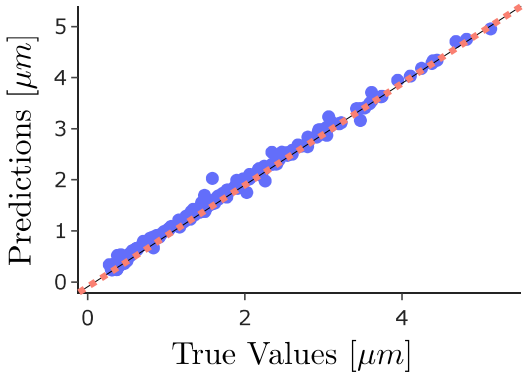
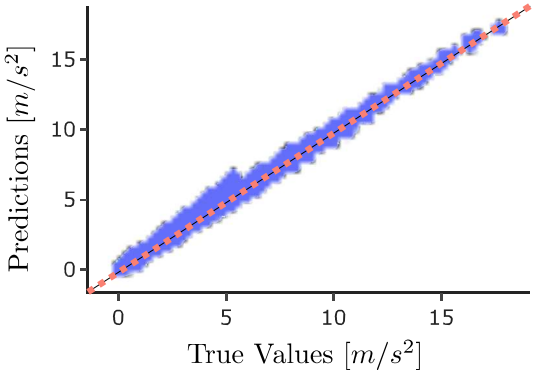


Figure 4: Representation of the Neural-Network used to implement the surrogate model.

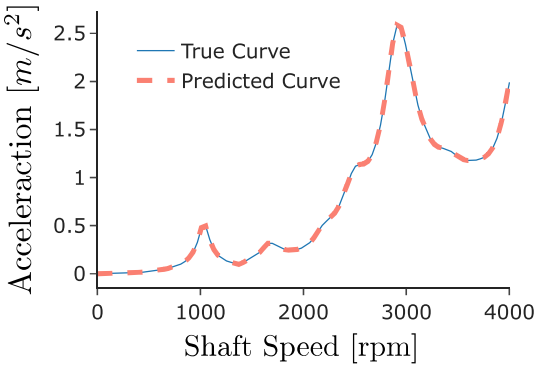
The NN training took 434.84 seconds and the final surrogate achieved a root mean squared error (RMSE) in the test database of 0.08 μm for the PPTE and 0.08 m/s^2 for the housing acceleration at any frequency. Figures 5a and 5b shows the scatter plot of the true values and the prediction values in the test dataset for PPTE and housing acceleration, respectively. Figure 5c shows the good agreement between the true and the predicted curve for the housing acceleration for an illustrative design sample from the test dataset. Once the NN-based surrogate is trained, it can predict new results in a negligible time.



(a) Scatter plot of testing data of true observations versus surrogate predictions of PPTE with $RMSE = 0.08\ \mu m$.



(b) Scatter plot of testing data of true observations versus surrogate predictions of housing acceleration with $RMSE = 0.08\ m/s^2$.



(c) True and predicted housing acceleration curves for one design in the test dataset.

Figure 5: Accuracy of the Neural Network-based surrogate model.

4.2. Uncertainty Propagation

Table 2: Design space of the gear teeth micro-geometry.

		$C_{\alpha_{Pinion}}$ μm	$C_{\beta_{Pinion}}$ μm	$C_{H\beta_{Pinion}}$ μm	$C_{\alpha_{Wheel}}$ μm	$C_{\beta_{Wheel}}$ μm	$C_{H\beta_{Wheel}}$ μm
Design 1	μ_1	5	5	0	7	5	-3
Design 2	μ_2	11	8	14	7	2	5
Design 3	μ_3	3	10	-10	2	10	-5
Tolerance	$\Delta_{1,2,3}$	1	1	1	1	1	1

The use of surrogate models becomes beneficial when multiple evaluations are necessary, as in the uncertainties propagation analysis by the MC method. The Monte Carlo simulation is performed for the three micro-geometry designs in Table 2 using both Romax and the surrogate in order to illustrate the time-saving capabilities of the surrogate. The input distribution is given by a uniform distribution $\mu \pm \Delta$, where μ is the design mean and Δ is the tolerance, and $M = 2500$ random samples from this distribution are evaluated in order to evaluate the output distributions, leading to an MC error of the order of 0.02 [17].

The time spent propagating the uncertainties for each design averages $4751.8\ s$ with Romax and $12.5\ s$ with the surrogate model, that is, the surrogate is 380 times faster than Romax. The sampling time ($1891.85\ s$) and the training time ($434.84\ s$) must be considered once since after creating the surrogate it can be used to propagate uncertainties of all designs contained in the defined space of interest.

Figure 6 shows the PPTE confidence interval obtained with both Romax and with the NN-based surrogate for the three designs. It is observed that the results obtained with the NN-based surrogate model are very close to those obtained with Romax, being that only the propagation of uncertainties of design 3 presents a visible difference in Figure 6, which is still acceptable. Figure 7 shows the $M = 2500$ housing acceleration curves of the MC estimator for design 1 obtained with Romax and with the surroate model.

Both static and dynamic results show a good agreement between Romax and surrogate results, therefore, the proposed NN-based surrogate model was successfully used to speed-up uncertainty propagation analyses of gear whine. Any other quantity of interest of the gear transmission model could be added to the NN training to be predicted by the surrogate.

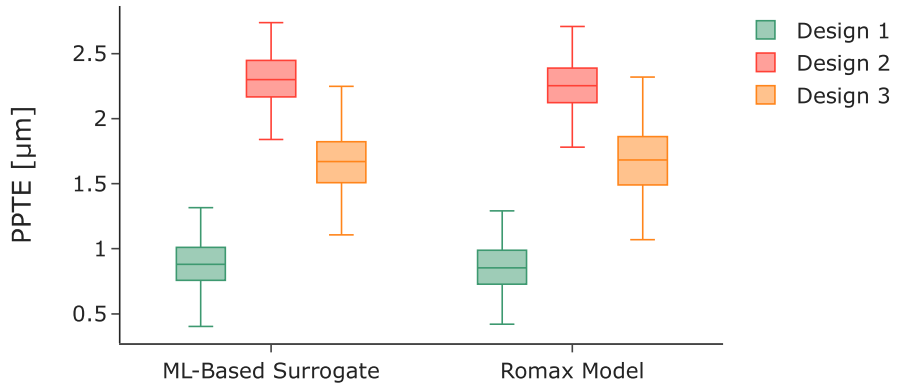
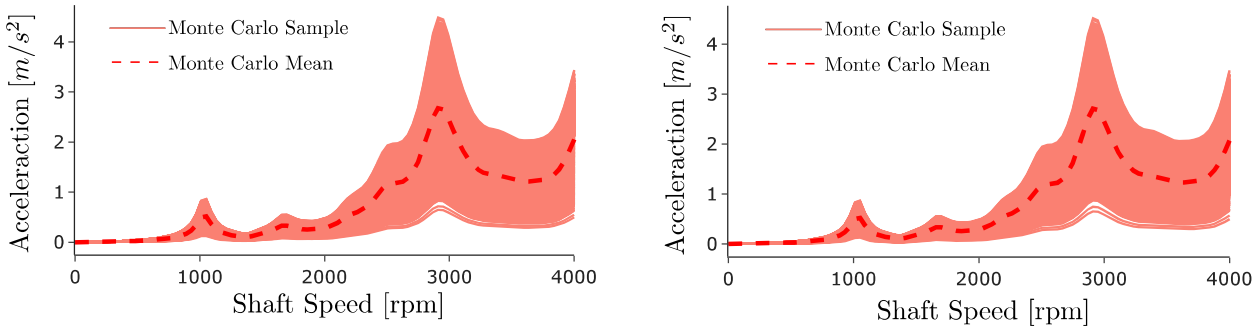


Figure 6: Comparison of the peak to peak transmission error uncertainty propagation using a Romax model and the correspondent surrogate model for three different gear micro-geometry designs.



(a) Results with Romax model.

(b) Results with ML-based surrogate.

Figure 7: Uncertainty propagation results of the housing acceleration curve using Monte Carlo method for the Design 1.

5. Conclusion

This paper investigates the use of Neural-Network (NN) based surrogate models applied to gear whine problems and its application to robust design modeling. An NN-based surrogate was constructed to predict the housing acceleration for several shaft speeds and the peak-to-peak transmission error (PPTE) regarding the gear micro-geometry parameters, namely lead crowning, lead slope, and profile crowning of wheel and pinion teeth. The surrogate uses a high-fidelity physical simulation modeled with Romax software as ground truth, including gears, shafts, bearings, and housing.

The NN-based surrogate has reasonable accuracy, with root mean square errors of $0.08m/s^2$ for the housing acceleration and $0.08\mu m$ for the PPTE. It was shown that the proposed surrogate is suitable to perform uncertainty propagation using methods like Monte Carlo, which relies on several evaluations of the model. The uncertainty propagation results with the surrogate are computed 308 times faster than with the high-fidelity model and present minor precision loss.

Therefore, the proposed surrogate model is adequate to assist the robust design of the gear micro-geometries considering static and dynamic results, making an extensive exploration of the design space feasible. Further work could use the proposed surrogate in a robust optimization analysis.

Acknowledgments The authors acknowledge the financial support of the European Union's Horizon 2020 research and innovation program under Marie-Curie grant agreement No 860243 to the LIVE-I project

References

[1] Mats Åkerblom. Gear noise and vibration: a literature survey. 2001.
[2] Ágnes Bárkányi, Tibor Chován, Sándor Németh, and János Abonyi. Modelling for digital twins—potential role of surrogate models. *Processes*, 9(3):476, 2021.
[3] Daniel A DeLaurentis and Dimitri Mavris. Uncertainty modeling and management in multidisciplinary analysis and synthesis. In *38th Aerospace sciences meeting and exhibit*, page 422, 2000.
[4] P. Garambois, J. Perret-Liaudet, and E. Rigaud. Nvh robust optimization of gear macro and microgeometries using an efficient tooth contact model. *Mechanism and Machine Theory*, 117:78–95, 2017.
[5] Ian Goodfellow, Yoshua Bengio, and Aaron Courville. *Deep learning*. MIT press, 2016.
[6] Yi Guo, Tugan Eritenel, Tristan M Ericson, and Robert G Parker. Vibro-acoustic propagation of gear dynamics in a gear-bearing-housing system. *Journal of Sound and Vibration*, 333(22):5762–5785, 2014.
[7] B. James, M. Douglas, and D. Palmer. Predicting the contact conditions for hypoid gear sets by analysis and a comparison with test data. *SAE Transactions*, 111:1489–1494, 2002.
[8] J.A. Korta and M. Domenico. Multi-objective micro-geometry optimization of gear tooth supported by response surface methodology. *Mechanism and Machine Theory*, 109:278–295, 2017.
[9] Nicholas Metropolis and Stanislaw Ulam. The monte carlo method. *Journal of the American statistical association*, 44(247):335–341, 1949.
[10] Michael A Nielsen. *Neural networks and deep learning*, volume 25. Determination press San Francisco, CA, USA,

2015.

[11] C.I.L. Park. Multi-objective optimization of the tooth surface in helical gears using design of experiment and the response surface method. *Journal of mechanical science and technology*, 24(3):823–829, 2010.

[12] Romax Technology Ltd. Romax spectrum.

[13] András Sobester, Alexander Forrester, and Andy Keane. *Engineering design via surrogate modelling: a practical guide*. John Wiley & Sons, 2008.

[14] M. Sun, C. Lu, Z. Liu, Y. Sun, H. Chen, and C. Shen. Classifying, predicting, and reducing strategies of the mesh excitations of gear whine noise: a survey. *Shock and Vibration*, 2020.

[15] Jan Troge, Eric Hensel, Sebastian Zumach, and Jan Bräunig. Acoustical optimization of a train gearbox based on overall system simulation. In *INTER-NOISE and NOISE-CON Congress and Conference Proceedings*, volume 253, pages 1–10. Institute of Noise Control Engineering, 2016.

[16] DB Welbourn. Fundamental knowledge of gear noise: a survey. Technical report, 1979.

[17] Jiaxin Zhang. Modern monte carlo methods for efficient uncertainty quantification and propagation: A survey. *Wiley Interdisciplinary Reviews: Computational Statistics*, 13(5):e1539, 2021.