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# PARAMETER ESTIMATION OF A SINGLE STAGE GEARBOX USING THE LEVENBERG-MARQUARDT METHOD

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***Abstract.*** *The transmission system is part of the longitudinal dynamics and influences the performance and safety of the vehicle. A transmission system can be subdivided into other geared pair subsystems, including pre-reduction and post-reduction. The mathematical model of a pair of gears is obtained analytically using Newton-Euler equations of motion resulting in a system of equations with four degrees of freedom and includes the definition of parameters such as inertia, damping, and stiffness, which are often unknown. Therefore, under these circumstances, the present work uses the concept of inverse problems to estimate the parameters of the dynamic model of a pair of gears, using the Levenberg-Marquardt (LM) method. Firstly, the sensitivity analysis is performed and indicates that it is possible to estimate the gearing stiffness, shaft damping coefficient, and gearing damping coefficient at the same time. Besides that, to initialize the LM algorithm, synthetic measurements of the angular position and velocity of the input and output gears are necessary, in addition to an approximation of the parameters. Aiming to demonstrate the effectiveness of the method, the algorithm is initialized with inaccurate values for the estimated parameters to verify if the method is capable of converging to the correct values of the parameters. Moreover, the algorithm is evaluated with noisy simulated data and different initial conditions, so that the robustness of the proposed method is demonstrated. The results show that the responses of the dynamic model with the estimated parameters are accurate, compared with the original data.*

***Keywords:*** *Gear Pair, Dynamic Model, Levenberg-Marquardt Method, Inverse Problem, Numerical Simulation*

## 1. INTRODUCTION

An important application of dynamic modeling is in the control of mechanical devices, however, knowledge about the model and its parameters is required. In the case of the dynamic model of a meshed pair, some parameters of the model that represent the influence of the interaction between the teeth of the gears have non-linearities and do not have a trivial analytical form. It is often not possible to define a parameter only analytically. In these cases, the technique of inverse problems can be used, which allows the estimation of such unknown parameters. This technique uses numerical methods to search for solutions computationally implemented in an iterative and optimized way.

## 2. Bibliographic Review

Moraes (2019) presents a dynamic model of a pair of spur gears. In the presented model, the parameters that influence the dynamics of the system are the inertia of the gears and shafts, the damping coefficient of the interaction between gear teeth, and shaft couplings. Moraes (2019) uses the dynamic model to help monitor the condition and prevent system failure through vibration data. Recently, Rosa *et al.* (2022) reviewed the main authors involving the dynamic model of meshed pairs, and presents a numerical solution method for the mathematical model and the analytical solution of each parameter of the model. Li and Kahraman (2013), study the aspects of tribological and dynamic in a pair of spur gears. Liang *et al.* (2018) point out that the dynamic model is an important tool for detecting failures in transmission mechanisms.

According to Orlande (2021), the theory and application of inverse problems have been discussed for more than half a century in several areas, including mechanical and aerospace engineering, and is often used to estimate parameters associated with heat transfer problems as well as for estimating dynamic states in general, being used even for weather forecast modeling. There are several inverse problem techniques for parameter identification, however, in this work, the Levenberg Marquardt (LM) method was adopted.

Pereira *et al.* (2021) and Simioni *et al.* (2021) mention that the LM method consists of estimating parameters through an iterative process using the maximum likelihood objective function. The objective function is derived from the likelihood function, which is the statistical model of measurement errors.

## 3. DYNAMIC MODEL

The 4-DOF Dynamic model of a pair of gears from Lin and Liou (1998) was used, including Rosa *et al.* (2022) adaptations. In this model, the input shaft, pinion, gear, and output shaft are considered, where such degree of freedom has inertia, damping, and torsional stiffness, as presented in Eq. (1) and shown in Figure 1.

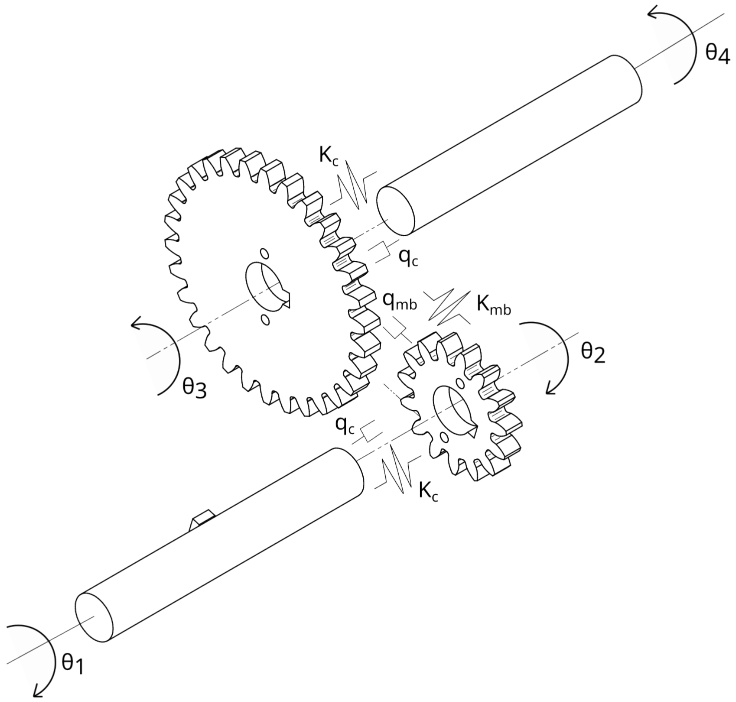


Figure 1. Dynamic model of a pair of gears.

$$[I]\{\ddot{\theta}\} + [Q]\{\dot{\theta}\} + [K]\{\theta\} = \{T(t)\}, \tag{1}$$

Where $[I]$, $[Q]$ and $[K]$ are the inertia, damping, and stiffness matrices, given by Eq. (2), Eq. (3) and Eq. (4), respectively, and $[\ddot{\theta}]$, $[\dot{\theta}]$, $[\theta]$, and $[T]$ are the angular acceleration, velocity, displacement, and torque vectors, given by Eq. (5), Eq. (6), Eq. (7), and Eq. (8) respectively.

$$\mathbf{I} = \begin{bmatrix} I_m & 0 & 0 & 0 \\ 0 & I_p & 0 & 0 \\ 0 & 0 & I_g & 0 \\ 0 & 0 & 0 & I_L \end{bmatrix} \tag{2}$$

In Equation (2), $I_m$ is the input shaft moment of inertia, $I_p$ is the pinion moment of inertia, $I_g$ is the gear moment of inertia and $I_L$ is the output shaft moment of inertia.

$$\mathbf{Q} = \begin{bmatrix} q_c & -q_c & 0 & 0 \\ -q_c & (q_c + r_p^2 q_{mb}) & -r_g r_p q_{mb} & 0 \\ 0 & -r_g r_p q_{mb} & (q_c + r_g^2 q_{mb}) & -q_c \\ 0 & 0 & -q_c & q_c \end{bmatrix} \tag{3}$$

In Equation (3), $q_c$ is the damping coefficient of the shafts, $q_{mb}$ is the gearing damping coefficient, $r_p$ and $r_g$ is the pinion and gear radius respectively.

$$\mathbf{K} = \begin{bmatrix} k_c & -k_c & 0 & 0 \\ -kc & (k_c + r_p^2 k_{mb}) & -r_p r_g k_{mb} & 0 \\ 0 & -r_p r_g k_{mb} & (kc + r_g^2 k_{mb}) & -k_c \\ 0 & 0 & -k_c & k_c \end{bmatrix} \tag{4}$$

In Equation (4), $k_c$ is the stiffness of the shafts and $k_{mb}$ is the gearing stiffness.

$$\ddot{\theta} = \begin{bmatrix} \ddot{\theta}_1 \\ \ddot{\theta}_2 \\ \ddot{\theta}_3 \\ \ddot{\theta}_4 \end{bmatrix} \tag{5}$$

In Equation (5), $\ddot{\theta}_1$ is the input shaft angular acceleration, $\ddot{\theta}_2$ is the pinion angular acceleration, $\ddot{\theta}_3$ is the gear angular, and $\ddot{\theta}_4$ is the output shaft angular acceleration.

$$\dot{\theta} = \begin{bmatrix} \dot{\theta}_1 \\ \dot{\theta}_2 \\ \dot{\theta}_3 \\ \dot{\theta}_4 \end{bmatrix} \tag{6}$$

In Equation (6), $\dot{\theta}_1$ is the input shaft angular velocity, $\dot{\theta}_2$ and $\dot{\theta}_3$ are the pinion and gear angular velocity respectively, and $\dot{\theta}_4$ is the output shaft angular velocity.

$$\theta = \begin{bmatrix} \theta_1 \\ \theta_2 \\ \theta_3 \\ \theta_4 \end{bmatrix} \tag{7}$$

In Equation (7), $\dot{\theta}_1$ is the input shaft angular displacement, $\theta_2$ and $\theta_3$ are the pinion and gear angular displacement respectively and $\dot{\theta}_4$ is the output shaft angular displacement.

$$\mathbf{T} = \begin{bmatrix} T_{in} \\ -r_p f_c \\ r_g f_c \\ T_{out} \end{bmatrix} \tag{8}$$

In Equation (8), $T_{in}$ is the electrical motor input torque, $f_c$ is the gearing contact force and $T_{out}$ is the output torque.

The mathematical model resolution requires a second-order ordinary differential equation solution and can be solved using the fourth and fifth-order Runge Kutta method implemented in MATLAB®.

## 4. INVERSE PROBLEMS

Inverse problems are classified as ill-posed, these problems do not satisfy the conditions of existence, uniqueness, or stability in small variations. Therefore, one way to assess whether the problem is ill-posed is by checking the existence and uniqueness through the determinant of the product of the sensitivity matrix by its transpose. If this matrix is singular, it does not admit a solution, or there are infinitely many solutions, in this case the mathematical problem is classified as ill-posed. As the ill-posed problem does not admit a solution, it is not possible to be really solved, however, the inverse problem technique makes it possible to find an approximate solution based on an approximate well-posed regularized problem. In this case of inverse problem, the mathematical model and output is known, but the parameters are unknown, and the respective parameters are found from system responses. Therefore, the solution of an inverse problem requires special stabilization techniques (Orlande, 2021).

### 4.0.1 Objective function

In this problem, the objective function is the statistical modeling of the angular velocity errors, where the objective is to minimize the errors between measurements and estimates. The objective function that provides minimum variance estimates is the norm of ordinary least squares. However, If the values of the standard deviations of the measurements are quite different, the ordinary least squares method does not produce minimum variance estimates. In which case, the objective function is given by the weighted least squares, and the maximum likelihood objective function $S_{ML}$ is given by Eq. (9) (Orlande, 2021).

$$S_{ML}(\mathbf{P}) = [\mathbf{Y} - \hat{\mathbf{Y}}(\mathbf{P})]^T W^{-1} [\mathbf{Y} - \hat{\mathbf{Y}}(\mathbf{P})] \tag{9}$$

Where $\mathbf{P}$ is the vector of unknown parameters, $\hat{\mathbf{Y}}(\mathbf{P})$ is the vector of the estimated solution, $\mathbf{Y}$ is a vector of the experimental measures, $W$ is the variance matrix, whose main diagonal is formed by $diag(W) = [\sigma_1^2, \sigma_2^2, ..., \sigma_I^2]$ with the other elements null, where $\sigma^2$ is the variance associated with each measure, assuming the errors are uncorrelated (Orlande, 2021).

### 4.1 Levenberg-Marquardt method

The method is used for parameter estimation and requires only an initial estimate and measurements of the system output. Often, when performing studies without experimental data, measurements can be substituted for a direct problem using approximate parameters. Therefore, having real or simulated measurements, it is possible to estimate the model parameters from an iterative process using a maximum likelihood objective function (Orlande, 2021).

In this procedure, the parameters are initialized with approximate values different from those used for the direct problem. In this step, a numerical solution $\hat{Y}_i(\mathbf{P})$ and an objective function $S^k$ are obtained. After initialization, each parameter is varied individually at a small rate $\epsilon$, and in each case, a different numerical solution is obtained. In this step, the Jacobian matrix $J$ is defined, whose elements are the first-order partial derivative of each numerical solution with respect to the variable parameter. The new $\mathbf{P}^{k+1}$ parameters are defined through the system solution, and with these parameters, a new numerical solution and a new objective function $S^{k+1}$ are obtained. Finally, the two objective functions are compared, and the new parameters can be accepted or not. The iterative process is repeated until the stopping criteria are satisfied.

### 4.1.1 Estimated parameters vector

The vector of estimated parameters $\mathbf{P}^{k+1}$ is given by Eq. (10).

$$\mathbf{P^{k+1}} = \mathbf{P^k} + [J^T W^{-1} J + \lambda^k \Omega^k]^{-1} J^T W^{-1} [\mathbf{Y} - \hat{\mathbf{Y}}(\mathbf{P^k})] \tag{10}$$

Where $\lambda^k$ is the damping parameter and $\Omega^k$ is the diagonal matrix, whose purpose of $\lambda^k \Omega^k$ term is to dampen oscillations and instabilities due to the ill-posted character of the problem, in which the damping parameter has greater weight at the beginning of the iterations. With such an approach, the matrix $[j^T W^{-1} J]$ does not necessarily have to be non-singular at the beginning of iterations and the Levenberg-Marquardt method adopts a steeper descent. The parameter $\lambda^k$ is gradually reduced as the iteration procedure progresses, making the problem better conditioned (Orlande, 2021).

### 4.1.2 Stopping criterion

There are three possible equations for the stopping criterion, they are Eq. (11), Eq. (12), and Eq. (13).

$$\mathbf{S_{ML}}(\mathbf{P^{k+1}}) < \epsilon_1 \tag{11}$$

$$||(J^k)^T W^{-1} [\mathbf{Y} - \hat{\mathbf{Y}}(\mathbf{P^k})|| < \epsilon_2 \tag{12}$$

$$||\mathbf{P^{k+1}} - \mathbf{P^k}|| < \epsilon_3 \tag{13}$$

### 4.1.3 Sensitivity analysis

The sensitivity analysis must be performed before applying the LM method, as it is responsible for identifying whether the parameters are sensitive to the model and whether they can actually be estimated by the method. In addition, the sensitivity analysis allows, through the reduced sensitivity coefficients $X_j$, to analyze the linear dependence between the parameters, which is important since parameters linearly dependent on each other cannot be estimated together. The elements of the sensitivity matrix are called sensitivity coefficients $J_{ij}$ and are defined by Eq. (14). The coefficients represent the rate of change of the simulated system output with respect to each parameter.

$$J_{ij} = \frac{\partial \hat{Y}_i(\mathbf{P})}{\partial P_j} \tag{14}$$

Where $i$ is the measurement index, $j$ is the parameters index, $\hat{Y}_i(\mathbf{P})$ is the solution of the direct problem for the estimated parameters and $P_j$ is the $j_N$ in the array of parameters to be estimated $\mathbf{P} = [P_1, P_2, ..., P_N]^T$. Therefore, the sensitivity matrix $J$ can be written as shown in Eq. (15).

$$J(\mathbf{P}) = \left[\frac{\partial \hat{Y}_i(\mathbf{P})}{\partial P_j}\right]^T = \begin{bmatrix} \frac{\partial \hat{Y}_1(P)}{\partial P_1} & \frac{\partial \hat{Y}_1(P)}{\partial P_2} & \frac{\partial \hat{Y}_1(P)}{\partial P_3} & \cdots & \frac{\partial \hat{Y}_1(P)}{\partial P_N} \\ \frac{\partial \hat{Y}_2(P)}{\partial P_1} & \frac{\partial \hat{Y}_2(P)}{\partial P_2} & \frac{\partial \hat{Y}_2(P)}{\partial P_3} & \cdots & \frac{\partial \hat{Y}_2(P)}{\partial P_N} \\ \vdots & \vdots & \vdots & & \vdots \\ \frac{\partial \hat{Y}_I(P)}{\partial P_1} & \frac{\partial \hat{Y}_I(P)}{\partial P_2} & \frac{\partial \hat{Y}_I(P)}{\partial P_3} & \cdots & \frac{\partial \hat{Y}_I(P)}{\partial P_N} \end{bmatrix} \tag{15}$$

where $N$ is the number of unknown parameters and $I$ is the total number of measurements.

## 5. RESULTS AND DISCUSSIONS

The generic problem allows the solution for the different degrees of freedom of the model, however, the LM method can be verified from any of them individually. In the context of failure analysis, the pinion is more requested than the gear because it has a higher working frequency, therefore, this work focuses on estimating parameters based on the angular velocity of the pinion. In a real situation, the angular velocity can be measured from an encoder, but in this study, measurements were simulated by numerical methods. The parameters used in the simulation is presented in Table 1, were

Table 1. Known parameters used for numerical simulation.

| Known Parameters | Value |
|---|---|
| $I_m/I_L$, [N· m·s$^2$/rad] | 0.0012 |
| $I_G$, [N· m·s$^2$/rad] | 0.0020 |
| $I_p$, [N· m·s$^2$/rad] | 0.0012 |
| $q_c$, [N· m·s/rad] | 0.06 |
| $f_c$, [N] | 2333 |
| $T_{in}$, [N· m] | 35.00 |
| $T_{out}$, [N· m] | 0.00 |
| $r_p$, [mm] | 0.015 |
| $r_g$, [mm] | 0.030 |
| $k_c$, [N· m/rad] | 163.33 |
| $k_{mb}$, [N· m/rad] | 4.85x10$^8$ |
| $q_{mb}$, [N· m · s/rad] | 9.42x10$^3$ |

obtained analytically, as detailed by Rosa *et al.* (2022), and in the case of parameters that have non-linearities, average values were used. Regarding the sensitivity analysis, the first step was to verify the ill-posted characteristic of the inverse problem through the determinant of the sensitivity matrix. If $|J^T J| \approx 0$, it means that the matrix is singular and therefore the problem is ill-posted. Then, the most influential parameters of the mathematical model were analyzed, those that when changed cause greater variations in the system response. This analysis is performed by comparing the reduced sensitivity coefficients of the parameters given by $X_j = P \cdot J_{ij}$. Figure 2 represents the reduced sensitivity coefficients of each parameter.

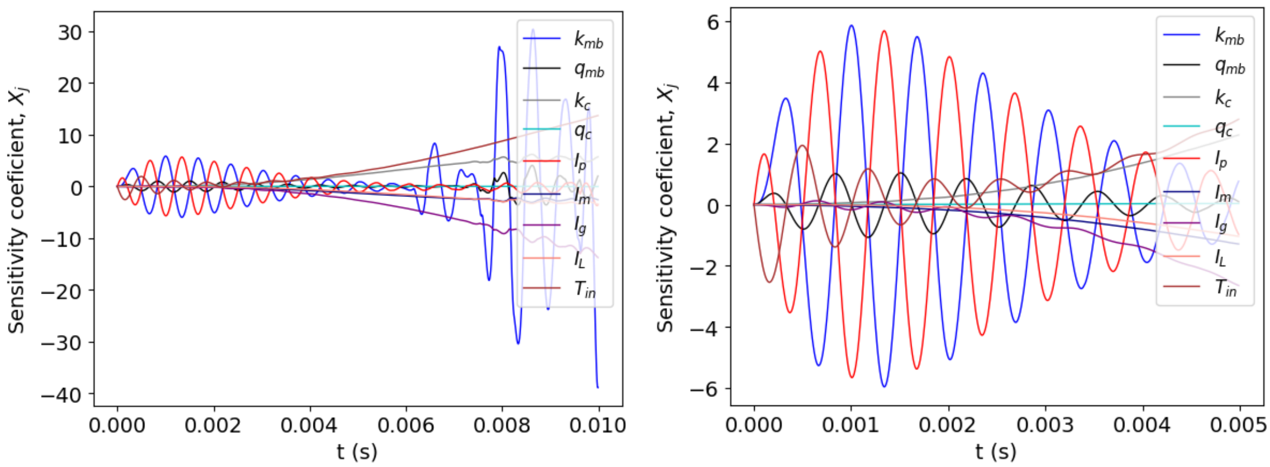


Figure 2. Reduced sensitivity coefficients for $t < 0.01$ s and $t < 0.005$ s.

As noted, the linear dependence between the parameters can change over time, making it necessary to isolate time intervals in the regions of interest. As mentioned by Rosa *et al.* (2022) and Moraes (2019), the dynamics of the system occurs in a time interval around 0.005 s, therefore, in this analysis we can isolate the region of interest as the region where the system dynamics occurs influence it, between $t = 0$ s and $t = 0.005$ s. As there are many parameters, it is difficult to visualize all of them simultaneously, for ease of visualization, each set has been plotted separately for parameters which are linearly dependent on each other. As stated earlier, these cannot be estimated together, therefore, a single parameter must be chosen among the linearly dependent ones. The first set of parameters linearly dependent on each other is the $I_p$ and $k_{mb}$ as presented in the Figure 3. Parameters that can be precisely calculated analytically, such as inertia and input torque are not a priority. Parameters that have little influence also need not be estimated too. In case of Figure 3, $I_p$ can be calculated analytically and accurately, whereas, on the other hand, $k_{mb}$ is more complicated to be modeled analytically. Therefore, in this situation, it is convenient to choose to estimate $k_{mb}$. In the same way, the second parameter set linearly dependent on each other is $I_L$, $I_m$ and $k_c$ as presented in Figure 4. In this case, both parameters can be calculated analytically, however, $I_L$ and $I_m$ can be accurately obtained from the measurement of their masses, while $k_c$ can be affected by a discontinuity within the material or by some tempering process that may have been carried out previously on which no information is available. In this context, it is more interesting to estimate $k_c$. Finally, the third set of linearly dependent parameters are $T_{in}$, $I_g$, $q_c$ and $q_{mb}$ as presented in Figure 5. Again, $I_g$ can be calculated analytically, while $T_{in}$

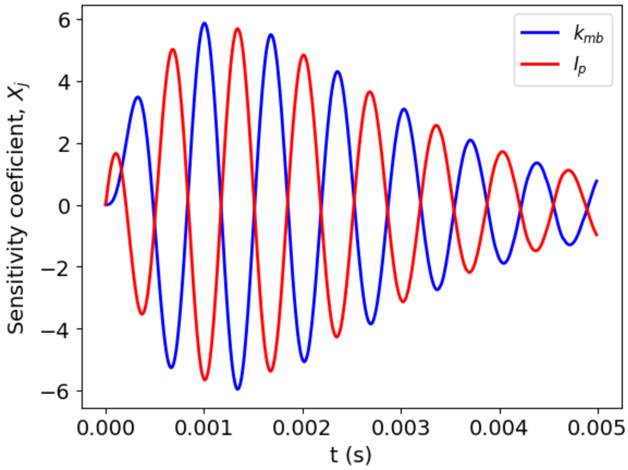


Figure 3. First set of parameters linearly dependent

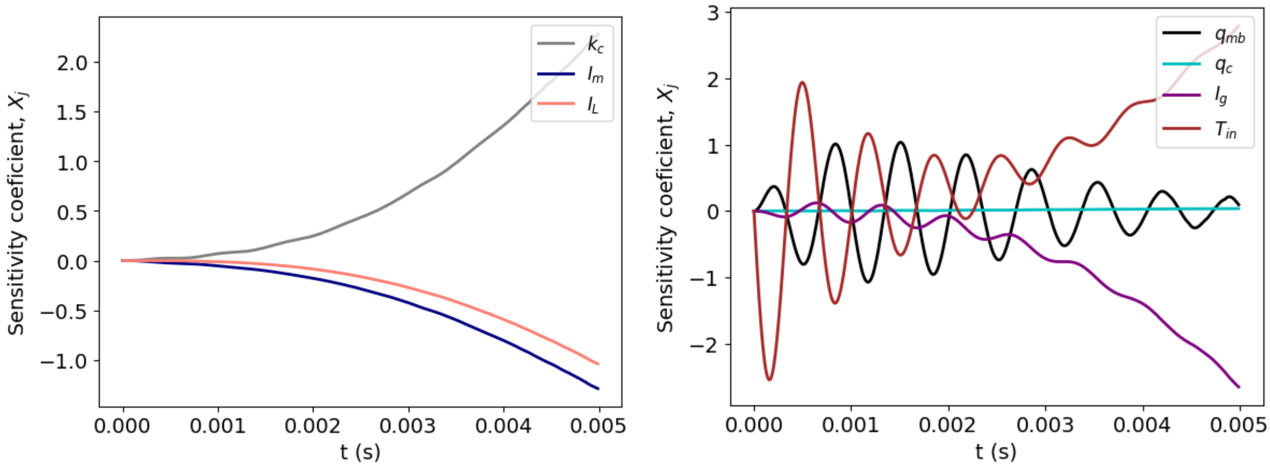


Figure 4. Second and third parameter set linearly dependent

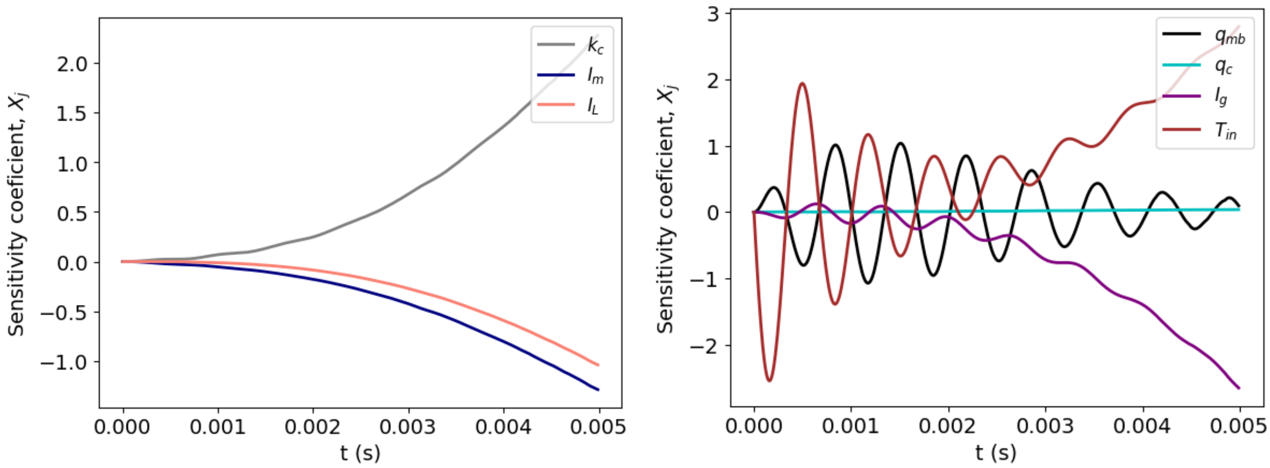


Figure 5. Second and third parameter set linearly dependent

is the maximum torque provided by the motor considered constant and previously known. The parameter $q_c$, as shown in Figure 5 is a very low value, which in addition to having less influence on the model, can generate inconsistencies in the estimation algorithm by causing occurrences of division by zero. The parameter $q_{mb}$ is more difficult to be modeled analytically, being therefore the best candidate to be estimated. In this context, the objective is to find, through inverse problems, the parameters $q_{mb}$, $k_c$ and $k_{mb}$ in which they are measures and an initial estimate are used, reinforcing that in this case the measures are simulated, but the procedure is also valid for real averages. Assuming that, by adopting an estimate intuitively, it is $50\%$ smaller than the real value of the parameter, the parameters to be estimated were initialized in the algorithm with half of their values that were previously used for generating measurements. The other parameters were obtained analytically, therefore the parameters were used as they appear in Table 1. After the parameters to be estimated are chosen and the initialization parameters are defined, the algorithm can be initialized. In addition to model parameters, some parameters related to measurements and algorithm execution must be defined. For the terms responsible for damping the oscillations and instabilities of the estimated parameters, $\lambda = 1$ and $\Omega$ equal to the identity matrix were used. The standard deviation $\sigma = 0.0137$ of the measurements supposedly obtained by an encoder was assumed based on the publication of Pereira *et al.* (2021). The stopping criterion used was that of Eq. (13), the parameter variation at each iteration is 1% and the initial conditions is a null vector. At each iteration, the algorithm varies the parameters, executes the ODE45 function with these new parameters and compare the simulation with the experimental data. Iterations are repeated until the change in parameters is less than $\epsilon_3 = 0.001$. The result of the algorithm using the Levenberg Marquardt method for the estimation of the parameters is shown in Figure 6.

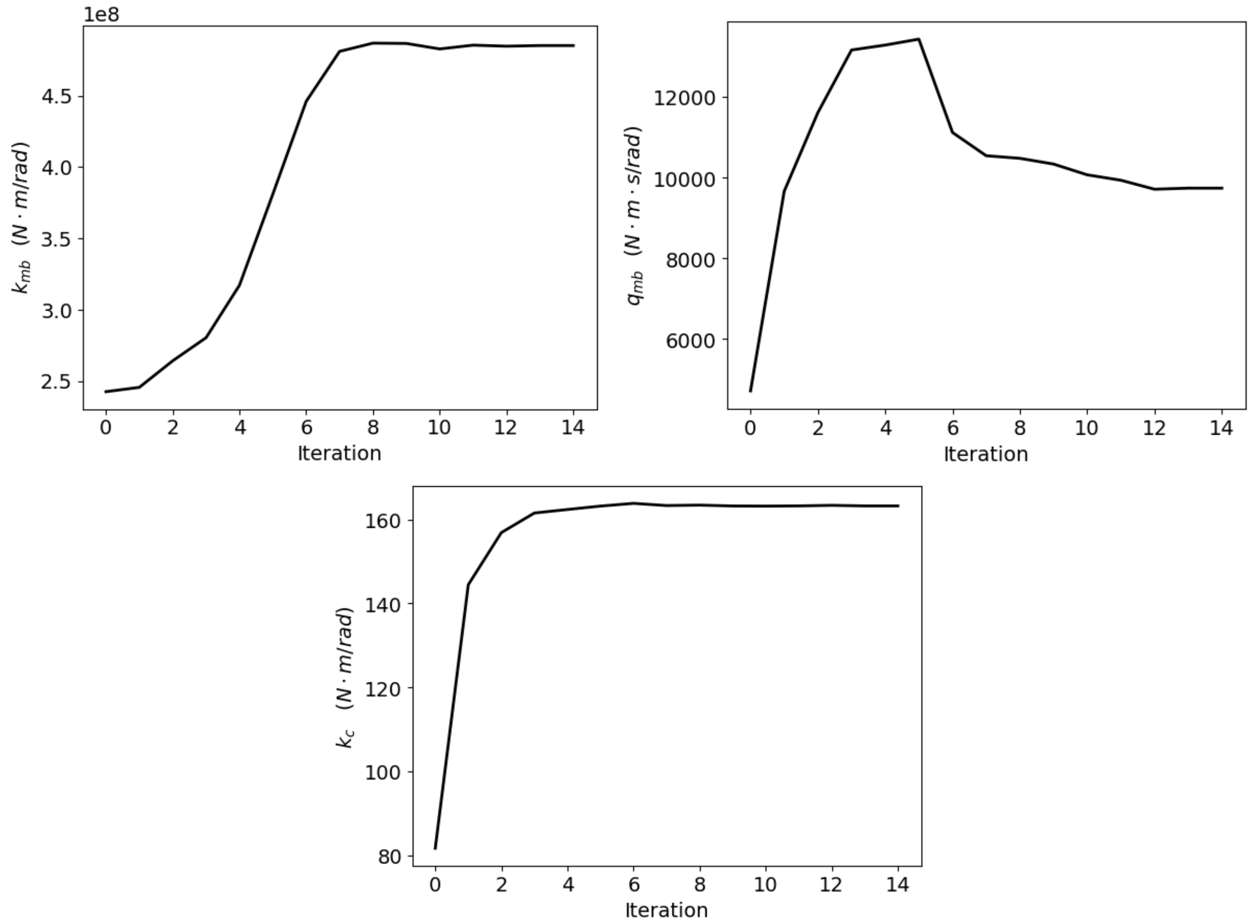


Figure 6. Estimated parameters.

The algorithm was tested by feeding the model with the parameters presented in Table 1, and the measurements were simulated with random errors that supposedly would be measurements of angular velocities obtained through the encoders. The value of the new parameters obtained from the estimation algorithms and the relative error, are presented in Table 2.

Table 2. Result of parameter estimation.

| **Unknown Parameters** | **Initial Value** | **True Value** | **Estimated Value** | **Error** |
|---|---|---|---|---|
| $k_c$, [N$\cdot$ m/rad] | 81.66 | 163.33 | 163.397 | 0.04% |
| $k_{mb}$, [N$\cdot$ m/rad] | 242651865 | 485303730 | 484528000 | 0.16 % |
| $q_{mb}$, [N$\cdot$ m $\cdot$ s/rad] | 4714.77 | 9429.55 | 9968.17 | 5.71 % |

The LM algorithm having as input the measurements and an estimate intuitively $50\%$ less than actual parameters, was able to return parameters with errors considered small, mainly for the parameter $k_{mb}$ which is a complex parameter to be obtained analytically. However, the parameter $q_{mb}$ which is also complex of be obtained analytically, it was estimated with a slightly larger error of $5.71\%$. Figure 7 compares the result of the simulated measurements with the model using the new parameters estimated. The simulations for generating initial measurements and for the model result were based on different temporal discriminations for avoid the problem of reverse crime. Despite the estimation error of the $q_{mb}$ parameter, the model response was very close to the average data, as shown in Figure 7.

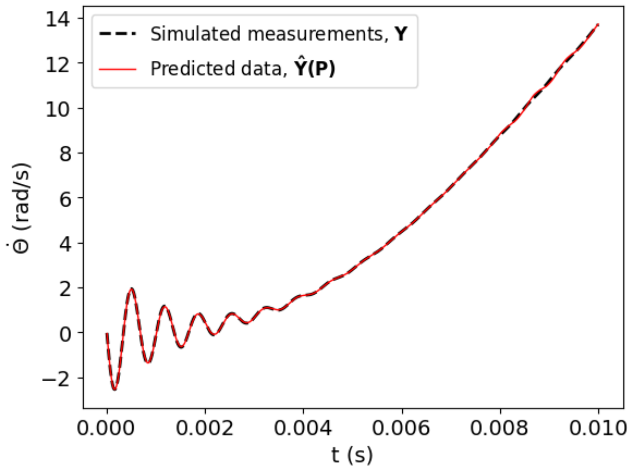


Figure 7. Dynamic model result with estimated parameters.

## 6. CONCLUSIONS

For longer time intervals, the linear dependence between the parameters may vary, being linearly dependent at some instants, and in others not, making the application of the method unfeasible. In these cases, a technique used that facilitates the use of the LM method is the limitation of the region of interest, which made it possible to analyze the region of the transitional period of the angular velocity.

Of the estimated parameters, $k_{mb}$ and $k_c$ presented values very close to expected, while $q_{mb}$ was skewed by 5% of expected. Despite the error presented, the simulated model with the estimated parameters presented results very close to the result of the simulated measurements, where the angular velocity for both sets of parameters is the same, indicating that the parameter estimation tool for inverse problems is efficient and, as seen in this work, can be used for parameter estimation for models of transmission systems by gear pairs. Two points that can be sequential to the present study would be the application of the method in the other degrees of freedom of the present model and an experimental study with the actual measurements.

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## 8. RESPONSIBILITY NOTICE