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Booklets

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Title: Unbalance identification method based on SINDy applied to a rotodynamic system supported by a SFD Aeronautics and A.I.

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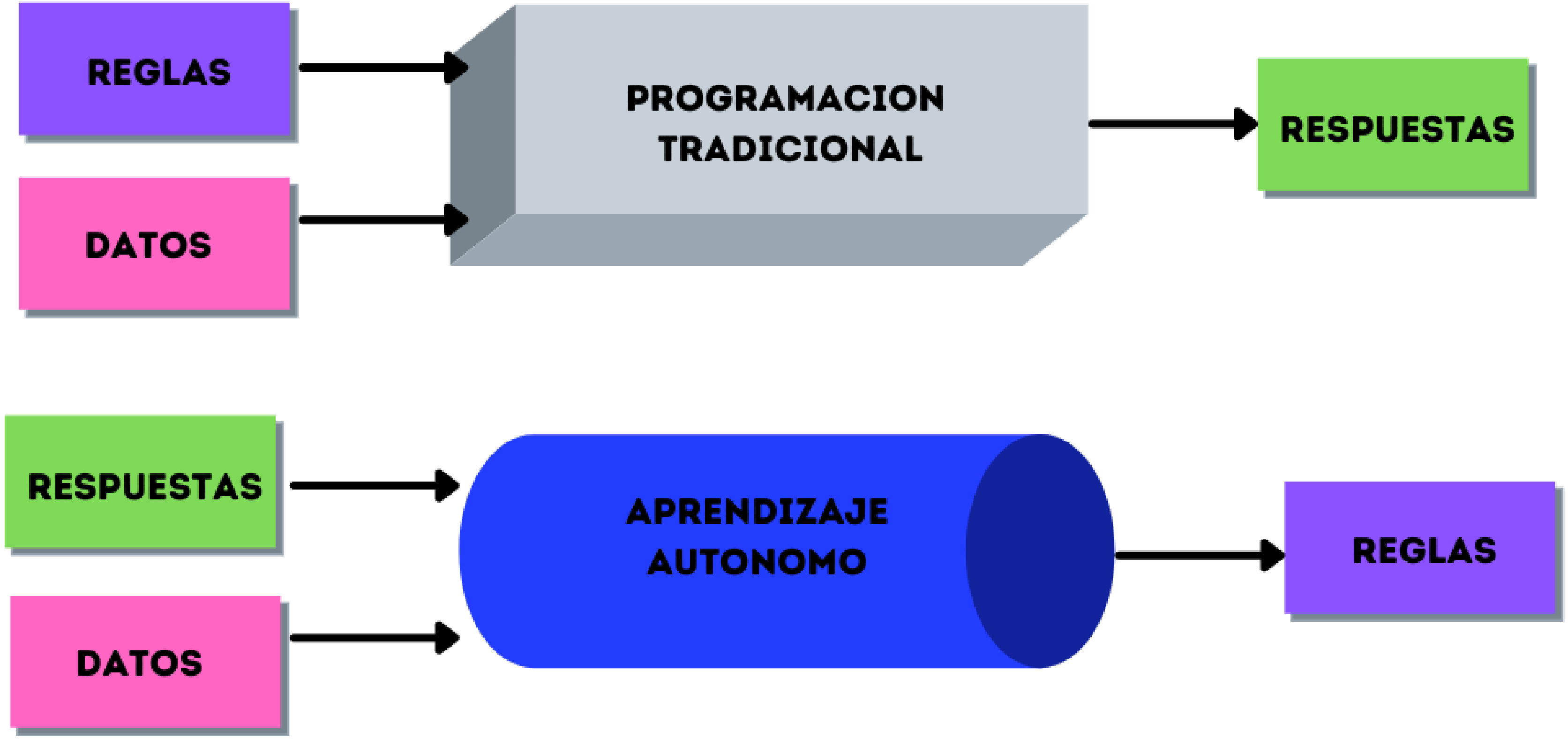
Introducción



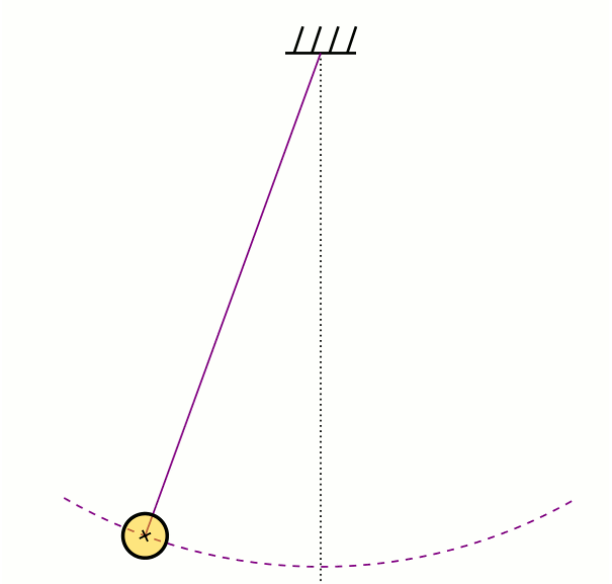
$$m\frac{dv}{dt} = -mg - cv$$

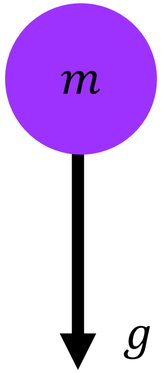
$$Velocidad\ de\ m_1:\ v_1 = l_1\dot{\theta}_1$$

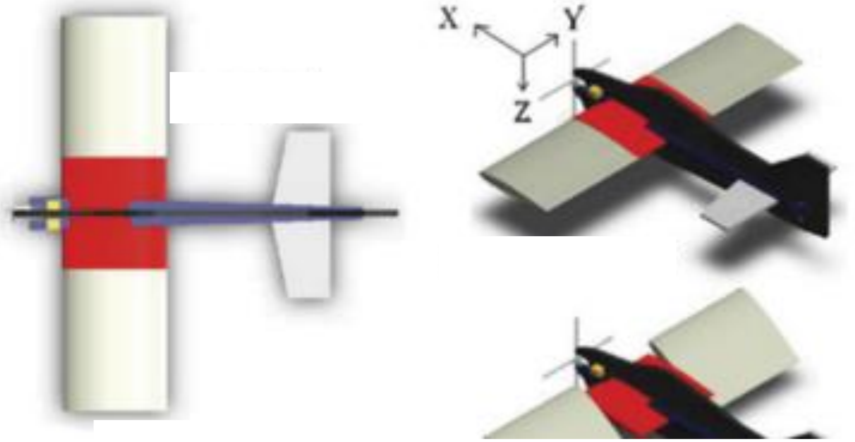
$$Velocidad\ de\ m_2:\ v_2 = (v_{2x}^2 + v_{2y}^2)$$

$$v_{2x} = l_1\dot{\theta}_1\cos(\theta_1) + l_2\dot{\theta}_2\cos(\theta_2)$$

$$v_{2y} = l_1\dot{\theta}_1\sin(\theta_1) + l_2\dot{\theta}_2\sin(\theta_2)$$







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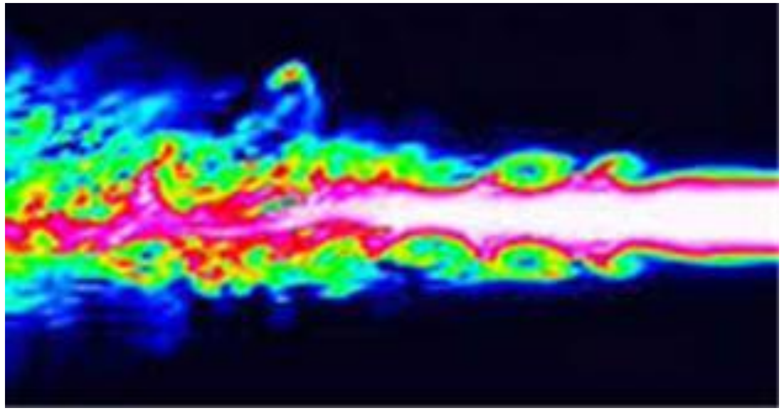
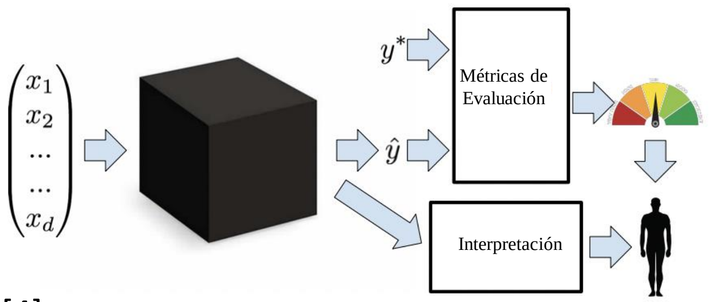


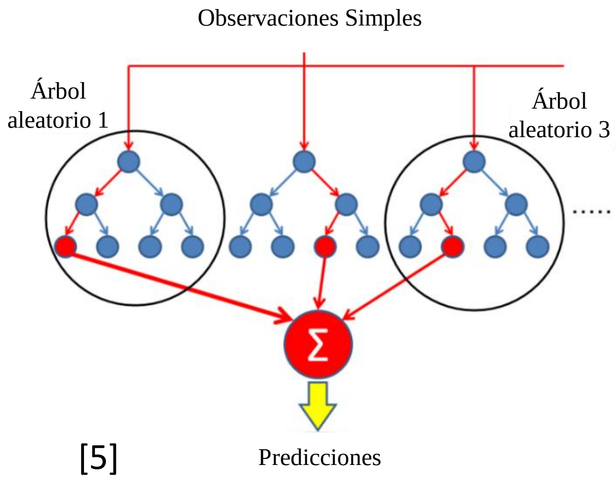
[1]

[3]

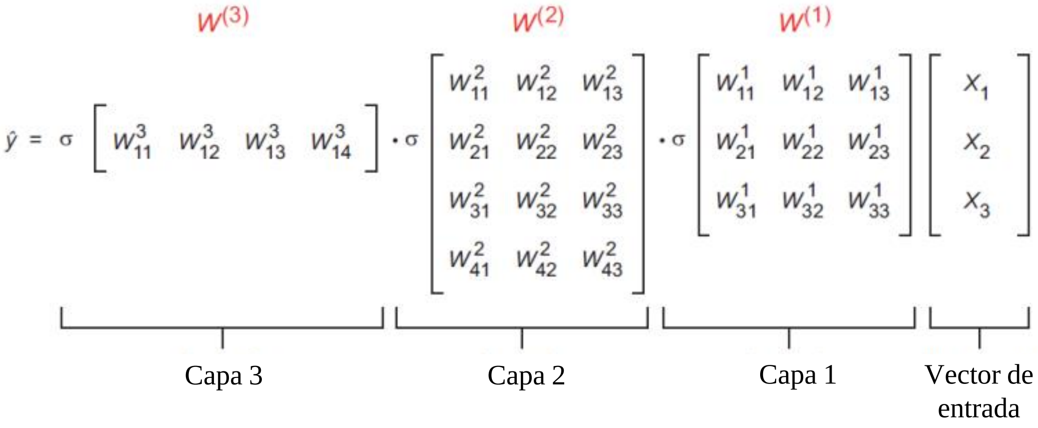
1. Development of a numerical and experimental framework to understand and predict the burning dynamics of porous fuel beds, Mohamad El Houssami, 2017
2. System identification method based on interpretable machine learning for unknown aircraft dynamics, Rui Cao, YuPing Lu, Zhen he, 2022
3. https://upload.wikimedia.org/wikipedia/en/thumb/6/60/Rolls-Royce_Pearl.jpg/1280px-Rolls-Royce_Pearl.jpg



[4]



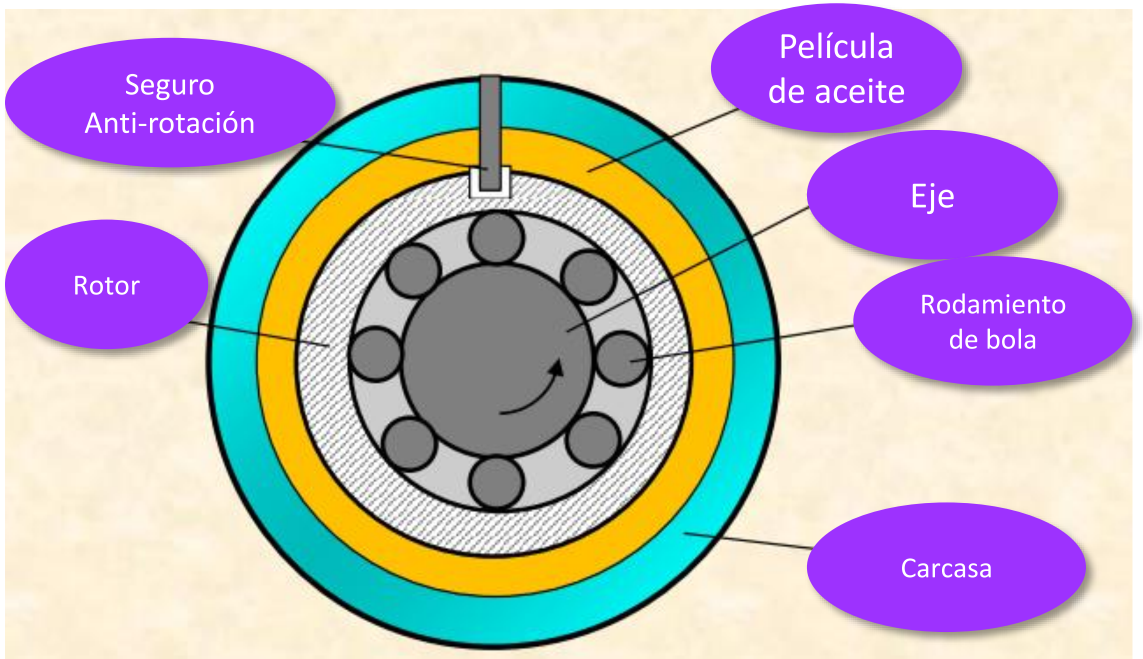
[5]



[6]

- Modelos interpretables para entendimiento científico y seguridad
- Modelos para problemas generales
- Modelos robustos al ruido
- Modelos obtenidos con pocos datos o con baja frecuencia de medición.

4. Deep neural networks are easily fooled. High confidence predictions for unrecognizable images. A. Nguyen, J.Yosinski, and J. Cluene. Proceedings of the IEEE conference on computer vision and pattern recognition 2015.
5. https://towardsdatascience.com/understanding-random-forest-58381e0602d2
6. https://www.jeremyjordan.me/intro-to-neural-networks/



[7]

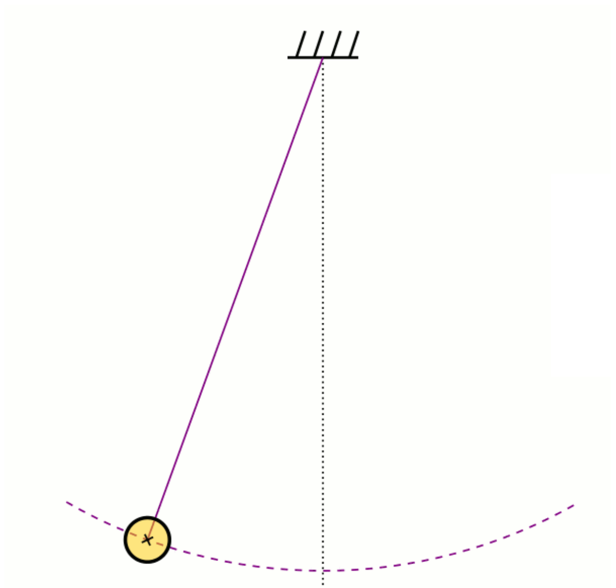
- Boeing 717, B-52
- Dassault Falcon 10X
- Gulfstream V, G550, G650, G700, G800
- Tupolev TU-334
- BAE Nimrod MRA4
- Bombardier Global Express
- Rolls-Royce de la familia BR700

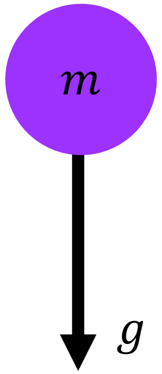
[3]

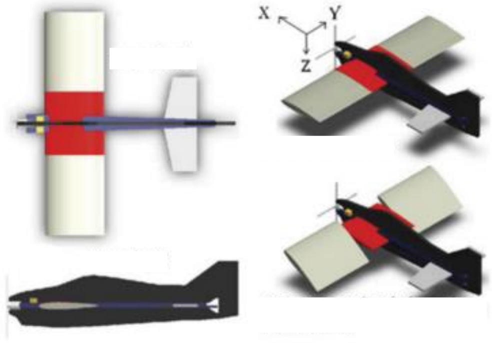
Rolls-Royce de la familia BR700

3. https://upload.wikimedia.org/wikipedia/en/thumb/6/60/Rolls-Royce_Pearl.jpg/1280px-Rolls-Royce_Pearl.jpg
7. Squeeze Film Dampers Do’s and Don’ts. , San Andres L. 2018

Metodología







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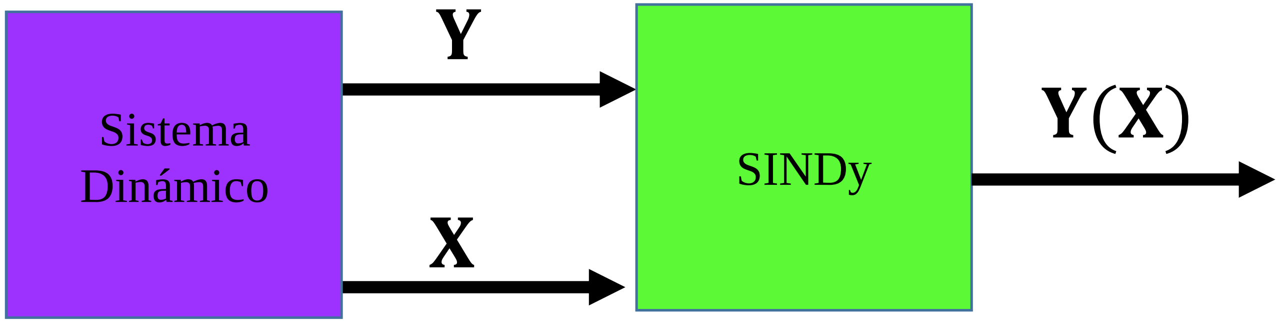
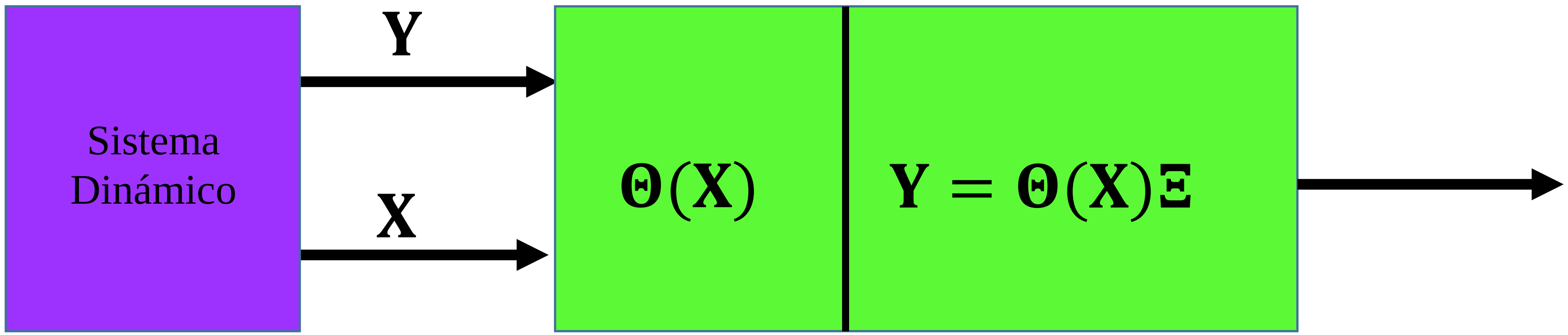


2. System identification method based on interpretable machine learning for unknown aircraft dynamics, Rui Cao, YuPing Lu, Zhen he, 2022



$$\boldsymbol{\Xi} = \begin{bmatrix} 0 & 0 & 0 \\ c_{2,1} & c_{2,2} & 0 \\ c_{3,1} & c_{3,2} & 0 \\ 0 & 0 & c_{4,1} \\ 0 & 0 & 0 \\ 0 & 0 & c_{5,1} \\ 0 & c_{7,1} & 0 \\ 0 & 0 & 0 \\ \vdots & \vdots & \vdots \\ 0 & 0 & 0 \end{bmatrix}$$

$$\mathbf{X} = \begin{bmatrix} x_1(t_1) & x_2(t_1) & \dots & x_M(t_1) \\ x_1(t_2) & x_2(t_2) & \dots & x_M(t_2) \\ \vdots & \vdots & \ddots & \vdots \\ x_1(t_N) & x_2(t_N) & \dots & x_M(t_N) \end{bmatrix}_{N\times M} \longrightarrow \boldsymbol{\Theta}(\mathbf{X}) = \begin{bmatrix} f_1(x(t_1)) & f_2(x(t_1)) & \dots & f_S(x(t_1)) \\ f_1(x_i(t_2)) & f_2(x(t_2)) & \dots & f_S(x(t_2)) \\ \vdots & \vdots & \dots & \vdots \\ f_1(x(t_N)) & f_2(x(t_N)) & \dots & f_S(x(t_N)) \end{bmatrix}_{NXS}$$

$$\mathbf{Y} = \dot{\mathbf{X}} = \begin{bmatrix} \dot{x}_1(t_1) & \dot{x}_2(t_1) & \dots & \dot{x}_L(t_1) \\ \dot{x}_1(t_2) & \dot{x}_2(t_2) & \dots & \dot{x}_L(t_2) \\ \vdots & \vdots & \ddots & \vdots \\ \dot{x}_1(t_N) & \dot{x}_2(t_N) & \dots & \dot{x}_L(t_N) \end{bmatrix}_{N\times L}$$

$$\mathbf{X}=\begin{bmatrix} x_1(t_1) & x_2(t_1) & \dots & x_M(t_1) \\ x_1(t_2) & x_2(t_2) & \dots & x_M(t_2) \\ \vdots & \vdots & \ddots & \vdots \\ x_1(t_N) & x_2(t_N) & \dots & x_M(t_N) \end{bmatrix}_{N\times M} \longrightarrow \boldsymbol{\Theta}(\mathbf{X})=\begin{bmatrix} f_1(x(t_1)) & f_2(x(t_1)) & \dots & f_S(x(t_1)) \\ f_1(x_i(t_2)) & f_2(x(t_2)) & \dots & f_S(x(t_2)) \\ \vdots & \vdots & \dots & \vdots \\ f_1(x(t_N)) & f_2(x(t_N)) & \dots & f_S(x(t_N)) \end{bmatrix}_{NXS}$$

$$\mathbf{X}_M=[x\,,y]$$

$$\mathbf{X}_{M+1}=[1,x,y]$$

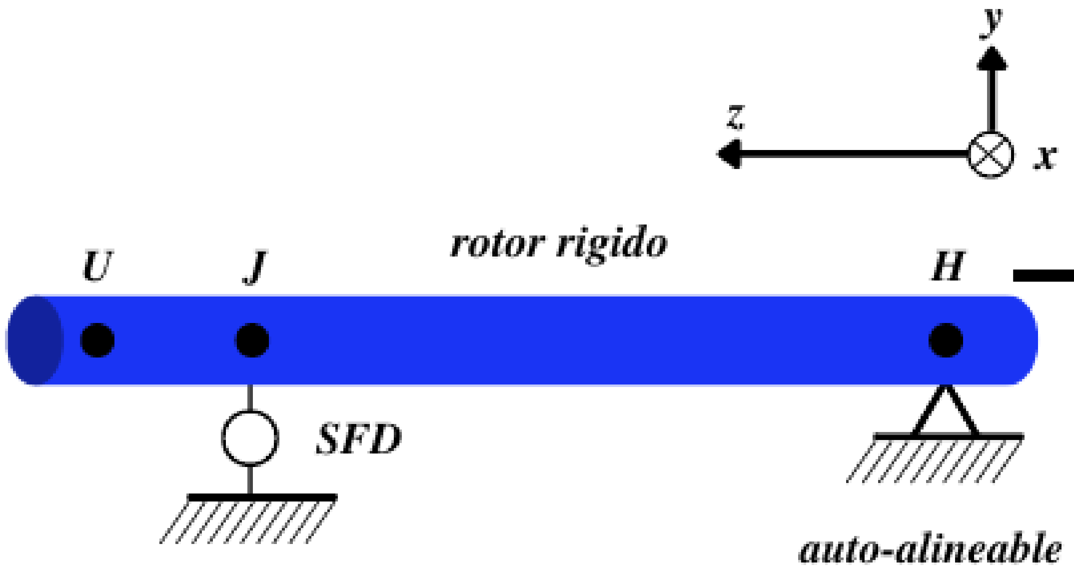
$$\mathbf{X}_{M+1}=\begin{bmatrix} 1 & x(t_1) & y(t_1) \\ 1 & x(t_2) & y(t_2) \\ \vdots & \vdots & \vdots \\ 1 & x(t_N) & y(t_N) \end{bmatrix}_{N\times M+1}$$

$$\boldsymbol{\Theta}(\mathbf{X})=\mathbf{C}'_{k(M+1)}=[1_{N\times 1}\; C^1_{N\times M}\; C^2_{N\times R_2}\; \cdots\; C^k_{N\times R_k}\;]$$

$$\mathbf{C}^1=\begin{bmatrix} x_1(t_1) & x_2(t_1) & \cdots & x_M(t_1) \\ x_1(t_2) & x_2(t_2) & \cdots & x_M(t_2) \\ \vdots & \vdots & \vdots & \vdots \\ x_1(t_N) & x_2(t_N) & \cdots & x_M(t_N) \end{bmatrix} \quad \mathbf{C}^2=\begin{bmatrix} x_1^2(t_1) & \cdots & x_1(t_1)x_2(t_1) & \cdots & x_M^2(t_1) \\ x_1^2(t_2) & \cdots & x_1(t_2)x_2(t_2) & \cdots & x_M^2(t_2) \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ x_1^2(t_N) & \cdots & x_1(t_N)x_2(t_N) & \cdots & x_M^2(t_N) \end{bmatrix}$$

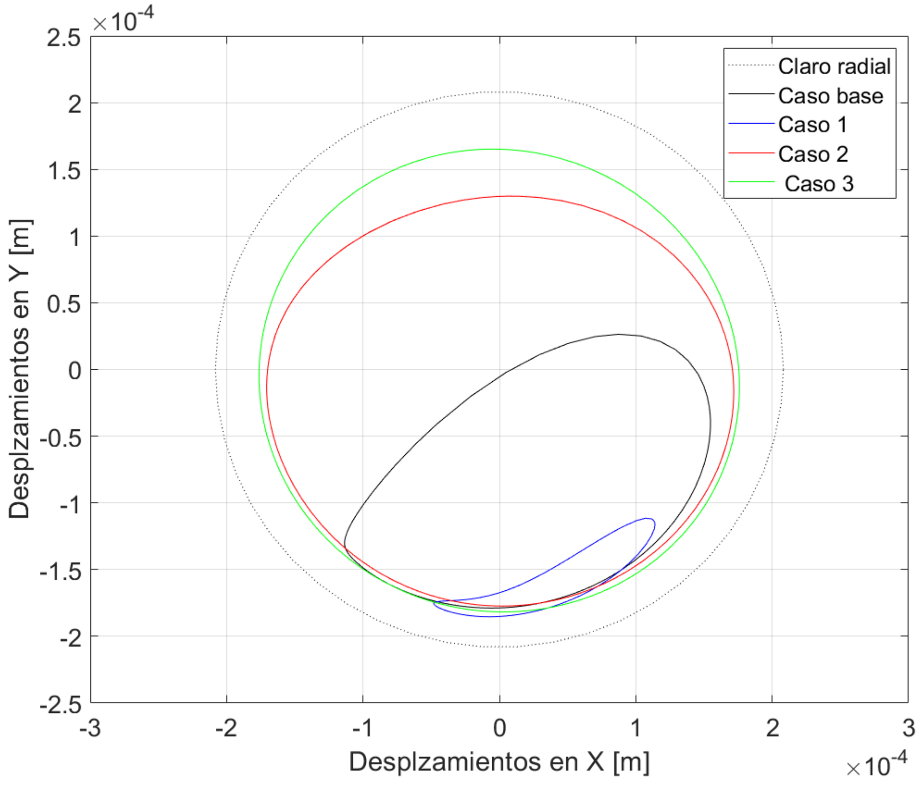
$$\boldsymbol{\Theta}(\mathbf{X})=\mathbf{C}'_{k(M+1)}=[1_{N\times 1}\; C^1_{N\times M}\; C^2_{N\times R_2}\;\; C^3_{N\times R_3}\;\;]$$

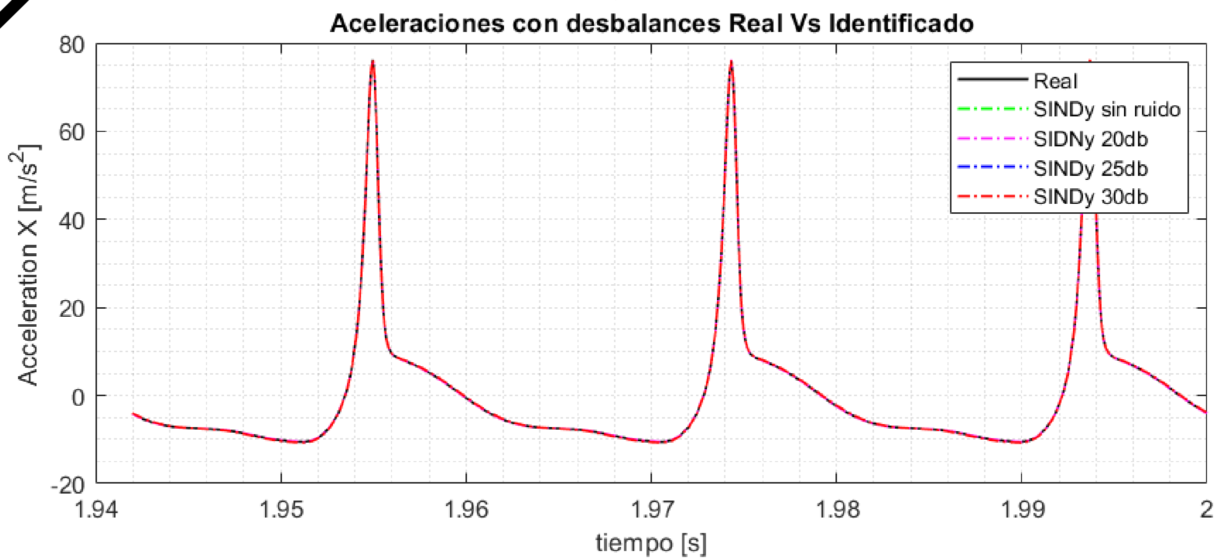
$$\mathbf{C}^1=\begin{bmatrix} x(t_1) & y(t_1) \\ x(t_2) & y(t_2) \\ \vdots & \vdots \\ x(t_N) & y(t_N) \end{bmatrix} \quad \mathbf{C}^2=\begin{bmatrix} x^2(t_1) & x(t_1)y(t_1) & y^2(t_1) \\ x^2(t_2) & x(t_2)y(t_2) & y^2(t_2) \\ \vdots & \vdots & \vdots \\ x^2(t_N) & x(t_N)y(t_N) & y^2(t_N) \end{bmatrix} \quad C^3=\begin{bmatrix} x^3(t_1) & x^2(t_1)y(t_1) & x(t_1)y^2(t_1) & y^3(t_1) \\ x^3(t_2) & x^2(t_2)y(t_2) & x(t_2)y^2(t_2) & y^3(t_2) \\ \vdots & \vdots & \vdots & \vdots \\ x^3(t_N) & x^2(t_N)y(t_N) & x(t_N)y^2(t_N) & y^3(t_N) \end{bmatrix}$$



$$M_{R,J}\ddot{X}_J = Q_x + U_{eq,J}\Omega^2 \sin \Omega t$$

$$M_{R,J}\ddot{Y}_J = Q_y - U_{eq,J}\Omega^2 \cos \Omega t - W$$





Casos	U_{eq} [kg*m]
base	0.0034
1	0.0028
2	0.0040
3	0.0055

$$M_{R,J}\ddot{X}_J = Q_x + U_{eq,J}\Omega^2 \sin \Omega t$$

$$M_{R,J}\ddot{Y}_J = Q_y - U_{eq,J}\Omega^2 \cos \Omega t - W$$

$\dot{\mathbf{X}}$

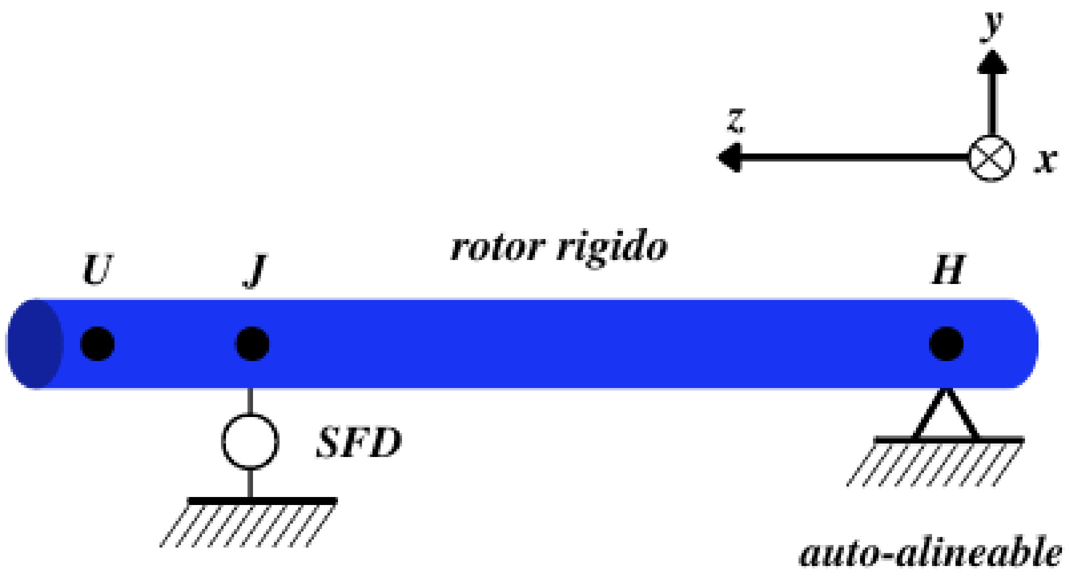
$\mathbf{X}$

$\boldsymbol{\Theta}(\mathbf{X}) = \mathbf{C}'_{3(4+1)}$

$\dot{\mathbf{X}} = \boldsymbol{\Theta}(\mathbf{X})\boldsymbol{\Xi}$

$$\boldsymbol{\Xi} = \begin{bmatrix} 0 & -1.00000541 \\ 1.00000126 & 0 \\ 0 & 1.00000479 \\ 0.00337285 & 0 \\ 0 & -0.00337282 \\ 0 & 0 \\ \vdots & \vdots \\ 0 & 0 \end{bmatrix}$$

Casos	U_{eq} **[kg*m]**
base	0.0034



$$\begin{cases} \dot{\mathbf{X}} = [\ddot{X}_J, \ddot{Y}_J] \\ SNR(\ddot{X}_J, \ddot{Y}_J) \end{cases}$$

20db, 25db y 30db

$$\mathbf{X} = \left[\frac{Q_x}{M_{R,J}}, \frac{Q_y}{M_{R,J}}, \frac{\Omega^2 \sin \Omega t}{M_{R,J}}, \frac{\Omega^2 \cos \Omega t}{M_{R,J}}\right]$$

Resultados

$$\boldsymbol{\Theta}(\mathbf{X}) = \mathbf{C}'_{3(4+1)}$$

$$\dot{\mathbf{X}} = \boldsymbol{\Theta}(\mathbf{X})\boldsymbol{\Xi}$$

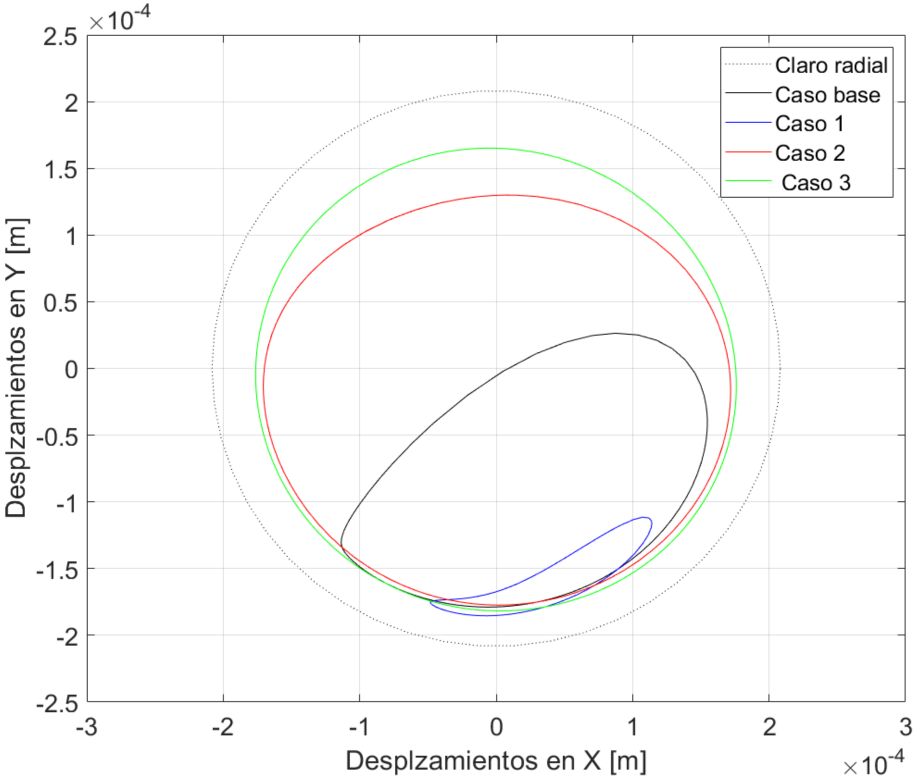
$$\boldsymbol{\Xi} = \begin{bmatrix} 0 & C_W \\ C_{Qx} & 0 \\ 0 & C_{Qy} \\ U_{eq,Jx} & 0 \\ 0 & U_{eq,Jy} \\ 0 & 0 \\ \vdots & \vdots \\ 0 & 0 \end{bmatrix}$$

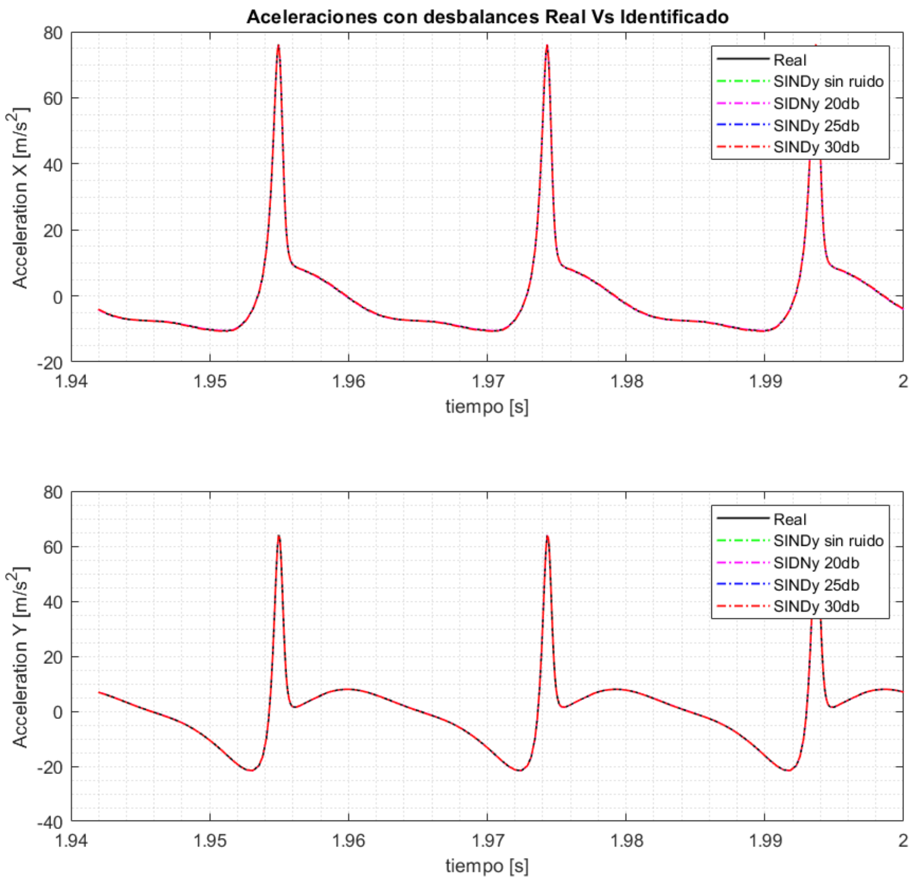
$U_{eq,Jx}$

$U_{eq,Jy}$

$$M_{R,J}\ddot{X}_J = Q_x + U_{eq,J}\Omega^2 \sin \Omega t$$

$$M_{R,J}\ddot{Y}_J = Q_y - U_{eq,J}\Omega^2 \cos \Omega t - W$$

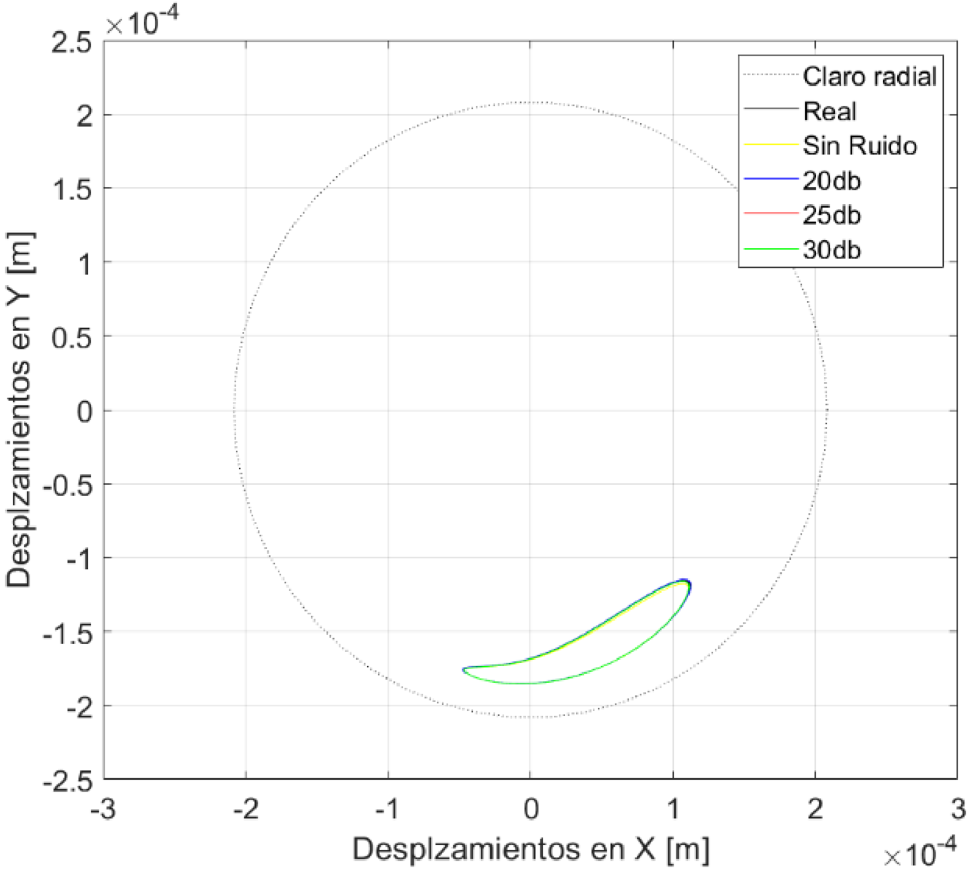


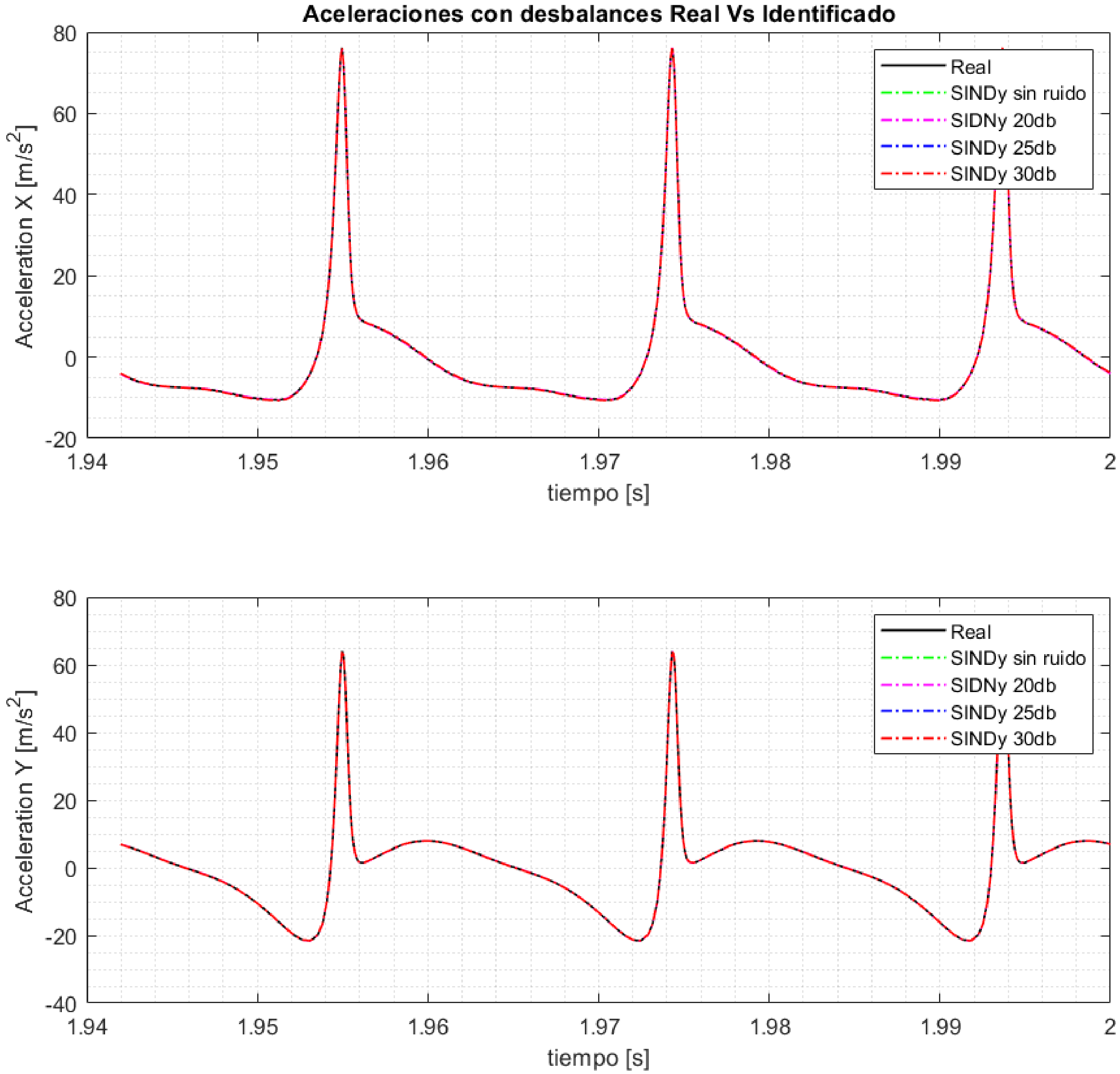


Caso base

$Ueq = 0.0034$

	$U_{eq,SINDy}$ [kg*m]	
Ruido	U_{eq,J_x}	U_{eq,J_y}
N/A	0.00337285	0.00337282
db20	0.00337226	0.00337809
db25	0.00340334	0.00336725
db30	0.00340334	0.00336725

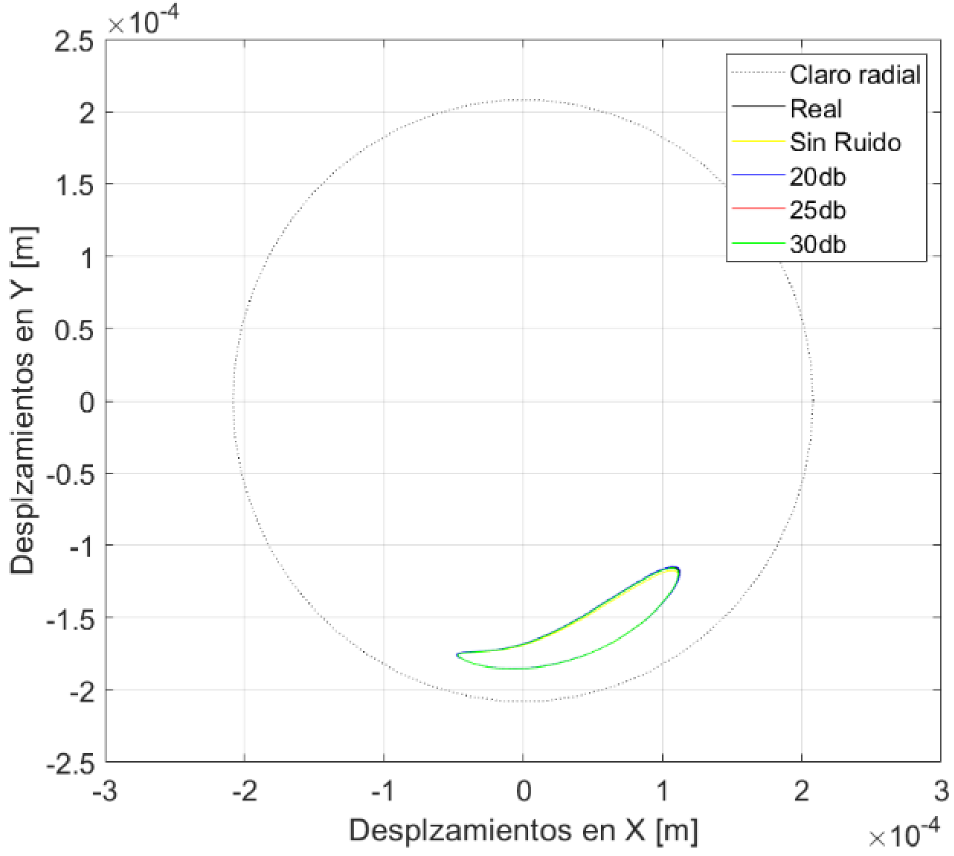


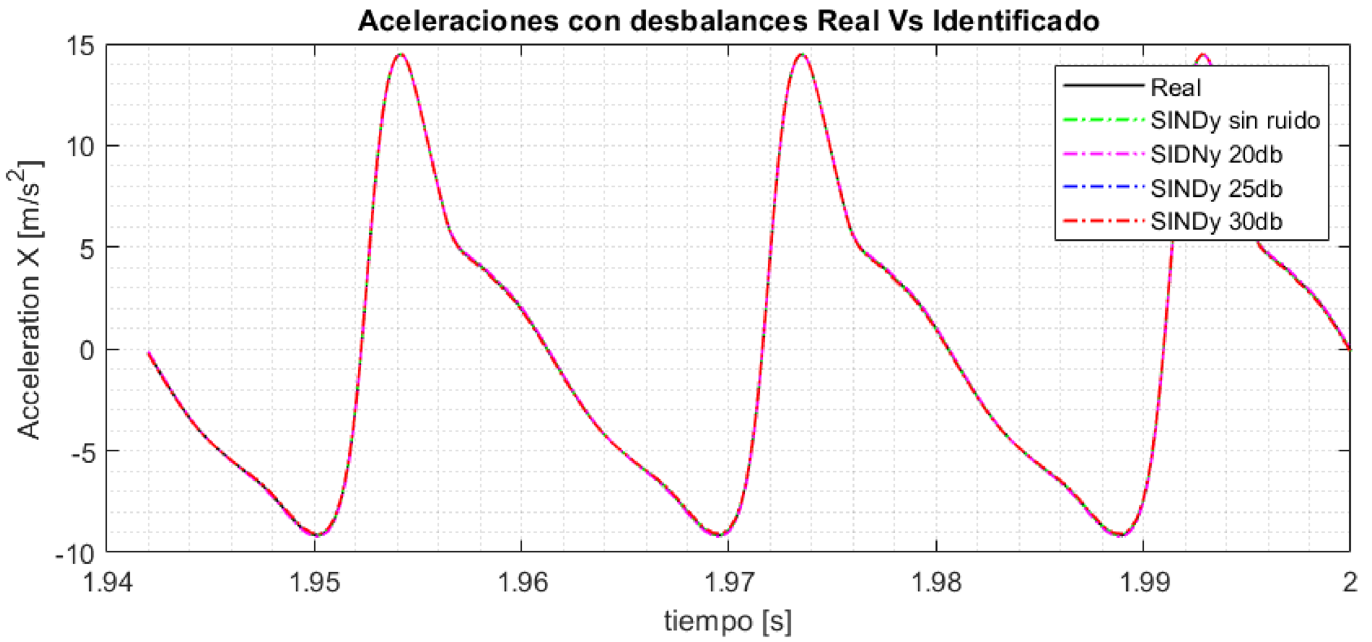


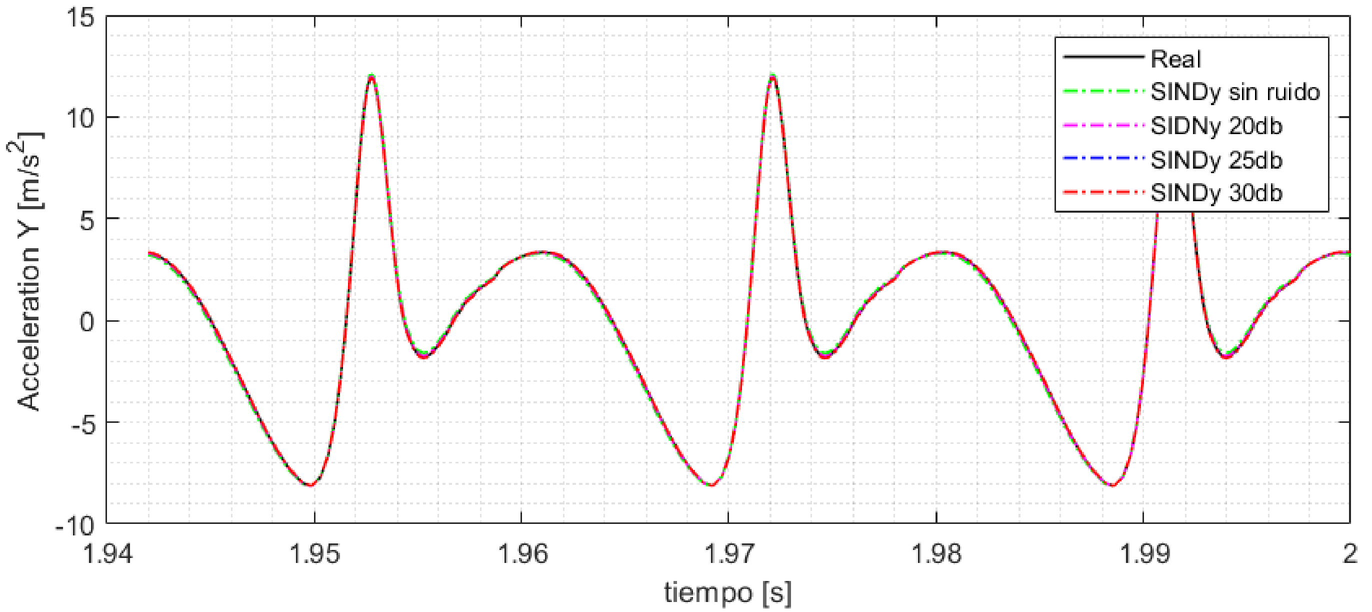
Caso 1

$Ueq = 0.0028$

	$U_{eq,SINDy}$ [kg*m]	
Ruido	U_{eq,J_x}	U_{eq,J_y}
N/A	0.00276859	0.0027404
db20	0.00278523	0.00276609
db25	0.00275921	0.00278326
db30	0.00275921	0.00278326



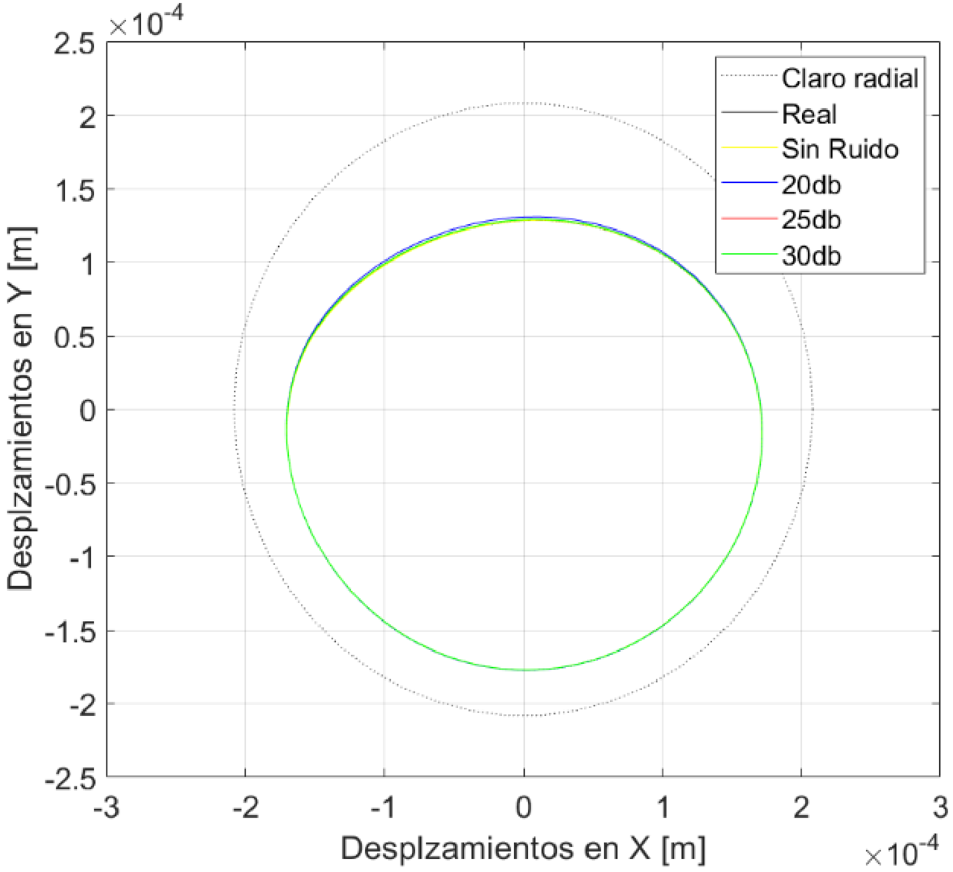


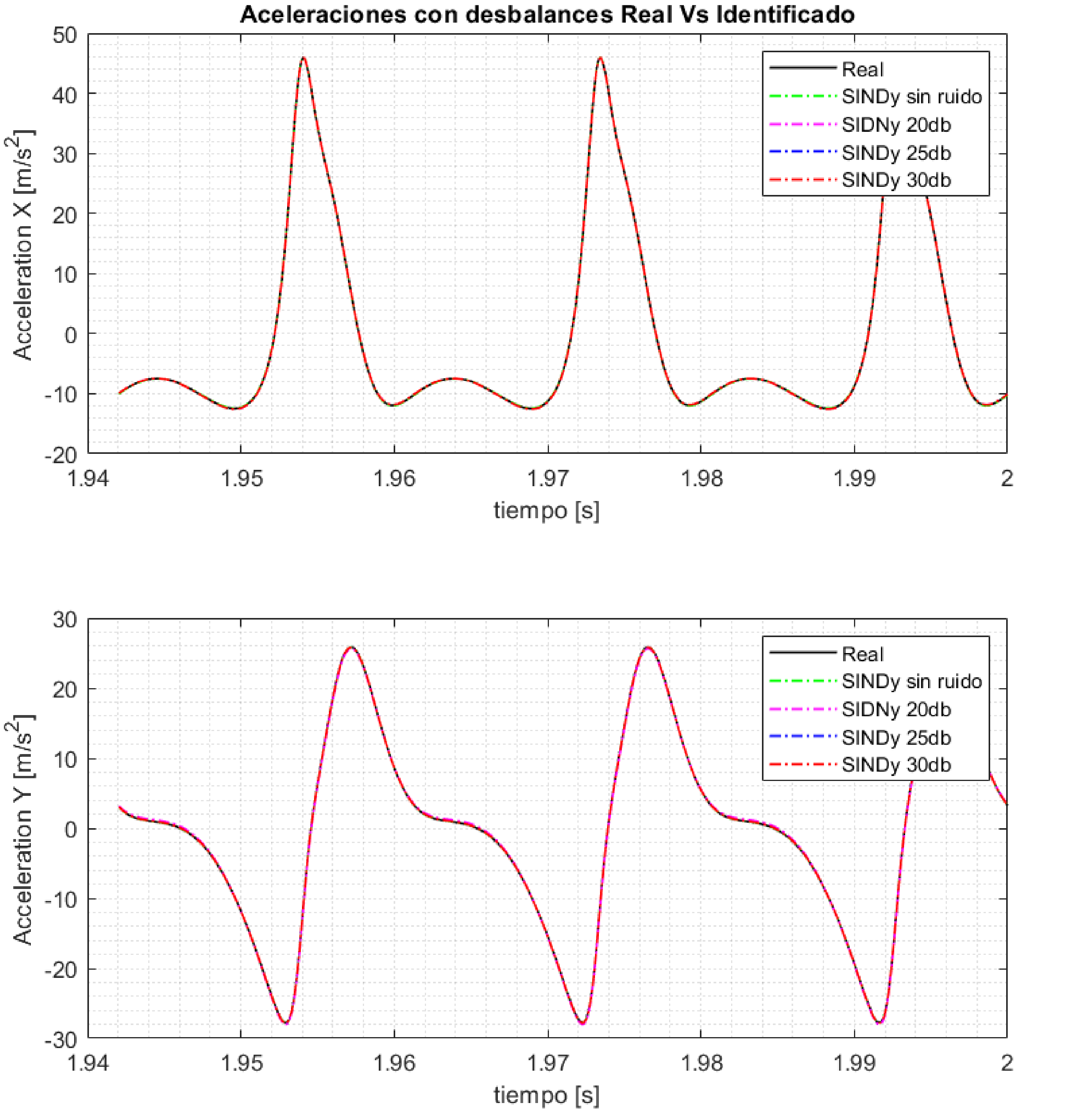


Caso 2

$Ueq = 0.0040$

	$U_{eq,SINDy}$ [kg*m]	
Ruido	U_{eq,J_x}	U_{eq,J_y}
N/A	0.00396606	0.00397528
db20	0.0039892	0.00402207
db25	0.00398733	0.00398227
db30	0.00398733	0.00398227

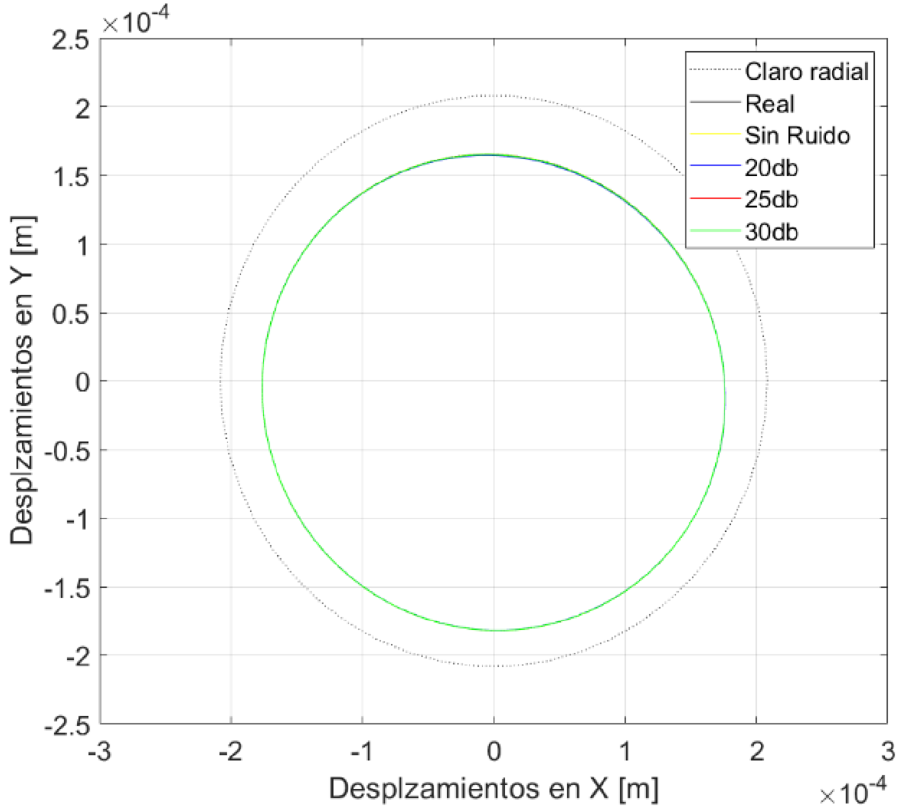


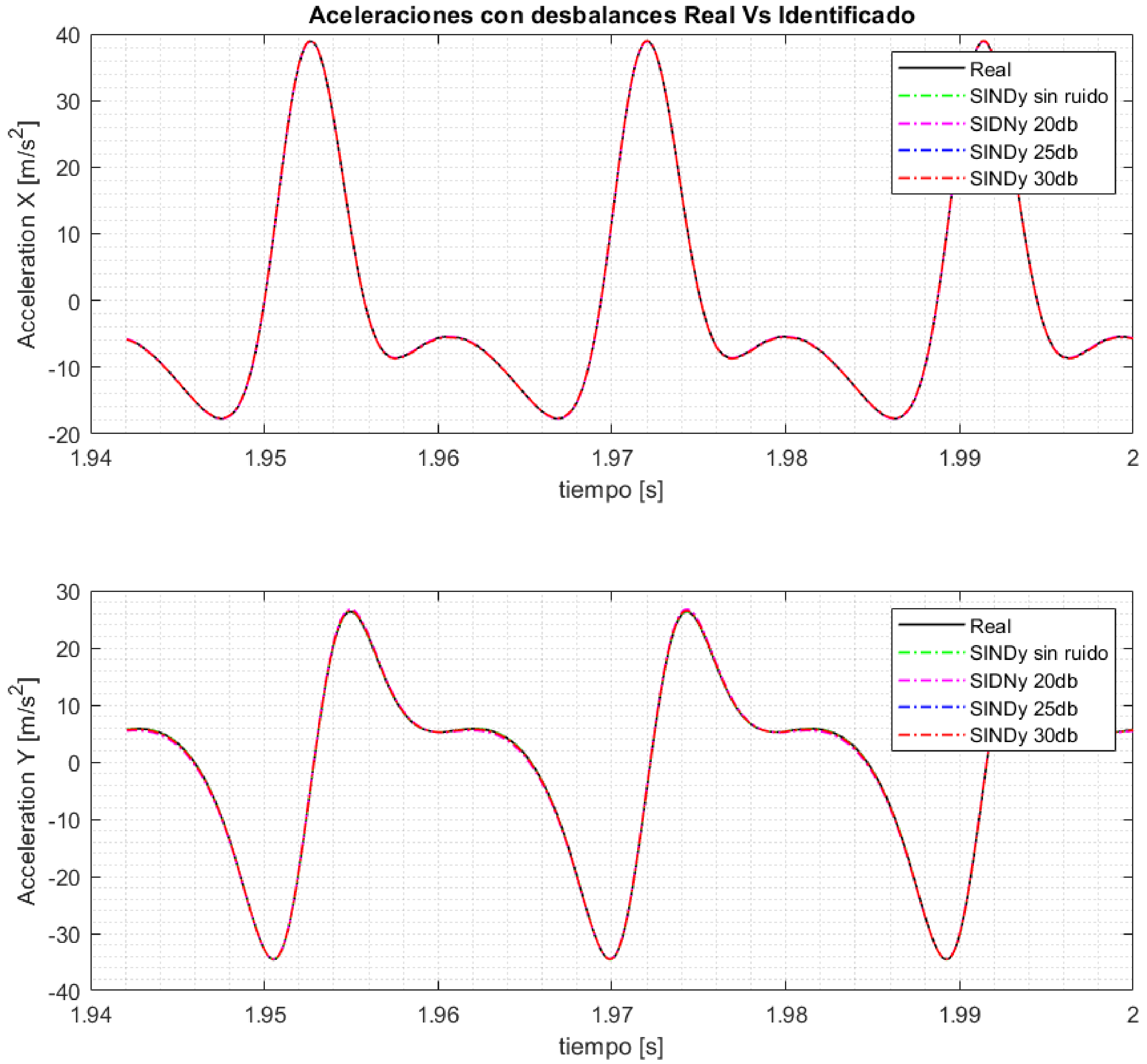


Caso 3

$Ueq = 0.0055$

	$U_{eq,SINDy}$ [kg*m]	
Ruido	U_{eq,J_x}	U_{eq,J_y}
N/A	0.00549583	0.0055019
db20	0.00550924	0.00543415
db25	0.00548761	0.00548324
db30	0.00548761	0.00548324





Conclusiones

El método de identificación de dinámicas no lineales ***SINDy***, presenta una gran capacidad para la obtención del desbalance equivalente del sistema del squeeze film damper bearing ***SFD*** bajo distintas condiciones de este con ruido en la aceleración. La alta precisión del método se debe a que el sistema fue simulado a 20 ciclos lo cual representa una amplia cantidad de datos para que ***SINDy*** identifique el sistema con una alta precisión.

SINDy puede llegar a ser un gran método de apoyo para la identificación de sistemas dinámicos no lineales acoplados, los cuales son comunes en la ingeniería y ciencias.

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