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Analytical models' driven machine learning modeling for the setting and control of the radial-axial ring rolling process

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Abstract

Radial axial ring rolling (RARR) forming is focal in seamless ring production for several industrial sectors. Although industrial settings and decisions are still largely driven by operators' experience, this work provides a real-time and interactive solution for parameters' settings and control. In fact, the high computational time required for a simulation together with the required knowledge to set a finite element model (FEM) disadvantages this solution when a fast and reliable decision is required. The proposed approach combines analytical and gradient boosting regression models based on experimental and simulated data, to develop a software that offers a real-time and interactive simulation for the production of flat rings. The algorithm predicts instantaneously the manufacturing forces, torques, and power required, starting from the final ring geometry, tools speeds, and machine data. The proposed solution has been verified with industrial case experimental data and with the replicated simulation on Simufact Forming 15 FEM software and predictions show an average which is above 90% on different process settings and ring materials and dimensions.

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Nomenclature

D_i, d_i initial external and internal ring diameter [mm]
 h_i initial ring height [mm]
 s_i initial ring thickness [mm]
 T ring average temperature [°C]
 D_f, d_f final external and internal ring diameter [°C]
 h_f final ring height [mm]
 s_f final ring thickness [mm]
 D_r, d_r radial area external and internal ring diameter [mm]
 h_r radial area ring height [mm]

s_r radial area ring thickness [mm]
 D_a, d_a axial area external and internal ring diameter [mm]
 h_a axial area ring height [mm]
 s_a axial area ring thickness [mm]
 D_m mandrel diameter [mm]
 D_{mr} main roll diameter [mm]
 α axial cone angles [°]
 μ Coulomb friction coefficient [-]
 v_m mandrel feeding speed [mm/s]
 v_a upper axial roll vertical feeding speed [mm/s]
 ω_r main roll rotational speed [rpm]

$\epsilon_{rad,r}$	radial strain on the radial area [-]
$\epsilon_{h,r}$	height strain on the radial area [-]
$\epsilon_{cir,r}$	circumferential strain on the radial area [-]
$\epsilon_{eq,r}$	equivalent strain on the radial area [-]
$\dot{\epsilon}_{eq,r}$	equivalent strain rate on radial area [1/s]
$\epsilon_{rad,a}$	radial strain on the axial area [-]
$\epsilon_{h,a}$	height strain on the axial area [-]
$\epsilon_{cir,a}$	circumferential strain on the axial area [-]
$\epsilon_{eq,a}$	equivalent strain on the axial area [-]
$\dot{\epsilon}_{eq,a}$	equivalent strain rate on axial area [1/s]
$k_{f,r}$	flow stress on the radial area [MPa]
$k_{f,a}$	flow stress on the axial area [MPa]
LC_r	contact length on the radial area [mm]
LC_a	contact length on axial area [mm]
γ_r	radial impact factor [-]
γ_a	axial impact factor [-]
F_r	Analytical radial force [kN]
$F_{r,tan}$	analytical radial force tangential [kN]
T_r	analytical radial torque [kNm]
F_a	analytical axial force [kN]
$F_{a,tan}$	analytical axial force tangential [kN]
T_a	analytical axial torque [kNm]
P	analytical required power [kW]
n	time step [s]

1. Introduction

Radial axial ring rolling (RARR) is a metal manufacturing process where the incremental rotation and movement of the tools deform in height and thickness the starting blank ring to obtain the final seamless ring. This process permits the production of different ring shapes with flat rectangular sections or more complex profiled shapes [1,2] obtaining a seamless product that finds application in several industries such as automotive, aerospace, and energy production [3]. The presence of 6 different tools (Fig. 1), namely mandrel, main roll, upper axial roll, lower axial roll, left and right centering rolls, as well as their feeding and rotational speed, make this manufacturing process difficult to control, especially if high-quality standards are required, such as material properties and dimensional accuracy [4,5].

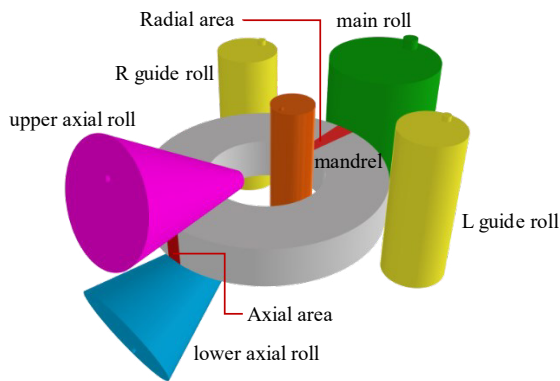


Fig. 1. Configuration of the radial axial ring rolling process.

Several studies can be found in literature to optimize the radial axial ring rolling process [6,7] and although it is a well-established process, it still found academic and industrial

interest. Conventional approaches for radial axial ring rolling studies involve analytical formulations [8–10] and computational simulations on FEM software [11,12]. While the first ones are limited in terms of accuracy and applicability by the required approximations to study analytically this complex process, the FEM approaches usually require high computational time and energy [13], together with computational skills prerequisites. The ever-growing development and interest in artificial intelligence AI approaches in industrial manufacturing fields [14,15] offers an innovative solution. In fact, several AI applications for the radial-axial ring rolling process can already be found in literature [13,16,17] to optimize the manufacturing of flat and profiled rings.

The proposed research involves a novel hybrid analytical-gradient boosting (GB) based algorithm to simulate interactively and in real-time the process parameters and to predicts required forces, torques, and power to produce rectangular section rings. The GB database, which includes 80 cases from FEM simulations and experimental cases, is used by the hybrid algorithm to improve the calculation accuracy of two empirical calculations. In fact, it has been observed that for rings with a height/thickness shape ratio high or low, the prediction of forces and torques involved loses accuracy. The proposed hybrid solution permits to overcome this problem enhancing the precision of the real-time prediction. Moreover, the integration of the proposed hybrid algorithm into an already existing commercial control software RollingCAD® of Project Group® s.r.l., allows a real-time and interactive prediction of forces, torques, and power as the operator changes any of the process parameters.

After a short introduction of the radial-axial ring rolling process and the already existing analytical formulations involved, the hybrid analytical-GB model is introduced and explained. A total of 4 industrial cases have been considered for the model validation with a comparison between the predicted value, the real value, and the FEM simulated value of forces, torques, and power.

2. Analytical Model

The analytical formulation to establish the lamination curve and the ring growth speed has been taken from Berti et al. [18]. In particular, the main formulations are the ideal lamination curve given by Keeton's rule (Eq. 1), the main roll rotation speed range (Eq. 2), and the radial feed speed range (Eq. 3)

$$h^2 - s^2 = const ; \frac{800}{D_{mr}} \leq \omega_r \leq \frac{3200}{D_{mr}} \quad (1-2)$$

$$\frac{\omega_r \cdot D_{mr} \cdot s_i^2 \cdot \left(\frac{1}{D_{mr}} + \frac{1}{D_m} + \frac{1}{D_i} - \frac{1}{d_i} \right)}{152.67 \cdot \pi \cdot D_i} \leq v_m \leq \frac{\omega_r \cdot \beta^2 \cdot D_{mr}^3 \cdot \left(\frac{1}{D_{mr}} + \frac{1}{D_m} + \frac{1}{D_i} - \frac{1}{d_i} \right)}{0.5 \cdot \pi \cdot D_i \cdot (1 + D_i / d_i)^2} \quad (3)$$

Where β is defined as follows (Eq. 4):

$$\beta = \arctan(\mu) \quad (4)$$

If the final ring geometry is given as height, thickness, and outer diameter, along with the material and the ring's initial temperature, it is possible to estimate the rolling time, the ideal lamination curve, and the ring growth speed under the hypothesis of volume conservation. With this information, a discretization of the ring evolution from the blank- to the final dimensions can be made using a time step of 0.1s from 0 to the total lamination time t . Once the geometry evolution is set, the strain and the strain rate that occur during the manufacturing process in the radial area and the axial area (Fig. 1) can be calculated by arranging the formulations of Quagliato et al. [10] and obtaining the following modifications (Eq. 5-7):

$$\varepsilon_n = \begin{bmatrix} \varepsilon_{rad,n} & 0 & 0 \\ 0 & \varepsilon_{h,n} & 0 \\ 0 & 0 & \varepsilon_{cir,n} \end{bmatrix} = \begin{bmatrix} \ln(\frac{S_n}{S_i}) & 0 & 0 \\ 0 & \ln(\frac{h_n}{h_i}) & 0 \\ 0 & 0 & \varepsilon_{cir,n} \end{bmatrix} \quad (5)$$

$$\varepsilon_{cir,n} = -\varepsilon_{rad,n} - \varepsilon_{h,n} = -\ln(\frac{S_n}{S_0}) - \ln(\frac{h_n}{h_0}) \quad (6)$$

$$\varepsilon_{eq,n} = \sqrt{\frac{2}{3} \cdot (d\varepsilon_{rad,n}^2 + d\varepsilon_{h,n}^2 + d\varepsilon_{cir,n}^2)} \quad (7)$$

Where n is the time step of 0.1s with $n \in [0;t]$ t total lamination time. With an additional step, it is possible to calculate the strain rate that corresponds to the chosen time step n (Eq. 8):

$$\dot{\varepsilon}_{eq,n} = \frac{d\varepsilon_{eq,n}}{dt} = \frac{\varepsilon_{eq,n} - \varepsilon_{eq,n-1}}{0.1} \quad (8)$$

With the formulations reported above is it possible to calculate the equivalent strain and strain rate in the radial area ($\varepsilon_{eq,n,r}$, $\dot{\varepsilon}_{eq,n,r}$) and in the axial area ($\varepsilon_{eq,n,a}$, $\dot{\varepsilon}_{eq,n,a}$) for every n th time step. Under the simplifying assumption of average constant temperature T of the ring during the lamination, it is possible to calculate the flow stress on the radial and axial area:

$$\sigma = C_1 \cdot e^{(C_2 \cdot T)} \cdot \varepsilon^{(n_1 \cdot T + n_2)} \cdot e^{\left(\frac{L_1 \cdot T + L_2}{\varepsilon}\right)} \cdot \dot{\varepsilon}^{(m_1 \cdot T + m_2)} \quad (9)$$

Eq. 9 is a Hansel-Spittel formulation available on the Simufact Forming Material database based on the material dependant coefficient C_1 , C_2 , n_1 , n_2 , L_1 , L_2 , m_1 , m_2 . Different Hansel Spittel formulations or other equations that describe the flow stress of the material under high temperatures and strain can be applied as well. The radial and axial forces required by respectively the mandrel and the upper axial roll can then be calculated by the following formulation (Eq. 10,11):

$$F_{n,r} = \frac{2}{\sqrt{3}} \cdot (\sigma \cdot \gamma \cdot LC \cdot h)_{n,r}; F_{n,a} = \frac{2}{\sqrt{3}} \cdot (\sigma \cdot \gamma \cdot LC \cdot s)_{n,a} \quad (10-11)$$

Where $LC_{n,r}$, $LC_{n,a}$ are respectively the contact length of the mandrel-main roll and the two axial rolls, and $\gamma_{n,r}$, $\gamma_{n,a}$ the impact factor relative to the radial and axial area. The contact lengths can be estimated with the following equation (Eq. 12,13) obtained from the research of Quagliato et Al. [8]:

$$LC_{n,r} = \sqrt{\frac{S_{n-1,r} - S_{n,r}}{\left(\frac{1}{D_{mr}}\right) + \left(\frac{1}{D_m}\right) + \left(\frac{1}{D_{r,n}}\right) - \left(\frac{1}{d_{r,n}}\right)}} \quad (12)$$

$$LC_{n,a} = m_n \cdot \tan\left(\frac{\alpha}{2}\right) \cdot ar \cos \left(\frac{1 - \frac{h_{n-1,a} - h_{n,a}}{2 \cdot \cos(\alpha)}}{m_n \cdot \tan\left(\frac{\alpha}{2}\right)} \right) \quad (13)$$

Where m_n is the distance between the axial cone tip and the middle radius of the ring at the n th step. To calculate Radial and Axial forces, respectively of the mandrel and upper axial roll, the following formulations (Eq. 14,15) from Hawkyard et al. [19] can be used.

$$F_{n,r} = \frac{2}{\sqrt{3}} \cdot LC_{n,r} \cdot h_{n,r} \cdot \sigma_n \cdot \gamma_{n,r}; F_{n,a} = \frac{2}{\sqrt{3}} \cdot LC_{n,a} \cdot s_{n,a} \cdot \sigma_n \cdot \gamma_{n,a} \quad (13-14)$$

For every n th step, it is necessary to calculate the pressure factor $\gamma_{n,r}$, $\gamma_{n,a}$ that is dependent on the ratio h/LC_r and s/LC_a respectively. Berti et al. [10] proposed a polynomial function (Eq. 16,17) based on the slip line theory to describe the γ value:

$$\begin{aligned} \gamma_{n,r} &= -0.0098 \cdot \left(\frac{h_{n,r}}{LC_{n,r}}\right)^2 + 0.2999 \cdot \left(\frac{h_{n,r}}{LC_{n,r}}\right) + 0.6909; \\ \gamma_{n,a} &= -0.0098 \cdot \left(\frac{s_{n,a}}{LC_{n,r}}\right)^2 + 0.2999 \cdot \left(\frac{s_{n,a}}{LC_{n,r}}\right) + 0.6909 \end{aligned} \quad (16-17)$$

Analyzing the experimental data it has been observed that different height/thickness ratios of the ring led to a deviation from the polynomial curve described by Eq. 15. For this reason, the machine learning regression model has been developed to calculate the pressure factors value for different flat ring shapes and tools dimensions, permitting an optimization of the force estimations as it is discussed in the next section. To calculate the radial and axial torque value, the tangential force of the main roll and the upper axial roll have been considered with the following formulations (Eq. 18,19):

$$\begin{aligned} T_{n,mr} &= \frac{D_{mr}}{\sqrt{3}} \cdot \Delta s_r \cdot h_{n,r} \cdot \sigma_n \cdot \gamma_{n,r}; \\ T_{n,a} &= \frac{2 \cdot m_n \cdot \tan\left(\frac{\beta}{2}\right)}{\sqrt{3}} \cdot \Delta h_a \cdot s_{n,a} \cdot \sigma_n \cdot \gamma_{n,a} \end{aligned} \quad (18-19)$$

Since the mandrel has a free rotation, the radial torque is calculated on the main roll, while the axial torque corresponds to the upper and lower axial rolls. Finally, the total power P has

been calculated considering the force of the mandrel, the torque of the main roll, the force required by the upper axial roll, and the torque generated by the two axial rolls (Eq. 20):

$$P_n = F_{n,r} \cdot v_{n,r} + F_{n,a} \cdot v_{n,a} + T_{n,mr} \cdot \omega_{n,mr} + 2 \cdot T_{n,a} \cdot \omega_{n,a} \quad (20)$$

3. Machine Learning Model

The machine learning ML regression model has been implemented in Python 3.11 and it has been based on the Gradient Boosting GB method. The latter has been chosen as the regression method due to its high accuracy flexibility and robustness to outliers. To train the GB algorithm, 80% of the hybrid FEM-experimental database of 80 simulations has been used, whereas the remaining 20% have been dedicated to validation. Moreover, a 5-fold cross-validation has been implemented to guarantee the absence of overfitting and the precision of the model. The input values for the regression model are the ring external diameter D , the radial and axial height $h_{n,r}$, $h_{n,a}$, thickness $s_{n,r}$, $s_{n,a}$, contact length $LC_{n,r}$, $LC_{n,a}$, the mandrel and main roll diameter D_m , D_{mr} , the cone angle α , and the cone position m . To predict the radial pressure factor γ_r , the algorithm utilizes radial ring height, thickness, and contact length, as well as ring diameter and mandrel and main roll diameters. On the other hand, to calculate the axial pressure factor γ_a , the algorithm considers the axial ring height, thickness and contact length, the ring diameter, the cones angle, and the cone position. The following Fig. 2 schematizes the input and the output of the GB regression model.

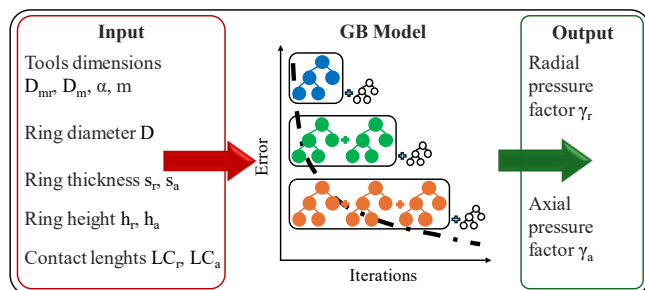


Fig. 2. Schematic diagram of the GB regression model with Input, Output, and point of strength of the chosen model.

As already mentioned, the GB database is a hybrid database composed of 70 FEM simulations and 10 real production case data provided by Project Group® s.r.l. Concerning the performance of the model, the mean squared error obtained in the validation phase with 20% of the database is 1.8% for the γ_r prediction, while 5.1% for the γ_a prediction, showing the high accuracy and robustness of the chosen machine learning regression model. Finally, the GB algorithm permits to estimate the radial and axial pressure factors for every n -th step of an input dataset of process parameters.

4. Results and discussion

In this chapter, the validation of the proposed hybrid algorithm has been summarized, showing the comparison between 4 real industrial cases with the relative calculated

predictions in terms of radial and axial forces and torques, and power during the complete rolling time. In the comparison, a FEM simulation of each of the 4 industrial cases has been considered also, to cross-check the values considered. Machine data, tools dimensions, and process parameters used in the production of the 4 industrial cases have been utilized as input for the proposed hybrid algorithm and the FEM simulation. In the following Table 1, a resume of blank and final ring main data of the 4 industrial cases are reported. This information as well as tools and machine data have been provided by Project Group® s.r.l.

Table 1. 4 case study blank and final ring data.

Case study	#1	#2	#3	#4
D_i [mm]	593	430	590	795
h_i [mm]	190	425	400	185
s_i [mm]	182.5	110	200	292.5
T [mm]	1075	1200	1150	1075
Material [-]	A350	A350	18CrNiMo7	42CrMo4
D_f [mm]	848	635	632	924
h_r [mm]	152	412	386	150
s_r [mm]	118	63	170	263.5

As can be seen from the previous table, different ratios of height/thickness have been considered, to verify the improvement in the prediction. The results of the case studies are here reported in Fig. 3-6.

Concerning industrial case 1, with an h/s ratio near 1, the analytical trends (green line) calculated with the proposed algorithm seem to replicate well the experimental values (red) and the simulated value (black) both in terms of forces, torques, and power. Concerning the radial and axial torques it seems that the analytical model estimates the experimental trend better than the simulated one (Fig. 3).

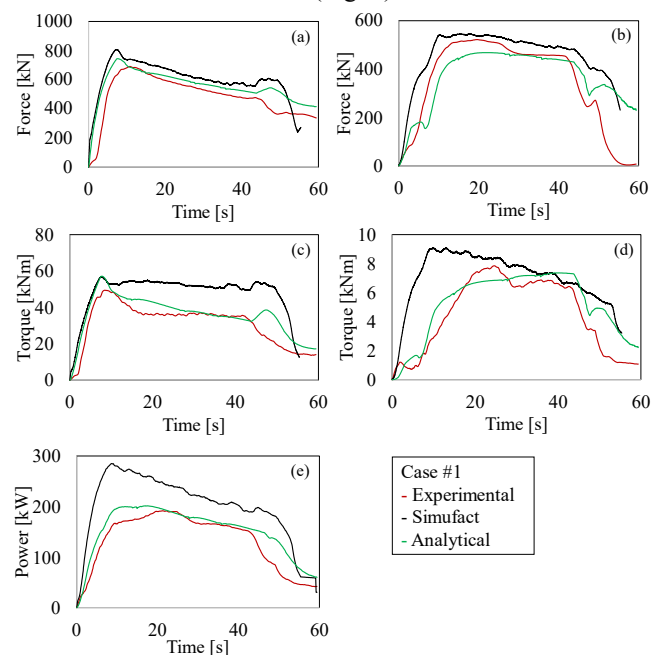


Fig. 3. Case#1 (a) Radial force; (b) Axial force; (c) Radial torque; (d) Axial torque; (e) Total Power.

Concerning industrial case 2, with an h/s ratio greater than 1, the analytical model seems to estimate well the radial force and torque. In contrast, for axial force and torque as well as the total power it appears that the hybrid model still needs some improvement on the accuracy (Fig. 4).

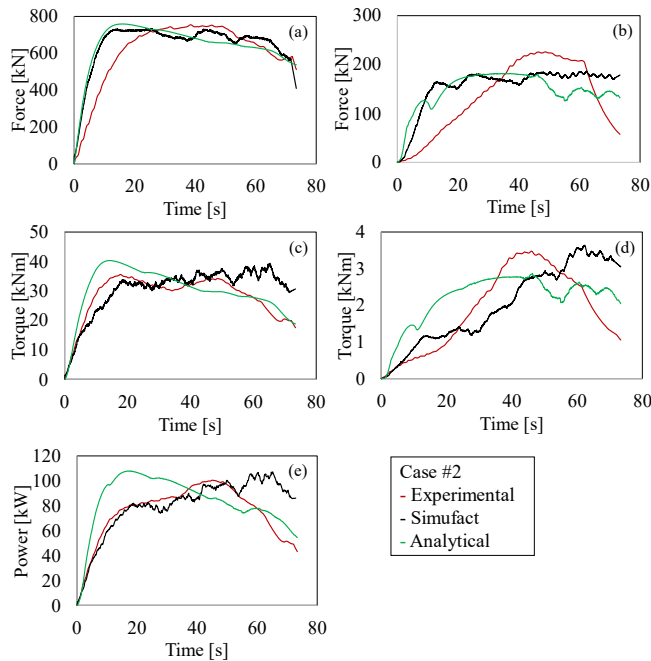


Fig. 4. Case#2 (a) Radial force; (b) Axial force; (c) Radial torque; (d) Axial torque; (e) Total Power.

For industrial case 3 (Fig. 5) the height/thickness ratio is also greater than 1 and for this production, the proposed algorithm calculates with a better accuracy the forces and torques trend. It seems that in the first 25 seconds, the FEM and analytical solutions are wrong, overestimating the forces and torques.

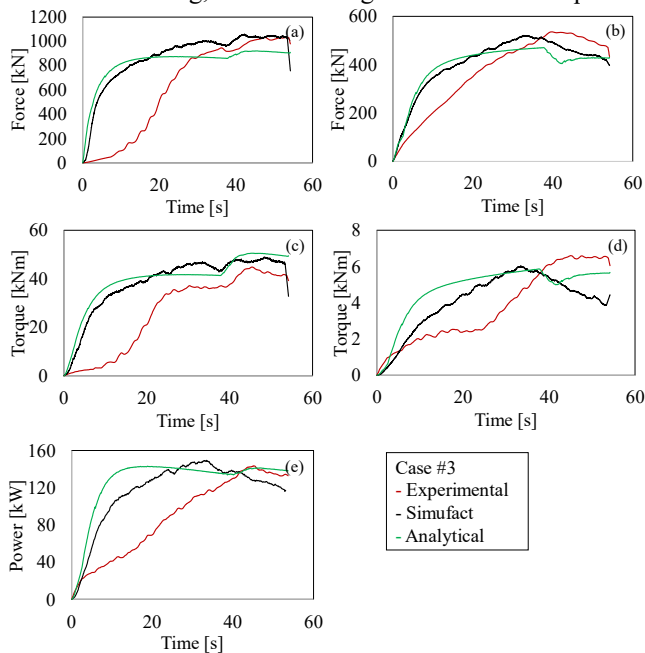


Fig. 5. Case#3 (a) Radial force; (b) Axial force; (c) Radial torque; (d) Axial torque; (e) Total Power.

It must be pointed out that for this case the experimental blank ring had an accentuated barreling effect due to the forming press that has not been replicated in the FEM model and the algorithm. In other words, the simulation and the analytical model considered the blank initial geometry as a perfect ring without defects. This explains the inaccuracy of the first part of the graphs.

Finally, for industrial case 4, with a h/s ratio less than 1, the proposed algorithm replicates well the experimental trend for both forces, torques, and total power, proving the reliability of the hybrid algorithm also compared to the FEM simulations (Fig. 6).

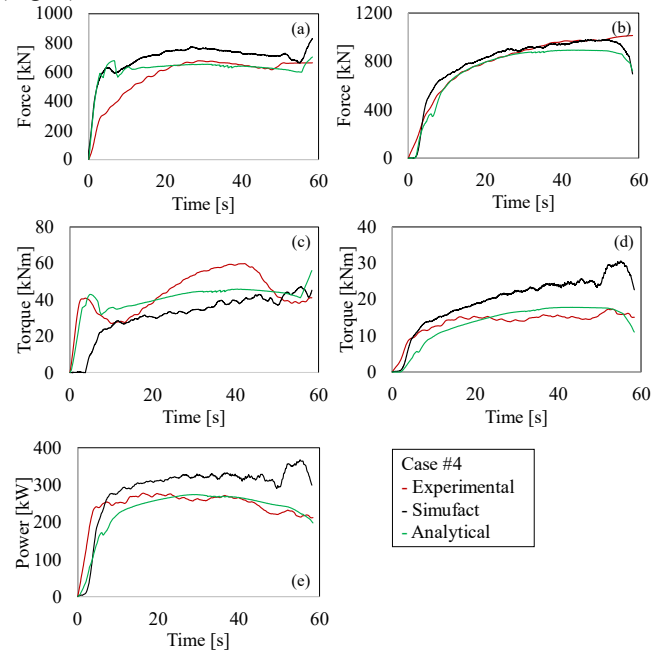


Fig. 6. Case#4 (a) Radial force; (b) Axial force; (c) Radial torque; (d) Axial torque; (e) Total Power.

In the following Table 2, the maximum value of Radial and Axial forces and torques, as well as total power, have been compared between the experimental data provided by Project Group® company s.r.l. and the analytical values calculated with the developed hybrid algorithm. The maximum error calculated is 19% while the average error is 9%.

Table 2. Results comparison between the experimental and the analytical maximum values of forces, torques, and power.

	Case study	#1	#2	#3	#4
Experimental	Radial Force [kN]	691	755	1033	678
	Axial Force [kN]	522	226	536	1014
	Radial Torque [kNm]	48	35.6	45	59.8
	Axial Torque [kNm]	7.8	3.5	6.6	17.4
	Power [kW]	192	101	158	277.9
Analytical	Radial Force [kN]	+8%	+1%	-11%	+4%
	Axial Force [kN]	-10%	+13%	+13%	-6%
	Radial Torque [kNm]	+16%	-19%	-12%	-12%
	Axial Torque [kNm]	-6%	-18%	-11%	+3%
	Power [kW]	+5%	+7%	+4%	-1%

As mentioned before, the hybrid algorithm still needs some improvements in accuracy, especially for a height/thickness ratio greater than 1. Nevertheless, it must be underlined that while for the FEM simulated results, high computational time and energy are required, the obtained analytical results are instantaneous.

5. Conclusions

The proposed hybrid algorithm for the radial axial ring rolling process is based on analytical formulations and a gradient boosting regression. The GB model permits to estimate more precisely the pressure factors allowing a reliable calculation in real time of forces, torques, and power for different process settings, materials, and shapes of flat rings. Compared with real production data and FEM replicated simulations, it shows good accuracy with a maximum error of 19% and an average error of 9%. Compared with FEM simulations of radial axial ring rolling that typically require more hours of computational time, the developed model permits to have instantaneous results to help the process engineer with quick decision-making or process settings analysis. Moreover, being implemented with a time step frame of 0.1s, this hybrid algorithm can be easily implemented in any control software of ring rolling machines to simulate offline the manufacturing forces, torques, and power for any production on different machines. More research should be oriented on the optimization of the accuracy of the analytical-machine learning algorithm to provide in real-time even more precise results as well as optimal lamination curve and growth curve to reduce the required power. Moreover, the implementation of more experimental data on the GB database is currently progressing to optimize the algorithm prediction.

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