The cold rolling load distribution of the nuclear power zirconium alloy based on the self-adaptive particle swarm optimization algorithm

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Received: 26 May 2021 / Accepted: 23 October 2021 / Published online: 18 January 2022
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Abstract
Aiming at the problem of load distribution during multi-pass cold rolling of nuclear zirconium alloy strip, the load distribution model with good plate shape is established by the self-adaptive particle swarm optimization (SAPSO) algorithm, considering the main constraint conditions including rolling force, reduction, and torque in cold rolling process. Based on the penalty function method transforming the constraint problem into the unconstrained problem, the particle swarm optimization algorithm (PSO) combined with self-adaptive inertia weight factor optimized the load distribution model is developed to improve the local search ability of the particle swarm optimization algorithm. Compared with the original nuclear zirconium alloy cold rolling schedule, the simulation results of load distribution based on the SAPSO algorithm can keep good plate shape in multi-pass cold rolling process with the high prediction accuracy. The industrial experiments demonstrate that the proportional crown difference value is consistent, and the plate shape flatness is good.

Keywords Zirconium alloy · Cold rolling · Rolling schedule · SAPSO · Penalty function

1 Introduction

The zirconium alloy is an important material in the field of the nuclear power zirconium alloy plate and strip; the plate shape is one of the key quality indicators. The zirconium alloy has poor plasticity and small deformation. However, this core skill is often conducted by manual experience, and the quality of plate shape depends on the accuracy of the control system model [1–3]. A reasonable rolling schedule is critical for the nuclear zirconium alloy cold rolling process, which can take full superiority of rolling mill equipment potential, reducing the energy consumption and ensuring accuracy and quality of plate products. The product quality and productivity effect are the most important factors to evaluate comprehensive engineering level of zircaloy cold multi-pass rolling process. Product quality mainly refers to strip flatness control and production efficiency requires fully bringing out mill motor potentiality. The dissimilarity of initial and outcoming proportional crown allowed varying within the acceptable limit during the actual rolling. Meanwhile, plate shape control and plate quality need to meet the requirements of the zirconium alloy plate rolling technology; this paper is based on the actual production data, which combines the rolling theory with the intelligent optimization algorithm to study the load distribution optimization in nuclear power zirconium alloy rolling [4, 5].

After a lot of industrial rolling, Xiong et al. [6] showed that the rolling schedule should be designed to ensure proportional crown as the constant, and the rolled piece does not easily cause a wave shape. In the first few passes, due to the large thickness of the rolled piece and the large fluctuation of the hot-rolled incoming material, the proportional crown needs to be relaxed. Chen et al. [7] use the penalty function method to deal with the constraint
conditions and transform the constrained optimization problem into an unconstrained optimization problem. By setting the optimization variable to a relatively large value that does not meet the constraints, the parameter is automatically discarded in the variable optimization process [8, 9]. It is important to study the nuclear power zirconium alloy multi-pass rolling schedule, combined with the artificial intelligence optimization algorithm [10, 11]. Chen et al. [12] use the method of rolling force model based on self-adaptive and BP neural network to carry out rolling force online forecasting. The accuracy is better than that of purely adaptive or neural network forecasting, and it fully meets the requirements of the rolling mill online rolling. Wei et al. [13] applied the genetic algorithm (GA) to optimize the rolling schedule of four-stand tandem cold rolling mill, binary-coded the exit thickness, and obtained the minimum friction coefficient model. Cao et al. [14] optimized the rolling schedule with the implicit parallelism of the GA. Cao et al. [15, 16] use the GA to set the bending force model of a six-high reversible cold rolling mill. Li et al. [17] established a single-stand cold rolling silicon steel load distribution optimization mathematical model based on the particle swarm optimization (PSO) and used the algorithm to achieve the multi-objective load distribution optimization of a single-strand cold rolling mill. The optimization model takes the plate shape control board thickness into account. Sun et al. [18, 19] applied the PSO to optimize the load distribution of the five-stand cold rolling mill and realized the proportional distribution of rolling force. Wang et al. [20] proposed the improved particle swarm optimization (IPSO) algorithm, by judging the fitness variance, which provides an effective method for the optimization of the load distribution of the rolling schedule. This paper uses the self-adaptive particle swarm optimization (SAPSO) algorithm to optimize the nuclear power zirconium alloy cold rolling schedule with the goal of good plate shape [21, 22].

Due to the lack of references on zirconium alloy plate and strip rolling, the rolling theory and intelligent optimization algorithm are combined to optimize its load distribution. In accordance with the production line of nuclear zirconium alloy, the objective function is the good flatness, and the constraint conditions include rolling force, reduction, and torque in cold rolling process. Furthermore, the penalty function method transforms the constraint problem into the unconstrained problem. Meanwhile, PSO algorithm with adaptive inertia weight factor optimized the load distribution model is developed to improve the local search ability of the particle swarm optimization algorithm. The actual industrial test is further investigated to verify the effectiveness of the cold rolling load distribution of zirconium alloy plate based on SAPSO algorithm.

# 2 Objective function and related mathematical models

The proportional crown criterion is a good method to determine whether the strip can meet the demand of flatness and good plate shape. The rolling force is an important factor in establishing the load distribution model. In the optimization algorithm design of the nuclear zirconium alloy load distribution, the objective function of multi-pass cold rolling of zirconium alloy is established, which aims to control the proportional crown during the rolling process. The objective function of the zirconium alloy rolling schedule is based on the SAPSO algorithm to achieve the goal of good plate shape.

## 2.1 Mathematical models of cold rolling force

In this work, the nuclear power zirconium alloy used is Zr-4 alloy. The chemical composition of Zr-4 alloy is more than 95% Zr, 1.2–1.7% Sn, and less than 0.3% Fe and 0.1–0.14% oxygen. The rolling force is related to many factors [9]. During the production process, some factors that affect the rolling force are the properties of the rolled material, the exit thickness, the reduction rate, and others. The friction coefficient is the main factor affecting the rolling force prediction model of the nuclear power zirconium alloy.

According to the measured parameters on-site, the PSO algorithm is used to regress parameters that are difficult to determine in the friction coefficient model. The friction coefficient is regarded as the correction value of determining process parameters. The error of sum square of the friction coefficient model (in Eq. (1)) is the objective function which is reverse obtained by regression of the measured parameters and the actual rolling force.

\[
J_i = \sum_{i=1}^{n} (\mu_i - f_i)^2
\]  

The regression model of the friction coefficient is shown in Eq. (2).

\[
f = (-0.5700 + 5.8241 h - 23.1075 \varepsilon) \frac{20.6763}{1.0 + N_r} \cdot 5.1705
\]

where, \(\mu_i\) is the friction coefficient calculated by the \(i\) pass; \(f_i\) is the actual friction coefficient of the \(i\) pass; \(N_r\) is the number of rolled steel coils after roll change; Where \(h\) is the exit thickness (mm); \(\varepsilon\) is the reduction rate; \(a_0, a_1, a_2, a_3, a_4\), and \(a_5\) are the regression coefficients of the model. The friction coefficient obtained from the reverse calculation by the PSO algorithm, and the corresponding parameters of the algorithm are given in Table 1.
Table 1 The parameters of PSO algorithm

| Parameter       | Particle dimension | Iteration steps | Initial particle number | Upper bound of weight $\omega_{\text{max}}$ | Lower bound of weight $\omega_{\text{min}}$ | Learning coefficient $c_1$ | Learning coefficient $c_2$ |
|-----------------|--------------------|-----------------|--------------------------|---------------------------------------------|---------------------------------------------|----------------------------|----------------------------|
| Value           | 1                  | 300             | 200                      | 1.2                                         | 0.2                                         | 2                          | 2                          |

Therefore, the Bland-Ford Hill model is used as the cold rolling force prediction model of the nuclear power zirconium alloy. Among then, the deformation resistance model must consider the work hardening in all previous pass rolling processes, using the hardening model [23] shown in Eq. (3).

$$
\begin{align*}
F &= BL'_iKKF_p \\
K &= 403 + 1.85569e^{5.68614e^{0.09311} - 28.4029e^{-2758.41756e^{-2.28922}}} \\
Q_p &= 1.1666 + 7.3755e \cdot f \cdot \sqrt{1 - \epsilon} \cdot \sqrt{\frac{R}{h}} - 23.3456e^f \\
f &= 0.0407 + 0.3875h - 1.1707e
\end{align*}
\tag{3}
$$

where $F$ is the rolling force (kN); $B$ is the width of strip (m); $K_T$ is the tension influence coefficient; $\tau_i$ is the front tension stress (MPa); $\tau_b$ is the post tensile stress (MPa); $Q_p$ is the external friction stress state coefficient; $a$, $b$, and $c$ are the coefficients to be estimated; $K$ is the deformation resistance (MPa), $K = 1.15\sigma_i$; $L'_i$ is the length of contact arc after roll flattening, and the Hitchcock formula is used to calculate. $\Delta h$ is the reduction (mm), $\Delta h = h_1 - h_0; R'$ is the flattening radius of roll (mm); $R$ is the original radius of the work roll (mm); $\zeta_0$ is the roll flattening coefficient, which is generally taken as $2.2 \times 10^{-5}$.

According to Fig. 1, the average prediction accuracy of the cold rolling force model is 95.36%, and the average prediction error rate of rolling force per pass is 4.64%. It found that the error rate increases significantly during the eighth pass. Considering the pressure sensor output the rolling force measuring error and data acquisition error, it will affect the actual prediction value of the rolling force. In the cold rolling force prediction of zirconium alloy, more than 60% rolling force error rate will be controlled below 5%. Therefore, the rolling force model has good calculation accuracy and can be applied for industrial control of the zirconium alloy cold rolling production process. Meanwhile, the model can preset the cold rolling schedule for zirconium alloy, and the industry test results are satisfactory. Figure 2 illustrate the cold rolling load distribution of zirconium alloy based on SAPSO algorithm. And Fig. 2 is the flow chart of this paper.

2.2 Objective function

According to the industry process, there are multi-pass and three schedules, and we take the second schedule as the study object in this paper. To obtain a good shape of the plate with a high precision proportional crown model, the objective function can be adjusted to be suitable for the actual situation. In addition to meeting the flatness of the exit strip, the final crown is also on the same strict claim in the actual production process. According to the paper of Cao et al. [24], to ensure the proportion crown of each pass in the rolling process is the constant, and the rolling force and exit thickness meet a linear relationship, we take the good plate shape as the load distribution objective function. That is shown in Eqs. (4) and (5).

$$
\frac{F_i - F_{i+1}}{F_i - F_{i+1}} = K_p \frac{\Delta}{H}
\tag{4}
$$

$$
F(x) = \min \sum_{i=1}^{n-2} (\frac{F_i - F_{i+1}}{h_i - h_{i+1}} - \frac{F_{i+1} - F_{i+2}}{h_{i+1} - h_{i+2}})^2
\tag{5}
$$

$F_i$ is the rolling force at pass $i$, kN; $h_i$ is the outlet thickness at pass $i$, mm.

The reduction rate of each stand, the total rolling force, and rolling torque are limited to the corresponding maximum values due to the design limits imposed by manufacturers of the rolling mill and electrical drive motors.
The constraint can be described as \( \varepsilon_i \leq \varepsilon_{\text{max}} \), \( F_i \leq F_{\text{max}} \), \( M_i \leq M_{\text{max}} \). Where, \( \varepsilon_{\text{max}} \) is the allowable maximum reduction rate of each stand; \( F_{\text{max}} \) is the allowed maximum rolling force for each stand, kN; \( M_{\text{max}} \) is the maximum rolling torque allowed for each stand, kN \cdot m.

3 Optimization of the load distribution model by SAPSO algorithm

The SAPSO algorithm optimized the load distribution of the nuclear power zirconium alloy with the goal of good plate shape [25, 26]. In the zirconium alloy rolling process, there are more than 60 passes. The load distribution process optimization takes the second schedule as an example for research and analysis. The thickness of the incoming zirconium alloy plate is 2.2 mm, the exit thickness of the plate is 1.2 mm, and the width of the zirconium alloy plate is 540 mm.

3.1 Basic particle swarm optimization (PSO) algorithm

PSO algorithm is an optimization algorithm based on the random intelligence optimization algorithm. Assuming that the size of the particle population is \( n \), the particle is randomly distributed in the \( N \) dimension space, and the individual extremum and the population extremum are continuously updated to make it close to the position of the global optimal particle. Updating the position and velocity of the particle and calculating the function fitness value. By comparing the fitness value of each particle, the better fitness value is assigned to the individual extremum and the population extremum, until the condition of iteration number is satisfied. Then output the optimal position of the population, and update the formula of the velocity and position of the particle. The formula is expressed as Eq. (6).

\[
\begin{align*}
    v_{ij}(t + 1) &= w \cdot v_{ij}(t) + c_1 r_1 [p_{\text{best}_i}(t) - v_{ij}(t)] + c_2 r_2 [g_{\text{best}_i}(t) - v_{ij}(t)] \\
    x_{ij}(t + 1) &= x_{ij}(t) + v_{ij}(t + 1)
\end{align*}
\]  

where \( v_{ij}(t) \) is the particle velocity, \( i \) is the iteration number, \( w \) is the inertia weight, \( p_{\text{best}_i}(t) \) is the individual extremum, \( g_{\text{best}_i}(t) \) is the population extremum, \( x_{ij}(t) \) is the particle position (the limit value of each pass reduction), \( M \) is the search dimension, and \( c_1 \) and \( c_2 \) are the acceleration factors.

3.2 Self-adaptive particle swarm optimization (SAPSO) algorithm

The basic PSO algorithm has the advantages of fast convergence speed and simple structure. However, the population diversity of this algorithm disappears quickly in the later stage of the search. It is easy to fall into a local minimum.
value and difficult to jump out of the local minimum. The increase and decrease of the inertia weight have a greater impact on the global search ability and local search ability of the particle swarm algorithm. Therefore, setting a reasonable inertia weight has always been the focus of promoting the particle swarm optimization algorithm for fast and efficient optimization.

Researching on the self-adaptive particle swarm optimization algorithm (SAPSO) algorithm, the fitness value of the particle swarm is used to judge the pros and cons of the particles. For particles with better fitness, the algorithm should be made to perform a fine search for the poor neighboring areas around them, that is, to appropriately reduce the inertia weight. For particles with poor fitness, it indicates that their location is not good. Jump out of the surrounding area where the modified particles are located, and perform a global search, that is, increase the weight value. Adjust the inertia weight as follows (Eq. (7)):

\[
\begin{align*}
  f_{avg} &= \frac{\text{sum}(f_i)}{N} \\
  f_i > f_{avg} &\Rightarrow w = w - (w - w_{min}) \cdot \frac{f_i - f_{min}}{f_{best} - f_{avg}} \\
  f_{avg} < f_i < f_{best} &\Rightarrow w = w + \frac{1}{1 + \exp(-[f_{best} - f_{avg}])} \\
  f_i < f_{best} &\Rightarrow w = 1.5 - \frac{1}{1 + \exp(-[f_{best} - f_{avg}])}
\end{align*}
\]

(7)

### 3.3 The penalty function method based on SAPSO algorithm

The penalty function for establishing the objective function of nuclear zirconium alloy cold-rolled flatness is in Eq. (8).

\[
\text{Const} = F_i \sum_{i=1}^{n} \{\text{min}(0, F_i)\}^2 + M_i \sum_{i=1}^{n} \{\text{min}(0, M_i)\}^2 + e_i \sum_{i=1}^{n} \{\text{min}(0, e_i)\}^2
\]

(8)

\[F_i, M_i, e_k\] are the larger values of rational numbers. The rolling force \(F_i\), rolling torque \(M_i\), and reduction ratio \(e_i\) of each stand can be calculated according to Eq. (9).

\[
\text{min}[0, X_i] = \frac{|X_i - X_{\max}| + (X_i - X_{\max})}{2}
\]

(9)

According to industry process requirements, considering the influence of pass reduction on the properties of rolling mill and zirconium alloy materials, the zirconium alloy cold rolling adopts a small reduction rate, and the single pass reduction rate does not exceed 10%. In the continuous tracking test in the single-stand reversible cold rolling mill, the maximum rolling force is 5500kN. When it exceeds this value, the rolling process is likely to be unstable. Table 2 shows the parameter settings in the particle swarm algorithm. The calculation results of each passed parameter of the optimized load distribution are shown in Table 3.

From the penalty function method based on SAPSO algorithm, we can see in Fig. 3 which is the optimization result used to calculate the rolling process parameters of each pass. In Fig. 3a–c, we can find that the exit thickness curve of cold rolling load distribution of nuclear power zirconium alloy with good plate shape shows a concave curve. The iterative calculation of the extreme value of the objective function in the optimization calculation process is shown in Fig. 3d; the extreme value of the objective function after optimization is \(jF_{min} = 36.57\). By the above analysis, the model could keep the good shape in the multi-pass reversing cold rolling process and the high prediction accuracy.

### 3.4 The discussions between original and optimization methods

In May 2019, three zirconium alloy plates (J-1–1, J-1–2, J-1–3) were rolled in the cold production line of zirconium alloy by rolling technique engineer based on their experience and knowledge. The width of J-1–1 plate is 540 mm, and the widths of J-1–2 and J-1–3 are 500 mm. The rolling velocity of is 10 m/min. In the rolling process, the bending force was not adopted. We record the relevant data shown in Fig. 4 by using the thickness gauge. Based on SAPSO algorithm, the objective function of establishing optimized rolling schedule is good plate shape by using on-site production data and rolling theory. Figure 4a indicates the comparison between the collected data which undergoes the complex working condition of repeated manual experiences and the optimized rolling distribution during the second rolling schedule [27, 28].

In Fig. 4, the new rolling schedule of nuclear power zirconium alloy reduces the number of original deformation system rolling passes, shortens the rolling time and rolling energy consumption, and improves the rolling efficiency. In Fig. 4a, the exit thickness of each pass of the original zirconium alloy shows the convex curve decreasing. In Fig. 4b, the reduction of each pass under the original schedule shows the upward trend. The new deformation schedule shows a downward trend, which meets the requirements of the plate pressure conditions for the material uniform deformation. Figure 4c, d shows the load distribution of original zirconium alloy. The rolling forces of each pass have no obvious consistency with the exit thickness; they are opposite to each
other. Under the new rolling schedule, the rolling force and the thickness of each pass satisfy the objective function of the good rolling shape.

### 4 Industrial experiments and results

Profile and flatness control are an important factor in determining strip quality. The crown and proportional crown are the important factors for the nuclear zirconium alloy cold rolling. In addition to meeting the flatness of the exit strip, the final crown is also on the same strict claim in the actual production process. The proportional crown is the deviation of crown that is a good way to judge if the plate can meet the demand of flatness. The equations of crown and proportional crown are shown in Eqs. (10) and (11). The schematic diagram of the nuclear zirconium alloy cold rolling plate measurement position is shown in Fig. 5.

\[
Ci = h \cdot \frac{h_{\text{oper}} - h_{\text{dri}}}{2} \tag{10}
\]

\[
CCi = \frac{C_{\text{exit}}}{h_{\text{exit}}} - \frac{C_{\text{entry}}}{h_{\text{entry}}} \tag{11}
\]

where, \(C_{\text{entry}}\) is the entry crown of plate; \(C_{\text{exit}}\) is the exit crown of plate; \(h\) is the thickness of the plate; \(CCi\) is the proportional crown; \(Ci\) is the crown; \(i\) is the mark point of the distance from the edge of the plate.

The practical industrial experiment is used to verify the effectiveness of the SAPSO for rolling schedule. According to the nuclear power zirconium alloy cold rolling production line, formulate the rolling schedule based on the self-adaptive particle swarm optimization algorithm. The cold rolling zirconium alloy plate process was tested on-site. Continuously track and collect test data of the five zirconium alloy plates, the plate numbers of which are U-1, U-2, U-3, U-4,
and U-5. The main rolling specifications and corresponding parameters of the five plates are illustrated in Table 4.

Five datasets were collected by continuous tracking test in the industrial test. Five plates were rolled according to the optimized load distribution principle. The rolling speed is the constant of 10 m/min. The bending force is not used in the rolling process.

The curve trend in the figure is consistent with the optimization goal. It can be seen from the thickness curves of each pass in Fig. 6a. Compared with the U-1 plate, the other four plates better meet the optimized thickness curve. In Fig. 6b, the pass reduction fluctuations of three pieces of plates (U-1, U-4, and U-5) are intense, but pass reduction fluctuations of plates (U-2 and U-3) are stable.

### 4.1 Crown results and analysis

The cold rolling of zirconium alloy plate has a feature of multi-pass, which undergoes the complex working condition of repeated manual experiences. The nuclear power zirconium alloy plate of cold rolling lacks a quality inspection system to adjust the plate shape, and needs to satisfy product quality special requirements. A reasonable range of crown control is critical for the nuclear zirconium alloy cold rolling. Considering the
rolling condition of the zirconium alloy strip, C25 and C40 are selected for the analysis of crown. According to the continuous tracking test of five groups of rolling pieces on the mark point, the crown values of each pass are calculated.

According to Fig. 7, the crown curves of five groups of data were collected by the continuous tracking test. The crown values of each pass show the downward trend. The crown changes of U-1, U-4, and U-5 plates were relatively intense, and the crown changes of U-2 and U-3 plates were relatively flat. The C40 crown curve of each pass also is conformed to the C25 crown change trend, and the crown change of U-2 and U-3 plates tends to be gentler.

4.2 Proportional crown results and analysis

Proportional crown is an important parameter to measure the wave shape in the rolling process of plate and strip. To control plate flatness in the cold rolling process, we compare and analyze the original process and optimized load distribution. According to continuous tracking test, collect five groups of data and plot the curve of proportional crown of each pass, as shown in Fig. 8.

In Fig. 8, by continuous tracking and testing process parameters, C25 and C40 proportional crown difference curve can be seen. Compared with other plate rolling processes, the difference values of U-2 and U-3 plate rolling proportion crown have small changes. The relative deviation of proportional crown is reduced significantly in each pass, and the relative deviation is slightly larger than the later pass, but the deviation and the fluctuations in the overall crown could be absorbed by reversing rolling, and the situation is consistent with the rolling process. Based on the above analysis, the model could keep the good shape in multi-pass reversing cold rolling process and the high prediction accuracy.

The cold rolling of zirconium alloy plate has a feature of multi-pass, which undergoes the complex working condition of repeated manual experiences. The nuclear power zirconium alloy plate of cold rolling lacks a quality inspection system to adjust the plate shape. The range of plate flatness and profile control are critical for the nuclear zirconium alloy cold rolling. In this paper, we use the mean and variance for data analysis and statistics. The calculation results are shown in Fig. 9. The variances of plates U-2 and U-3 are $9.72 \times 10^{-6}$ and $8.06 \times 10^{-6}$,
respectively, which are smaller than the other three plates. The mean value of the proportional crown difference value is close to zero. And the calculation variance fluctuation is small.

According to the industrial experiment, compared with the traditional process, the advantages of the optimized process specifications are mainly reflected in the following two aspects: firstly, shortened number of rolling passes, and improved the rolling efficiency. Secondly, the optimized process schedule does not produce an obvious wave shape during rolling production, and the proportional crown value is constant. Based on the above analysis and the industry results, the shape quality can be improved.

5 Conclusions

To satisfy the premise of good pressure and flatness conditions during the cold rolling of nuclear power zirconium alloy, the objective function of multi-pass nuclear power zirconium alloy cold rolling with the good plate shape was established. The constraint conditions include rolling force, reduction, and torque in cold rolling process. Based on the penalty function method, transform the constraint problem into the unconstrained problem.

We adopted SAPSO algorithm to optimize the load distribution of nuclear power zirconium alloy. The optimized model can keep good shape in multi-pass cold rolling process with the high prediction accuracy. The industrial experiments demonstrate that the proportional crown difference value is consistent, and the plate shape flatness is good.

Author contribution Cao Jian-guo: conceptualization, supervision, project administration.
Cao Yuan: investigation, validation, writing (review and editing).
Wang Tao: investigation, theoretical analysis, validation, writing (original draft).
Wang Lei-lei: investigation, validation, writing (review and editing).
Li Fang: supervision, validation.
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Funding This work was supported by the National Science and Technology Major Project of China (2019ZX06002001-004), the Scientific and Technological Innovation Foundation of Shunde Graduate School of University of Science and Technology Beijing (BK19A006), and the Innovation Method Fund of China (2016IM010300).

Data availability The datasets used or analyzed during the current study are available from the corresponding author on reasonable request.
Declarations

Ethics approval The authors claim that they are non-life science journals and there are no ethical issues.

Consent to participate The authors claim that they agree to participate.

Consent for publication The authors claim that they agree to publish.

Competing interests The authors declare no competing interests.

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