JMEPEG (2009) 18:263–272
DOI: 10.1007/s11665-008-9289-2

1059-9495/$19.00

Automated Procedure for Roll Pass Design

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(Submitted July 3, 2008; in revised form July 12, 2008)

The aim of this work has been to develop an automatic roll pass design method, capable of minimizing the number of roll passes. The adoption of artificial intelligence technologies, particularly expert systems, and a hybrid model for the surface profile evaluation of rolled bars, has allowed us to model the search for the minimal sequence with a tree path search. This approach permitted a geometrical optimization of roll passes while allowing automation of the roll pass design process. Moreover, the heuristic nature of the inferential engine contributes a great deal toward reducing search time, thus allowing such a system to be employed for industrial purposes. Finally, this new approach was compared with other recently developed automatic systems to validate and measure possible improvements among them.

Keywords automated process design, expert system, roll pass design, process simulation

1. Introduction

Hot rolling is a basic metal forming process used for transforming preformed shapes, usually square billets, resulting from the fusion process, into final products, e.g., bars, rods, section bars, plates, etc., or into forms suitable for further processing. Hot shape rolling typically involves passing billets through multiple sets of forming rolls until the desired cross-sectional shape is obtained. The resulting deformation is usually a matter of metal elongation in the rolling direction. The material being compressed will, however, always flow in the direction of least resistance. Thus, the elongation effect also produces lateral spreading perpendicular to the rolling direction (Ref 1). The maximum compression is limited by the bite angle and/or the mill load (roll force, torque, power). Lateral spreading reduces the elongation and area reduction in the pass. Hence, it is desirable to reduce lateral spreading as much as possible, and above all, keep it under control (Ref 2). This is a requirement that presents a key practical problem for rolling designers, who have to estimate what fraction of the total deformation produces elongation, and what fraction produces spreading. Incorrect spreading estimations result in underfills or side fins.

Several approaches have been used to forecast the rolled bar shape profile, including analytical, semi-empirical, and numerical ones.

Despite the great improvements in recent years in roll pass design, the technology is still, to a high degree, based on the empirical rules developed a century ago.

The traditional approach to the design of the profile of the roll passes is based on subdividing the entire sequence into sub-sequences (Ref 1), e.g., diamond-diamond, square-diamond-square, square-oval-square, and round-oval-round (Fig. 1). The calculation of the number of passes is then made by considering an average elongation ratio. Finally, the sequence is subdivided into the above-mentioned sub-sequences, and the grooves are defined according to empirical rules.

Although this approach continues to be successfully employed, it does, unfortunately, suffer from a number of limitations. First of all, the complexity of the shape rolling process requires the hiring of highly expert designers, who often base their designs on experience and intuition, rather than on a well-structured scientific approach and this leads to high development and introduction costs for new passes and sequences.

On the other hand, a growing number of researchers have, in recent years, introduced a more scientific approach to roll pass design. Perotti and Kapai (Ref 3) conducted a pioneer study on automatic roll pass design of round bars using geometrical data available in literature. The results of the calculation showed good agreement with industrial rolling sequences. Although they did attempt to perform some sort of process optimization, their system was still based on the old approach, which forced the expert system to choose from among a low number of predefined passes, thus limiting the flexibility and expandability of the system.

Kim and Im (Ref 4) developed an expert system for shape rolling of round and square bars based on a backward chaining algorithm. In particular, the inference engine determined the manufacturing sequences in reverse order based on design rules extracted from the literature. Relevance was also placed on expandability and flexibility; for instance, object-oriented programming was used to permit the addition of new shapes for the groove. This attempt too, however, was based on empirical rules (Ref 1). Hence, single pass optimization was not yet functional. Moreover, the total number of passes were, therefore, not given as input.

Kwon and Im (Ref 5) developed a computer-aided-design system to support roll pass and roll profile design of bar rolling of simple shapes to reduce the trial and error in industry. Furthermore, an algorithm for generating automatic roll pass design of local passes was proposed. That system allowed the forecast of material flow and engineering data such as roll

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Nomenclature

A	Cross-sectional area
A_h	Parameter of Shinokura's model
A_s	Parameter of Shinokura's model
Available list	List that stores the nodes that are not still inspected
$D(x)$	Difference function
Dep	Depth level in the search tree. Number of passes which precede the current one
H	Height
Hi	Maximum function (choice the highest value)
ID	Identification of a node during path search
INPUT	Defined as an input of sequence search
Lo	Minimum function (choice the lowest value)
MPN	Most promising node
N	Number of sequence passes
NAID	Next available ID
NotAvailable list	List that stores the nodes already inspected
R	Rolls radius
Ratio	Ratio of horizontal to vertical cross-section dimensions of rolled shape
S	Shape
W	Width
f	Evaluation function
ε	Convergence parameter used for the evaluation of W_{gropt}
γ	Shinokura's model costant
λ	Elongation ratio
λ_N^k	Elongation ratio of the kth pass of a sequence composed of N passes

Subscripts

c	Current
circ	Circumscribed groove shape
dad	Parent node
gr	Rolls groove
gropt	Optimized groove
inc	Entering Bar
ins	Inscribed groove shape
max	Upper limit of groove dimension
mid	Average value of lower and upper limits of groove dimension
min	Lower limit of groove dimension
out	Rolled bar
tot	Entire sequence

Superscripts

e	Equivalent rectangle
i	Optimal groove dimension iteration

separating force and required power. Although this system represents a powerful tool for roll pass design, it does not provide sequence optimization. This limit is intrinsically related to the interactivity of its procedure. In reality, it merely allows the designer to check whether or not a pass satisfies the design requirements.

An automated procedure aimed at the automatic design and optimization of roll pass sequences has been put forward as part of ongoing research. As the efficiency of a roll pass can be expressed in terms of its capacity to reduce the bar cross-section, an algorithm has been developed to evaluate the maximum values of elongation ratios.

With the adoption of the empirical knowledge elaborated recursively by an inferential engine, an optimal search sequence can be developed. The reliability and effectiveness of such an approach has been tested using several comparisons with sequences provided by the expert system from Perotti and Kapai (Ref 3).

2. The Expert System Program

Artificial intelligence technologies, particularly, expert systems have already been successfully adapted to aid design of roll pass sequences (Ref 6). The application of expert systems facilitates the introduction of new passes without changing the entire system structure, modularity, flexibility, abstraction, etc. As a result, a heuristic search has been employed to automate the roll pass design completely. The problem has been tackled with the application of space of states (Ref 7). Incremental sequences of states are constructed, starting with an initial state; subsequently, predefined operators

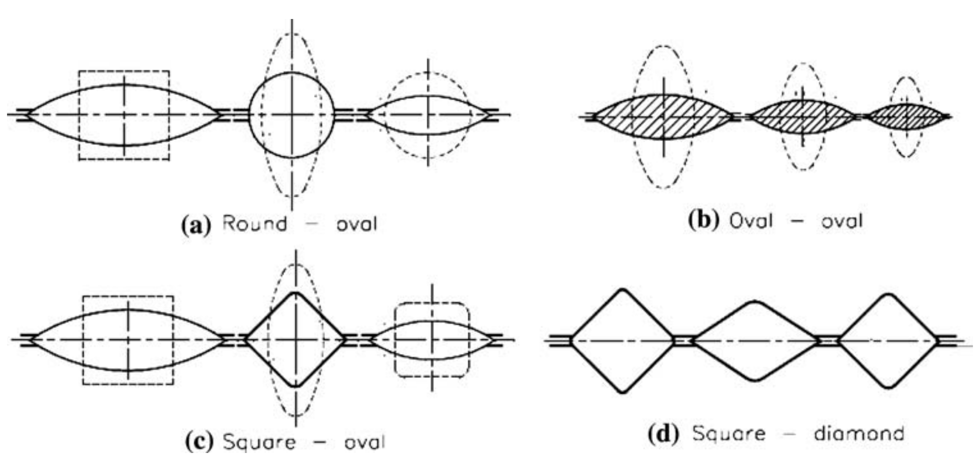

Fig. 1 Examples of rolling sub-sequences

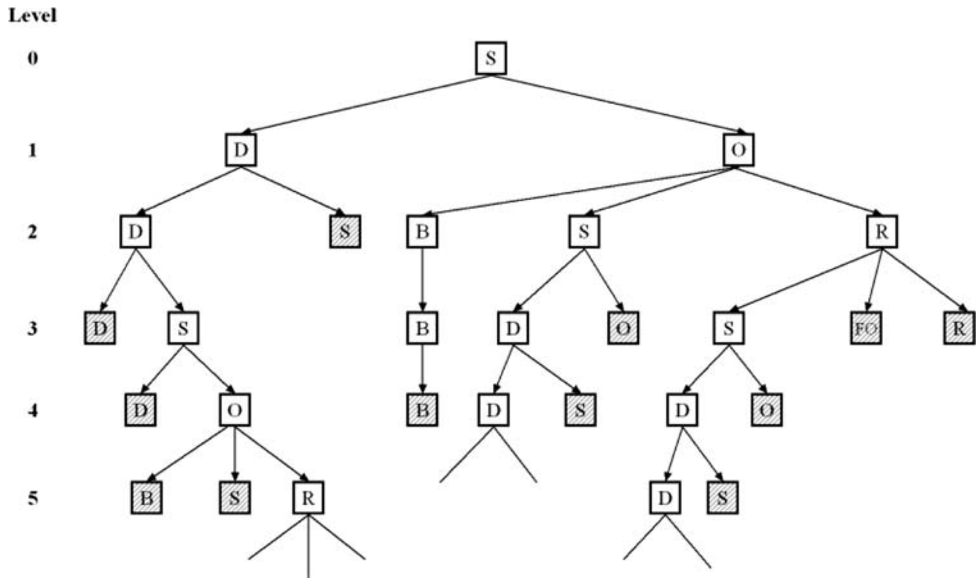

Fig. 2 Graphical representation of the graph approach for path search. The letters represent the geometry of the workpiece's cross-sectional shape. (S) Square, (D) Diamond, (O) Oval, (R) Round, (FO) Flat Oval

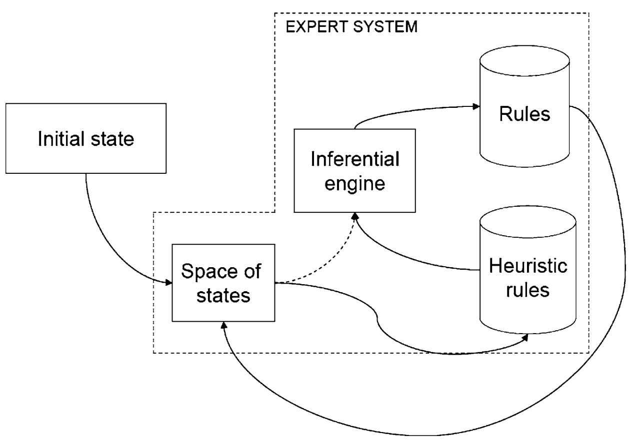

Fig. 3 Expert system module interaction scheme

are applied to the existing state enlarging the space of states and discovering new paths toward the goal state. Such an expansion is represented by a tree graph reported in Fig. 2, where each state is represented as a node (leaf).

There are several ways of conducting the goal state search. However, to achieve an effective search, it is necessary to minimize the proliferation of nodes. This type of search often requires a great deal of time, due to computer memory requirements and may even terminate prematurely.

Generally speaking, the main techniques may be subdivided into two groups, blind search (breadth first and depth first) or heuristic search. The breadth-first method expands nodes in the order in which they are generated (therefore, it is guaranteed to find the shortest-length path to a goal node in the tree). Otherwise, the most recently generated nodes are expanded using the depth-first method (Ref 7).

On the other hand, heuristic search is often difficult to represent and it does not always ensure that the goal node is reached. Deep knowledge of the problem could, however, provide the necessary background for developing efficient and consistent rules to reduce node exploration considerably. An evaluation function (Ref 7) that converts heuristic knowledge into a mathematical form has been used to drive node expansion toward the most probable sequence.

The proposed method is based on an expert system, comprising an inferential engine that interacts with several modules (input, output, elongation, and possible pass modules) as represented in Fig. 3. However, since several roll pass sequences can be engaged to work a given profile starting from a fixed billed, the shortest sequence should be used to increase the efficiency of the process (Ref 8). Therefore, an evaluation function f that sorts the list of nodes to be investigated was employed to favor the shortest sequence.

The expert system inputs are:

– the entry billet size;
– the finished bar size and dimensions;
– the nominal roll radius;
– the initial billet velocity (optional for continuous rolling).

The outputs are:

– the optimal shapes and dimensions of the passes;
– the elongation ratio in each pass;
– the roll velocities (for continuous rolling).

The objective of the search is both to find "the best" roll sequence, (the shortest node path) and to reduce search efforts.

2.1 State Definition, Initial and Goal States

Expert systems generally work with a space of states problem scheme, in which the generic state must represent the information concerning the problem in its entirety. While, in a space of states graph representation, a state is represented by a node, such a representation is not applicable when codifying a computer program; hence, a state is generally represented by a database record (Ref 7), as shown in the first row of Table 1. This table also shows the features of initial and goal states.

Table 1 Characteristics of the initial and goal states and node generation process

	ID	S_{inc}	ID_{dad}	λ	λ_{tot}	λ_{dad}	f	f_{tot}	f_{dad}	Area	Dep	Dep_{dad}
Initial state	0	S_{inc}^{INPUT}	−1	1	1	1	1	1	1	A_{inc}^{INPUT}	0	−1
Goal state		S_{out}^{INPUT}			$> \frac{A_{inc}^{INPUT}}{A_{out}^{INPUT}}$					$> A_{out}^{INPUT}$	0	
Node generation	NAID	S_{out}^{MPN}	ID_C	λ	$\lambda \times \lambda_{tot}^{C}$	λ_{tot}^{C}	f	f_{tot}	f_{dad}	$\frac{Area^c}{\lambda}$	$Dep^C + 1$	Dep^C

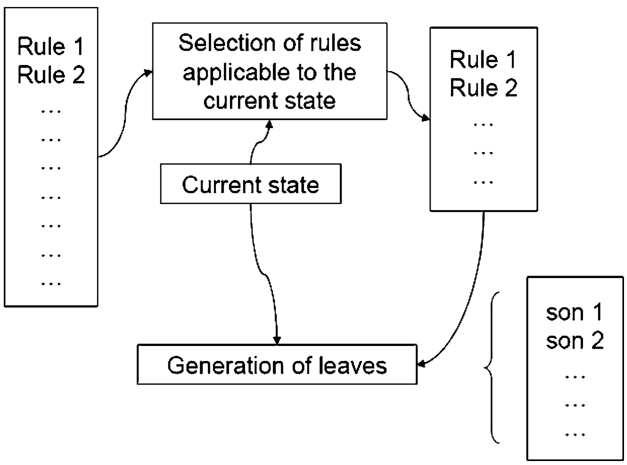

Fig. 4 Scheme for generation of nodes

In this context, the initial state represents the graph tree root. The values of the generic record are, therefore, initialized at the input values of expert system data (second row of Table 1).

The goal state includes the bar characteristics to be produced. These are defined by two features. The cross-sectional shape and cross-sectional area. As the goal state is defined by a disequation, once a node satisfies both requirements, a balancing routine is called upon to modify the elongation ratio of the last two passes to reconcile the dimensions of the finished bar with those desired.

2.2 Set of Rules

As mentioned above, the expert system is based on the incremental proliferation of states, starting with the initial state. Such a node explosion is brought about by the rules that connect a state with all possible states achievable by that state (Ref 7). The procedure scheme of rule selection is shown in Fig. 4. Therefore, the expert system proceeds to select the rules applicable to a state/node to be expanded. The application of a rule to a state causes the generation of another state.

In the case of the hot shape rolling process, the rules contain information about the possible passes employable in rolling sequences (these passes have been gathered using both industrial cases and available bibliographies). The rules can be arranged in a two-column matrix. In the first column is the incoming bar sectional shape (Fig. 5-7), while in the second is the shape of the grooves, as shown in Table 2. The applicability of a rule to a given node is achieved by a ready comparison between the node shape and the left hand side of the rule. Should this comparison provide a positive response, the rule is applied to the current state and a node is generated. The shape of this new state is defined by the right hand side of the rule.

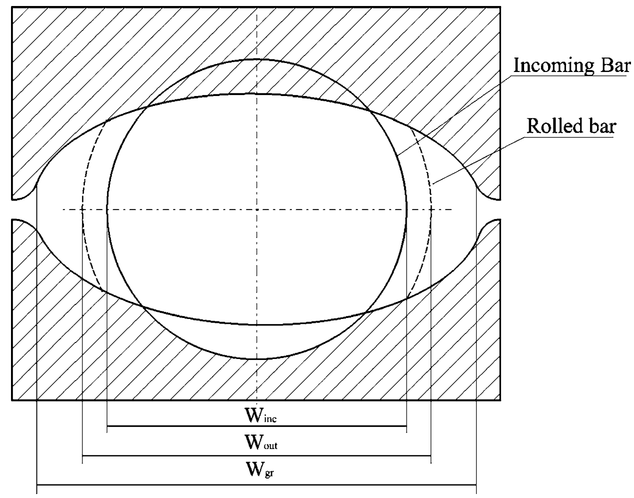

Fig. 5 Representation of the three possible states of a bar inside the groove

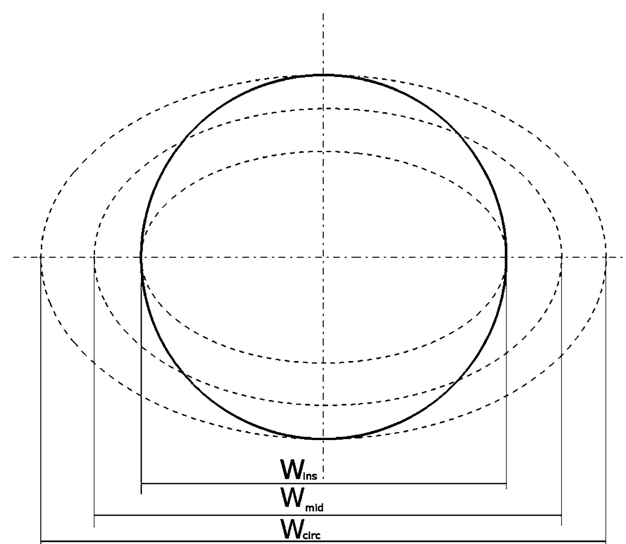

Fig. 6 Initial boundary conditions for the evaluation of the maximum elongation ratio

2.3 Evaluation of the Maximum Elongation Ratio

Since the efficiency of a roll pass depends on the groove filling behavior, a method to evaluate the maximum elongation, achievable in a given pass, was developed. The basic idea is that the maximum elongation ratio for a given pass is achieved

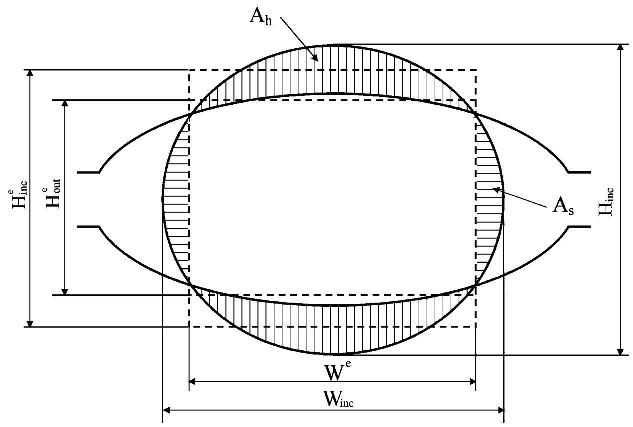

Fig. 7 Geometrical parameters used by Shinokura and Takai (Ref 9) for maximum spread evaluation of a round-oval pass

Table 2 Possible passes used to build heuristic knowledge of the process. The table contains *N* rules; hence, *N* passes can be used

ID	Incoming bar's shape	Groove shape
1	Round	Oval
2	Oval	Round
…		
…		

once the rolled bar width equals that of the groove, so that no material overflow or incomplete filling occur.

Let W_{out} and W_{gr} represent the outgoing bar and the groove widths, respectively. Should the conditions, expressed by Eq 1 arise, part of the rolled material will overfill the groove. On the other hand, if Eq 2 is verified, the groove is not properly filled, and maximum elongation has not been reached. Therefore, the minimum cross-sectional area achievable by a given pass must satisfy Eq 3.

$$W_{out} > W_{gr} \quad \text{(Eq 1)}$$

$$W_{out} < W_{gr} \quad \text{(Eq 2)}$$

$$W_{out} = W_{gr} \quad \text{(Eq 3)}$$

Once the incoming bar dimension is fixed, it is necessary to find the groove geometry which ensures that the optimal filling conditions arise. Hence, a trial approach driven by a bisection rule was used. Let W_{gropt} represent the optimal value of groove width such as would satisfy Eq 3. W_{gropt} certainly undergoes the relation in Eq 4.

$$W_{ins} < W_{gropt} < W_{circ} \quad \text{(Eq 4)}$$

$$W_{gr} = W_{ins} \quad \text{and} \quad H_{gr} < H_{inc} \quad \text{(Eq 5)}$$

$$W_{gr} = W_{circ} \quad \text{and} \quad H_{gr} = H_{inc} \quad \text{(Eq 6)}$$

Equation 5 and 6 represents the boundary conditions for rolling since they involve material overflowing and no contact between rolls and workpiece, respectively. Let $D(x)$ be defined by Eq 7 and W_{out} calculated by Shinokura and Takai model (Ref 9).

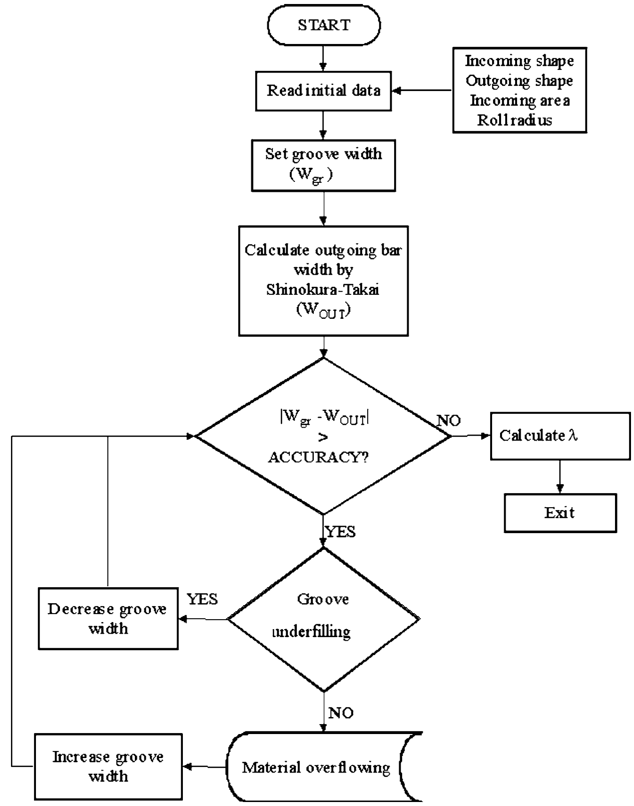

Fig. 8 Flow chart of maximum elongation ratio search

$$D(x) = x - W_{out} \quad \text{(Eq 7)}$$

$$D(W_{ins}) < 0 \quad \text{and} \quad D(W_{circ}) > 0 \quad \text{(Eq 8a)}$$

$$\frac{dD(W_{gr})}{d(W_{gr})} \geq 0 \quad \text{(Eq 8b)}$$

Equation 7 and 8 satisfy the Bolzano theorem hypothesis, since $D(W_{gr})$ is a continuous function and:

$$D(W_{ins}) \times D(W_{circ}) < 0 \quad \text{(Eq 9)}$$

Hence, the root of $D(W_{gr})$, which is the solution of Eq 9, exists and is unique.

In order to find this root value, a bisection rule was employed, which involved building the numerical successions W^i_{min} and W^i_{max} that represent the lower and upper limits of W_{gropt} at the i^{th} iteration. The convergence of these successions allows us to discover the value of W_{gropt}. An iterative algorithm has been developed to solve this issue. The steps are summarized as follows (the flow chart is shown for the purpose of greater clarity in Fig. 8):

1. Evaluate W^{i+1}_{mid} and W^{i+1}_{gr}:

$$W^{i+1}_{gr} = W^{i+1}_{mid} = \frac{W^i_{min} + W^i_{max}}{2}; \quad \text{(Eq 10)}$$

2. Calculate H^i_{gr}:

$$H^{i+1}_{gr} = \frac{W^{i+1}_{gr}}{\text{Ratio}} \quad \text{(Eq 11)}$$

3. Evaluate W^{i+1}_{out} using the model of Shinokura and Takai (Ref 9) as follows:

$$W_{out}^{i+1} = W_{inc}^{i+1}\left(1+\gamma\frac{\sqrt{R\left(\left(H_{inc}^{e}\right)^{i+1}-\left(H_{gr}^{e}\right)^{i+1}\right)}}{W_{inc}^{i+1}+0.5H_{inc}^{i+1}}\times\frac{A_{h}^{i+1}}{A_{inc}^{i+1}}\right) \quad \text{(Eq 12)}$$

$$\left(H_{gr}^{e}\right)^{i+1}=\frac{A_{inc}^{i+1}-A_{h}^{i+1}-A_{s}^{i+1}}{\left(W^{e}\right)^{i+1}} \quad \text{and} \quad \left(H_{inc}^{e}\right)^{i+1}=\frac{A_{inc}^{i+1}-A_{s}^{i+1}}{\left(W^{e}\right)^{i+1}} \quad \text{(Eq 13)}$$

4. Evaluate the convergence:

$$\left|W_{gr}^{i}-W_{out}^{i}\right|<\varepsilon \quad \text{(Eq 14)}$$

The value of ε must guarantee a good groove filling condition. When ε is too small, material overflow could occur due to unexpected rolling conditions, e.g., the incoming bar cross-section is larger than it should be, etc. If ε is too large, incomplete fulfilling takes place. Therefore, a reference value for ε is 0.1 mm.

5. If the relationship is verified, go to step 6. Otherwise, proceed with the comparison of W_{out}^{i} with W_{gr}^{i} and go to step 1:

$$\text{If}: W_{out}^{i+1} > W_{gr}^{i+1} \qquad \text{(Material overflowing)}$$

Increase "i" by one and:

$$W_{max}^{i+1} = W_{max}^{i} \quad \text{and} \quad W_{min}^{i+1} = W_{mid}^{i}$$

$$\text{Else, if}: W_{out}^{i} < W_{gr}^{i} \qquad \text{(Incomplete filling)}$$

Increase "i" by one and:

$$W_{max}^{i+1} = W_{mid}^{i} \quad \text{and} \quad W_{min}^{i+1} = W_{min}^{i}$$

6. Evaluate the λ_{gropt}.

2.4 Inferential Engine

The expert system starts with the search tree initialization by defining the root and the goal node, defined with an implicit approach. Subsequently, the expert system proceeds with the total elongation ratio λ_{tot} evaluation. Thus, the root node is created, and it is put into the *Available* list, where the unexpanded nodes are stored, and the inferential engine starts working. For every pass (represented as a node), the inferential engine evaluates the elongation ratio up to that pass λ_c and compares it with λ_{tot}.

The choice of a pass, among those contained in the *Available* list, is driven by the evaluation function *f*. If λ_c is higher than λ_{tot}, the expert system reduces the elongation ratios of the last two passes of the sequence so that λ_c equals λ_{tot}. Otherwise, the expert system applies the compatible rules to the pass, puts the passes just produced in the *Available* list, and the analyzed pass in the *NotAvailable* list, as shown in Fig. 9.

2.5 The Evaluation Function

An efficient search method has to find the goal solution and contemporaneously reduce the nodes to analyze. When process

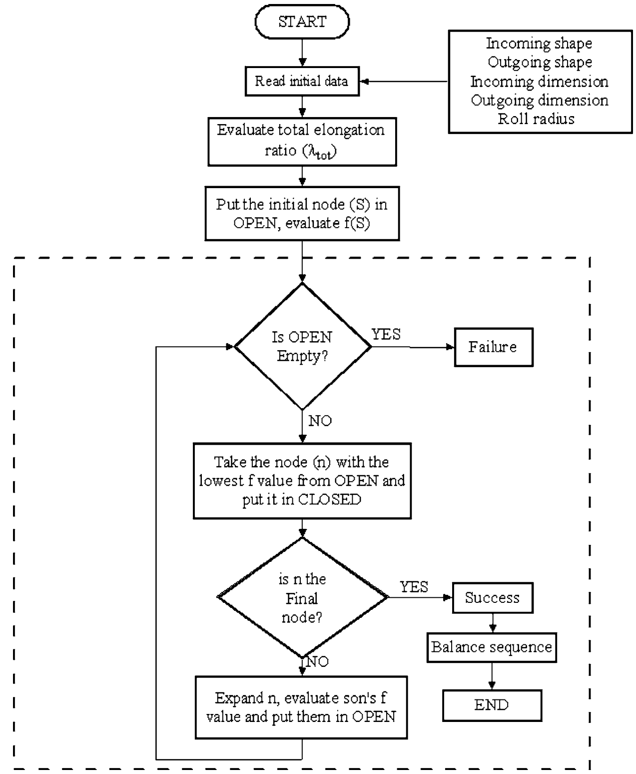

Fig. 9 Flow chart of the minimum path search algorithm. CLOSED is a list of the nodes already investigated (that did not match the goal state)

knowledge is available, it can be used improve the search performances by restricting the possible paths to the solution involving an evaluation function. Therefore, such an evaluation function has to incorporate information about the real process for which the expert system is developed.

Since the efficiency of a roll pass can be measured by the elongation ratio, the idea was that the evaluation function has to be somehow related to λ.

$$f_1 = \sum \lambda \quad \text{(Eq 14a)}$$

$$f_2 = \sum \frac{1}{\lambda} \quad \text{(Eq 14b)}$$

$$f_3 = \prod \lambda \quad \text{(Eq 14c)}$$

$$f_4 = \prod \frac{1}{\lambda} \quad \text{(Eq 14d)}$$

The evaluation functions, Eq 14(c) and (d), are reciprocal to each other; hence, minimizing Eq 14(c) has the same effect as maximizing Eq 14(d) and vice versa. The admissibility and efficiency of evaluation functions Eq 14 can be compared by analyzing the behavior of the search strategy suggested by each one.

The efficiency of some functions (i.e., Hi$\{f_1\}$, Hi$\{f_2\}$, and Lo$\{f_2\}$) is lower than that of breadth first. For these functions, the search strategy penalizes passes with high elongation ratio values.

Like breadth first, the functions Lo$\{f_1\}$ and Lo$\{f_3\}$ are sure to find the shortest sequence, since the search strategy is "horizontal". Until a level contains a node not explored, the search does not jump to a deeper level. Hence, their admissibility is unitary.

The functions Hi$\{f_1\}$ and Hi$\{f_3\}$ are more effective than depth first, since they cause the search to converge toward those passes with the highest elongation ratio values. On the other hand, the functions Hi$\{f_1\}$ and Hi$\{f_3\}$ (and Hi$\{f_2\}$) are very low in terms of admissibility because of their constant expansion of new level nodes, they by no means ensure that the right solution is found.

Considerations on Lo$\{f_2\}$ are even more qualitative. In fact, only upper and lower limits are available on the efficiency and admissibility of this function. Certainly, Lo$\{f_2\}$ is more admissible than Hi$\{f_1\}$, Hi$\{f_2\}$, Hi$\{f_3\}$, and depth first since it allows a return to the upper levels of the tree; hence, this represents the lower limit of Lo$\{f_2\}$ admissibility. Moreover, the efficiency of Lo$\{f_2\}$ is higher than breadth first since complete analysis is not required on an entire level before proceeding to deeper levels. These considerations are summarized in Fig. 10. In order to demonstrate the admissibility of the evaluation function Lo$\{f_2\}$, it is crucial to analyze its behavior during the search. Indeed, when the numerical succession of Lo$\{f_2\}$ is strictly increasing, this means that:

$$\forall N_1, N_2 \in N : N_1 < N_2 \quad \mathrm{Lo}(f_2(N_1)) < Lo(f_2(N_2)) \qquad \text{(Eq 15)}$$

Hence, if node proliferation is driven by Lo$\{f_2\}$, the first pass matching the goal state also defines the shortest sequence.

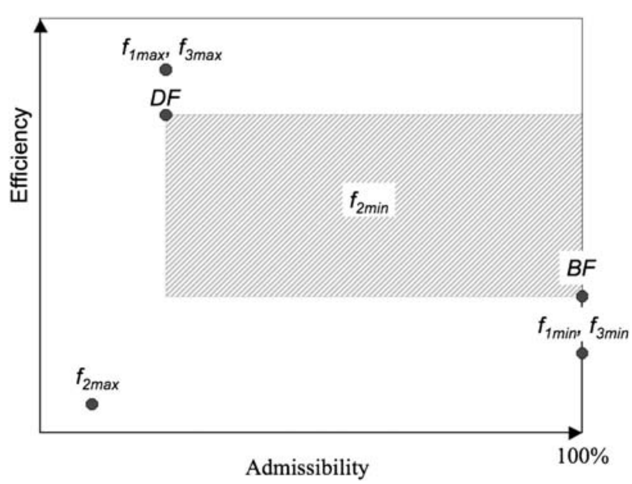

Fig. 10 Qualitative comparison of the features (efficiency and admissibility) of the evaluation functions (15). No information is available on the efficiency of $f_{2\min}$. It is only possible to estimate the upper and lower bounds of its efficiency

Then:

for $N = 1$

$$\lambda_1^1 = \lambda_{\mathrm{tot}} \quad \text{and} \quad \mathrm{Lo}(f_2(1)) = \frac{1}{\lambda_1^1} = \frac{1}{\lambda_{\mathrm{tot}}}$$

for $N = 2$

$$\lambda_2^1 \times \lambda_2^2 = \lambda_{\mathrm{tot}} \rightarrow \lambda_2^2 = \frac{\lambda_{\mathrm{tot}}}{\lambda_2^1} \quad \text{and}$$

$$\begin{aligned}\mathrm{Lo}(f_2(2)) &= \frac{1}{\lambda_2^1} + \frac{1}{\lambda_2^2} = \frac{1}{\lambda_2^1} + \frac{\lambda_2^1}{\lambda_{\mathrm{tot}}} = \frac{1}{\lambda_{\mathrm{tot}}}\left(\frac{\lambda_{\mathrm{tot}}}{\lambda_2^1} + \lambda_2^1\right)\\ &= \frac{1}{\lambda_{\mathrm{tot}}}\left(\lambda_2^1 + \lambda_2^2\right) > \frac{1}{\lambda_{\mathrm{tot}}} \end{aligned} \qquad \text{(Eq 16)}$$

therefore

$$\mathrm{Lo}(f_2(1)) < \mathrm{Lo}(f_2(2)) \qquad \text{(Eq 17)}$$

Equation 16 is verified because the terms inside the round brackets are both higher than one. By induction of Eq 17, it follows that Lo$\{f_2\}$ is a strictly increasing numerical succession.

3. Comparison with Automatic System Developed by Perotti

Since Kim and Im (Ref 4) did not report all the geometrical input data of their sequences, it was only possible to perform a comparison of the model developed by Perotti and Kapai (Ref 3). The reliability and effectiveness of the developed evaluation function were evaluated by a direct comparison with breadth first and depth first search strategies.

Perotti and Kapai showed the results of their model applied to three cases. The geometrical characteristics, summarized in Table 3, were used to replicate the experiment and find the optimal sequence according to the new automated rolling sequence designer. The expert system inferential engine also used breath first and depth first approaches to provide a comparison of these methods with the evaluation function proposed, in terms of accuracy (number of passes composing the rolling sequences) and effectiveness (number of investigated nodes), as reported in Table 4.

4. Results of Simulations

Table 3 summarizes the characteristics of the simulated sequences with regard to the previous automated system. In all

Table 3 Characteristics of the sequences designed by Perotti and Kapai (Ref 3)

Sequence	S_{inc}	S_{out}	A_{inc}, mm^2	A_{out}, mm^2	R, mm	Older approach N	Older approach λ_{mean}	Newer approach N	Newer approach λ_{mean}	Percentage passes reduction
1	Square	Square	13,903	6812	500	4	1.195	2	1.42	50
2	Square	Square	6200	243	500	10	1.382	7	1.59	30
3	Square	Square	875	138	350	6	1.36	5	1.30	18

Table 4 Characteristics of the sequences proposed by the expert system relative to sequences 1, 2, and 3.

Sequence	N			Number of investigated nodes			λ_{mean}
	HE	BF	DF	HE	BF	DF	
1	2	2	3	8	11	2	1.42
2	7	7	9	1211	2787	10	1.59
3	5	5	6	174	287	8	1.30

HE—heuristic search; BF—breadth first; DF—depth first

Table 5 Measurements of search strategy performance.

Sequence	N	Number of nodes generated (T)		Penetrance		Effective branch	
		BF	HE	BF	HE	BF	HE
1	2	21	21	0.09524	0.09524	4.00	4.00
2	7	8710	3574	0.00080	0.00196	3.48	3.05
3	5	898	541	0.00557	0.00924	3.65	3.28

HE—heuristic search; BF—breadth first; DF—depth first

the three cases, the developed method reduced the number of passes by 18-50% compared to the model of Perotti and Kapai (Ref 3).

The comparison of the number of passes, calculated by the heuristic, the breadth first, and the depth first approaches, and reported in columns 2, 3, and 4 in Table 4, provides important information about the reliability of search strategies. Since the breadth first approach analyzes all nodes, it is fully reliable. Therefore, this represents a good means of comparison for analyzing the heuristic and depth first approaches.

Because columns 2 and 3 of Table 4 are equivalent, the heuristic search finds rolling sequences equivalent to the breadth first approach, and the proposed method is fully reliable. On the contrary, since columns 3 and 4 are unequal, the depth first approach finds sequences with more passes than the breadth first method does, and the depth first approach is not reliable. The number of investigated nodes, as shown in columns 5-7 of Table 4, provides a direct way to evaluate the effectiveness of the search strategies. The sensible difference between the columns 5 and 6 of Table 4 underlines the extreme effectiveness of the heuristic approach over the breadth first method, which examines even more than 230% of the nodes inspected by heuristic search for the second sequence of Table 3. Moreover, the sensible difference in terms of penetrance and especially effective branching coefficient, which are summarized in Table 5, confirms the previous consideration. The penetrance of a search measures the extent to which the search has focused toward a goal rather than wandered off in irrelevant directions. Penetrance is defined as the ratio of the length of the path found to the goal to the total number of nodes generated during the search. However, penetrance can be affected by the solution length. Indeed, increasing the length of the solution path usually causes the total number of generated nodes to increase even faster (Ref 7). The effective branching factor is nearly independent of the length of the optimal solution path. Its definition is based on imagining a tree having a depth equal to the path length and a total number of nodes equal to the number effectively generated during the search. Then, the effective branching factor is the constant number of successors that would be possessed by each node in such a tree (Ref 7).

The behavior of the heuristic approach during the goal node search is shown in Fig. 11, which plots the elongation ratio trend versus the iteration evolution. Indeed, while the breadth first method produces a chaotic search, as shown in Fig. 11(a, c, e), the heuristic strategy presents a clear tendency and data are less scattered, as shown in Fig. 11(b, d, f). Indeed, the evaluation function generates several separated iso-level curves on which are placed the nodes belonging to same depth level are placed.

Each iso-level presents a decreasing trend. Hence, the passes with the higher elongation coefficient are the first investigated. Furthermore, there is a partial vertical overlap among these curves that permits a jump from one level to a deeper one, without fully investigating the last one. This improves search efficiency, as it causes the search to be streamed toward the most probable solution without any constraint.

5. Conclusions

An expert system for an automatic roll pass design has been developed. In order to gain maximum efficiency from this process, an attempt has been made at geometrical optimization through the use of complete groove filling criteria.

Actually, by increasing the draught of the material, not only does the elongation increase, but also the spread. The relation between draught and elongation was used to evaluate the maximum obtainable elongation in a pass, under the circumstance that the bar fills the groove in a proper way.

The maximum elongation ratio evaluation allows us to avoid the use of the old approach that forced the roll pass designers to rely on empirical rules. Indeed, the employment of Shinokura and Takai's model, based on the equivalent rectangle method, represents a more flexible way to analyze roll passes. However, since this model was validated for a limited number of passes,

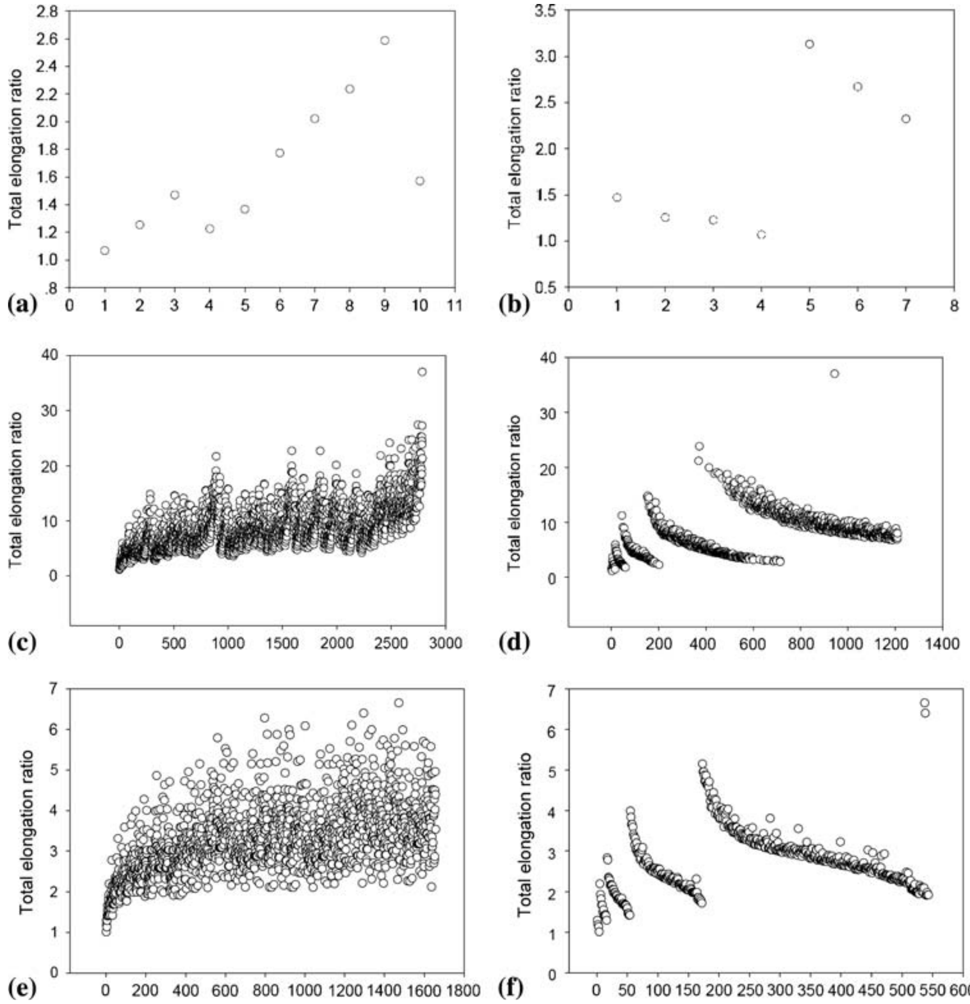

Fig. 11 Elongation coefficient values versus number of iterations performed by the expert system while finding the optimal sequence for comparison with Perotti and Kapai (Ref 3). The successions obtained by breadth first and heuristic approaches are reported on the left hand side and on right hand side, respectively

finite element methods were used for the validation of the remaining passes.

FEM support has proved to be extremely important, given the lack of experimental data and the many difficulties involved in reproducing hot rolling process with in house tests. FEM remains, moreover, as an excellent way of accurately simulating new roll passes for further development and expansion of the expert system.

The authors have attached a great deal of importance to the expansibility, and to this end, have attempted to develop a fully modular system that may be further developed with ease, thanks to the employment of object oriented programming.

The implementation of this expert system, along with hybrid data provided by finite element simulations, has proved to be a very effective and flexible solution. The application of these tools may therefore represent valuable support for multi-step process design and optimization.

6. Future Perspectives

Although the proposed system for the automated design of roll pass sequences can be effectively employed for industrial purposes, it still needs some integrations. Indeed, it does not take into account the power requirements and specific contact pressure between the rolls and the incoming work-piece. These limitations will be overcome in the future by the development of a new module for power forecasting. Such a module will define the available values of mill motors as an input function, and appropriately adjust the rolling sequence by limiting the maximum elongation ratio.

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