ABSTRACT
This paper describes a new approach towards optimum selection of the different parameters of the mould oscillation system in the continuous casting process of steel manufacturing. The objective of optimization is to enhance lubrication within the mould, especially at higher casting speeds, and reduce the intensity of oscillation marks. The need to improve lubrication conditions is primarily addressed by making the mould oscillate on its longitudinal axis. It is known that non-sinusoidal oscillation, where the time for upward motion of the mould is longer than that of downward motion in an oscillation cycle, reduces depth of oscillation marks while providing better lubrication. In the present work, a Genetic Algorithm is applied to optimize the amplitude, frequency, and waveform of the oscillation of the continuous casting mould based on objective functions that maximize the lubrication, and minimize the depth of oscillation marks and the cycle peak friction. Optimization is performed within constraints imposed by machine limits. The objective function and constraints are extracted from an analysis of the physics of oscillation, lubrication and heat transfer within the continuous casting process. The application of the Genetic Algorithm within a unified framework encompassing all oscillation performance metrics and constraints is seen to generate an optimal parameter set that provides better performance than existing oscillation parameters supplied by Original Equipment Manufacturers.

Index Terms Continuous casting process, oscillation marks, lubrication, peak friction, amplitude, frequency, casting speed, waveform, Genetic algorithm, fitness, constraints.

INTRODUCTION
Continuous casting is a critical step in the steel manufacturing process where molten metal is solidified in the form of slabs of rectangular cross-section. Minor variations in this step can impact the production process widely – from excellent product quality to breakdown in the production chain.

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In continuous casting the steel from a ladle is teemed to a tundish that acts like a buffer vessel. From the tundish, through a bifurcated submerged entry nozzle, the liquid steel is poured into a water-cooled copper mould about a meter in length. Water is circulated through slots in the mould to extract heat transferred from the liquid steel. Consequently, a thin solidified steel shell develops next to the mould inner walls whereas the steel remains liquid inside this shell. The solidified shell grows in thickness even as it is continuously withdrawn from the mould on rollers and further cooled using water sprays. Finally, the completely solidified slab of required length is cut from the continuously cast ‘strand’. The schematic representation of continuous casting is shown in fig 1, see also [1].

The continuous casting process itself is facilitated by two interlinked sub-processes, namely, mold oscillation and lubricant addition. These essentially seek to neutralize two major problems associated with continuous casting – sticking of the formative steel shell to the internal walls of the mould, and non-uniform development of shell across the strand perimeter due to uneven heat transfer.

The mold is made to oscillate along its longitudinal axis with an amplitude less than 10 mm and frequency between 50 and 250 cycles per minute (cpm). The oscillation directly helps in detaching the solidified shell from the mould wall (like an AC current ‘disengages’ a human finger in touch with a live wire), and indirectly enables the lubricant placed at the meniscus of the strand to penetrate uniformly further down into the small gap between the shell and mould.

Lubricant in the form of solid powder is poured from the top onto the meniscus where it melts in contact with the hot material. The liquid ‘lubricant’ then penetrates into the gap between strand and mould. Both upward and downward movements in the oscillation cycle enable this penetration. Since the strand inside the mould is always moving downwards with a certain speed (the ‘casting speed’), in relative terms the mold moves downward only when its downward speed is greater than strand speed. This part of the oscillation cycle is referred to as “negative strip” while its supplement is “positive strip”. While negative strip aids in deeper penetration of lubricant, the positive strip pulls the lubricant from meniscus top towards the sides and also enables uniformity of spread within this gap.
Neutralization of the prime problems of continuous casting using oscillations leaves certain side effects. These are, firstly, the formation of ‘oscillation marks’ on the slab surface during negative strip [2] that look like cracks. Apart from being a quality issue in itself, these marks also tend to degenerate into fault lines for the formation of transverse cracks. Secondly, during the positive strip the relative speed between strand and mould maximizes leading to a ‘peak friction’ which is higher than what would have been under non-oscillating conditions. This peak friction can potentially cause tearing of the formative shell near the meniscus, leading to sticking. Thus it is apparent that the designer of oscillation strategies has to plan for maximizing the desirable effects, while minimizing the undesirable ones.

The oscillation designer does not have too many degrees of freedom in his hand for effecting an optimization as above. Only the oscillation frequency $f$ and amplitude $s$ (stroke) are available. Suzuki and others [3] showed that the waveform could also be varied from the sinusoidal with gainful effects. Slower speed and longer time for upward movement, accompanied by faster and shorter downward plunge, as shown in fig. 2., will result in smaller negative strip time (time spent in negative strip within one cycle) as well as lower peak friction. Reduction in negative strip time is illustrated in fig. 3, while the reduction in peak friction with lower upward maximum speed is obvious. Using $\tau$ (=0.5 for sinusoidal and 0.5 < $\tau$ < 1 for gainful non-sinusoidal) to indicate degree of variation from sinusoidal, the designer now has $s$, $f$ and $\tau$ as free parameters. He has to select an optimum schedule of these parameters across the range of casting speed $v$ to achieve maximum lubrication with minimum peak friction and oscillation mark depth. The quality and productivity of steel manufacture depends significantly on this choice.

In this work a Genetic Algorithm (GA) is used for the above optimization. Oscillation performance metrics are constructed based on calculated Lubrication Index and predicted peak friction and depth of oscillation marks. These metrics are used within an objective function to be optimized to achieve that scheduling of $s$, $f$ and $\tau$ with $v$ that provides best oscillation performance.

The section below describes the oscillation performance metrics. The next section outlines the optimization method, with fitness functions and constraints. Finally results are discussed and conclusions drawn.

**OSCILLATION PERFORMANCE METRICS**

The primary function of oscillation is to maximize lubrication between the strand and mould. As explained in the last section, this is effected in two ways, first, by creating a detachment between the strand and mould, and second, by facilitating entry and spread of lubricant into the thin gap between the two. Using LI to denote Lubrication Index, it follows that one of the tasks of optimization is to maximize LI.

Likewise one may denote Peak Friction and depth of Oscillation Marks as PF and OM respectively. As discussed, these are the two undesirable side effects of oscillation and obviously they are sought to be minimized.

From above considerations one may define a performance metric $PM_1$ for maximization as

$$PM_1 = w_1 \times (LI)^2 - w_2 \times (PF)^2 - w_3 \times (OM)^2$$  \hspace{1cm} (1)

For the purpose of optimization a fitness function needs to be defined that can be expressed in terms of the free parameters $v$, $s$, $f$ and $\tau$ denoting casting speed, stroke,
frequency and deviation from sinusoid, respectively. This function would provide the performance ‘fitness’ of any selected parameter set \( \{v, s, f, \tau\} \). It is shown in the next section that the effect LI can be explicitly defined in terms of these parameters. However, PF and OM are dependent on many lateral conditions and a reliable mapping between the parameter set and these effects cannot be easily extracted, thus ruling out direct use of metric PM1 within a fitness function for simulated optimization.

Figure 4 provides a view of the physical relationship between the free parameters and the three effects. Each effect is shown as a circle, with a ‘+’ or ‘-’ at the top denoting desirability or otherwise. The arrows represent the four free parameters, with a ‘+’ or ‘-’ next to the arrow denoting direct, indirect or no relationship with the effect shown in the corresponding circle, when other parameters are held constant. If the product of the sign shown near an arrow and the sign within the circle is a plus, the parameter is desirable from the viewpoint of that effect, else it is undesirable. Thus, if a circle is negative, and a parameter varies inversely with the effect shown in that circle, then it is desirable to increase this parameter.

The figures themselves need a physical explanation. As stated in the introduction, also [3], [4], increasing \( \tau \) reduces peak friction as also the depth of oscillation marks. Thus \( \tau \) contributes negatively to these circles. From detailed analysis of the mechanism of formation of oscillation marks, as in [5] or [2], it is known that higher frequency damps oscillation mark depth while stroke increases it. The signs are shown accordingly. Considering peak friction, both frequency and stroke increase mold upward velocity and hence amplify PF. As for lubrication, it is understood that higher stroke has a beneficial effect while frequency tends to mildly damp it ([2], [4]), the figures reflect accordingly.

From an analysis of the above figures, and the physics behind these figures, one can generate a substitute for PM1 bypassing the need for explicit mathematical relationship between PF & OM, and the parameter set \( \{v, s, f, \tau\} \). Since LI can be expressed mathematically, the focus is on PF and OM. From fig. 4, one may see that stroke \( s \) is undesirable for both. Frequency \( f \) is undesirable from the viewpoint of PF, but desirable for OM. If one considers OM as more critical, then it is desirable to increase \( f \) but the relationship is not as explicit as in case of stroke. Accordingly, a new performance metric PM2 may be created for maximization as

\[ \text{PM2} = w_1 \times (LI)^2 - w_2 \times (s)^2 + w_3 \times (f)^2 \] (2)

where one would like to choose

\[ w_3 \ll w_2 < w_1 \] (3)

Different choices of the weights representing physical conditions as described above will produce a Pareto front upon optimization; the designer’s engineering preferences will enable him to select his own choice of weights.

OPTIMIZATION USING GENETIC ALGORITHM

In this section the mathematical relationship between Lubrication Index LI and the parameter set \( S = \{v, s, f, \tau\} \) is described, from which an explicit expression for fitness function can be constructed. The constraints based on machine limits are stated. Features of the Genetic Algorithm (GA) used for optimization are then described.

Araki and Ikeda [4] have proposed a relationship between LI and other intermediate casting variables, which in turn may be described in terms of parameter set \( S \). This relationship has been shown to be working well on comparing computed LI with rate of powder (lubricant) consumption, which is an indication of the effectiveness of oscillation in enhancing lubrication. The authors have independently verified this relationship by performing simulations on the IISI website [1]. The relation states

\[ LI = R_{NA}^{0.3} \times \rho_p^{0.5} \] (4)

where \( R_{NA} \) is defined as

\[ R_{NA} = \frac{N_d}{V_c} \times 100 \] (5)

with \( N_d \) the negative strip distance, i.e. distance covered in negative strip in one cycle, \( V_c = v \), and \( t_p \) the positive strip time.

Further, the negative strip distance \( N_d \) may be expressed as

\[ N_d = s \sin(\pi f t_{neg}) - V_c t_{neg} \] (6)

where \( t_{neg} \) is the negative strip time expressed as

\[ t_{neg} = \frac{2(1-\tau)}{\pi f} \cos^{-1}\left(\frac{4(1-\tau)V_c}{\pi^2 sf}\right) \] (7)

Equations (6) and (7) for non-sinusoidal oscillations are according to [6], under sinusoidal conditions, i.e. \( \tau = 0.5 \), they reduce to standard equations for negative strip found in open literature, i.e.

\[ t_{neg} = \frac{60}{\pi f} \times \cos^{-1}\left(\frac{V_c}{\pi sf}\right) \] (8)

with positive strip time \( t_p \) defined as

\[ t_p = \frac{60}{f} - t_{neg} \] (9)

In the above expressions all times \( t \) are defined in seconds, frequency in cycles per minute, speeds in millimeters per sec and stroke \( s \) in millimeters.

Substituting eq. (7) in eqs. (6) and (9), eq. (6) in eq. (5), and eqs. (5) and (9) in eq. (4), one may write the expression for LI as

\[ LI = \left[ \frac{100 f s \sin^{-1}\left(\frac{2V_c (1-\tau)}{\pi fs}\right)}{V_c} - \frac{2V_c (1-\tau) \cos^{-1}\left(\frac{2V_c (1-\tau)}{\pi fs}\right)}{\pi fs} \right]^{0.3} \times \]

\[ \left\{ \frac{60}{f} \times \frac{2V_c (1-\tau)}{\pi fs} \frac{2V_c (1-\tau) \cos^{-1}\left(\frac{2V_c (1-\tau)}{\pi fs}\right)}{\pi fs} \right\}^{0.35} \] (10)
The fitness function is obtained by substituting eq. (10) in eq. (2) for PM2, thus providing a performance measure for any selected parameter set S.

Constraints are defined in terms of the following expressions:

\[ 80 \leq f \leq 200 \]  
\[ 2 \leq s \leq 10 \]  
\[ 0.5 \leq \tau \leq 0.7 \]  
\[ \frac{s\pi f}{2(1-\tau)} \leq 0.8 \times V_{\text{max}} \]  
\[ \frac{s\pi^2 f^2}{2(1-\tau)^2} \leq 0.8 \times a_{\text{max}} \]

While relations (11-13) are generally taken as standard limits for mold oscillation and considered here accordingly, the LHS of relations (14-15) are derived from equations describing non-sinusoidal waveforms and correspond to the maximum attainable values of velocity and acceleration for a selected waveform. These are set to be less than 80% of the machine limits, expressed as \( V_{\text{max}} \) and \( a_{\text{max}} \).

A GA is used to derive that parameter set \( S \) which maximizes the fitness function defined by performance metric PM2. In this process the casting speed \( v \) is fixed, and \( s \), \( f \), and \( \tau \) are evaluated as a function of \( v \). Different values of \( v \) are fed as input, the GA generates corresponding optimal sets of \( s \), \( f \) and \( \tau \).

A baseline GA process is well known and not described here. The parameters to be optimized, namely \( s \), \( f \), and \( \tau \), are binary coded and concatenated to form bit strings (chromosomes) that constitute the population members operated upon in parallel. Each of the parameters are encoded using 10 bits, which implies that their respective ranges of variation, eqs. (11-13), are discretized into 1024 intervals, and that each chromosome is 30 bits long. In every generation the fitness of a population member is evaluated by calling the fitness function, expressed as eqs. (2) & (10).

Genetic Algorithms tend to slow down after nearing an optimum solution point in the n-dimensional (here \( n = 3 \)) solution space, and some means are usually implemented for accelerating the GA process. The acceleration methods used here are, first, elitism [7] where the best solution obtained in a certain generation is preserved in succeeding generations until a better one is found thus preventing ‘loss’ of good solutions, second, cyclical variation of mutation rate across generations [8], and third, differential mutation of bits according to significance in good and bad schema in solution strings [9][10].

RESULTS

The Genetic Algorithm as described above is used to optimize the oscillation parameters stroke, frequency and deviation from sinusoid, with the objective of maximizing lubrication and minimizing peak friction and oscillation marks. This is achieved by optimizing the fitness function according to eqs. (2) and (10), under the constraints expressed in relations (11-15).

The GA is tested with different population sizes and a size of 20 is selected for performing downstream executions. A test case with \( w_1 = 0.85 \), \( w_2 = 0.13 \) and \( w_3 = 0.02 \) (refer eq. 2) is taken at \( v = 1.4 \), and the variation of convergence history and final converged solution with arbitrary changes in initial population is observed. The solution is stopped after 5000 generations, a stage when it is assumed to have fully converged. Variations in convergence are seen only within the first 1000 generations; the final solution is always same with practically no variation. The convergence history is shown in figs. 5 & 6 for this test case, fig. 5 shows convergence of fitness function, and fig. 6 the evolution of stroke and frequency for first 600 generations. This case takes less than a minute of computation time on a Pentium D 2.6 GHz desktop.

Production runs are executed to cover the entire range of casting speed, from 0.05 meters/min to 1.95 m/min, at intervals of 0.05 m/min. The resultant values of \( s \), \( f \), and \( \tau \) for each case were tabulated, with the objective of generating a schedule for the oscillation parameters against casting speed. In each speed case the complete GA solution over 5000 solutions was executed. The net computation time is approximately 30 mins. on the mentioned desktop.

Figure 7 shows variation of stroke and frequency with casting speed as obtained from the above runs. The value of \( \tau \) quickly converges to the maximum (0.7) and hardly moves from there across the speed range, and hence this is not plotted. Recall from fig. 4 that increased \( \tau \) was desirable from the perspective of all 3 effects, and the GA solutions strongly confirm this. Fig. 7 shows that the trends in stroke and frequency undergo reversal within the speed band of 1-1.4, this happens due to the nature of the fitness function in eqs. (2) & (10).

This optimization approach will add genuine value to the steel manufacturing process only if it can be demonstrated that better lubrication with reduced peak friction and oscillation marks are attained in comparison to running oscillation conditions provided by the Original Equipment Manufacturer (OEM). To examine this, the oscillation schedule set by the OEM was extracted. Permission to show plots of frequency and stroke against casting speed for this case, akin to fig. 7 for the GA solution, is not available. However, the effects of the two oscillation schedules, in terms of lubrication index, peak friction factor and negative strip time – proportional to depth of oscillation marks – are compared in figs. 8-10.
The values of s, f and τ, both from GA and OEM, at different v are used in eq. (10) to obtain the corresponding variation of LI with casting speeds. The comparison is shown in fig. 8. In the speed range 0.6 to 1.3 (meters/min always), LI from GA is observed to be nearly twice of that from OEM. A similar advantage is seen at speeds above 1.6, while at all other speeds GA solution invariably provides better lubrication index.

At a given value of v (≥\(V_c\)), the peak friction PF may be expressed as

\[ PF = \eta \frac{V_{up}^{\text{max}} - V_c}{d} \]  

(16)

where \(V_{up}^{\text{max}}\) is the maximum upward speed in a cycle, \(\eta\) is the viscosity of lubricant and \(d\) the thickness of lubricant film in the gap between strand and mould. The latter two being extraneous factors to an oscillation schedule, a Peak Friction Factor PFF may be defined such that

\[ PF = k \cdot \text{PFF} \]  

\[ \text{PFF} = \frac{V_{up}^{\text{max}} - V_c}{\eta / d} \]  

(17)

and

\[ k = (\eta / d). \]

PFF obtained from the two approaches are plotted in fig. (9). It is seen that PFF from GA is significantly less in comparison to OEM up to speed of 1.3, and again above speed of 1.5. In the intermediate range, GA solution continues to provide lower PFF.

Negative strip times \(t_{\text{neg}}\) (eq. 7) from GA and OEM are compared in fig. 10. It may be noted that negative strip time directly relates to depth of oscillation mark, but it also contributes directly to lubrication. However, the latter functionality is accounted for in the expression for LI, and if the latter values are satisfactory one only needs to look at variation of oscillation mark depth in fig. 10. It is seen that in the entire range of casting speed, the oscillation parameter schedule provided by GA generates shallower oscillation marks as compared to the OEM-provided schedule.

CONCLUSIONS

An optimal free parameter set consisting of stroke s, frequency f and deviation from sinusoidal waveform τ, for the oscillating mould in the continuous casting process of steel manufacturing, has been designed using a Genetic Algorithm where the fitness functions and constraints have been synthesized from prior knowledge of cross-parametric physical relationships. Compared to the parameter set implemented according to the Original Equipment Manufacturer, the GA set provides favorable performance for all individual oscillation effects like lubrication, peak friction and depth of oscillation mark across the entire range of casting speed.

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Fig. 2. Displacements in Sinusoidal & Non-sinusoidal oscillations

Fig. 3. Negative strip time along with velocity in sinusoidal and non-sinusoidal oscillations

Fig. 4: Impacts of different parameters on described effects, LILubrication Index, PF-Peak Friction, OMOscillation Mark. Casting speed- \( v \), Stroke- \( s \), Frequency- \( f \), Dev. from sinusoid- \( \tau \); a ‘+’ or a ‘-’ next to a directed line denotes that the impact of the parameter on the effect is direct or inverse.
Fig. 5. Convergence history of fitness value; converged after 2500 generations, however, all optimization runs allowed to continue till 5000 generations for perfect repeatability.

Fig. 6. Evolution of stroke and frequency across generations, practically converged after 2500 generations.

Fig. 7. Variation of frequency and stroke with casting speed, as generated by Genetic Algorithm.

Fig. 8. Variation of Lubrication with casting speed, comparing GA solution with OEM-provided values.

Fig. 9. Variation of Peak Friction Factor (PFF) with casting speed, comparing GA solution with OEM-provided values.

Fig. 10. Variation of negative strip time with casting speed, comparing GA solution with OEM-provided values.