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Model-based multi-objective optimisation of reheating furnace operations using genetic algorithm

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Abstract

An effective optimisation strategy for metal reheating processes is crucial for the economic operation of the furnace while supplying products of a consistent quality. An optimum reheating process may be defined as one which produces heated stock to a desired discharge temperature and temperature uniformity while consuming minimum amount of fuel energy. A strategic framework to solve this multi-objective optimisation problem for a large-scale reheating furnace is presented in this paper. For a given production condition, a model-based multi-objective optimisation strategy using genetic algorithm was adopted to determine an optimal temperature trajectory of the bloom so as to minimise an appropriate cost function. Definition of the cost function has been facilitated by a set of fuzzy rules which is easily adaptable to different trade-offs between the bloom desired discharge temperature, temperature uniformity and specific fuel consumption. A number of scenarios with respect to these trade-offs were evaluated and the results suggested that the developed furnace model was able to provide insight into the dynamic heating behaviour with respect to the multi-objective criteria. Suggest findings that current furnace practice places more emphasis on heated product quality than energy efficiency.

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Keywords: zone model; reheating furnace; multi-objective optimisation; genetic algorithm

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1. Introduction

In every hot rolling plant steel reheating represents a critical process to ensure optimal end-product quality. Energy consumption in a reheating furnace highly depends on a number of factors such as steel grade, stock dimension, production rate, and desired reheating temperature and temperature uniformity. Improved reheating furnace operation may lead to indirect energy saving through improving product quality and thereby reducing product rejects. Estimated energy savings based on reducing rejects from 1.5% to 0.2% was 9% of energy consumption or approximately 0.3 GJ/tonne-product [1]. As such, optimisation of furnace operations has received considerable attention in the past decade or so. Of all the work reported, it may be concluded that experiment based optimisation is generally unfeasible from the economical point of view due to the high operating cost of the furnace system [2]. Alternatively, model based optimisation is more favourable, at least for initial design study, as it is possible to explore a wide range of design options rapidly and at low cost. As a result, by eliminating non-feasible cases, the findings from model based optimisation studies would considerably reduce the amount of experimental studies necessary for further validation and fine tuning [3]. As the name implies, an important pre-requisite of any model based optimisation study is the availability of a process model of reasonable fidelity. In general, this can be divided into two categories, namely those which are based on first principles [4] or alternatively based on the so-called black-box approaches [5]. The latter usually involves gathering a representative amount of actual plant data from which, through the use of appropriate system identification tools such as deterministic regression [6] or artificial intelligent techniques [7-10], an approximate model of the actual process is derived. These types of model, although superior for its computational speed, suffer from a limited scope of operating conditions beyond which the risk of misrepresentation to the actual process behaviour may be high. In contrast, the former relies on understanding the actual physics behind the process from which approximate mathematical models may be derived [11-14]. The computational requirement of these models varies widely depending on their level of complexity [15].

Since the advent of more affordable computing power, the use of mathematical models in steel reheating furnaces has become widespread nowadays. Examples are those so-called on-line reheating models [16-19] which are often used to predict stock temperatures within the furnace which cannot be otherwise measured. This information is then used by the primary furnace control system to regulate heat input to the different region (so-called control zones) within the furnace chamber, with the aim of achieving target heating profile of the stock as they are transported through the furnace. While these models have, in the past, been used effectively to optimise furnace control scheme, i.e., by minimising the deviation between the desired and actual (albeit predicted) stock temperature profile, their scope for optimisation of the desired heating profile is limited. This is mainly due to the fact that energy balance is not inherently encapsulated within their associated mathematical formulation. Consequently, there is further scope in improving existing simplified models. These more comprehensive mathematical models (so-called zone models), based predominantly on the zone method of radiation analysis developed by Hottel and his co-workers [20], take into account full energy balance of the entire reheating furnace with more rigorous treatment of radiation heat exchange within the furnace enclosure filled with non-grey atmosphere. The widespread application of zone models in high temperature furnaces is well documented but previous work has predominantly focused on studies relating to furnace design and operation; see for example [21-23]. The scope of the current paper is thus concerned with demonstrating an integrated approach of adopting zone model in a robust optimisation framework, with the aim to optimise the desired stock heating profile for a given set of process constraints relating to energy consumption and/or product quality.

2. Scope for optimisation within existing process control of reheating furnaces

The furnace studied is a large-scale walking-beam bloom reheating furnace, illustrated in Fig. 1. In total 71 burners are installed within 6 control zones, and control zones 2 and 4 are slaves to control zones 1 and 3 respectively. The thermal inputs of the slave control zones are set implicitly in proportion to the thermal inputs of the master control zones.

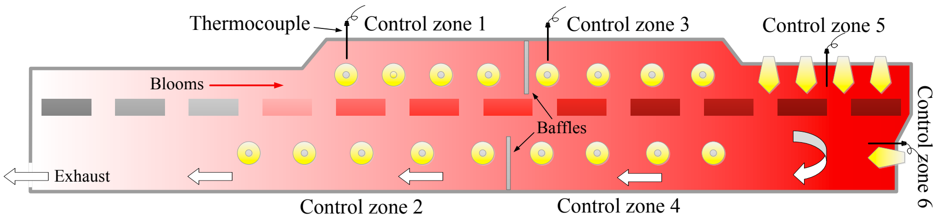

Fig. 1. Outline of the reheating furnace

The existing process control solution for the reheating furnace is shown in Fig. 2. The control utilises a calibrated reheating model based on a 2-dimensional finite difference heat conduction model for calculating the temperature distributions of the blooms as they pass through the furnace. The heat flux on the surfaces of individual bloom is determined from the knowledge of the furnace temperatures and bloom positions which in turn are obtained through communication with the Supervisory Control and Data Acquisition (SCADA) [24] and Material Tracking System (MTS), respectively. A forward prediction of the final discharge temperature distribution is made using the reheating model, the current zonal temperature set-points, and the zonal temperature increase/decrease capabilities of the furnace. This information is subsequently transformed into a new set of furnace set-points, at every model's iteration, which is then used to regulate the burner heat input accordingly.

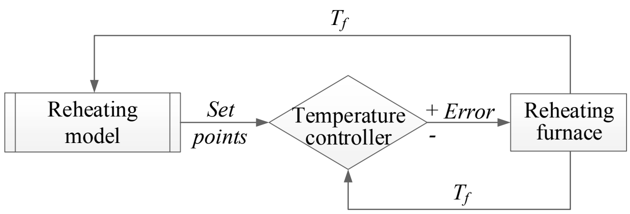

Fig. 2. Level 2 module based process control solution

As mentioned previously, the new furnace set-points are often determined by comparing the desired and predicted bloom temperature profiles. However, the desired temperature profile varies depending on factors such as the dimension and material properties of the bloom as well as throughput rate of the furnace. Unfortunately, information on the know-how of optimising this desired temperature profile is rarely published. In particular, what existing constraints has the furnace operator typically based their desired temperature profile on and how this could be more effectively managed based on a new set of constraints?

3. Development and validation of the process model

In order to better understand the impact of operational constraints on a desired heating profile, it is necessary to develop more comprehensive mathematical models. It is rarely the case that an 'off-the-shelf' validated process model is immediately available. Instead models are generally developed using process knowledge and experience, and then validated by comparison with known data. Consequently, recent studies [14] have led to a validated zone model which can simulate the heating of blooms as they are moved through the furnace. For brevity of this paper, the following points attempt to summarise only the key features of the improved model as compared to the existing one described in section 2.

(a) The improved model was based on a rigorous treatment of radiation using the well-known zone method [14].
(b) The improved model allows prediction of fluid flow pattern within the three-dimensional furnace enclosure.
(c) Full energy balance of the furnace was taken in to account, including thermal mass of refractory structure.
(d) The non-grey behaviour of the furnace atmosphere was accounted for using sum of mixed grey gases approach.

(e) An implicit finite differencing scheme for simulating two-dimensional heat conduction within the blooms allowed more flexibility for larger simulation time-step.

(f) A furnace temperature controller was also incorporated to mimic the behaviour of burner modulation with respect to furnace set-points.

4. Optimisation algorithm

The purpose of the optimiser is to form furnace set-points which satisfy a set of constraints. The core algorithm used in the multi-objective optimisation is the Genetic Algorithm (GA), which mimics the process of natural biological evolution [25]. It operates on a population of potential solutions by applying the principle of survival of the fittest to produce better and better approximations to a solution of the objective function(s). At each generation, a new set of approximations is created by the process of selecting individuals according to their level of fitness in the problem domain and breeding them together using operators (like selection, recombination, and mutation) borrowed from natural genetics following the principle of survival of the fittest. In the proposed set-point temperature optimisation, the GA modifies the furnace control-zone set-point temperatures such that the optimal solutions would converge with respect to minimisation of an objective function. Fig. 3 illustrates the overall program flow chart of the multi-objective optimisation where the 'zone model' serves as a predictor.

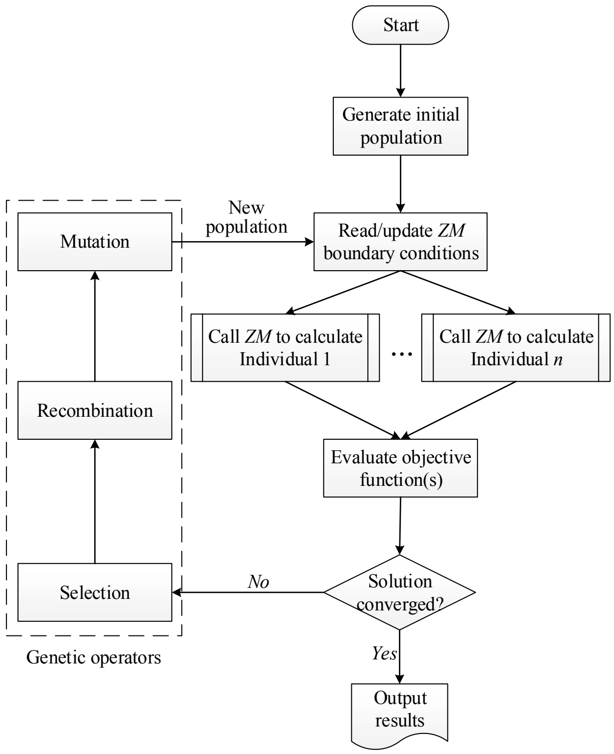

Fig. 3. Program flow chart for GA-based multi-objective optimisation

At the beginning of the computation a number of individuals (the initial population) are randomly initialised according to their actual physical meanings (in this study, each individual represents a set of firing rates of the furnace). Then, zone models are called to calculate each individual's performance, in other words, to calculate the thermal performance of the furnace with a different set of firing rates. The objective function is then evaluated for these individuals and the first/initial generation is thus produced. If the optimisation criteria are not met the creation of a new generation starts. Individuals are selected according to their fitness for the production of offspring and the results of the fittest individual are saved to update the boundary conditions in the zone modelling for the offspring. All offspring will be mutated with a certain probability and their fitness is then computed. The old individuals are replaced by the mutated offspring, and a new generation is produced in turn. The cycle is performed until the optimisation criteria are reached. In this study, the zone modelling was performed by the executable file generated by a FORTRAN coded mathematic model [14]; and the GA was implemented in MATLAB. In the GA, the population consisted of 50 individuals; a generation gap of 0.9 was used in the selection process; a randomly chosen parent contributes its variables to the offspring with equal probability (discrete recombination); a probability of 0.25 was adopted in the mutation process.

4.1. Objective functions

The primary objectives of reheating furnaces are to reheat blooms to desirable discharge temperature (heating accuracy) and to ensure through-thickness temperature uniformity (heating uniformity) while minimising fuel energy (specific fuel consumption). In the present study, fuzzy logic [26] is used to encode the multi-objective function in a set of fuzzy rules (listed in Table 1).

Table 1. Fuzzy rules of the multi-objective fitness function

Penalty cost [1]	Heating uniformity [3] (or Specific fuel consumption [4])		
Heating accuracy [2]	S	M	L
NL	XL	XL	XL
NM	VL	XL	XL
NS	S	M	L
PS	VS	S	L
PM	M	M	L
PL	L	VL	VL

[1] Penalty cost (shown in body of table 1), VS (very small), S (small), M (medium), L (large), VL (very large), XL (extreme large).
[2] Heating accuracy, represented by the difference between the desired and the realized discharge temperature, °C; NL (negative large), NM (negative medium), NS (negative small), PS (positive small), PM (positive medium), PL (positive large).
[3] Heating uniformity, represented by the maximum temperature difference in bloom cross section, °C; S (small), M (medium), L (large).
[4] Specific fuel consumption, represented by fuel consumption of heating 1 tonnage blooms to the desired discharge temperature, GJ/ton; S (small), M (medium), L (large).

Input values are mapped through set membership functions to degrees of membership in multiple sets of fuzzy variables (in this case, 'Heating accuracy' and 'Heating uniformity'). Each membership function is a curve that maps a point in the input space to a degree of membership between 0 and 1, with their shapes normally derived from the knowledge of a human expert; the membership functions for this application are illustrated in Fig. 4. The fuzzy sets are typically described by linguistic qualifiers (such as Positive Small (PS)) related to the variables' difference between desired discharge temperature and realized discharge temperature in relation to the input fuzzy variable Heating accuracy. The fuzzy rules then map degrees of membership in the sets of the fuzzy input variables to degrees of membership in sets corresponding to a fuzzy output variable, in this case a 'Penalty cost'. For example, if Heating accuracy is Positive Small (PS) and Heating uniformity is Medium (M), then Penalty is Small (S). The final degrees of membership in the output fuzzy variable are combined to give a single numerical value, for the penalty cost in this case. During the optimisation, constraints (as shown in Table 2) on the ranges of firing rates in the control zones are set according to practical experience of furnace operation.

Table 2. Constraints for GA-based multi-objective optimisation

	Control zone 1	Control zone 3	Control zone 5	Control zone 6
Firing rate, %	30 - 80	30 - 80	0 - 30	0 - 30

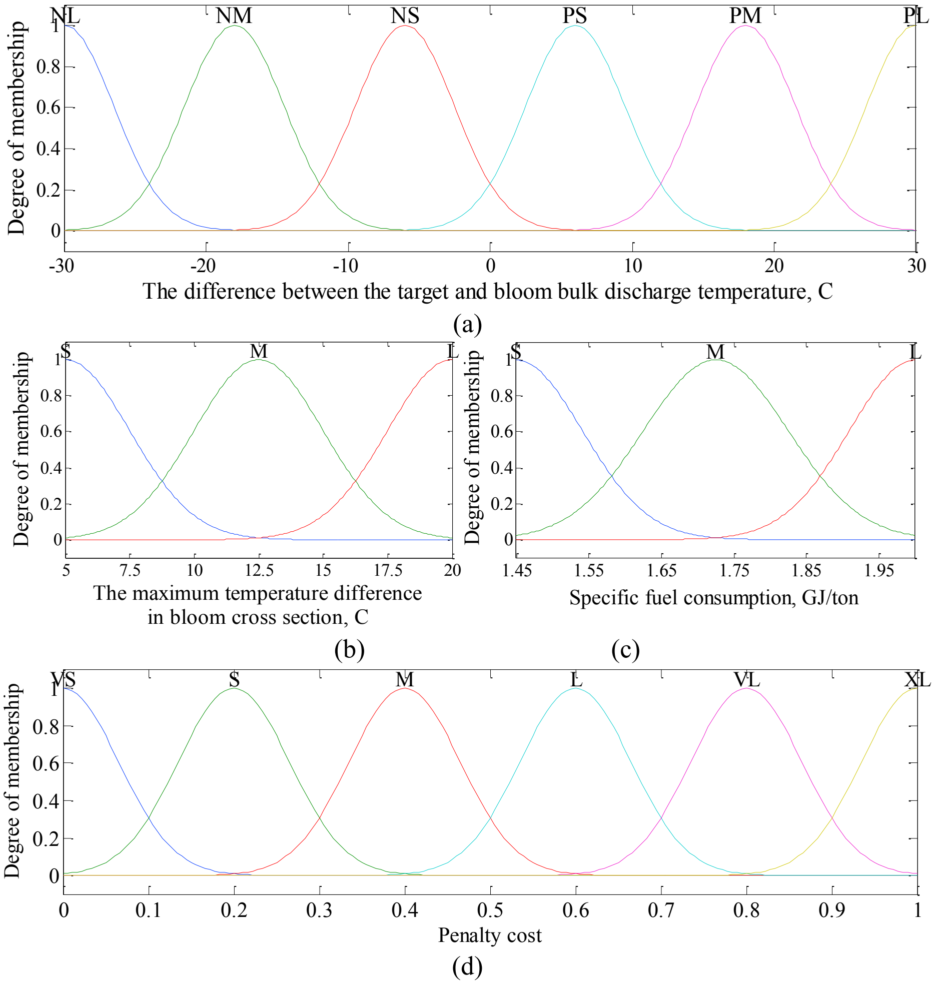

Fig. 4. Fuzzy membership functions

4.2. Optimisation scenarios

In this study, several optimisation scenarios are considered as shown in Table 3. In all cases, the heating accuracy (ΔT_{dis}) is given priority since it represents the primary target in any reheating process. Furthermore, specific fuel consumption (SFC) is closely related to the distribution of thermal input along the furnace length, which in turn also impacts on the profile of heating rates experienced by an individual bloom as it moves from the charge to discharge end. The production rate also impacts on the residence time of bloom and hence upon fuel consumption and heating uniformity (ΔT_{max}).

Table 3. Specification of different optimisation scenarios

Scenario	Production rate, ton/hr	Optimisation objectives[1]	
I	127	ΔT_{dis}	ΔT_{max}
II	127	ΔT_{dis}	SFC
III	65	ΔT_{dis}	ΔT_{max}
IV	65	ΔT_{dis}	SFC

[1]ΔT_{dis}, the difference between the desired and the realized discharge temperature (°C), which represents heating accuracy.
ΔT_{max}, the maximum temperature difference in bloom cross section (°C), which represents heating uniformity.
SFC, the specific fuel consumption (GJ/t).

5. Results and discussion

Fig. 5 illustrates the optimised heating curves for the different scenarios described in Table 3 above. Note that trial data is only available for higher production at 127 tonnes per hour. It can be observed from Fig. 5 (a) that the existing furnace operating strategy emphasises heating accuracy and uniformity regardless of fuel consumption as indicated by its close behaviour to scenario I. This could well stem from the fact that the existing *level 2* model used in the plant is not capable of predicting the energy consumption due to the lack of fundamental modelling of the furnace energy balance. When the objective of specific fuel consumption is emphasised, as in scenario II, the heating curve is optimised such that blooms are heated at a slower rate in the beginning in control zones 1 and 3. The rate of heating then picks up again later in control zones 5 and 6, as indicated by changes in their respective set-point (sp) temperatures in Table 4.

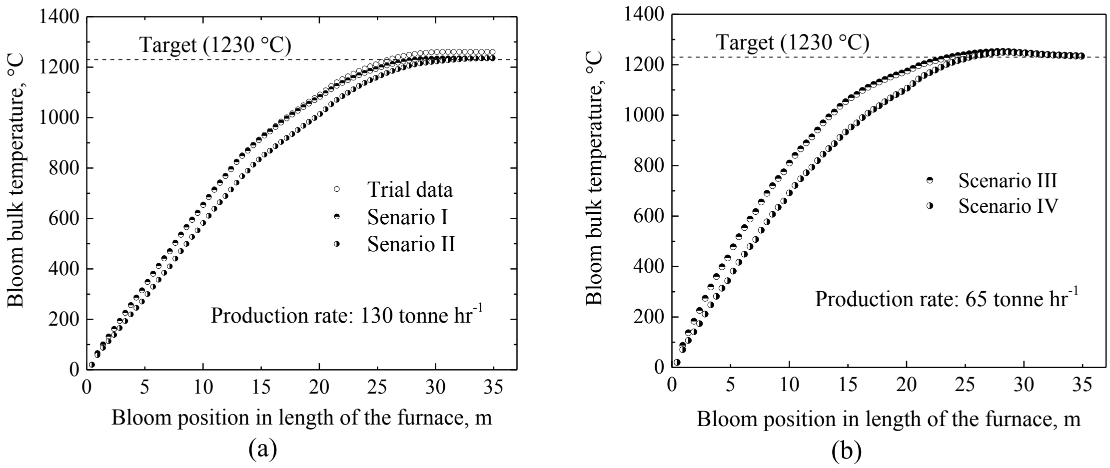

Fig. 5. Comparison of heating curves under different optimisation scenarios

Table 4. Optimal furnace set-point temperatures of different optimisation scenarios

Scenario	T_{sp1},°C	T_{sp3},°C	T_{sp5},°C	T_{sp6},°C
Trial	1200	1300	1250	1250
I	1196	1282	1231	1220
II	1137	1275	1245	1227
III	1196	1272	1231	1225
IV	1121	1268	1228	1221

However, outcomes from scenario II also highlighted poorer heating uniformity (ΔT_{max} in Table 5) as the objective of specific fuel consumption is emphasised, since a faster rate of heating in the region of the soak zones (control zones 5 and 6) will incur a larger conduction time-lag. This would have necessitated longer residence time in the soak zone to compensate for the faster heating rate. Nevertheless, both optimisation strategies (emphasise $\Delta T_{dis\ and}\ \Delta T_{max}$ or *SFC*) also improve the heating accuracy (ΔT_{dis} in Table 5). Similar results are obtained when the furnace is operating at a lower production rate of 65 tonnes per hour, although the side-effect from emphasising the objective of specific fuel consumption is almost non-existent as faster heating rates in the region nearer to the soak zones are being compensated by a longer residence time. However, the results indicate that specific fuel consumption is jeopardised at lower throughput rate.

Table 5. Heating performance of different optimisation scenarios

Scenario	ΔT_{dis}, °C	ΔT_{max}, °C	*SFC*, GJ/tonne
Trial	35	9	1.50
I	5	7	1.49
II	7	24	1.43
III	5	8	1.79
IV	3	8	1.76

The above discussion is also supported by comparing the energy audit for the furnace as presented in Table 6 below. It is noted that heating the blooms faster in the early part of the furnace (as suggested by scenarios I and III) can certainly lead to higher exhaust losses but this negative impact may partly be compensated by the increase in the recovered thermal energy of the combustion air.

Table 6. Furnace energy audit for different optimisation scenario

Scenario	Units	Energy input		Energy output				Performance	
		Q_f[1]	Q_a[2]	Q_b[3]	Q_e[4]	Q_{wc}[5]	Q_l[6]	E_c[7]	E_f[8]
Trial	MW	54.4	6.2	28.8	20.1	7.4	4.5	74.5	52.9
	$\%Q_f$	100.0	11.5	52.9	36.9	13.5	8.2		
I	MW	52.7	6.5	26.4	19.5	7.9	4.6	75.4	50.1
	$\%Q_f$	100.0	12.3	50.1	36.9	15.1	8.1		
II	MW	50.8	5.7	26.5	17.1	7.7	4.4	77.6	52.1
	$\%Q_f$	100.0	11.3	52.1	33.7	15.2	8.7		
III	MW	31.7	3.6	12.5	10.6	7.8	3.6	77.8	39.4
	$\%Q_f$	100.0	11.2	39.4	33.4	24.5	11.2		
IV	MW	31.2	3.0	12.9	9.0	7.4	4.1	80.9	41.5
	$\%Q_f$	100.0	9.8	41.5	28.8	23.8	13.1		

[1] Fuel energy input.
[2] Preheated air energy input.
[3] Energy transferred to steel blooms.
[4] Energy in exhaust gases as they leave the furnace.
[5] Energy transferred to the furnace water cooling.
[6] Energy losses to furnace walls.
[7] Combustion efficiency, $1+(Q_a/Q_f)-(Q_e/Q_f)$ as a percentage.
[8] Furnace efficiency, Q_b/Q_f as a percentage.

6. Conclusions

This paper details a zone model based multi-objective optimisation of reheating furnace operations, and highlights a novel approach of incorporating the zone model directly into a population based genetic algorithm. A set of fuzzy rules was defined taking into account of bloom desired discharge temperature, temperature uniformity and specific fuel consumption. The results show that the proposed optimisation strategies can improve heating accuracy and the average deviation was less than 10 °C from the desired discharge temperature, while a trade-off existed between the optimization objectives of temperature uniformity and specific fuel consumption. The optimisation studies also suggested that the zone method based furnace model was able to provide insight into the dynamic heating behaviour with respect to multi-objective criteria and that it was found that current furnace practice places more emphasis on heated product quality than energy efficiency.

Acknowledgements

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