Optimisation frame work based on machine learning model to improve energy utilisation

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Abstract

Due to the inherent uncertainty and potential disruptions in the supply chain, the global community is adopting a more cautious approach to meeting its energy needs. Climate change, material availability, and recycling for sustainability are also pressing issues. The material processing industries, which encompass activities such as mining ore, extracting materials, melting them, and manufacturing components, require a large amount of energy. These industries often include a heat treatment process as part of the manufacturing process, which can be a major energy consumer. For example, heat treatment can account for 20% of energy usage in a non-ferrous foundry. Pre-heating and heat treatment also requires a significant amount of energy in the ferrous-based industry. In this work, our goal is to increase the efficiency of energy usage in these industries through the use of machine learning models to optimize processes. We will analyze the processes in these industries and create machine learning models to identify the optimal operating parameters for the best output with minimal energy consumption.

IEECP'23, July 11-12, 2023, 3rd European Conference

I. INTRODUCTION

Heat treatment is a critical step in materials processing that involves altering the properties of components to suit a specific application. This process allows for changes in mechanical and physical characteristics such as ductility, hardness, toughness, wear resistance, and strength without altering the designed shape and size of the component [1]. In general, heat treatment is used to improve strength in loaded members and wear resistance in moving parts, but it can also be used to enhance machinability and formability of materials. The modification of material properties is made possible by changes at the molecular structure/microstructure level. The structure of the material is determined by two factors: grain size and grain structure. These elements of the material's microstructure influence its mechanical and physical properties. Heat treatment is often paired with pre- and post-heating processes to improve energy efficiency and product performance.

There are a number of variables involved in the heat treatment process, including the chemical composition of the alloy, the dimensions and shape of the component being treated, microstructural, physical, and mechanical properties, and the energy required for the process. Depending on the specific goals, some of these parameters will be input before or during heat treatment, while others will be output parameters. When there are more than four variables that vary, it can be challenging to determine the effect of each parameter on the desired output parameters. In these cases, regression models can be used to solve this complex problem. A literature review of the regression models used to link input to output parameters in heat treatment processes is provided below.

Johnson [2] and Avrami [3] developed analytical models for the heat treatment of metals. These models were used to create numerical simulations to study the heat treatment process, which can reduce the need for extensive experimentation and energy consumption. However, these simulations have been found to lack accuracy [4]. For example, Maisuradze [5] demonstrated that simulations may inaccurately predict strength parameters in heat treatment processes. To improve accuracy, computer-aided simulations have been developed [6 – 9] as an alternative to traditional simulations.

Accurate prediction of microstructural properties is crucial in heat treatment model development as they significantly affect output quality parameters. This enables the identification of appropriate initial/input parameters for a heat treatment process. Data-driven solutions have been shown to be effective in speeding up problem-solving in this area [10, 11]. Previous research in this field includes work by Homer et al. [12] and Zhu et al. [13], who used machine learning tools to examine grain boundaries in a polycrystalline material, and Raccuglia et al. [14], who developed a classification model to predict successful and failed experiments using a large amount of experimental data on materials. Agrawal et al. [15, 16] created a machine-learning model that predicts the fatigue strength of steel using composition and processing parameters. In [17], regression models were used to predict four mechanical properties after the heat treatment process. The authors tested five different regression models and found that random forests performed well in predicting the mechanical properties, and they derived mathematical expressions from the model.

Heat treatment and other processes used on glass can also alter the microstructure and therefore the mechanical properties. Masai H et al. [18] used regression analysis to evaluate the structural and physical properties of strontium borate glass against chemical composition. Samuel B. O. et al. [19] developed an optimization technique using Taguchi and general regression to model the glass material for composite components with a specific flexural strength. In the case of glass, there is a lot of focus on manufacturing processes such as cutting and grinding. In [20, 21], the authors created a neural network (NN) model to predict the material removal rate and surface roughness parameters in a laser machining process. Shimaa et al. [22] developed a machine-learning model for abrasive jet machining of glass, in which the material removal rate is related to the process variables of the machining process. Bezzera et al. [23] created a machine-learning model using NN to predict the shear stress-strain behavior of CFRP material.

There is a significant amount of research literature that explores the use of optimization methods with regression models as a basis for prediction. While regression models developed with machine learning techniques can be effective, they can also have disadvantages such as referring to a local maxima or minima, overfitting or under fitting, and slow convergence. These issues can be addressed by implementing optimization techniques to search the solution space thoroughly for a specific solution that fits the application [24, 25, 26]. In recent research, deep learning models such as deep neural networks (DNN), convolutional neural networks (CNN), and recurrent neural networks (RNN) have been used for energy demand forecasting. Studies [27, 28] have shown that using multiple types of deep neural networks for forecasting energy demand can provide accurate results. Khan A. et al. [29] used a machine learning algorithm in conjunction with the cuckoo search method for forecasting energy requirements. Almalaq, A. et al. [30] employed long short-term memory networks with a genetic algorithm (GA) to create prediction and optimization models for energy consumption in buildings. Wen L. et al. [31] used LSTM with a particle swarm algorithm (PSO) to link load dispatch in a community microgrid with solar power assistance. Similar work was done by Ceylan H. et al. [32], who used GA to estimate energy demand in Turkey using economic indicators.

Other relevant works include [33, 34], in which researchers used PSO to optimally configure the weights of NN to create an accurate model of energy consumption. While the literature includes the use of GA and PSO, there are other heuristic algorithms such as Tabu Search, Simulated Annealing, and Travelling Salesman that can also be utilized. A review of these algorithms is provided in [35]. Of these algorithms, GA and PSO are particularly popular due to their effectiveness when applied to engineering problems. These methods are similar, but they differ in their fundamental search techniques. GA is based on evolution, while PSO is based on swarm intelligence. A detailed comparison of these two techniques is presented in [36], and R. Kshirsagar et al. [37] showed that PSO can be derived as a special case of GA for a class of engineering problems. GA is particularly suited for nonlinear problems.

In this work, we used simulation model results from a case study in the glass industry to create a regression model, and an optimization framework using the regression model. The framework is a multi-objective and multi-constraint based prediction model that can generate input parameter values for a specific desired output.

II. OPTIMISATION FRAMEWORK

In the optimization framework we aim to create a model which is capable of predicting output parameter values based on the values of input parameters. And then later a closed loop optimization models is created which can provide the values of input parameters based on the required output parameters. This optimization frame work is a multi-criteria and multi-objective problem solver.

For this purpose, we selected a case study of heat treatment of lime-soda glass material in a furnace. In particular, we aim at cooling of the material after attaining certain temperature. In this process, we identified the parameters which can independently influence to be exit temperature (^{0}C), cooling rate (^{0}C/min), and annealing temperature (^{0}C). Maximum, minimum and average values of these parameters are evaluated based on the actual industrial scenario in Glass Technology Services Ltd (Unitec Kingdom). The values are listed in Table 1.

Table 1. Maximum, minimum and mid value of independent parameters.

	Independent Parameters	**Max**	**Mid**	**Min**
1	Exit Temperature (^{0}C)	150	110	70
2	Cooling rate above S.T (^{0}C/min)	9	6	3
3	Annealing Temperature (^{0}C)	605	565	545

Details of regression model is given in the following section.

A. REGRESSION MODEL

In the first step of creating an optimization framework, a regression model is created. For this purpose, an initial data set is required. To create the data set, a full factorial design of the experiments list is created using the information in Table 1. The design of the experiments set is presented in Table 2. Each set of the design of experiments is simulated in ANSYS. The simulation is a cooling process in which glass material is cooled from the annealing temperature to the exit temperature with a cooling rate (as listed in Table 2). In each simulation, the maximum value of stress and energy consumed is evaluated. These two parameters are the output parameters for the regression model.

Table 2: List of experiment. Input parameters and output parameter values

Input parameters			Output parameters (Simulation results)	
Exit temperature (^{0}C)	Cooling rate (^{0}C/min)	Initial temperature (^{0}C)	Max Stress (von-Mises) Pa	Energy (J)
150	6	605	476420	73309
70	6	545	476350	76573
150	9	545	714670	63029
110	3	545	238230	70496
70	6	605	476350	86364
70	3	545	238200	77017
150	3	545	238270	63975
110	6	545	476390	70045
150	6	545	476420	63516
70	9	545	714440	76090
110	9	545	714540	69560
70	3	565	238200	80276
110	3	565	238230	73756
150	3	565	238270	67236
70	6	565	476350	79837
110	6	565	476390	73309
150	6	565	476420	66780
70	9	565	714510	79355
110	9	565	714620	72825
150	9	565	714490	66295
70	3	605	238200	86795
110	3	605	238230	80276
150	3	605	238270	73756
110	6	605	476390	79837
70	9	605	714440	85886
110	9	605	714540	79355
150	9	605	714660	72824

To create a regression model, a neural network with the architecture shown in Fig. 1 is used. It takes three input parameters and gives two output parameters using three hidden layers with ReLU and Sigmoid activation functions.

In order to feed the data to the neural network, the data is normalized using the fowling formula

$$Y_{norm} = \frac{Y - Y_{min}}{Y_{max} - Y_{min}} \qquad \text{Eq. (1)}$$

Here, referring to the variables and their values in Table 2, Y is actual value of a variable, Y_{min} is the minimum of a variable, Y_{max} is the maximum value of a variable and Y_{norm} is the normalized value. After normalization, all the values of variables will be mapped between 0 and 1.

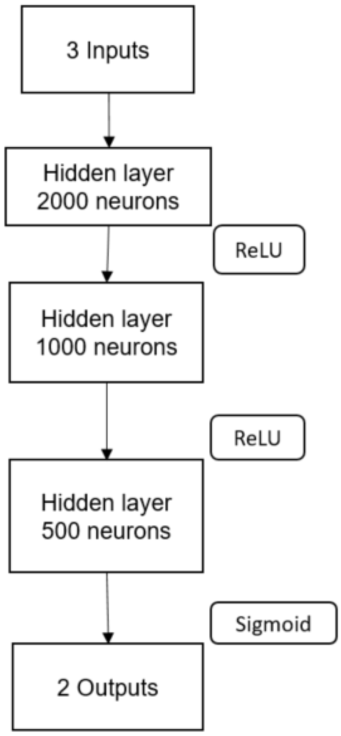

Figure 1: Neural Network architecture

The data after normalization is divided into training and testing data set. 80% of the data is used as training data and 20% is used for testing. Neural network is trained using training data set and in each iteration mean squared error is evaluated on both training and testing data set. Training is carried out till the percentage error between predicted value and the actual value is less than 1% and mean squared error calculated on training set and testing set is equal. So the neural network model is accurate to 1% error and also not an overfitting model to the dataset.

A specific architecture as shown in Fig 1 is used to create regression model. The architecture is finalized after several trial and error attempts [25].

B. OPTIMISATION

In the next stage of creating the optimization framework, we aim to create an algorithm that can predict the input parameter values for particular output parameters. In the case of the regression model, parameters namely annealing temperature, cooling rate, and exit temperature are used as input parameters and output parameters namely maximum stress and energy consumed are predicted using the regression model. In this stage, we aim to create an algorithm that evaluates the three input parameters for a particular output parameter specified. Genetic algorithm is used for this purpose.

Using the regression model an objective function is defined as

$$\begin{aligned} &Objective\ function \\ &= Minimise\{abs(stress\ evaluated\ by\ regression\ model \\ &- target\ stress\ value) \\ &+ abs(energy\ evaluated\ by\ regression\ model \\ &- target\ energy\ value)\} \end{aligned}$$

Eq. (2)

The stress and energy value in Eq. (2) are normalized using Eq. (1) before the objective function is evaluated.

The algorithm solves a minimization problem which leads to the input parameter values for a particular stress and energy value. The steps in genetic algorithm are

Step1: Create initial population of n×3 randomly of values between 0 and 1. Here, n is the length of population and 3 is for the three input parameters of the data.

Step 2: Calculate stress and energy values for each set in the n×3 using regression model and then evaluate the objective function given by Eq. (2).

Step 3: As the objective function is a minimization function, rows in n×3 population set are rearranged in the ascending order based on the corresponding value of the objective function.

Step 4: First half of the population is assumed as fit. Using the fit population, same number of (half of n) population is created by cross over operation.

Step 5: Each value in the set n×3 is referred as a gene and each row is referred as a chromosome. Mutation operation is carried out by changing randomly selected gene in a randomly selected chromosome.

Step 6: The algorithm is iterated from step 1 to step 5 till the percentage error calculated between predicted value of maximum stress and energy and the required values is less than 1%.

Flow chart of the steps mentioned above is presented in Fig 2.

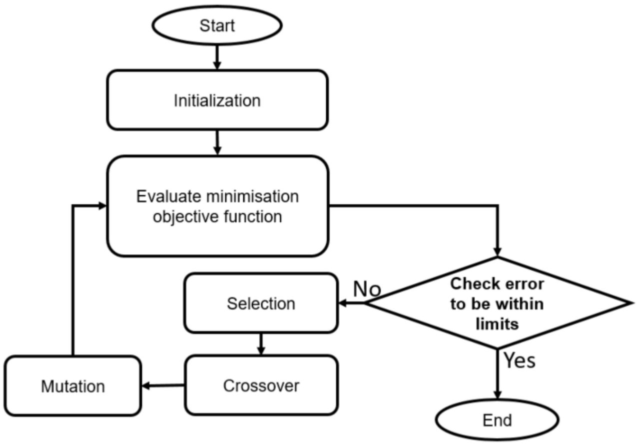

Figure 2: Genetic algorithm flowchart

In order to initiate the algorithm, an initial value of stress and energy are given and a population size of 50 is used. Algorithm breaks when the percentage error is less than 1%. Top chromosome after sorting is the best solution for the required stress and energy values. To demonstrate the results, a set of 5 stress and energy values are used. Corresponding three input parameters are evaluated using the optimization process and all the values are tabulated in Table 3. In the table, label "Target value" refers to the target stress and energy value to be achieved, "GA result" refers to the input parameter values evaluated using optimization and "NN result" refers to the stress and energy value evaluated using regression model using "GA result".

Table 3: Target stress and energy value, GA results and regression model result

Max Stress (von-Mises) Pa (Target value)	Energy (J) (Target value)	Temp (GA result)	Exit temp (GA result)	Cooling rate(^{0}C/min) (GA result)	Max Stress (von-Mises) Pa (NN result)	Energy (J) (NN result)
476435	74912	561.049	5.991	96.83	472724	74809.2
333494	74912	557.11	4.38	95.65	336661	74870.7
476435	67782.2	563.5	5.98	142.78	476012	67772.7
524082	70158.8	582.8	6.6	146.5	523640	70172.2
381141	77288.6	571	4.9	93.13	380441	77301.7

Percentage errors between "Target value" and "NN result" are calculated and presented in Table 4. It can be noted that the percentage error calculated is either less than or equal to 1%.

Table 4: Percentage error between target value of stress, energy and the stress, energy value obtained using optimization process

Optimization frameworks results		Target values		Percentage error	
Energy (J)	Max Stress (von-Mises) Pa	Max Stress (von-Mises) Pa	Energy (J)	Max Stress (von-Mises)	Energy
74912	476435	472724	74809.2	0.78%	0.14%
74912	333494	336661	74870.7	1%	0.06%
67782.2	476435	476012	67772.7	0.89%	0.01%
70158.8	524082	523640	70172.2	0.084%	0.02%
77288.6	381141	380441	77301.7	0.18%	0.02%

III. CONCLUSION

In this study, the optimization of heat treatment process of soda lime glass was investigated. The required pattern of heat treatment and cooling to obtain the desired properties in the glass material was determined. A list of input parameters with their minimum and maximum values was created for the purpose of the study. Computer simulations were conducted using a full factorial design of experiments set. The output parameters, stress and energy, were evaluated using the simulations. A multi-objective and multi-criteria optimization framework was developed using a regression model and genetic algorithm. The results obtained using both the regression model and the optimization model were accurate, with an error of less than or equal to 1%. Although only one case study was used for the analysis, the proposed optimization framework is robust and can be applied to any industry problem. Note that the data, regression model and optimization process is carried out on the basis of data created using computer simulations. It important to verify the results using experiments. Experimental verification is not in the scope of this work and we intend to do it in future.

IV. ACKNOWLEDGMENTS

This project is being funded by Innovate UK with title "AI lean six-sigma process optimization for energy efficiency and waste reduction in foundation industries". We thank Innovate UK for funding this work.

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