Energy Modeling and Efficiency Analysis of Aluminum Die-Casting Processes

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Abstract

Energy modeling and efficiency analysis are considered the foundation of manufacturing process optimization to improve quality and efficiency and reduce energy consumption and carbon emissions during aluminum die casting processes. This paper proposed an energy modeling method to connect gas and electric energy consumption with production rate of aluminum die casting processes based on data collected at workshops with various combination of machines and products. The detailed modeling process involved the development of a data-acquiring system and the comparison of various kinds of nonlinear regression methods. The resulting models were validated with actual production data and were further used to improve production scheduling. It was found that if the modeling results are reasonably used and production is accordingly well-scheduled, 10 to 15 percent of energy savings could be realized without sacrificing profits.

Keywords： Die casting; Energy consumption modeling; Data acquisition; Energy efficiency analysis

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Keywords: Aluminum die casting process; Energy consumption modeling; Data acquisition; Energy efficiency analysis

1. Introduction

The manufacturing industry accounts for a significant part of the world's energy consumption and waste and is responsible for nearly one third of global energy consumption and 29.2% of global electricity-related CO_2 emissions (Dunham 2015; Sieminski 2016). Energy efficiency has become one of the key factors of the manufacturing industry (Anderberg et al. 2010). Die casting processes are widely known for being highly energy demanding. Approximately 25% of the total cost for die casting products is associated to energy consumption (Brevick et al. 2004). In many countries, legislations have become stricter and stricter over the years regarding the energy consumption and emissions of die casting processes (Salonitis et al. 2016a). Production managers face great challenges when trying to implement energy efficiency initiatives under productivity concerns (Mohr et al. 2012; Andrea Trianni et al. 2013). It is also noted that increasing resource utilization during production could reduce the amount of energy consumption in die casting processes by 20 to 30 percent (Shao 2017; Trianni and Cagno 2012).

Researchers suggest that the efforts to reduce energy consumption should start with evaluating the energy consumption of manufacturing systems more accurately (Cao et al. 2012; He et al. 2017; Zhong et al. 2016). However, traditional methods of studying energy consumption of die casting processes heavily depend on experiments. Parameter calculation for resulting models are widely considered weak due to the lack of the needed data or model validation. For high energy consumption processes like die casting, modeling their energy consumption is complex, time-consuming and challenging. Specifically, aluminum casting has experienced continuous growth (Das and Yin 2007; Heinemann 2016) and dominates the nonferrous sector in general, comprising 78% of total nonferrous shipments (Rosen and Lee 2009). Some researchers also pointed out that the energy consumption of the aluminum casting process is of the order of 6–17 GJ per tonne in using electricity and natural gas, which means the order of 36-100 billion GJ for the global industry in 2017. Saloniti`s et al. (2017) stated that there are huge opportunities for the metal casting industry to adopt the best energy practices based on energy modeling. Therefore, energy modeling and efficiency analysis of aluminum die casting processes are

crucial for the energy efficiency of the manufacturing industry.

Using real data of multiple machines and products at aluminum die casting workshops through an energy data-acquiring system, this research built the mathematical relationship between specific energy consumption (*SEC*), including both gas and electricity, and production rate for aluminum die casting processes. The high energy efficiency zone was defined after various nonlinear regression methods were investigated. The performance of different methods was compared to obtain the optimum one, which was further validated by experiments. The modeling results can be used to analyze the energy efficiency of aluminum die casting workshops and further to support production scheduling with consideration on energy usage. The study showed that the modeling results can lead to 10 to 15 percent of energy savings without sacrificing profits. All the data-acquiring and case studies were carried out in die casting workshops of a furniture manufacturer in Zhejiang Province, China.

2. Literature Review

Energy consumption of die casting processes has been long studied in literature. Much of the research focused on energy consumption using measurement and statistical methods. For example, Lazzarin and Noro (2015) presented energy audits performed in five Italian cast iron foundries and identified energy utilization in various processes, from iron melting to the end of casting. They further discussed energy efficiency opportunities in service plants of cast iron foundries in Italy (Lazzarin and Noro 2016). A report of the Office of Scientific and Technical Information Technical (Schwam 2012) addressed multiple aspects of the aluminum smelting and handling in die operations for energy efficiency improvement based on data from North American Die Casting Association (NADCA). Eglins and Röders (2005) presented a model about the overall heat transfer within an aluminum die casting cell to find measures for an energy demand reduction. DETR (Department of Environment 1997) analyzed the energy ratio of the key energy-consuming equipment and phases in the casting process. However, energy consumption data are scattered, inconsistent, and not helpful to guide energy saving measures.

Simulation and visualization techniques have been used by several researchers to calculate and compare the energy and material flows without a physical implementation. For example, Salonitis et al. (2017) presented a case study of selectting energy and resource efficient casting processes based on simulation. Mishra and Sharma (2017) investigated melting of the bulk Al-7039 alloy during in-situ microwave casting through experimental trials in a multi-mode applicator cavity and numerical simulation. Pagone et al. (2016) developed a simulation tool to undertake a systematic analysis of energy and material flows in the casting process. Henninger et al. (2016) conducted simulations based on studies of energy saving measures in the aluminum tooling and die casting industry. Krause et al. (2012) provided a discrete event simulation (DES) based model of an aluminum die casting process to represent energy oriented material flows. Singh et al. (2012) proposed a new computer-aided system named Sustainability Analyzer for die casting processes using three sustainability indicators including energy use, solid water and carbon emissions. However, the energy data for simulations are mostly based on earlier data and statistical analysis.

Meanwhile, the overall life cycles of products made by die casting processes are also common research topics. For example, Yilmaz et al. (2015) used life cycle assessment (LCA) as a decision support tool to evaluate best available techniques (BATs) for cleaner production of iron casting. Mitterpach et al. (2017) conducted environmental evaluation of grey cast iron via LCA. LCA is mostly used under certain conditions, such as

neglecting complicated real-time situations and variations of the parameters, and does not provide accurate energy data. There is also much research using modeling methods to look into the relation between energy consumption and other process parameters. From the process viewpoint, Selvaraj et al. (2017) presented mathematical modeling of raw material preheating in metal casting processes. Børset et al. (2016) explored the potential for waste heat recovery during metal casting with thermoelectric generators by using on-site experiments and mathematical modeling. Salonitis et al. (2016b) pointed out that Constrained Rapid Induction Melting Single Shot Up-casting (CRIMSON) has advantages compared to conventional sand casting processes regarding energy savings. Watkins et al. (2013) used the sustainability characterization methodology to evaluate the sustainability of die casting manufacturing processes. Thiriez and Gutowski (2006) studied the energy consumption of an injection modeling process and created a model to represent the *SEC* trends exhibited by each machine. However, the applications of process improvement for energy savings are often restricted because of the difficulty of its implementation and expansion. Respectively, from the operational viewpoint, Sharma et al. (2017) conducted the sustainability modeling of die-casting processes based on the process plan information. Bettoni and Zanoni (2011) presented a power model focusing on the relationship between *SEC* and the production rate in order to improve energy efficiency in die casting processes. The model was based on previous work by Gutowski et al. (2006). However, the data provided by them are insufficient and there is no clear evidence to support that the power form used by them is the optimum one to characterize the regressive relation between *SEC* and production rate.

In summary, energy modeling and efficiency analysis of die casting processes and the relationship with production rate deserve further study.

3. Energy Data Acquisition and Analysis System of Aluminum Die Casting Processes

This research collected energy consumption data for die casting processes at a typical die casting workshop with two casting machines. Each machine was designed to produce two product types with corresponding types of dies equipped. They are automatic, middle-sized, horizontal cold chamber die casting machines using electricity as their power supply. Each was also equipped with a continuous furnace using natural gas. During data collection, the workshop was under full operations with three shifts per day and six days per week. In order to maintain their temperature, the furnaces were continuously operated except cases of emergency and necessary maintenance. We developed an energy data acquisition and analysis system with four main modules. The first module consisted of digital meters for measuring energy consumption, including voltage and current sensors for electricity and flow sensors for gas. In addition, infrared sensors were used to measure the production rate; and digital platform scales were used to obtain weight of used materials. Once the real-time energy and other data were collected by the first module, they were transferred to the second module by the standard serial communication protocol of RS232/RS485. The second module was an integrated control panel with the installed data acquisition software, which received the original data, transformed them to the html form, and then transferred them to the system server. The data acquisition software was developed with the Microsoft Foundation Class (MFC) framework on the Visual Studio 2015 platform. The database was developed using SQL Server 2010. The relevant analysis tools and interfaces were developed using Java Spring MVC framework. The third module was used to receive and store the data and to respond to query requests for analysis. The last module was the analysis kit to conduct the energy efficiency analysis and then assist users in making decisions for improving production schedules. The four modules worked together to monitor the real-time state of energy efficiency so that managers were able to control

the production rate or adjust the production plan. Fig. 1 depicts the structure of the energy data acquisition and analysis system developed in this research. Table 1 shows example data of energy consumption and production rates for machines producing different products, including gas consumption in m^3, electricity consumption in $KW{\cdot}h$, used material in kg, and pieces of products produced. A sample data for gas consumption is shown in Fig. 2.

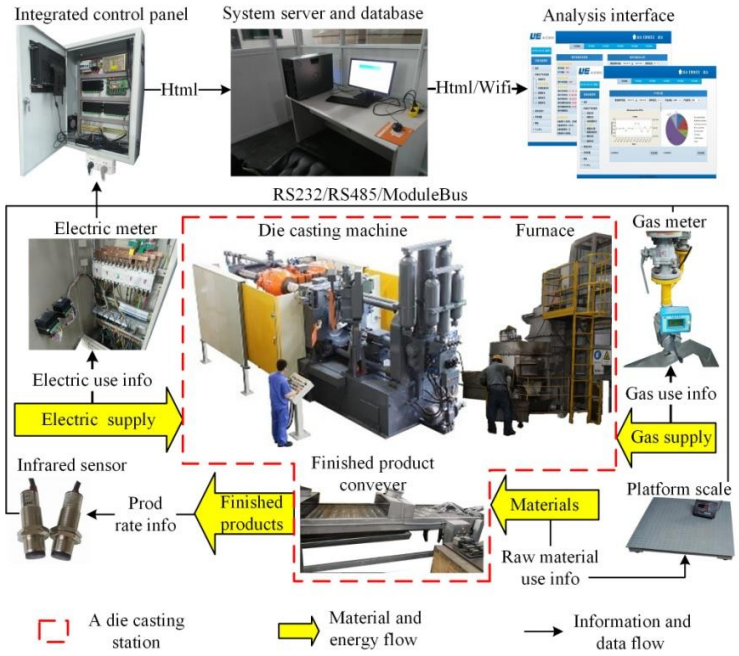

Fig. 1 Structure of the data acquisition and analysis system

Table 1 Examples of data of energy consumption and production rate

	Shift group No.1				Shift group No.2				Shift group No.3				Shift group No.4				Shift group No.5			
	Gas [m^3]	Elect. [kwh]	Mat. [kg]	Piece	Gas [m^3]	Elect. [kwh]	Mat. [kg]	Piece	Gas [m^3]	Elect. [kwh]	Mat. [kg]	Piece	Gas [m^3]	Elect. [kwh]	Mat. [kg]	Piece	Gas [m^3]	Elect. [kwh]	Mat. [kg]	Piece
Mach A & Prod a	113.3	56.92	295.34	112	167	90.65	1358	543	121	56.34	560	223	166	96.89	1354	541	124.5	58.45	586	234
Mach A & Prod b	90.45	43.56	528.45	173	134	85.23	1284	427	157	98.43	1560	520	108	65.34	658	219	166.9	105.34	1693	565
Mach B & Prod c	130.6	60.23	475.89	125	136	59.34	470.5	122	256	134.76	1281	341	233	123.54	1175	312	243.5	123.45	1206	321
Mach B & Prod d	126.5	56.34	625.87	123	144	75.32	1108	221	165	80.34	1233	246	178	90.23	1446	289	289.3	123.34	1940	388

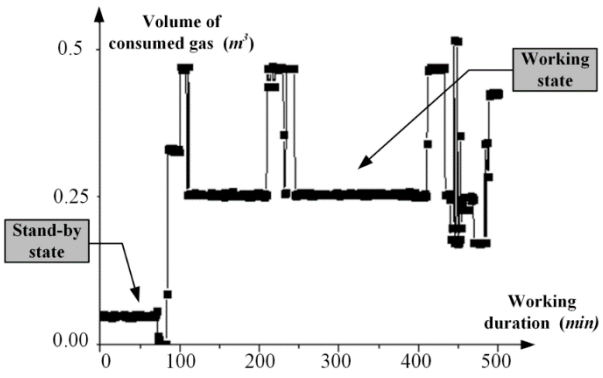

Fig. 2 Sample data for gas consumption

4. Energy Modeling of Aluminum Die Casting Processes

This study built the regressive relation model between *SEC* and production rate *P* in [*piece/h*] or [*kg/h*] following Gutowski et al. [28]. The *SEC* is defined as the amount of energy required for processing a certain amount of one kind of product. For casting processes, it can be expressed as SEC_{gas} in [m^3/kg] for gas used in the furnace for melting raw materials; and SEC_{elec} in [*KW·h/piece*] for electricity used for machining finished products. The production rate P is defined as the production rate of quality products rather than the overall one and varies over shifts. Managers are able to control the energy consumption state and effective production rate P of each shift by taking measures such as rescheduling the production plan to accelerate or decelerate the production rate, reducing the machine idle time, optimizing machine parameters, and enhancing workers' skills to improve the energy efficiency and quality rate. Since there are two machines producing two kinds of products, capital letters are used to denote the machine and lowercase letters are used to denote the product type. For example, SEC_{gasAb} means the *SEC* of furnace *A* melting raw material for product *b* using gas; and SEC_{elecBb} is the *SEC* of machine *B* producing product *b* using electric energy. P_{gasAb} in [*kg/h*] and P_{elecAb} in [*piece/h*] are production rates for furnace A and machine A for producing product b respectively. For a fixed cycle time T_c of process c, the production rate P is related to stand-by idling time t_{idle} and production time t_p. P increases when t_{idle} decreases and t_p increases. Moreover, the *SEC* decreases when the production rate *P* increases (Gutowski et al. 2006; Bettoni and Zanoni 2011). Fig. 3 illustrates the general relationship between SEC_{gasAb} and production rate P_{gasAb} based on data acquired by the developed system. The area circled out in red is considered the high efficiency zone, which is defined as the aggregation of data points near the Pareto frontier of productivity and energy efficiency. The energy model is used to describe the relation between *SEC* and *P* within the zone, which is marked by green. Once the mathematical model is established, the real-time state of the production should be within the high efficiency zone as much as possible to improve the energy efficiency and productivity of the overall production.

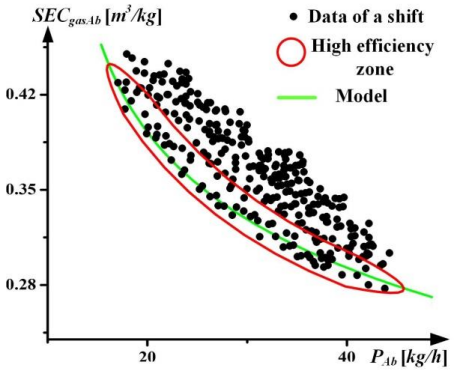

Fig. 3 Relationship between SEC_{gasAb} and P_{gasAb}

To obtain the specific optimum mathematical form for the nonlinear regressive relation between *SEC* and *P*, the most used modeling method in literature is nonlinear regression. The general mathematical form for the relation can be represented by $f_{SEC\text{-}P}$ in Eq. (1), where $\theta_1, \theta_2, \dots, \theta_n$ represent the unknown coefficients, and *n* represents the number of coefficients. Apparently, the meaning and number of $\theta_1, \theta_2, \dots, \theta_n$ are determined by the specific mathematical form of $f_{SEC\text{-}P}$. ε is the error between the calculation result by $f_{SEC\text{-}P}$ and the real value of *SEC*.

$$SEC = f_{SEC-P}(P, \theta_1, \theta_2, \dots, \theta_n) + \varepsilon \quad (1)$$

Following the least square method, the optimum $f_{SEC\text{-}P}$ under a certain mathematical form can be found by determining the optimum group of $\theta_1, \theta_2, \dots, \theta_n$ leading to the least aggregation of ε, as Eq. (2). Here, θ represents the vector of $(\theta_1, \theta_2, \dots, \theta_n)^T$, $F(\theta)$ is the function to get the least relative error, N represents the sample group number of observed *SEC* and *P* used for the modeling, SEC_i represents one of the observed value of *SEC*, and P_i represents the relevant observed value of *P*.

$$\min_{\theta} F(\theta) = \min_{\theta} \sum_{i=1}^{N} \left(SEC_i - f_{SEC-P}(P_i, \theta_1, \theta_2, \dots, \theta_n)\right)^2. \quad (2)$$

The minimum value of $F(\theta)$ can be obtained by solving a differential equation group (3), formed by *n* equations of f_{SEC-P}'s partial deviation to θ_i $(i = 1,2, \dots, n)$. The optimum values of $\theta_1, \theta_2, \dots, \theta_n$ are represented by a vector of $\hat{\theta} = (\widehat{\theta_1}, \widehat{\theta_2}, \dots, \widehat{\theta_n})^T$. This research used the Newton iterative method to obtain the solution of $\hat{\theta}$

$$\left.\frac{\partial F}{\partial \theta_i}\right|_{\theta_i=\hat{\theta}_i} = -2\sum_{j=1}^{N}\left(SEC_j - f_{SEC-P}(P_j, \hat{\theta})\right)\left.\frac{\partial f_{SEC-P}}{\partial \theta_i}\right|_{\theta_i=\hat{\theta}_i} = 0 \quad (3)$$

Based on the data collected over five months, various none-linear regression curves, such as reciprocal, power, polynomial cubic, exponential, and logarithmic functions, were analyzed to obtain the optimum one for each pair of machine and product. The expression and coefficients of each f_{SEC-P} is listed in Table 2, in which A_P, B_P, C_P and D_P are the coefficients of polynomial cubic, and a_R, b_R, a_P, b_P, a_E, b_E, c_E, a_L, b_L, c_L are the coefficients of reciprocal, power, exponential and logarithmic respectively.

Table 2 Forms and coefficients of none-linear curves used

None-linear Curves	Expression and Coefficients
Reciprocal	$SEC = 1/(a_R + b_R P)$
Power	$SEC = a_P P^{b_P} (b_P < 0)$
Polynomial cubic	$SEC = A_P + B_P P + C_P P^2 + D_P P^3$
Exponential	$SEC = a_E - b_E {c_E}^P$
Logarithmic	$SEC = a_L - b_L In(P + c_L)$

For each form of regression model f_{SEC-P}, adjusted coefficient of determination $adjR^2$ and residual standard deviation *s* are used to evaluate its performance. Their calculation formula are as follows.

$$adjR^2 = 1 - (1 - R^2)\frac{(N-1)}{(N-k)}, \quad (4)$$

$$R^2 = 1 - \frac{SSE}{SST}, \quad (5)$$

$$SSE = \sum_{i=1}^{N}(y_i - \hat{y}_i)^2, \text{ and} \quad (6)$$

$$SST = \sum_{i=1}^{N}(y_i - \bar{y})^2. \quad (7)$$

Eq. (8) is used for calculating residual standard deviation *s*.

$$s = \sqrt{SSE/(N-n)} \quad (8)$$

Here, *SSE* is the sum of residual squares, *SST* is the sum of the total square, y_i is the true value of the sample of SEC_i, $\hat{y}_i$ is the value of the model output, and *n* is the number of factors in the model. Apparently, $adjR^2 \leq 1$.

A greater $adjR^2$ implies that the fitted values are closer to the observations. Similarly, s can be considered the estimation of the mean square variance. The smaller its value is, the better the model. The final regression results for gas are listed in Table 3, in which the optimum ones are highlighted. Table 4 is for electricity consumption.

Table 3 Regression results for gas consumption for each pair of machine and product

		Mach A & Prod a	**Mach A & Prod b**	**Mach B & Prod c**	**Mach B & Prod d**
Reciprocal	Model	$SEC_{gasAa} = \frac{1}{1.013 + 0.0468P_{gasAa}}$	$SEC_{gasAb} = \frac{1}{3.482 + 0.035P_{gasAb}}$	$SEC_{gasBc} = \frac{1}{2.746 + 0.015P_{gasBc}}$	$SEC_{gasBd} = \frac{1}{2.72 + 0.032P_{gasBd}}$
	$adjR^2$	0.975	0.963	0.935	0.931
	s	0.00955	3.72E-4	4.852E-3	4.74E-3
Power	Model	$SEC_{gasAa} = 5.469P_{gasAa}^{-0.746}$	$SEC_{gasAb} = 1.6P_{gasAb}^{-0.527}$	$SEC_{gasBc} = 1.152P_{gasBc}^{-0.35}$	$SEC_{gasBd} = 2.64P_{gasBd}^{-0.6}$
	$adjR^2$	0.989	0.967	0.958	0.952
	s	9.976E-3	7.518E-4	1.506E-3	1.592E-3
Polynomial cubic	Model	$SEC_{gasAa} = 0.725 - 0.0128P_{gasAa} + 9.938 \times 10^{-5}P_{gasAa}^{\ 2} - 2.638 \times 10^{-7}P_{gasAa}^{\ 3}$	$SEC_{gasAb} = 0.22 - 4.393 \times 10^{-4}P_{gasAb} - 5.34 \times 10^{-6}P_{gasAb}^{\ 2} + 2.246 \times 10^{-8}P_{gasAb}^{\ 3}$	$SEC_{gasBc} = 0.548 - 0.00724P_{gasBc} + 5.46 \times 10^{-5}P_{gasBc}^{\ 2} - 1.44 \times 10^{-7}P_{gasBc}^{\ 3}$	$SEC_{gasBd} = 0.4128 - 0.00403P_{gasBd} + 1.885 \times 10^{-5}P_{gasBd}^{\ 2} - 3.102 \times 10^{-8}P_{gasBd}^{\ 3}$
	$adjR^2$	0.988	0.982	0.954	0.937
	s	9.052E-3	2.594E-4	2.297E-3	1.452E-3
Exponential	Model	$SEC_{gasAa} = 0.126 - 0.692 \times 0.973^{P_{gasAa}}$	$SEC_{gasAb} = 0.0828 + 0.225 \times 0.987^{P_{gasAb}}$	$SEC_{gasBc} = 0.193 + 0.385 \times 0.975^{P_{gasBc}}$	$SEC_{gasBd} = 0.1 + 0.391 \times 0.983^{P_{gasBd}}$
	$adjR^2$	0.985	0.969	0.961	0.954
	s	9.063E-3	5.542E-4	2.095E-3	1.356E-3
Logarithmic	Model	$SEC_{gasAa} = 0.513 - 0.0794In(P_{gasAa} - 31.91)$ $(P_{gasAa} > 31.91)$	$SEC_{gasAb} = 0.358 - 0.051In(P_{gasAb} - 29.1)$ $(P_{gasAb} > 29.1)$	$SEC_{gasBc} = 0.359 - 0.034In(P_{gasBc} - 49.41)$ $(P_{gasBc} > 49.41)$	$SEC_{gasBd} = 0.294 - 0.0369In(P_{gasBd} - 66.27$ $(P_{gasBd} > 66.275)$
	$adjR^2$	0.997	0.954	0.971	0.944
	s	8.567E-3	8.695E-3	9.806E-3	1.573E-3

Table 4 Regression results for electricity consumption for each pair of machine and product

		Mach A & Prod a	**Mach A & Prod b**	**Mach B & Prod c**	**Mach B & Prod d**
Reciprocal	Model	$SEC_{elecAa} = \frac{1}{0.99 + 0.078P_{elecAa}}$	$SEC_{elecAb} = \frac{1}{2.46 + 0.045P_{elecAb}}$	$SEC_{elecBc} = \frac{1}{1.819 + 0.019P_{elecBc}}$	$SEC_{elecBd} = \frac{1}{1.54 + 0.048P_{elecBd}}$
	$adjR^2$	0.969	0.974	0.908	0.965
	s	0.0157	1.3906E-3	8.6589E-3	4.5074E-3
Power	Model	$SEC_{elecAa} = 2.891P_{elecAa}^{-0.67}$	$SEC_{elecAb} = 1.047P_{elecAb}^{-0.41}$	$SEC_{elecBc} = 0.86P_{elecBc}^{-0.21}$	$SEC_{elecBd} = 1.54P_{elecBd}^{-0.45}$
	$adjR^2$	0.986	0.985	0.958	0.986
	s	0.0068	7.40173E-3	2.0796E-3	1.86101E-3
Polynomial cubic	Model	$SEC_{elecAa} = 0.88 - 0.037P_{gasAa} + 7.05 \times 10^{-4}P_{gasAa}^{\ 2} - 4.7 \times 10^{-6}P_{gasAa}^{\ 3}$	$SEC_{elecAb} = 0.379 - 0.00372P_{elecAb} - 1.737 \times 10^{-5}P_{elecAb}^{\ 2} + 4.509 \times 10^{-7}P_{elecAb}^{\ 3}$	$SEC_{elecBc} = 0.698 - 0.019P_{elecBc} + 3.89 \times 10^{-4}P_{elecBc}^{\ 2} - 2.42 \times 10^{-6}P_{elecBc}^{\ 3}$	$SEC_{elecBd} = 0.867 - 0.04067P_{elecBd} + 0.00104P_{elecBd}^{\ 2} - 9.441 \times 10^{-6}P_{elecBd}^{\ 3}$
	$adjR^2$	0.977	0.994	0.976	0.987
	s	0.0095	1.654E-4	3.9815E-4	1.56933E-3
Exponential	Model	$SEC_{elecAa} = 0.174 + 0.772 \times 0.938^{P_{elecAa}}$	$SEC_{elecAb} = 0.162 + 0.3 \times 0.963^{P_{elecAb}}$	$SEC_{elecBc} = 0.387 + 0.526 \times 0.897^{P_{elecBc}}$	$SEC_{elecBd} = 0.249 + 0.545 \times 0.937^{P_{elecBd}}$
	$adjR^2$	0.976	0.987	0.994	0.9792
	s	0.0111	4.613E-4	2.678E-4	2.99718E-3
Logarithmic	Model	$SEC_{elecAa} = 0.589 - 0.103ln(P_{elecAa} - 11.82)$ $(P_{elecAa} > 11.82)$	$SEC_{elecAb} = 0.482 - 0.073ln(P_{elecAb} - 8.792)$ $(P_{elecAb} > 8.792)$	$SEC_{elecBc} = 0.518 - 0.038ln(P_{elecBc} - 13.01)$ $(P_{elecBc} > 13.01)$	$SEC_{elecBd} = 0.569 - 0.0826ln(P_{elecBd} - 11.$ $(P_{elecBd} > 11.46)$
	$adjR^2$	0.995	0.978	0.986	0.993
	s	2.186E-3	8.603E-3	5.3645E-3	7.42702E-4

Fig. 4 shows the regression results of gas usage for each pair of machine and product; and so does Fig. 5 for electricity consumption. The data regression processes were carried out by the software of MATLAB 2016, Origin 8 and SPSS 2016.

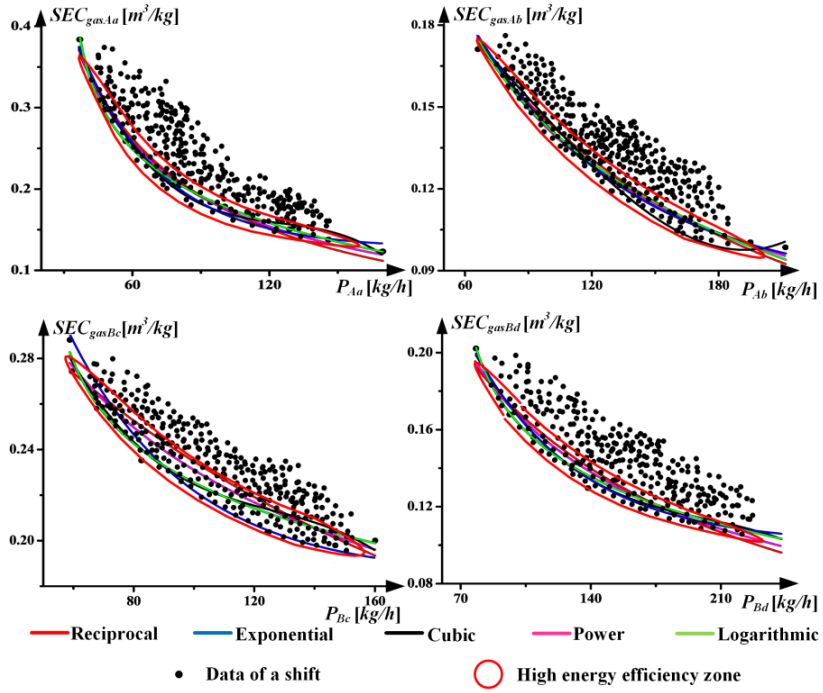

Fig. 4 Regression results for gas consumption

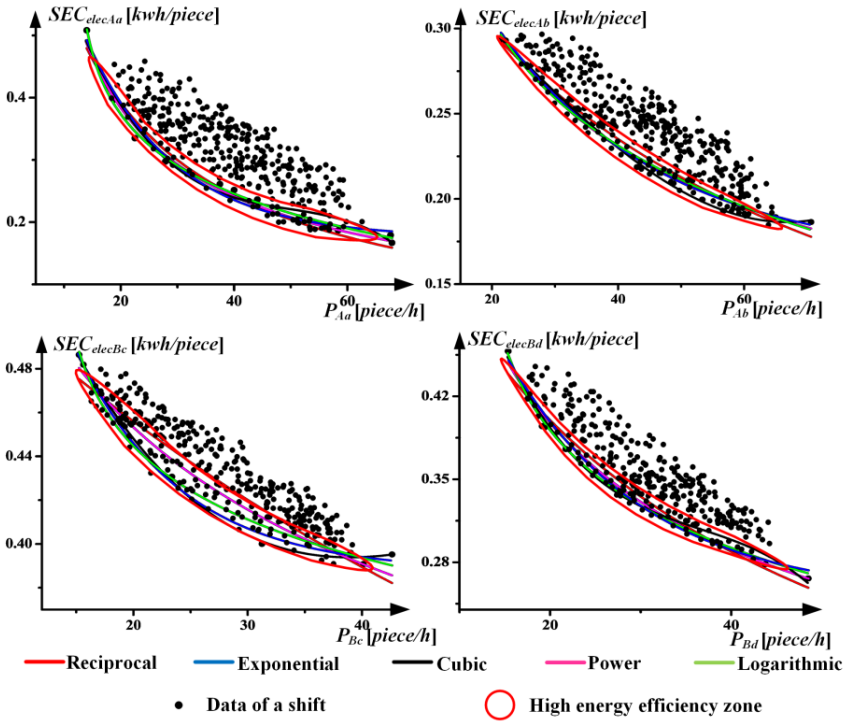

Fig. 5 Regression results for electricity consumption

From Tables 3 and 4, the best regression model for each group of machine and product can be easily selected using the performance indices (i.e., $adjR^2$ and s). Specifically, Eq. (9) and Eq. (10) can be used to calculate and

evaluate the gas and electricity consumption for machine A producing product a respectively.

$$SEC_{gasAa} = 0.513 - 0.0794In(P_{gasAa} - 31.91)(P_{gasAa} > 31.91), \text{ and} \quad (9)$$

$$SEC_{elecAa} = 0.589 - 0.103In(P_{elecAa} - 11.82)(P_{elecAa} > 11.82). \quad (10)$$

Similarly, for the case of machine A producing product b, the energy consumption models are

$$SEC_{gasAb} = 0.22 - 4.393 \times 10^{-4} P_{gasAb} - 5.34 \times 10^{-6} {P_{gasAb}}^2 + 2.246 \times 10^{-8} {P_{gasAb}}^3, \quad (11)$$

$$SEC_{elecAb} = 0.379 - 0.00372 P_{elecAb} - 1.737 \times 10^{-5} {P_{elecAb}}^2 + 4.509 \times 10^{-7} {P_{elecAb}}^3. \quad (12)$$

For the case of machine B producing product c, the regression models are

$$SEC_{gasBc} = 1.152 P_{gasBc}^{-0.35}, \text{ and} \quad (13)$$

$$SEC_{elecBc} = 0.387 + 0.526 \times 0.897 P_{elecBc}. \quad (14)$$

For case of machine B producing product d, the regression models are

$$SEC_{gasBd} = 0.1 + 0.391 \times 0.983 P_{gasBd}, \text{ and} \quad (15)$$

$$SEC_{elecBd} = 0.569 - 0.0826 ln(P_{elecBd} - 11.46) \text{ when } P_{elecBd} > 11.46. \quad (16)$$

In order to validate the resulting models (9-16), validation experiments for the high energy efficiency zones were carried out. The energy consumptions of the overall processes in real practice, G_{real} for gas and E_{real} for electricity, were measured and compared to the calculation results using the corresponding regression models. For each model, the validation experiments were conducted five times using different production rates. The relative errors between the calculation results (i.e., G_c and E_c) and the real energy consumption during experiments (i.e., G_{real} and E_{real}) were calculated by using Eq. (17) and Eq. (18), where δ_{gas} and δ_{elec} represent the relative errors of the prediction results of gas and electricity consumptions.

$$\delta_{gas} = \frac{|G_{real} - G_c|}{G_{real}} \times 100\% \quad (17)$$

$$\delta_{elec} = \frac{|E_{real} - E_c|}{E_{real}} \times 100\% \quad (18)$$

The resulting δ_{gas} and δ_{elec} are listed in Table 5. All values of δ_{gas} and δ_{elec} are lower than 5%, meaning that the proposed models are rather accurate in predicting energy consumption of the overall shifts.

The modeling results also show that there is no clear evidence to imply that a certain form of model can be used as the optimum one to characterize the regressive relation between *SEC* and production rate *P* in the high energy efficiency zone. However, for each pair of machine and product and for either gas or electricity, a specific optimum model can be established. Managers can use the models to predict energy consumption under a certain production rate and further use the relational models to support production scheduling with the consideration on the trade-off between energy efficiency and productivity. In general, the production should be kept within the high efficiency zone as much as possible.

Table 5 Relative errors between validation experiments and regression models

		Mach A &prod a	Mach A &prod b	Mach B &prod c	Mach B &prod d
Exp shift group No.1	MAT used[kg]	477.56	478.97	387.65	637.98
	Num of pieces	189	156	101	124
	G_{real} [m^3]	116.343	84.343	112.124	130.765
	G_c [m^3]	118.997	86.716	114.820	127.352
	δ_{gas}	2.281%	2.814%	2.404%	2.61%
	E_{real} [$KW \cdot h$]	64.654	48.983	54.456	55.345
	E_c [$KW \cdot h$]	63.266	47.299	52.555	56.255
	δ_{elec}	2.147%	3.438%	3.491%	1.644%
Exp shift group No.2	MAT used[kg]	614.34	662.87	563.65	843.87
	Num of pieces	244	221	148	167
	G_{real} [m^3]	132.987	109.345	143.234	137.234
	G_c [m^3]	129.655	105.870	146.45	138.459
	δ_{gas}	2.506%	3.178%	2.245%	0.893%
	E_{real} [$KW \cdot h$]	68.984	62.987	70.567	66.987
	E_c [$KW \cdot h$]	70.143	60.219	67.697	64.092
	δ_{elec}	1.680%	4.395%	4.067%	4.322%
Exp shift group No.3	MAT used[kg]	864.54	1107.87	775.98	1080.34
	Num of pieces	345	367	205	215
	G_{real} [m^3]	151.788	129.876	184.346	154.98
	G_c [m^3]	146.131	128.961	180.276	149.735
	δ_{gas}	3.727%	0.705%	2.208%	3.384%
	E_{real} [$KW \cdot h$]	82.908	80.765	90.345	76.987
	E_c [$KW \cdot h$]	80.830	79.023	85.988	73.758
	δ_{elec}	2.506%	2.157%	4.823%	4.194%
Exp shift group No.4	MAT used[kg]	1142.45	1238.98	1013.59	1394.09
	Num of pieces	456	412	269	278
	G_{real} [m^3]	163.876	136.435	217.455	170.345
	G_c [m^3]	158.997	132.960	214.459	166.877
	δ_{gas}	2.977%	2.547%	1.378%	2.036%
	E_{real} [$KW \cdot h$]	88.982	82.987	109.543	88.943
	E_c [$KW \cdot h$]	89.605	83.611	107.762	85.895
	δ_{elec}	0.695%	0.752%	1.626%	3.427%
Exp shift group No.5	MAT used[kg]	1330.87	1630.76	1179.09	1638.76
	Num of pieces	532	543	314	326
	G_{real} [m^3]	161.897	159.987	230.234	180.456
	G_c [m^3]	164.862	161.123	236.613	182.988
	δ_{gas}	1.831%	0.71%	2.771%	1.403%
	E_{real} [$KW \cdot h$]	96.887	103.345	126.876	93.234
	E_c [$KW \cdot h$]	94.082	101.801	123.835	94.987
	δ_{elec}	2.895%	1.494%	2.397%	1.88%

5. Energy Efficiency Analysis

The case studies carried out in this research were targeted to meet orders with the certain amount of D units and a delivery time T. Two production strategies were further studied. Under the first strategy, the machines were

operated causally without considering energy consumption, which was the current practice. The second strategy was to keep the operations within the high energy efficiency zone as much as possible based on the proposed models. The energy consumptions of both strategies were measured using the data acquisition system and were compared to analyze the energy-saving potentials of the workshops.

The detailed operating information and results of the three cases are listed in Table 6, where T_{ca} ,G_{ca} and E_{ca} are defined as the operational time, gas consumption, and electric energy consumption to meet demand D under the first strategy. T_h ,G_h and E_h are those under the second strategy. Relative energy efficiency evaluation indices R_{gas} and R_{elec} were calculated using Eq. (19) and Eq. (20) to compare the energy usage of the two strategies. Fig. 6 shows the energy consumption data details, and Fig. 7 shows the comparison of energy use under the two production strategies.

$$R_{gas} = \frac{G_{ca} - G_h}{G_{ca}} \times 100\% \tag{19}$$

$$R_{elec} = \frac{E_{ca} - E_h}{E_{ca}} \times 100\% \tag{20}$$

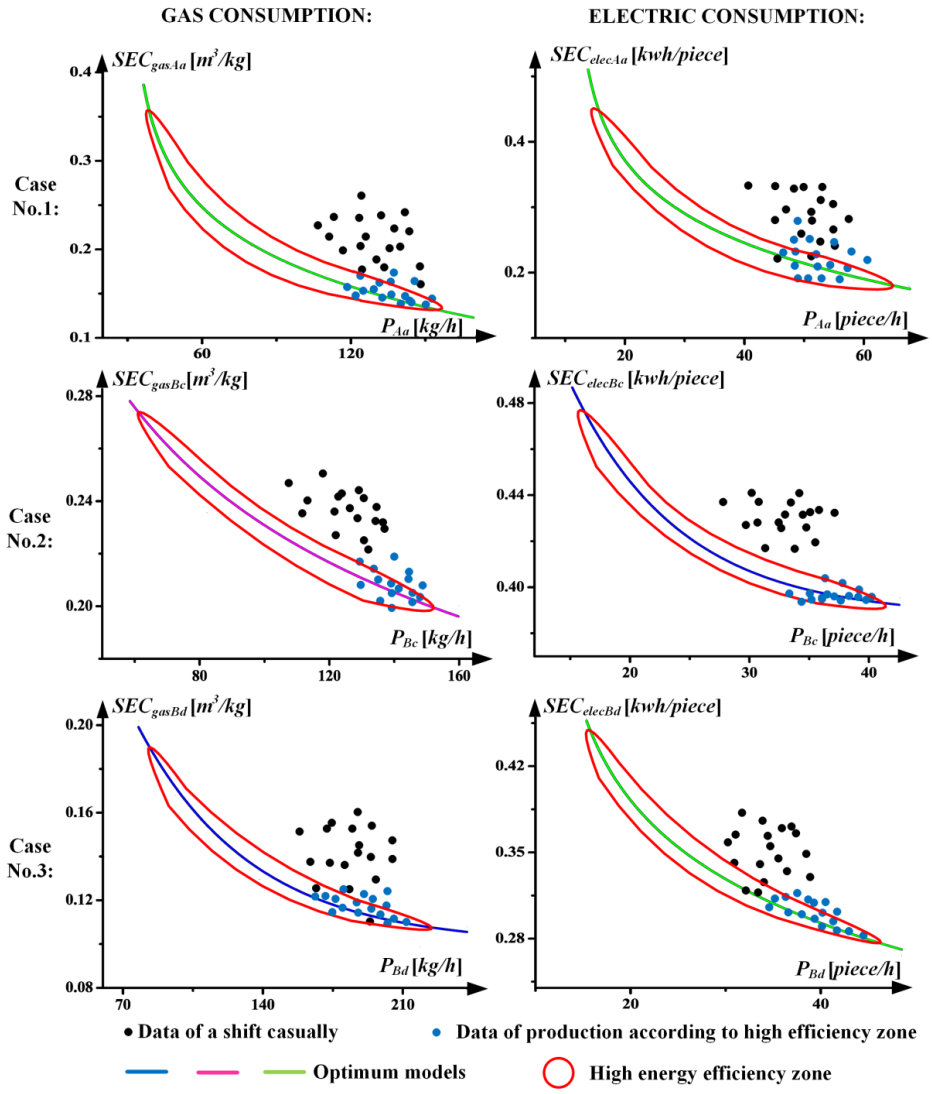

Fig. 6 The energy consumption details of the three cases under both strategies

Table 6 Detailed information and measuring results of the three objective cases

Case	Mach & Prod	T_{ca} [*shift*]	G_{ca} [m^3]	E_{ca} [$KW{\cdot}h$]	T_h [*shift*]	G_h [m^3]	E_h [$KW{\cdot}h$]	R_{gas}	R_{elec}
1	Mach A & Prod a	18	3261.65	1827.654	17	2788.35	1562.77	14.51%	14.49%
2	Mach B & Prod c	18	4426.19	2235.105	16	3929.44	1995.37	11.22%	10.73%
3	Mach B & Prod d	18	3580.92	1879.402	17	3123.96	1618.67	12.76%	13.87%

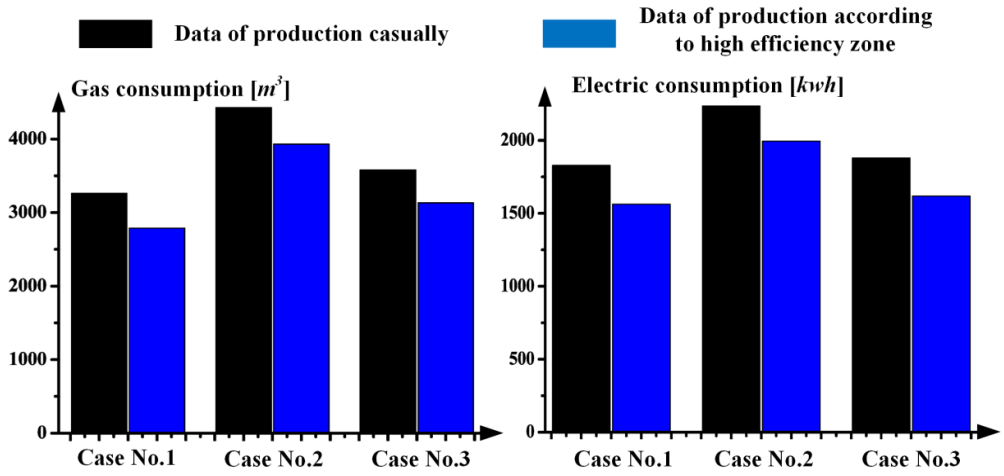

Fig. 7 Comparison of energy use under the two production strategies

As indicted by Table 6, Fig. 6 and Fig. 7, if the production was well-scheduled within the high energy efficiency zone, 10 to 15 percent of the currently used energy can be saved without sacrificing profits or production efficiency. There was even a potential to improve both energy efficiency and productivity.

6. Conclusions and Future Work

An improved method was proposed in this paper for modeling gas and electric energy consumption of aluminum die casting processes. The modeling objective is to represent the mathematical relation between *SEC* and production rate. The modeling process can be well-adjusted according to complex conditions of multi-combinations of machines and products so that it can be easily extended to other die casting situations. Environmental concerns can be well addressed together with the productivity objective. The detailed process was based on the development of an intelligent data-acquiring system (DAQS) aiming at collecting energy-related data, transferring and storing data, and conducting analysis. The metering devices and communication protocols are all standard ones in the industry and support both discrete and continuous information. Comparison among a family of nonlinear regression methods was conducted, and performances of different regression methods were analyzed using certain regression evaluation indices to obtain the best one for each engineering situation. Furthermore, the modeling results are validated by a comparison against data for validation experiments. The models were further used to support production scheduling considering both energy use and productivity. Final reports of case studies showed that if the modeling results were reasonably used and production was accordingly well-scheduled, the production rate would be kept being within the high energy efficiency zone as much as

possible, and 10 to 15 percent of energy saving can be realized without losing profits. The possibly broad application of the proposed modeling method has the potential of saving energy and improving profitability of the die-casting industry. It is estimated that the overall operation costs can be reduced by 5 to 10 percent.

In the future, we will investigate other die casting processes and situations to further verify the proposed procedure. Rather than monitoring production rate, we will also explore other optimization techniques, such as optimization of process parameters and engineering conditions, to obtain balanced solutions for equilibrium of energy saving and economic objectives based on the proposed modeling procedure. The data acquisition, related information collection and model validation may also be applied to other complex engineering situations beyond casting processes. Since scheduling is just one aspect of the overall die casting process optimization, we will study how to incorporate the proposed energy modeling method to improve the overall die casting processes, such as job sequencing, choice of die tools, and others.

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Nomenclature

A_P, B_P , C_P , D_P	Coefficients of polynomial cubic
$adjR^2$	Adjusted coefficient of determination
a_E, b_E, c_E	Coefficients of exponential functions
a_L, b_L, c_L	Coefficients of logarithmic functions
a_R, b_R	Coefficients of reciprocal functions
a_P, b_P	Coefficients of power functions
D	Demanding amount of products of orders
E_c	Calculation result of energy consumption of the overall processes for using electric energy [$KW{\cdot}h$]
E_{real},	The energy consumptions of the overall processes in real practice for using electric energy [$KW{\cdot}h$]
F	Coefficient of F test
$F(\theta)$	The function to get the aggregation of least relative error
$f_{SEC\text{-}P}$	The alternative mathematical form to be used during the modeling process
G_c	Calculation result of energy consumption of the overall processes for using gas [m^3]
G_{real}	The energy consumptions of the overall processes in real practice for using gas [m^3]

N	The sample group number of observed *SEC* and *P* used for the modeling
n	The number of unknown coefficients of the regression model
P	Production rate
P_{elec}	Production rate of die casting machine producing finished products [*piece/h*]
P_{gas}	Production rate of furnaces using gas [*kg/h*]
R^2	Coefficient of determination
R_{gas} , R_{elec}	Relative energy efficiency evaluation indexes
SEC	Specific energy consumption. The amount of energy required for processing a certain amount of one kind of product
SEC_{elec}	*SEC* of producing finished products from the machine using electric energy [*KW·h/piece*]
SEC_{gas}	*SEC* of melting raw materials using gas in furnace [m^3/kg]
SSE	Sum of residual squares
SST	Sum of the total square
s	Residual standard deviation
T	Delivery time
Tc	Cycle of time of process
T_{ca} ,G_{ca} , E_{ca}	The real time, gas consumption, and electric energy consumption of meeting the demand *D* operating casually
T_h ,G_h ,E_h	The real time, gas consumption, and electric energy consumption of meeting the demand *D* using high energy efficiency strategy
t_{idle}	Stand-by idling time
t_p	Production time
x_i	One of the observed value of production rate *P*
y_i	One of the observed value of *SEC*
$\hat{y}$	One of the the value of the model output
δ_{elec}, δ_{gas}	Relative error indexes to measure the accuracy of the prediction results
θ	The unknown coefficient vector of the regression model
$\theta_1, \theta_2, \dots, \theta_n$	The unknown coefficients of the regression model
$\hat{\theta}$	Optimum solution vector of the unknown coefficients

$\widehat{\theta_1}, \widehat{\theta_2}, \ldots, \widehat{\theta_n}$	Optimum solution group of the unknown coefficients
ε	The relative error between the calculation result by regression model and real value
A_P, B_P , C_P , D_P	Coefficients of polynomial cubic
a_E, b_E, c_E	Coefficients of exponential functions
a_L, b_L, c_L	Coefficients of logarithmic functions
a_R, b_R	Coefficients of reciprocal functions
a_P, b_P	Coefficients of power functions
D	Demanding amount of products of orders
E_c	Calculation result of energy consumption of the overall processes for using electric energy [$KW{\cdot}h$]
E_{real},	The energy consumptions of the overall processes in real practice for using electric energy [$KW{\cdot}h$]
F	Coefficient of F test
$F(\theta)$	The function to get the aggregation of least relative error
$f_{SEC\text{-}P}$	The alternative mathematical form to be used during the modeling process
G_c	Calculation result of energy consumption of the overall processes for using gas [m^3]
G_{real}	The energy consumptions of the overall processes in real practice for using gas [m^3]
N	The sample group number of observed *SEC* and *P* used for the modeling
n	The number of unknown coefficients of the regression model
P	Production rate
P_{elec}	Production rate of die casting machine producing finished products [*piece/h*]
P_{gas}	Production rate of furnaces using gas [*kg/h*]
R^2	Coefficient of determination
R_{gas} , R_{elec}	Relative energy efficiency evaluation indexes
SEC	Specific energy consumption. The amount of energy required for processing a certain amount of one kind of product
SEC_{elec}	*SEC* of producing finished products from the machine using electric energy [$KW{\cdot}h/piece$]

SEC_{gas}	*SEC* of melting raw materials using gas in furnace [m^3/kg]
s	Residual standard deviation
T	Delivery time
Tc	Cycle of time of process
T_{ca} ,G_{ca} , E_{ca}	The real time, gas consumption, and electric energy consumption of meeting the demand *D* operating casually
T_h ,G_h ,E_h	The real time, gas consumption, and electric energy consumption of meeting the demand *D* using high energy efficiency strategy
t_{idle}	Stand-by idling time
t_p	Production time
x_i	One of the observed value of production rate *P*
y_i	One of the observed value of *SEC*
δ_{elec}, δ_{gas}	Relative error indexes to measure the accuracy of the prediction results
θ	The unknown coefficient vector of the regression model
$\theta_1, \theta_2, \dots, \theta_n$	The unknown coefficients of the regression model
$\hat{\theta}$	Optimum solution vector of the unknown coefficients
$\widehat{\theta_1}, \widehat{\theta_2}, \dots, \widehat{\theta_n}$	Optimum solution group of the unknown coefficients
ε	The relative error between the calculation result by regression model and real value

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