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An empirical calibrated energy model of a CNC machine case study using process output data to reduce energy consumption.

Abstract

With an ever growing need to reduce energy consumption in the manufacturing industry, process users need to become more aware on how production impacts energy consumption. Computer numerically controlled machining tools are a common manufacturing apparatus, and they are known to be energy inefficient. This paper describes the development of an empirical energy consumption model of a CNC with the aim of predicting energy consumption based on the number of parts processed by the machine (both successful and scrapped). In using the Calibrated Model Method, the data undergoes initial preparation followed by exploratory data analysis and subsequent model development via iteration. During this analysis, relationships between parameters are explored to find which have the most significant on energy consumption. A training set of 191 datapoints yielded a correlation value of 0.95, between the power consumption and total units produced. RMSE, MAPE and MBE validation test yielded results of 0.198, 6.4% and 2.66% respectively showing high confidence in prediction.

Introduction

In recent years, energy consumption has been an increasingly important consideration in the manufacturing industry, both in the fight against climate change, and as a means of making financial savings [1]. With global energy demand estimated to increase by 45% from today's levels to 2030, all aspects of our energy system must be analysed [1]. The industrial sector plays a large role in this increase, currently accounting for 41.9% of final electricity consumption [1]. By improving energy use in the industrial sector, substantial improvements can be made in global energy demand and carbon emissions.

Numerical modelling is increasingly being used in the design and optimization of manufacturing processes in order to increase the quality of the produced parts and improved production yield [2]. Traditionally, production is assessed by monitoring four main manufacturing attributes; cost, time, quality and flexibility [3]. While there is an increased awareness around energy consumption in the production industry [4], energy consumption modelling for processes is far less common. Many studies look at particular processes in great detail or apply a bespoke prediction model to a certain process, however this makes it difficult to apply to other scenarios [5] and hence the outputs from this research is not easily replicable. Energy consumption can be collected by various means, such as internal energy reading or by utilising external sensors. It was found that in manufacturing, energy consumption can be recorded, stored and used in varying formats, with no standardisation. Because of this, general models are not very common to apply to different manufacturing settings so bespoke models are developed[6]. Due to the nonlinear nature of energy consumption within manufacturing, data science and machine learning approaches would need to be considered [4].

This study focused on the development of an empirical energy consumption model of a CNC machine, which seeks to predict energy consumption based on product throughput. The development of the model can also provide analysis into means to assess where potential energy reduction strategies can also applied. This paper looks at current empirical energy modelling practices from literature, provides an overview of the methodology used then describes an implantation of the developed model on real world manufacturing data.

Literature Review

The machining process is a fundamental manufacturing technique, where parts are shaped by the removal of unwanted material. Various techniques are applied to remove this material such as milling, grinding, and turning. Machining equipment are a high energy consumer within manufacturing and not very energy efficient, at less than 30% [7]. This is due to the varying nature of the tools within the machines and the materials being used. Machining tools contain many motors and auxiliary devices, with varying energy consumptions. Behrendt et al. (2012) found that in a CNC machine, the spindle's work drives near peak power during rough cuts, while the consumption at the finishing cuts can be significantly lower [8]. Various studies exist in trying to further understand machining energy consumption. They also found that the power required to remove material has a small impact on the overall consumption, which means savings could stem from the overall cycle time [8]. Energy modelling can be a challenging task due to the complexity of machining tools [9]. This environment is often characterised by large variety in products in small batches, requiring real-time monitoring, dynamic scheduling and decision making, and adaptive capability. Energy modelling of this task also needs to have a dynamic approach, as every time distributed resource or multiple objectives are considered, the energy usage needs to be updated [9].

Empirical modelling is a data driven approach where the performance of the item being modelled is translated into one or a set of algebraic equations [10]. The use of empirical modelling denotes defined algebraic relationships between the input and the required output. These types of models are constructed with regards to prediction ability or model fit (data approximation), prognostic ability (forecasting) and model structure (agreement with theories and facts). They are becoming more and more common as the systems being modelled are becoming more complex and less structured [11]. Overall, empirical models offer simplistic solutions for quantitative comparisons between different operating conditions. Studies show that empirical models can be greater than 90% effective [12]. Garg et al. (2018) sought to develop an empirical model of machining tools by building empirical models focusing on optimising process parameters to efficiently machine parts, thus reducing overall consumption. The model inputs on this study were identified as spindle motor power rating (W), maximum spindle speed (rpm), maximum turning diameter and length (mm). From literature, it was found that many of the energy models of CNC machines rely on tool parameter data to drive prediction. In many cases, data to that level of detail can be difficult to install recorded. By deriving a relationship between process output and energy consumption data, this approach to modelling may be a more simplistic first step for many CNC users to predict machine energy consumption. Peng et al. (2014) highlights that empirical models use actual production data to establish relationships between main variable and the energy consumption. Methodology

A common approach with empirical modelling in manufacturing is the use of the Response Surface Method (RSM) [7,9,13,14]. The RSM works best between several explanatory variables and one response variable. Due to this model only containing one explanatory variable and one response variable, and limited available data, the RSM output could be ineffective. The methodology selected to develop the model is based on the Calibrated Model Method, a modelling methodology originally created to optimise the energy consumption of a building [15]. The methodology is based on a similar approach where prepared data is inputted to an initial model and the model is iteratively calibrated with the data to improve predictability. While applications vary between building and machine modelling, the approaches do not. Both scenarios see a basic initial model developed, following iterative data improvements, this calibrates the model further to the eventual creation of an effective final model. This method is especially useful for when limited data is available and assessment sees modifications that can improve the final model.

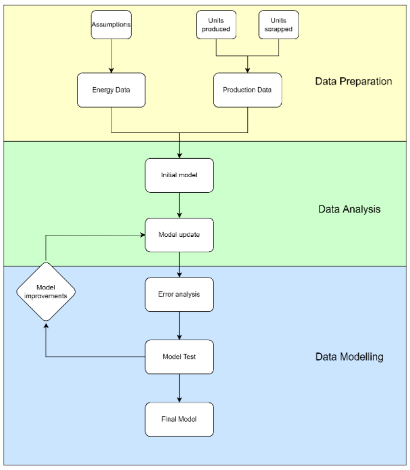

Figure 1 Modelling Methodology

In data preparation stage, the data is gathered, formatted, and standardised for use in the energy model. The model requires two inputs, from energy data and production data. It is only after significant data preparation that both sets of data are ready for analysis. Both input files are indexed to be compatible with one another then merged for data analysis. In the case of time series data, ensuring data sets are sampled to the same time frame.

With the prepared data, the relationship between datapoints is examined. This includes data correlation, causation and understanding. From data visualisation, explanations for major outliers that could hinder model performance as well as other relationships can be assessed. Through iterative adjustments, relationships between datapoints are calculated to potentially generate assumptions, assess machine performance, and increase machine understanding. Examples of such assumptions may be assuming idling energy consumption from shifts with zero throughput, approximating the active energy consumption from this and using scrap data to calculate the amount of energy lost due to scrap. It is recommended to document each iteration on a model version log, documenting what changes were made, any new assumptions, assumptions removed and validation scores.

Once data preparation and exploratory analysis is complete, the data can then be modelled using datapoints with the highest correlation using the most appropriate empirical modelling method (linear regression, multivariate regression etc.). The predicted results can then undergo validation using methods such as root mean squared error (RMSE), mean absolute percentage error (MAPE) and mean bias error (MBE).

Case Study

Description

This methodology was applied to a medical device manufacturing process where a CNC lathe was utilised to remove material. The CNC operates in two 12 hour shifts daily, which formed the measured timeframe of the study. The CNC machines parts, where a raw block of material is machined into the required shape.

Production data (parts produced, parts scrapped) was readily available via an OSI PI network connection to the physical machine. Realtime power consumption at the time of development was not available however, so power consumption was collected using a Fluke 1734 Energy Logger over five different production shifts recording consumption every one minute. Four of the five energy datasets were used as a training set while the fifth was retained as the testing set for model validation.

Model

Data Preparation

The input data first underwent data preparation ahead of the data analysis. The power training data, power testing data and production data were used as inputs in this stage. Firstly, the power datasets were resampled from their original 1 minute granularity to 12 hour production shifts, with the power data during the shifts summed. As the collection of power data involved a temporary energy tracker over five different production shifts, this created inconsistencies within the power data as was addressed. With the tracker being installed and removed mid shift, the data from the first and last shift were excluded as data was collected for a partial shift and not reflective of the entire shift. The production data from the CNC's shifts were then extracted to its own dataset. In this dataset, the total quantity of parts produced during the shift was calculated by summing the number of successful parts with the parts that were scrapped. A scrap yield percentage was also calculated. Following this, both datasets were merged ahead of the next stage of the analysis.

Data Analysis

With the prepared data, initial analysis included assessing the correlation between the power consumed per shift and the total units produced. Over iterative adjustments, it was found that power consumption during the installation and removal from the CNC were incomplete, reducing model efficiency. These datapoints were then removed. The data was assessed to obtain the assumed idling consumption of the CNC. Various datapoints in the set showed when instances when no parts were produced, the power consumption remained relatively static and the average power value was assumed as the idling power value of the CNC. The active power per shift was then calculated by subtracting the assumed idling power from the total power consumption. By utilising the scrap yield percentage, when applicable, the power consumed on parts that were ultimately scrapped was also calculated, as seen in Table XXX.

Table 1 Data Analysis example

DateTime	Power [kW]	Total Units	Parts successful	Parts scrapped	% scrapped	Active Power [kW]	Power scrapped [kW]	Power per Part
2022-01-12 19:00:00	1781.665599	45	45	0	0.000000	596.598943	0.000000	13.257754
2022-01-13 07:00:00	1955.644445	59	58	1	1.694915	770.577789	13.060640	13.060640
2022-01-13 19:00:00	2005.026689	55	55	0	0.000000	819.960033	0.000000	14.908364
2022-01-14 07:00:00	2085.867077	63	63	0	0.000000	900.800421	0.000000	14.298419
2022-01-14 19:00:00	1206.358962	0	0	0	0.000000	21.292305	0.000000	0.000000

Data Model

From iterative improvements during analysis, the training was used to create a linear regression energy model of the power consumption. Iterative changes made to the model included data manipulation, visualisation and interpretation. Examples of such changes include ensuring duplicate and non-numerical values were addressed, contextual outliers were understood and appropriate visualisation methods for process users. The training set of 191 datapoints yielded a high instance of correlation (0.95) between the power consumption and total units produced, which formed the input for the linear regression model. This model was then tested on a set of 41 datapoints. The accuracy percentage was calculated for each of the datapoints with a mean average of -0.68%.

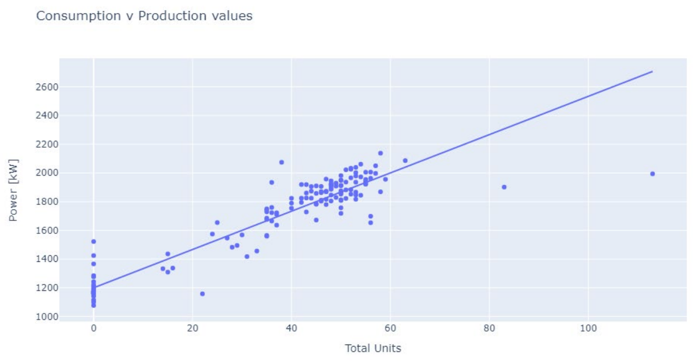

Figure 2 Power consumption v Total units produced

Results

Data Analysis

The findings from each iteration showed improvements from the data analysis. The analysis provided quantification on the energy consumed due to parts scrapped per production shift (Figure XX), and the amount of active energy consumed per part. As expected, the majority of the energy consumption came from active production however the quantification of energy consumed when the CNC was idle and parts were scrap may be useful for machine users. These insights give process users further insight into how much energy is consumed per part through the machine and could foster future improvements.

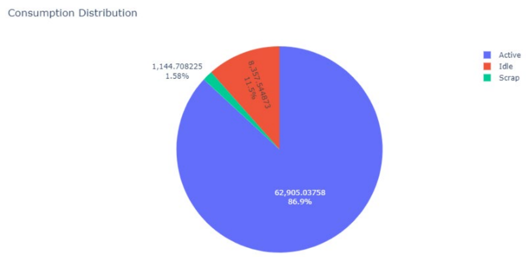

Figure 3 Power consumption based on status (Energy consumption in kW, distribution in %)

Data Modelling

Figure XX shows the comparison between the actual and predicted energy consumption values of test data. Numerous validation methods were used to validate the energy consumption model's performance, namely normalised RMSE, MAPE and MBE. These validation methods yielded results of 0.198, 6.4% and 2.66% respectively. For the normalised RMSE, a value of less than 0.5 indicates a high level of predictability whereas for MAPE and

MBE, a percentage score of close to zero indicates a high level of predictability. Overall, these values showed a high predictive capability for the model for future use on the CNC.

Figure 4 Actual Power Consumption v Predicted Power Consumption

Key Performance Indexes

From the data analysis, various performance observation could be obtained:

Energy Scrapped: Although the scrap yield is commonly accessible based on the production data alone, by quantifying the amount of energy lost due to scrap, this could highlight the further monetary on top of loss from scrapped materials. In the case of this study, out of 71MW consumed during the testing period, 1.5MW was scrapped. Power Consumed Per Part: Indicator of machine performance, during the study the mean and median value of this parameter was approximately 12.33 and 13.65 kW/part respectively. Should the machine operate outside a confidence interval, this may indicate the machine requires attention. Normalised Predicted Energy Score: This KPI was calculated as another indicator on machine and model performance. Calculated by obtaining the product of the predicted consumption and the inverse of the actual consumption, a value of 1 shows ideal performance and performance outside certain criteria could require further attention. From the testing period, the mean of values returned was 1.002. Should these KPIs return greater than expected, this could indicate machine errors, however, should a the power consumed per part KPI remain satisfactory, this could indicate issues with model performance.

Discussion

The adapted calibrated model method used to develop the empirical energy consumption model, provided an effective means when data availability was scarce. With a training dataset of 191 points, the data was prepared and underwent initial analysis. Determining the CNC's baseline energy consumption, the amount of active energy consumed on top of the baseline and the average consumption per part. The analysis also quantified the energy lost due to parts scrapped, an effective means for waste reduction. This dataset identified a correlation of 0.95 between energy consumption and total parts produced, which were then inputted into a linear regression model. The model was tested on a 41 point dataset. Fig XXX conveys the comparison between the actual values and predicted values in the model. To validate model, RMSE, MAPE and MBE validations methods were used and returned values of 0.198, 6.4% and 2.66% respectively. Each value indicted a high confidence of predictability from their respective metric. From the iterative analysis of the results, better correlations were established which ultimately made the model more predictable. It was found that in preparing the data model, it could be reusable across any similar CNC.

Future Work

Following the use of temporary energy trackers, next steps would include the installation of EpiSensors wireless energy meters. The collection of energy data can facilitate real time modelling of the CNC. The model will also be trialled on other CNC machines to assess the model's applicability on other machines, including other CNCs and other machining assets, such the saw and cleanline.

Likewise, from the analysis, the quantification of the relationship between energy consumption and process improvements could foster energy savings. Examples that can be explored include the means to reduce scrap and alternative approaches when the machine is not in use other than remaining idle.

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