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TOWARDS DATA–DRIVEN SUSTAINABLE MACHINING – COMBINING MTCONNECT PRODUCTION DATA AND DISCRETE EVENT SIMULATION

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ABSTRACT

Recently there has been an increased focus on the environmental aspects of the manufacturing industry across the world. Boeing and the National Institute of Standards and Technology (NIST) have studied the incorporation of Life Cycle Analysis (LCA) parameters into Discrete Event Simulation (DES) as a means to analyze sustainable performance in the manufacturing area. For machining, accurate analysis of manufacturing processes using Discrete Event Simulation requires detailed Computer Numerical Control (CNC) production data. Using MTConnect, production LCA data from Boeing shop floor machine tools was acquired and was used as input to Discrete Event Simulation models. We will discuss our implementation, and analyze results of incorporating shop floor LCA data directly in DES models.

Keywords

MTConnect, Life Cycle Analysis, finite state machine, machine tool, sustainable manufacturing, Computer Numerical Control, open–architecture

Nomenclature

CNC	Computer Numerical Control
DES	Discrete Event Simulation
FEPC	Front End PC
FSM	Finite State Machine
HTML	Hypertext Markup Language
HTTP	Hypertext Transfer Protocol
HVAC	Heating, Ventilating, and Air Conditioning
LCA	Life Cycle Analysis
MTC	MTConnect
MTBF	Mean Time between Failure
MTTR	Mean Time to Repair
OEE	Overall Equipment Effectiveness
OMAC	Open Modular Architecture Control
NC	Numerical Control
PLC	Programmable Logic Controller
RPM	Revolutions per minute
XML	eXtensible Markup Language

INTRODUCTION

There was a time in manufacturing when sustainability referred to lean and agile production in order to keep a business profitable for the long term. Over time, the definition of manufacturing sustainability has been broadened from a financial viewpoint to also considering environmental integrity and social equity. The U.S. Department of Commerce defines sustainable manufacturing as “the creation of manufactured products that use processes that are non–polluting, conserve energy and natural resources, and are economically sound and safe for employees, communities, and consumers.” To be sustainable, companies must analyze their current processes, innovate, and identify new sources of revenue and cost reduction, but with a broader social and environmental agenda.

For machining applications, the question arises, “What does it mean to be sustainable?” Life Cycle Analysis (LCA) is one of several techniques to evaluate the sustainability of a system by classifying the consumption data into various impact categories, (e.g., global warming, stratospheric ozone depletion, photochemical smog, and energy consumption), and then perform analysis and estimation of the magnitudes of potential impacts for each impact category. The ISO standard for life cycle impact assessment, ISO 14042 [1, 2], considers classification and characterization to be mandatory elements of LCA. More specifically, a first step towards sustainability involves the identification and accounting for materials, energy, and wastes, compliance with regulations, and the reduction of toxics [3].

To develop metrics for in–house sustainable manufacturing, companies must intelligently study their operations at a finer granularity, such as on actual machines during production, within processes, and over extended periods of time. For the discrete parts industry this can be difficult as detailed process analysis on the factory floor has been limited. This is primarily due to closed, proprietary CNC architectures that make sustainable manufacturing assessment difficult. This paper will perform a baseline LCA analysis of the energy and global warming aspects of a machine tool and its data requirements. Machine data acquisition will be done in a non–intrusive manner, i.e., no extra equipment or special metering, and thus will be easy and cost–effective for companies wishing to perform LCA. For our test case using LCA applied to a machine tool, we will use a five–axis machine tool and its energy ratings found in a Boeing plant. After establishing a model of instantaneous energy and emissions, we will compare these findings to values computed from actual shop floor data and also by projecting long–term LCA metrics using DES.

In manufacturing, Discrete Event Simulation (DES) simulates a real or virtual model of production based on statistical characterization of a shop floor process, such as cycle time, idle time, failure rates. Once developed, the DES model can then be used to simulate a prolonged length of operation, such as a period of a year, in a short order of time to forecast expected long term values. DES is aptly suited as a way to predict LCA metrics for long term energy consumption and Greenhouse gas emissions. However, accurate DES projections require high–quality data. For our DES models, the LCA estimations will be based on actual data collected from production machine tools on a plant floor. Collecting shop floor machine tool data can be difficult, yet the advent of MTConnect, a new standard for data exchange on the manufacturing floor, has made this easier.

This paper will study the use of shop–floor data in the LCA of the energy and environmental aspects of a machine tool. Section 2 will give a brief overview of LCA and then do a baseline data analysis for the cutting aspects of a CNC milling machine tool. Section 3 will investigate a case study of LCA for machine tools in a production workcell at a Boeing plant. The calculation of the LCA machine tool metrics for energy and emissions machine tool LCA metrics using MTConnect and DES will be discussed. Finally, a discussion of the results and future directions will be given.

LIFE CYCLE ANALYSIS

In the current paradigm, sustainability has become the catch–all phrase when referring to production improvements and covers numerous techniques. The complexity and interaction of all the sustainable constituent elements, such as profit, environmental, life cycle, user experience, recyclability, etc., make it very difficult to measure and assign numbers in evaluating sustainability. Clearly, applying logical measurement strategies with better evaluation benchmarks would help deepen the understanding of how sustainable manufacturing works. One of the more popular methodologies in evaluating sustainability is LCA, which is a technique to assess the environmental aspects and potential impacts associated with a product, process, or service, by:

- compiling an inventory of relevant energy and material inputs and environmental releases;
- evaluating the potential environmental impacts associated with identified inputs and releases;
- interpreting the results to help make a more informed decision [4].

Figure 1 shows the stages of a LCA manufacturing product: material extraction and production, manufacturing, packaging and shipping, use phase, and end–of–life phase. In the LCA approach, the product perspective is extended beyond the traditional total cost of ownership, i.e., cost of acquisition, operation, maintenance, and disposal, to include the product's environmental impact and energy consumption during all product phases - from raw materials extraction to disposal. The LCA emphasis on environmental impact attempts to rectify such issues as build–up of greenhouse gas, ozone layer depletion, de–forestation, exhausting non–renewable energy sources, water and air contamination, and dealing with hazardous waste.

There are many processes used by the metalworking industries each with its own energy and emissions profile [5]. The focus of this paper will be on the real–time ongoing LCA analysis of energy and emissions for the cutting process on CNC milling machines. We assume a semi–automated production scenario relying heavily on automated machining with a full compliment of auxiliary equipment such as tool changers, chillers, etc. Production machining covers a wide spectrum of different activities, and the focus will be on subset of potential processes aimed at five–axis milling of prismatic and contoured non–prismatic parts. In contrast to many of the findings in literature, performing sustainability analysis of the material removal process, the calculated LCA metrics in this paper will be based on actual production data. Given the current data monitoring capabilities, the production data may only provide some of the necessary parameters for a thorough LCA analysis. Part of the goal of the paper is to identify the missing data elements that would help assist machine in–situ sustainability analysis.

LCA presents an extensive system view of the machining process and includes activities such as material production, ma-

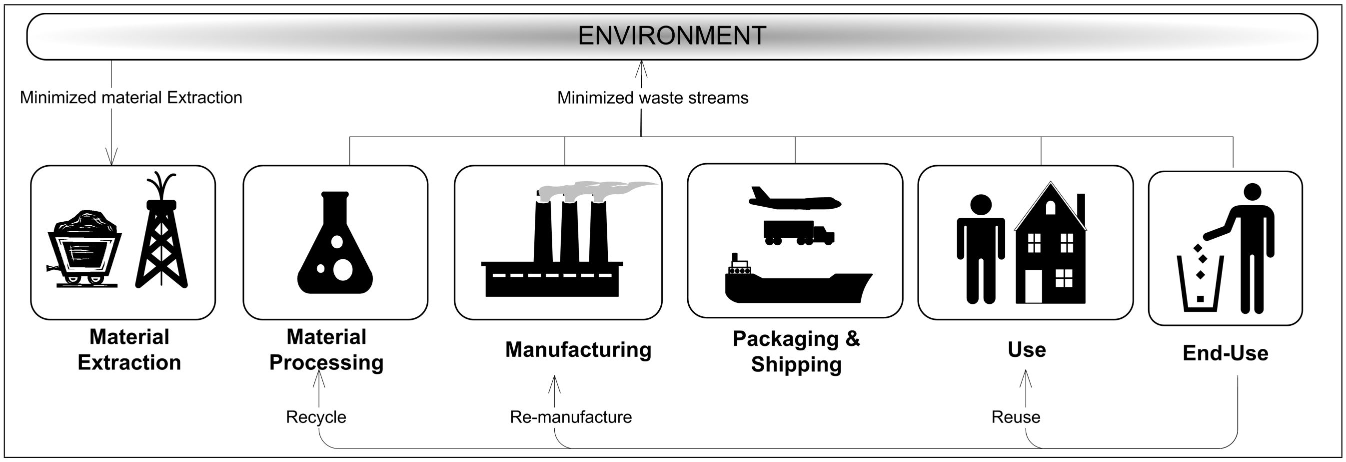

FIGURE 1. Life Cycle Model

terial removal, tooling, setup, coolant, among others. Material removal will be the primary focus of the analysis in this paper. Material extraction and processing is covered here [6]. Issues relating to coolant and dry or near dry machining is covered here [7–9]. A significant amount of work has been conducted on sustainable machining with a great deal of effort being focused on the study of energy consumption and environment impact [10–13]. These papers discuss energy consumption and provide models that were validated by research experiments. Most research has been conducted using a test and measure model that yields a linear model relationship between material removal rate and power consumption. There is little research on achieving machining sustainability that is cost–effective, implemented in a timely manner, and has been studied under actual production operation. Our preliminary work has focused on developing a sustainable model validated by factory testing that will help understand the implications of a continuous, on–line machining sustainability system.

The underpinning of the sustainability work is the development of a finite–state–machine (FSM) model to model all LCA involved in machining production. But first, the scope of sustainability is narrowed to understand and categorize energy and emissions during the material removal process, as these are perceived as having the largest benefits. The FSM can then be used to categorize energy data during material removal to be later used by DES [14]. Figure 2 shows the LCA using FSM to understand material removal on a machine tool. The process contains physical inputs: raw or forged stock, tools and coolant, lubricants, and compressed air. The primary output is the part. The primary consumable is energy, typically electrical, which powers the machine servo drives, related auxiliary equipment and CNC computer. Indirect energy consumption includes such items as factory lights, HVAC, and miscellaneous plant functions and is out of scope for our analysis. Electrical energy can be some combination of renewable or non–renewable sources, and we will use table lookup to approximate emissions based on the energy generation in a specific region.

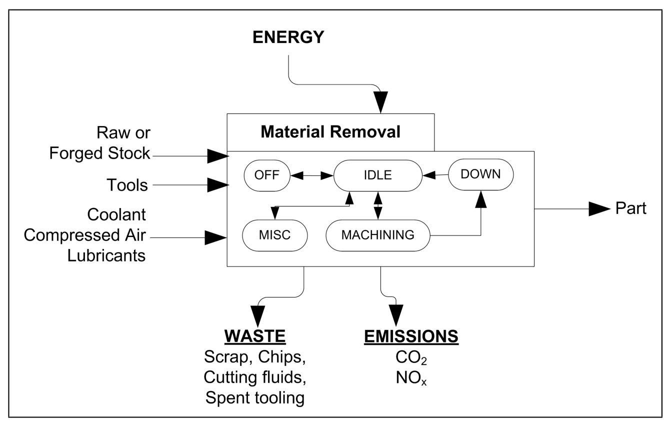

FIGURE 2. Product LCA involving Machine Tool

During part production there are instantaneous wastes that accumulate while machining and periodic wastes that occur intermittently. Instantaneous wastes consist of material chips, vibration, heat, and possibly compressed air. Over time, periodic waste would include disposal and recycling of accumulated chips, coolant/cutting fluid, tools, fixtures, and lubricants. The machining emissions include air emissions and noise emissions. Any potential water emissions would be a by–product from coolant operational loss and disposal. Most emissions are by–products from energy consumption and the energy to make stock material (e.g., casting or blank) and tools.

Next we map the FSM formalism of the energy states of the machine tool during material removal process into a DES model. From [15], the basic definition of a controlled discrete–event process is

$$G = (\sum, Q, \delta, q_0) \tag{1}$$

where "Q" is the set of states, "q_0" is the initial state, "δ" is a finite set of output symbols, and $\delta : \sum \times Q \to Q$ is the state transition function. For a material removal process, "G" defines a function that starts in the state q_0 and generates a sequence of events, i.e. state transitions, subject to the range of transitions permitted by the function "σ". Each event results in an output from the set δ. This DES model of the machine tool behavior can be equivalently described as a Finite State Machine (FSM), which is a more common paradigm to modeling machine control logic. A FSM model is a set of finite states together with a set of state transitions, a machine controller as being in one of a finite set of the possible states, known as the state–space, at any given time.

The machining energy models found in the literature hint at the FSM methodology, establishing an "Idle" or "Ready" machine energy baseline for power consumption, and implicitly assume a "Machining state" as well. We will attempt to formalize the Machine component based on enumerating the states required for the machine removal process. Inside the Material Removal Process box shown in Figure 2, the basic FSM formalism is given as these states: OFF, DOWN, IDLE, MISC, and MACHINING.

OFF refers to the machine being off due to inactivity.
DOWN refers to the machine being idle/off due to an alarm or fault.
IDLE refers to the state where the material removal process is in manual mode during setup and takedown.
MACHINING refers to the state where the material removal process is occurring.
MISC refers to CNC maintenance and other intermittent activities.

Adopting hierarchical state machine terminology, MISC is a superstate that contains nested substates for tool changes, lubrication cycles and other miscellaneous intermittent activities, and is out of scope for detailed analysis. As a point of reference, the FSM formalism could be adapted to a more detailed sustainability analysis by including substates for machining such as DRY MACHINING, WET MACHINING, HIGH SPEED MACHINING, ROUGHING, FINISHING, HOGGING, etc.

Given this state model, the energy consumption of machine tool states computed over the time interval in that state is calculated as follows.

$$E_{down} = 0 \tag{2}$$
$$E_{idle} = E_m + E_{sp} \tag{3}$$
$$E_{machining} = E_m + E_{sp} + E_{cp} + E_{cs} \tag{4}$$
$$E_{misc} = E_{idle} + (E_{cc} | E_{tc} | E_{lp}) \tag{5}$$
$$\tag{6}$$

where:
E_m: energy consumption of servo motors [kWh]
E_{sp}: energy consumption of spindle motor [kWh]
E_{cs}: energy consumption of cooling system of spindle [kWh]
E_{cp}: energy consumption of coolant pump [kWh]
E_{tc}: energy consumption of tool changer [kWh]
E_{cc}: energy consumption of chip conveyor [kWh]
E_{lp}: energy consumption of lubrication pump [kWh]

CASE STUDY

The goal of the Boeing/NIST work was to combine MTConnect and DES modeling to derive sustainable manufacturing LCA benchmarks and cost projections based on plant floor data. For our initial sustainability analysis, we concentrated on understanding the machining process within an integrated workcell at Boeing that is primarily dedicated to making aluminum plane shims, brackets and body joints. The workcell operates on batch lots of aluminum parts with part runs ranging from one shim to hundreds of brackets with assorted milling, drilling, facing and probing operations. Cycle times for these parts vary from twenty minutes for a bracket to approximately five hours for a body joint. Each CNC features a high–speed spindle and other options for high–speed machining. Production volume varies, generally a little under 24/7 capacity, with most machines running 3 shifts a day.

MTConnect

Closed architecture machine tools force the gathering of production knowledge at a higher level of operation. In this scenario, workorders enter the shop floor and then overall performance is measured upon completion. Intermediary analysis of the process steps and costs involved are then generally estimated. Clearly for any system of reasonable complexity, the farther the data is gathered from the real world, the greater the difficulty in analyzing the data. Further, it is difficult to improve systems if they cannot be accurately measured and quantitatively characterized. In order to reduce costs, increase interoperability, and maximize enterprise integration, the MTConnect standards have been developed to "open" machine tools and factory floor devices for the manufacturing industry [16–18].

One of the major machine tool suppliers for Boeing added MTConnect functionality to their machine tools making shop floor data acquisition possible. The MTConnect Version 1.0 specification, which we used, provides data models for: position, feeds, speeds, program, control logic, and some tooling. The goal was to supplement this basic device knowledge in order to couple sustainability energy consumption data with DES model parameters: cycle time, setup time, and downtime. To implement these sustainability requirements, Boeing requested the machine tool vendor add the data items: 1) part count to understand cycle time and 2) servo and spindle loads to assist in energy management.

Figure 3 shows the DES–MTConnect data flow as deployed at Boeing. On the shop floor, the MTConnect Agent runs continuously as a Windows Service on a Front End PC (FEPC) as constrained by the network security within the factory. MTConnect Agent collects CNC data from an MTConnect Adapter that outputs TCP/IP socket data messages that was provided by machine tool vendor.

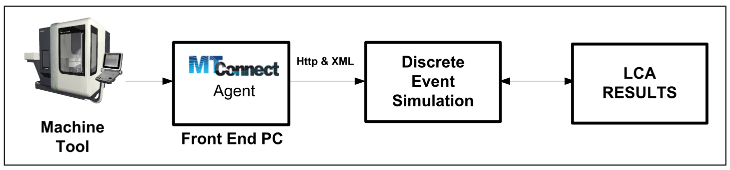

FIGURE 3. MTConnect Data Flow

For our initial tests, we relied on the ease of MTConnect remote connectivity to perform the data collection. Using VBScript, data was collected every 10 seconds over the course of several weeks and was logged to Excel files. The Excel file contained data for timestamp, machine state, program info, part count, servo loads, tool info, alarms and feeds/speeds.

Discrete Event Simulation

DES was used to project long–term LCA metrics based on production statistics. DES models a system as a chronological sequence of discrete events and is especially popular where the complexity of real world makes analytical "closed–form" solutions impossible. It was necessary to transform the raw MTConnect data into DES production model data. Figure 4 shows the sequence of events to transform raw Excel data into projected LCA metrics.

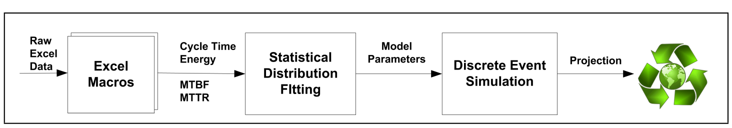

FIGURE 4. DES Data Flow

The Excel data contained controller state and mode information such as power on/off, manual/automatic mode, executing/paused program execution, program status, and loads. First, Excel macros were developed to filter the raw ten–second data into DES compatible event data to assist in calculations that were required in order to translate the data into OEE statistics for breakdowns, repair times, cycle times and process related times. The OEE data used a change of the MTConnect Part Count data item as the basic cycletime discriminator. Although not perfect, the change of the Part Count value was used as a reasonable approximation to the end of one part program and the beginning of the next.

Table 1 summarizes the MTConnect data collected and the logic used to calculate the DES model parameters, where $E(x)$ means the expected value and $t = T(a,b)$ means the elapsed time t from the beginning of event "a" until the occurrence of event "b" and $t = T(a)$ means time t spent in state "a". Cycle Time per part was calculated based on the time spent between increments of the MTConnect "PartCount" data item.

The OEE statistics for machining time, setup time, and idle time were calculated based upon subinterval time spent in the part cycle time. The machining time per part was calculated as the summation of time spent while the mode was auto, and the feed and speed were greater than zero. The monitoring of setup time was triggered by the change of $MTC_{program}$ from a unique machine pallet load/unload program to a machining part program. After this event transpired, setup was determined as the amount of time spent while the MTC_{mode} was manual. This would include activities such as setting a work offset. The Idle time was calculated as the amount of time spent while the Execution status was Paused. The Off time was calculated as the amount of time spent while the MTC_{power} was Off. The Down time was calculated as the amount of time spent while the MTC_{alarm} was active. Mean Time between Failure (MTBF) was also derived from the spreadsheet as estimated by the time spent with the Alarm data set to Active. Likewise, Mean Time to Repair (MTTR) was estimated from the time spent in the Alarm state.

For our initial experiments, energy consumption for Off, Down, Idle and Machining states were used in the DES analysis. Intermittent and periodic energy consumption (e.g., tool change, chip conveyor, pallet shuttle, lubrication cycle) were not addressed. Emissions were calculated based on the energy consumption of the process and the material processing. It is desirable for emission estimate to be a single number, but characterizing emissions is challenging due to uncertainties as they can vary over time and from one source to another and because of differences in design, ambient conditions, and maintenance and repair [22].

In DES, statistical distributions are models used to create sequences of events while simulating. A good statistical distribution fit to the data is essential in the analysis, since an erroneous distribution will yield inaccurate results, leading to flawed decisions. In order to better characterize the machine tool OEE

TABLE 1. Mapping Data into Sustainability Metrics

Data Item	Mapping
MTConnect Data	Timestamp(ts), Machine, Power, Mode, Execution, Program, Line, Sload, Xload, Yload, Zload, Aload, Bload, Cload, Toolnum, RPM, Alarm, AlarmState, AlarmSeverity, PartCount, Feedrate
Cycle Time	$MTC_{mode} = Auto\ and\ MTC_{rpm} > 0\, and\, MTC_{feed} > 0$
Setup Time	$MTC_{program}(t) \neq MTC_{program}(t-1) \rightarrow T(MTC_{mode} = Manual)$ excluding pallete shuttle program
Machining Time	Cycle Time
Off Time	$MTC_{power} = Off$
Down Time	$MTC_{alarm} = active$
Idle Time	$T(MTC_{execution} = Paused\, or\, MTC_{mode} = Manual)$
Misc Time	Not addressed in this analysis
Mean Time Between Failure	$E(x)$, $where\ x = T(MTC_{alarm} \neq active, MTC_{alarm} = active)$
Mean Time To Repair	$E(x)$, $where\ x = T(MTC_{alarm} = active, MTC_{alarm} \neq active)$
Power kWh	$= \int_0^t (MTC_{spindle} \times 15.0 + MTC_{Xload} \times 3.5 + MTCYload \times 3.5 + MTC_{Zload} \times 3.5 + MTC_{Aload} \times 1 + MTC_{Cload} \times 1)/(100.0 + 10.0) + E_{cp} + Baseline$
Coolant Energy	$MTC_{mode} = Auto\ \&\ MTC_{rpm} > 0 \rightarrow$ Coolant max rated kW load, else 0.0
Aluminum 7075 Density	0.00273 g/mm3 [19] or 0.0975 lb/in3
Aluminum Primary, Ingot Energy Consumption	13.2 kWh/kg of alumina [20]
CO2 Emissions	0.588 kg CO2 per kWh [21]
NOx Emissions	0.00181 kg NOx/kWh [21]
Waste - chips, coolant, heat, etc.	Not addressed in this analysis

data, the DES software calculated the statistical distributions for the Machining State, the Idle State, while the Down state was calculated using MTTF and MTBF. Currently the statistical distribution fitting is done in a separate software package and then loaded into Excel. Underway in the next phase of our research is to embed the statistical and LCA analysis directly into the machine tool to allow MTConnect to provide in situ OEE and sustainability data.

TABLE 2. MACHINE TOOL POWER RATINGS

Mechanism		Output (kW)
Spindle		15.0
X-axis		3.5
Y-axis		3.5
Z-axis		3.5
A-axis		1.0
C-axis		1.0
Hydraulic Pump		1.5
Coolant Pump		0.37
Chiller		
	Spindle	0.4
	Chiller unit	1.1
	Fan	0.15
Chip Conveyor		0.2
Magazine Rotational Motor		0.6
ATC drive motor		0.4
CNC Computer Electronics		0.2

Energy for Idle and Machining were derived by using the load data from MTConnect computed as a percentage of the maximum servo power rating, as shown in Table 2. We assume all motors comply with the Energy Policy Act of 1992 (EPACT) that requires that many commonly used motors comply with NEMA "energy efficient" ratings if offered for sale in the United States. This compliance gives an energy efficiency rating of about 90 %. Baseline machine ready–state energy loading and energy loss elements were added into the power calculations.

Analysis of the actual energy consumption reveals that machining costs are around 50 cents per hour given the Seattle area industrial power rates of 5 cent per kWh. Inspecting the data, we found the spindle was generally never highly loaded. The lower loads can be attributed to the use of high–speed machining, where the machine tool takes small depth of cuts using high feeds and speeds.

With the DES model in place, longitudinal simulations were performed to analyze energy and emissions for extended periods of time. The breakdown of parameters to calculate the DES energy and emission is as follows. First, the Parts Parameters model was characterized by the expected overall machining percentage and the average weight of the aluminum stock in grams. The weight was calculated based on the average size of the size per part type (shim, bracket or body joint) and multiplied by the nominal density for the material type from Table 1. The CNC model was characterized by the cycle time per part type, the failure and recovery rate, and the energy consumption for the different machine states. Part of the longitudinal sustainability calculation accounts for the production of the virgin aluminum stock as indirect energy costs and emissions.

Table 3 shows the DES longitudinal estimations for 1 day, 1 week, 1 month, 3 months, and 1 year ignoring major machine breakdowns and preventive maintenance. To make the DES numbers more transparent to the reader, zero variance was used for

TABLE 3. DES LONGITUDINAL ESTIMATES

Time Frame	Part Count	Direct Energy (kWh)	Direct Energy Cost	Indirect Material Energy (kWh)	CO2 Emissions (mt)	NOx Emissions (kg)
7 days/week, 3 shifts/day, 100% capacity, 0 minutes break time/shift						
1	72	80.08	$4.00	549.05	.32	.99
7	504	559.60	$27.98	3843.35	2.26	6.96
30	2160	2397.76	$119.89	16471.51	9.69	29.81
90	6480	7192.96	$359.65	49414.54	29.06	89.44
365	26280	29170.96	$1458.55	200403.40	117.84	362.73
6 days/week, 2 shifts/day, 90% capacity, 50 minutes break time/shift						
1	44	51.51	$2.58	335.53	.20	.61
7	264	308.59	$15.43	2013.18	1.18	3.64
30	1144	1336.92	$66.85	8723.80	5.13	15.79
90	3344	3907.72	$195.39	25500.34	14.99	46.16
365	13552	15836.27	$791.81	103343.49	60.77	187.05

part cycle times. Other data such as idle energy and down times were omitted for space consideration. The first set of data in the longitudinal table was generated assuming a 7 day/week, 3 shifts/day machine operations with a single part mix (brackets), no operator breaks, and 100 % capacity. In our DES model, any combination of 5/6/7 days/week, 1/2/3 shifts/days, multiple parts mixes were allowed, and the second set of data in the longitudinal table shows 6 days/week, 2 shifts/day machine operations with single part mix (brackets), 50 minute operator break/shift, and 90 % capacity. The independent nature of the part to machine scheduling at the Boeing plant means that multiple machine tools can be simulated simultaneously, with mix and match scheduling assignments used to understand factory capacity on a larger scale.

The immediate impact of DES analysis is to provide an assessment of the machine tool sustainability, which although possible, is not readily amenable to other types of analysis. The importance of evaluating the machine tool with DES is the ability to now optimize the process based not only on throughput or bottleneck performance, but also based on sustainability criteria. More importantly, the integration of DES with the sustainability data provides not only a single–point solution to optimize the machine tool, but also scales well, as it can be incorporated into a larger DES simulations that model the entireplant operations. Finally, DES plant models can be integrated to assess the enterprise sustainability.

The DES analysis has established feasibility of performing real–time machine tool sustainability analysis. While this is a first step, the DES model could be enhanced if additional MTConnect data were available from the machine tool. Currently, several material aspects were hard–coded due to the limitations of the "M&G" CNC programming sophistication: part material and part size. Regarding tool changes, MTConnect specifically provides for NC blocks, but our implementation did not support this parameter so we could not establish the time frame when tool changes occurred. However, long–term LCA for tool life would require a globally unique tool identification scheme that was not available. Coolant energy was only approximated as "on" for spindle positive RPM during Auto mode. Dry machining or air cuts during warm up cycles would require more detailed data to understand the nuances of coolant use. The energy consumption of the auxiliary equipment, such as lubrication cycle or chiller, could be accessed through the PLC, but this is something MTConnect would not be expected to support, unless there is deemed a large enough payback which could lead to widespread adoption of this sustainability metric.

DISCUSSION

LCA is a technique to assess environmental aspects associated with a product or process by identifying energy, materials, and emissions over its life cycle. Although important, a set of principles does not necessarily help companies take tangible steps towards attaining sustainability. With the use of MTConnect, real–time shop floor data was collected to understand sustainability while monitoring manufacturing. With the FSM–based Material Removal model in place, data for the major relevant sustainable issues on a machine tool energy consumption and its relationship to greenhouse gas emissions was collected. The importance of the DES is the ability to change various production parameters and see the effect of throughput and capacity on energy and emission. It must be noted that this work is based on a small sample of energy data, and thus provides only preliminary results of actual energy use. We did not measure the energy use of the machine tool at the power source, but have confirmed that the machine tool energy data correlates with other related NIST work [23]. Strategically however, due to the cost and inconvenience to instrument machine tools with energy management equipment, it is important to develop a non–invasive energy–monitoring approach that is in–situ as well as cost effective.

There are other benefits to real–time energy and emission data that could lead to more sustainability successes. The process monitoring as it relates to quality and scrap offers a most compelling benefit. By comparing energy and process numbers over a long time period, one can determine if there is any correlation to quality, scrap, and energy consumption. For example, an unexpected rise in energy consumption could indicate an underlying process error. Risk avoidance could also be performed using the Sustainable DES model to understand the impact of rising energy prices or the negative effect of material or energy shortages.

In general, we have seen that Life Cycle studies are often unnecessarily difficult because of differences and unclarity with regard to methodology and reporting process. This confusion could be remedied by assigning formal state–based energy models to specific pieces of equipment that could be reused or refined depending on the quantitative data required. Couple the library of formal LCA state energy models with automated data acquisition, and the facility to calculate hard LCA numbers is in place. Only with hard LCA, can informed sustainability decisions be made.

DISCLAIMER

Commercial equipment and software, many of which are either registered or trademarked, are identified in order to adequately specify certain procedures. In no case does such identification imply recommendation or endorsement by the National Institute of Standards and Technology or Boeing Aerospace, nor does it imply that the materials or equipment identified are necessarily the best available for the purpose.

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