Application of advanced methods for the prognosis of production energy consumption

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Abstract. This paper, based on a current research project, describes the application of advanced methods that are frequently used in fault-tolerance control and addresses the issue of the prognosis of energy efficiency. Today, the energy a product requires during its operation is the subject of many activities in research and development. However, the energy necessary for the production of goods is very often not analysed in comparable depth. In the field of electronics, studies come to the conclusion that about 80% of the total energy used by a product is from its production [1]. The energy consumption in production is determined very early in the product development process by designers and engineers, for example through selection of raw materials, explicit and implicit requirements concerning the manufacturing and assembly processes, or through decisions concerning the product architecture. Today, developers and engineers have at their disposal manifold design and simulation tools which can help to predict the energy consumption during operation relatively accurately. In contrast, tools with the objective to predict the energy consumption in production and disposal are not available. This paper aims to present an explorative study of the use of methods such as Fuzzy Logic to predict the production energy consumption early in the product development process.

1. Introduction, background and overview

The energy necessary for the production of goods, e.g. the energy for raw material generation, for casting or for milling, can very often not be analyzed in depth in early stages of product development processes. This is because today's common tools used for today's product development, such as geometry generating CAD tools (computer aided design tools), do not have the ability to support designers and engineers in this endeavor [2]. The energy consumption in production and disposal is determined very early in the product development process by designers and engineers, for example, through the selection of raw materials, explicit and implicit requirements concerning the manufacturing and assembly processes, or by decisions concerning the product architecture. Today, designers and developers must more or less "blindly" decide, because it is impossible in today’s industrial reality to predict the energy consumption in the production. It is hypothesized that intelligent tools and procedures, which allow a prognosis of the energy consumption in production, can shift the knowledge concerning production energy consumption into earlier phases and can increase the potential for energy savings (compare [3]). It is, for instance, only possible to change the architecture of a product i.e. the logical arrangement, early in the conception phase. Similarly, if a raw part is made by casting or cutting, the decision has to be made very early in the process and has immense consequences concerning the energy necessary for production. Figure 2 shows a representation, which
is based on similar representations in the area of early determination of product properties (compare [3]), in which it is clearly recognizable that in the early phases of the product development, the energy consumption can be influenced significantly more through by product changes and which also results in considerably smaller change costs.

Figure 1. Early evaluation of production energy consumption.

The manufacturing and assembly processes of products consume a considerable amount of the overall energy consumed during the lifetime of a product, ranging from 20% for conventional products, such as cars (compare [4]), up to 80% for products with a large share of electronic components (compare [1]). In the production of goods, several processes lead to the consumption of energy. Figure 2 lists the different sources of energy consumption in the production of parts together with possibilities to achieve a prognosis of this energy.
For typical manufacturing operations, conventional approaches can be applied, which are, for instance, based on the volume to be removed by a cutting operation. One example of how this approach is carried out is described in Section 2. However, the application of such methods can be complicated by the complexity of today’s products (compare [2]). Some alternatives are advanced approaches, for instance, based on fuzzy logic (see Section 3). Such approaches are explored in this publication together with realization scenarios based on work done through networks of engineers and companies. The processes of surface treatment (e.g. painting), joining (e.g. welding) and logistics (e.g. transportation with vehicles of any kind) can be taken into consideration roughly by means of overhead factors estimating typical energies used in such processes. A promising possibility for a more refined prognosis is the application of trajectory planning methods in order to improve estimation capabilities; such approaches are also the emphasis of this publication (see Section 4). The vision is that all approaches can be combined in a future system, here referred to as PEEPS (Production Energy Estimation and Prognosis System).

2. Analytical approach
Calculations of the energy consumption in production can conventionally be based on certain volumes and/or weights of the components, or of certain sections of the components. For example, the milling volume for milling operations can be used to determine the energy necessary for this milling operation. Research in production technology can provide the necessary tables and equations to determine this energy, if only the milling volume and the milling operation are defined accurately enough. The geometry is developed today almost exclusively in three-dimensional CAD systems. In such systems, the volumes and weights of all components are available; therefore the possibility to couple future systems with CAD systems is very promising.
It is important to note that most of the current CAD systems (CREO, CATIA, NX,) build the products in a tree-like structure and add features to a certain “starting” geometry in order to achieve the final geometry. Usually, these features are representative of manufacturing operations, e.g. a hole might be the representative of a drilling operation. Therefore, these features are appropriate objects for analyzing the energy necessary for certain manufacturing steps. Many works of research have described energies for certain manufacturing operations, such as drilling, milling and grinding. Very often, the resulting equations have a general form similar to Equation 1, describing the ideal material removal energy (compare Deneka&Tönsdorf [6]):

$$E_c = k_{c.1} \cdot \left( \frac{h}{h_0} \right)^{-m_c} \cdot \Delta V$$  

(1)

with $K_{c.1}$ as specific heat capacity, $m_c$ as XXX, H as density and $\Delta V$ as volume difference. The energy for manufacturing is usually higher because of several sources of losses and additional processes which can be necessary or superfluous. The influence of these losses can be covered using equation 2:

$$E_G = E_R + E_F + E_M + E_I + E_A$$  

(2)

with $E_R$ as initial object creation energy, $E_F$ as ideal final object creation energy, $E_M$ as energy lost by the machine, $E_I$ as energy for the infrastructure and $E_A$ as assembly energy. The features which describe subtracted volume can be understood and described as an information object thus allowing object oriented programming. CREO 2.0 offers the possibility to program additional functionalities using the ProToolkit. Therefore it is possible to integrate the functionalities of PEEPS smoothly into CREO – the user will experience the tool as additional functionality of his/her well-known CAD system. This system is currently implemented and will be finished as a functional prototype at the end of 2014.

3. Application of Fuzzy Logic

The use of fuzzy logic creates a possibility to integrate human decision-making ability into technical systems, instead of using purely mathematical models (see e.g. [7], [8]). This section explains the application of fuzzy logic for estimating production energy consumption. For this explanation, the proposed procedure scheme is first explained (compare Figure 3).
Secondly, the proposed input product characteristics are described. Thirdly, the relevant indexes are listed and elucidated. Finally, the fourth subsection is giving the results of a sample application.

3.1. Proposed procedure scheme
The inputs of a fuzzy logic system are the fuzzy variables. For the given system, six sensible fuzzy variables were found (compare Section 4.2). In the main part of the system, these fuzzy variables are first used in two fuzzy engines in order to determine the first indices (compare Section 4.3). The results, which, after defuzzification, are once again crisp values, are then given to a third fuzzy engine in order to find two important indices – the “production energy consumption index” and the “CO2 production index”. Figure 2 depicts the proposed procedure scheme.

3.2. Definition of fuzzy variables
Defining the input variables is a very demanding task. In this case, an extensive survey in production engineering was carried out. The main idea behind the fuzzy variables goes back to research works by Achiche & Ahmed [9]. In this research, comparable indices were used in a fuzzy engine in order to investigate 3D shapes and the way they are perceived. One example for an indicator is the surface/volume ratio; this first indicator is mainly for the complexity of a product and is the ratio between surface and volume. Simple forms which can be produced with a small amount of energy, such as simple cylinders, are characterized by a small surface/volume ratio. This ratio is defined as shown in Equation 3:

\[
\frac{\text{surface}}{\text{volume}} \text{ ratio} = \frac{s}{v} = \frac{\text{component surface}}{\text{component volume}} \left[ \text{mm}^2 / \text{mm}^3 \right]
\]  (3)

In a similar manner, five other indicators are defined in order to capture certain characteristics of the respective product.
3.3. Definition of output indices

Two main influences characterize the energy consumption in production: the complexity of the component, leading to many subsequent energy consuming production and transportation processes, and the material of the component – the density, hardness and other material properties, which can lead to a multiplication of energy expenditure for the production of the respective component. On the one hand, the complexity index summarizes the influences of other indices which indicate the complexity of a product's component. On the other hand, the influences of indices which indicate the material difficulty of a component are summarized in the material index.

Both influences need to be combined in order to assess the energy necessary for production – thus forming the production energy consumption index. In a similar manner, the CO2 production index can also be generated.

3.4. Exemplary application and results

For an exemplary application, four different parts from the CAD training and developments for a formula student race car were chosen. The data was taken from the CAD model and for some of the entities, sensible estimations were made. The main parameters of the four parts were given to the initial two fuzzy engines and the first two indices were determined. The results in Figure 3 show clear distinctions.

The high complexity index of the housing is definitely a consequence of the hollow structure. Such structures are relatively light and have a small volume but require a lot of energy in order to produce. On the other hand, the low material index of the housing is influenced by the rather low hardness of this part and because of no necessary surface treatment – in contrast, for instance, to the piston with elaborate surface treatment for the running socket.

In the second fuzzy engine, these results were combined leading to the production energy consumption index (Figure 4 – right side).

![Figure 4](image)

The results show clear differences. For instance, part 4 is a hollow housing with a complex geometry, but will be produced from a soft material.

4. Realization Scenario

One approach for applying the proposed method in industry is the formulation of rules (compare [2]). The authors believe that such a procedure will be a good start to enhancing the prognosis possibilities for production energy consumption. However, in the long run, intelligent, learning systems may lead
to superior performance. The process of realizing this (Figure 5) is generally comparable to a data mining approach.

5. Framework for trajectory planning

This section is aimed at logistics and transportation and the prognosis of the energy consumption of these processes. It starts with a short description of the situation of an engineer who is planning the geometry of components and the architecture of a new product. The energy consumption during the production of the product is, amongst other things, dependent on the transportation processes [8]. In
order to estimate the energy for these transportation processes, the first main piece of information is
the distance to be covered between the different stations where manufacturing, assembling or surface
treatment processes are performed. Consequently, the engineer would need to plan the whole
manufacturing, assembling and surface treatment process. For products which are not completely new
(which is the case for more than 90% of all products), these processes are captured in the enterprise
resource planning (ERP) systems, such as SAP, and can be used for the sake of the estimation. The
next step would be a mapping of the stations to physical locations in order to measure the distances
between the stations [11]. Again, for products which are not completely new, these locations are
available in the layout planning tools, which are usually part of the digital manufacturing and
production systems, such as DELMIA. Today, these tools are connected in the IT infrastructure of
many companies by certain connectors, such as DESC. A component of a production energy
efficiency prognosis system could obtain this information from the interfaces of a digital
manufacturing and production system, and could transfer them into a form useable by other
components of this system (Figure 6).

As stated above, one important entity of information is the list of manufacturing, assembling and
surface treatment processes, which can be referred to as a mission list. Essentially, a mission list (ML)
is a vector with as many elements as necessary operations:

$$ML = [PSP]_{i=0}^{n}; \text{ for } i = 1, \ldots, n$$

(1)

with $PSP_i$ representing production steps with a respective specific ID, and $n$ being the necessary
number of such production steps. The next task is the assignment of production steps to production
stations. This assignment can be done in a $2 \times n$ assignment matrix (AM):

$$AM = [PSP, PST]_{i=0}^{n}; \text{ for } i = 1, \ldots, n$$

(4)

with $PSP_i$ representing production steps with a respective specific ID, and $PST_i$ being production
stations with a respective, specific ID. As stated above, a further important entity of information is the
arrangement of the production station, captured in a production layout. Here, only a probable layout
can be hypothesized during prognosis. A probable production layout matrix (PPLM) is an $n \times m$-matrix
using an appropriate grid:
with \( PPST_{ij} \) being the diagonal elements, which describe probable production stations with their respective ID. For the trajectory generation, information about obstacles in the production environment is also necessary. This can also be generated from information in the digital manufacturing and production system and formulated in an obstacle matrix. An obstacle matrix (OM) is a \( n \times m \)-matrix using an appropriate grid:

\[
OM = \begin{bmatrix} OP_{ij} \end{bmatrix}^{n \times m} ; \text{for } i = 1, \ldots, n \text{ and } j = 1, \ldots, m
\]  

(6)

with \( OP_{ij} \) being the diagonal elements which describe probable obstacles. Here, a value of “0” denotes “no obstacle” at this position of the grid and “1” denotes “obstacle present” at this position of the grid. Additionally, regions of danger, particularly security around obstacles, can be indicated in this matrix (compare ). With the listed information, a second section of a production energy efficiency prognosis system could generate probable trajectories (compare Seybold et al. [10]) and a third section of this system could then estimate the energy consumption for instance based on the traveled distance, probable velocities and rolling friction, probable air drag, probable inclination and probable acceleration (Figure 7).

The result of this step is an estimation of the probable energy consumption in production; in the final vision of the project, all intermediate steps are carried out automatically by the production energy efficiency prognosis system, allowing the engineer to test several product component and product architecture alternatives. On this basis, he may consciously choose the most sustainable alternative with the smallest energy consumption possible; this possibility is currently not available to engineers in industrial practice.

Figure 7. Trajectory kernel and estimation kernel.
6. Conclusion

Product development engineers currently have nearly no support concerning the consumption of energy in the later production when they are determining product architecture and product geometry. This paper explored approaches which presents a basis to develop tools which can provide engineers with a prognosis of the energy consumption in production very early in the product development process. One main possibility is analytical approaches based on product geometry and choice of material. Fuzzy logic can be used to estimate a production energy consumption index, based on six indices which can relatively easy be collected in a CAD system which contains extended information, such as material and surface hardness – information which is important for the product drawing anyway. An energy consumption prognosis of the transportation processes in manufacturing and assembly can, amongst other things, be realized by means of trajectory planning based on probable manufacturing layouts and probable obstacle locations. Today, the information about these steps is present in the numerous systems which build up the digital factory. However, the connection with and processing of this information is missing. The presented research is a first step into the direction of enhanced prognosis possibilities. In the further course of the project, detailed mathematical formulations and verifications are planned to provide assistance to engineers who must make far-ranging decisions in the early phases of product design.

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