Evaluation of Environmental, Technical, and Economic Indicators of a Fused Deposition Modeling Process

M. Yosofi, S. Ezeddini, A. Ollivier, V. Lavaste, C. Mayousse

***Abstract*—**Additive manufacturing processes have changed significantly in a wide range of industries and their application progressed from rapid prototyping to production of end-use products. However, their environmental impact is still a rather open question. In order to support the growth of this technology in the industrial sector, environmental aspects should be considered and predictive models may help monitor and reduce the environmental footprint of the processes. This work presents predictive models based on a previously developed methodology for the environmental impact evaluation combined with a technical and economical assessment. Here we applied the methodology to the Fused Deposition Modeling process. First, we present the predictive models relative to different types of machines. Then, we present a decision-making tool designed to identify the optimum manufacturing strategy regarding technical, economic, and environmental criteria.

***Keywords*—**Additive manufacturing, decision-makings, environmental impact, predictive models.

I. Introduction

ADDITIVE manufacturing (AM) technologies evolved significantly over the last few decades resulting in major technical advances. Initially restricted to the manufacture of prototype parts, AM is now a fully-fledged manufacturing process offering capabilities for functional part production [1]. AM processes have been used in industry for a long time, and plenty of research has been conducted on aspects of process control and product quality [2]. The same goes for the cost of these processes [3]. These processes are often described as clean processes, as they only use the exact amount of material needed to build functional parts, thus limiting waste, which makes it a good alternative to reduce the environmental impact compared to conventional processes such as machining. Nowadays, environmental footprint consideration during the manufacturing step of a part has become an important issue in our society [4]. In the near future, the choice of machines or processes that will minimize environmental impacts will be more common.

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Environmental analysis of AM processes is based on multiple criteria. For many years, even after the first studies regarding the environmental aspects of AM processes [5], electrical energy consumption was the only consumption source studied in the literature. These studies were oriented towards the definition of the specific energy consumption (SEC) [6]. The SEC is the amount of energy consumed in kWh for 1 kilogram of processed materials.

Mognol et al. [7] studied the influence of part orientation on the SEC values for three AM processes: powder bed fusion, material jetting and material extrusion. They showed that it is possible to achieve a substantial energy (43-61%) saving by choosing the set of parameters that will minimize the height of the part.

Baumers et al. [8] explored the SEC by studying the effect of packing density of the space machine and part geometry on the electrical energy consumption of powder bed fusion and material extrusion processes. They determined that the SEC decreased when multiple parts are manufactured on the same time [9].

Junk and Côté [10] studied the effect of the part placement on the build platform on the electrical energy consumption for material extrusion and material jetting processes. They found that the SEC is lower when the part is manufactured near the machine zero point [11].

Other studies on the SEC of AM processes are reported in [12]-[14]. Thus, the SEC is no longer sufficient as soon as we need to predict the electrical energy consumption of AM processes. Therefore, it is necessary to set up predictive models in order to consider all the manufacturing parameters of the part. Based on the inventory data presented previously, various authors developed parametric models for AM processes in order to estimate the environmental impact and related environmental footprint during the manufacturing step.

Baumers et al. developed models that estimate the electrical energy consumption and the costs occurring during the manufacturing of the part with an accuracy of +/-10% for powder bed fusion process (EOSINT M270 DMLS system). They concluded that cost minimization in AM leads to the minimization of electrical energy consumption [15].

LeBourhis et al. presented a method to evaluate the environmental impact of direct energy deposition process using direct additive laser manufacturing technology [16]. Based on both analytic and experimental models and using the computer-aided design (CAD) model with the energy and resource consumption, the authors estimated the related environmental impact.

Xu et al. developed a model that calculates the total energy consumption of binder jetting process during the manufacturing step [17]. The authors took into account the electrical energy with layer thickness, part geometry and part orientation. Energy demands of the curing and sintering step should be included in the study in order to quantify the total environmental impact of the process.

Kellens et al. developed a parametric process model to estimate the environmental impact of powder bed fusion processes using selective laser sintering technology with PA2200 and PA3200GF polymer materials [18]. The models are based on the volume and the total build height of the part. Their models estimated total electrical energy and resource consumption as well as the environmental impact [19].

Yosofi et al. presented a method which makes it possible to obtain energy models for AM processes [20]. For a high precision energy consumption prediction, they divided the manufacturing process into different stages and obtain the energy consumption of each stage through experiment with an accuracy of +/-10%. They applied their methodology on multiple AM processes: material extrusion, material jetting and powder bed fusion [21].

These studies have improved knowledge around the environmental footprints of AM. However, there is still a lack of information for some processes. Indeed, more research must be done in order to fulfill the life cycle inventory database for AM. Nevertheless, it is possible to predict information thanks to parametric models and therefore to make a choice of process or machine. However, making a choice of process from an environmental point of view is not representative of the industry. Indeed, choosing a process rather than another in the industrial sector is mainly governed by the feasibility and the cost price. That is why it is important to combine environment information with technical and economic information.

AM techniques have been applied in various domains, such as the aerospace, automotive and biomedical industries. Nowadays, many works can be found on the mechanical properties of the parts made by AM processes. The first studies were focused on the influence of processes parameters on the flexural properties [22]-[25]. These studies led to work on improving these processes by reducing build time [26], material consumption and part weight [27]. Many authors have developed predictive models to determine the mechanical properties before the part production. Carneiro et al. developed a parametric model to estimate the tensile strength of ABS parts made by material extrusion processes [28]. Other studies on ABS can be found in [29]-[32]. Since the main defect of these processes is poor surface condition, Boschetto et al. developed parametric models of surface quality indicators in order to predict the surface roughness of parts made by the material extrusion process [33], [34].

Cost estimation for AM processes has evolved from rather crude initial models [35] to more accurate estimates [36]. The late models tend to consider all the activities involved in AM in order to calculate the full cost of a finished part [37].

All this work on improving these processes is a sign of the latter's technical and economic maturity. Some authors work on the linkage between technical and cost criteria [38] or environmental and cost criteria [39]. However, more research needs to be done in order to continue in multicriteria evaluation of AM processes [40].

This paper therefore presents predictive models using a methodology in order to evaluate three material extrusion machines from a technical, economic and environmental point of view. The remainder of this paper is divided into three sections. Section II describes the current status of the state of the art regarding the multicriteria evaluation of AM processes. Section III explains the methodology used in this study. Finally, Section IV presents the application of the methodology on a use case.

II. Methodology

The applied methodology, described in detail by Yosofi et al. [40], consists to evaluate AM processes from a technical, economic and environmental point of view (Fig. 1). Its purpose is to enable manufacturers to choose between different manufacturing processes or machines based on multiple criteria. The methodology is decomposed of two major steps. First, all the data needed to create the models are collected. The authors proposed accurate models, leveraged on experimental measurements for the electrical energy consumption. They break down the process into different manufacturing stages to make a power study of each stage. Subsequently, a time study is performed in order to calculate the total electrical energy consumption. Simple models are presented regarding fluid and material consumption. Empirical formulae for cost models and equations for the technical model are extracted from the literature. These models allow consumption flows to be predicted for parts of any shape.

Once all the different data have been acquired, either directly from the literature or the process, it is possible to create the different predictive models related to the technical characteristics, cost, and inventory data of the machine used. All the acquired data are entered in a numerical tool developed in Visual Basic Application (VBA). The models can be used by entering the following data provided by the CAD or slicing software:

- Layer height;
- Manufacturing angles;
- Preprocess duration;
- Postprocess duration;
- Part volume;
- Density of material used.

Finally in step two, the different consumption flows are simultaneously displayed in a single graph. More information about the experimental protocol and method for obtaining the different models are available in [21]. In this paper, the methodology has been applied on three machines of the material extrusion process:

- Prusa i3 MK3S

- Ultimaker 3
- Ultimaker 2 Go

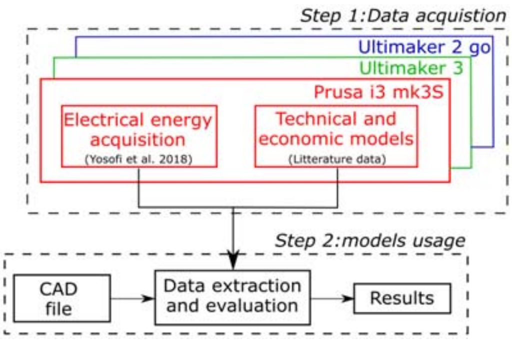

Fig. 1 The two steps of the methodology

III. Result and Discussion

The evaluation of AM processes focused on consumption (inventory data) during the part manufacturing. In the case of AM processes, the flows are split into three categories:

- Electrical energy,
- Material consumption,
- Compressed air and water consumption and waste.

The methodology does not take the machine's particle emissions into account nor does it consider the material and energy used to manufacture the machine tool, material, part, or machine tool recycling. However all the data on this consumption should be considered in any lifecycle analysis.

A. Machines Studied

The methodology has been applied on three material extrusion machines. The Prusa I3 MK3S, the Ultimaker 3 and the Ultimaker 2 Go. Fig. 2 shows the three machines studied.

Fig. 2 Machines studied

B. Parametric Model of the Electrical Energy Consumption

Breaking the process down into its various stages makes it possible to have a generic formula for the total consumption of electrical energy during the production of a part (1). The total electrical energy consumption is equal to the sum of the electrical energy consumed during each stage.

$$Etotal = E\,Idling + E\,preparation + Eforming + Epostprocess \quad (1)$$

where EIdling is the electrical energy associated with the idling stage, EPreparation is the electrical energy associated with the preparation stage, $E_{Forming}$ is the electrical energy associated with the forming stage, and $E_{Postprocess}$ is the electrical energy associated with the postprocess stage. Electrical energy measurements are performed with an energy analyzer (Voltracft 4000f).

Table I shows the measured average power and average duration of each stage of each machine.

TABLE I
AVERAGE POWER AND DURATION OF EACH STAGE

Machine	P_{Idling} (W)	$P_{Plate\ preparation}$ (W)	$P_{Plate\ temp\ maintenance}$ (W)	$P_{Head\ preparation}$ (W)	$P_{Head\ temp\ maintenance}$ (W)	$P_{Forming}$ (W)	$T_{Plate\ preparation}$ (s)	$T_{Head\ preparation}$ (s)
Prusa i3 MK3S	8.10	146.6	34.7	25.1	11.6	48.6	124.2	78.0
Ultimaker 3	5.31	139	47.8	16.6	1.37	35.0	181.1	76.9
Ultimaker 2 Go	4.25	0.0	0.0	58.8	0.0	74.8	0.00	67.8

Table II presents the parametric electrical energy models for the three machines. In this table, $T_{Preparation}$ is the sum of $T_{Plate\ preparation}$ and $T_{Head\ preparation}$. T_{Total} is total duration estimated by the slicing software.

TABLE II
PARAMETRIC MODELS OF THE ELECTRICAL ENERGY CONSUMPTION OF EACH MACHINE

Machine	Electrical Energy Consumption
Prusa i3 MK3S	$Etotal = (8.10\ x\ Ttotal) + (146.6\ x\ 124.2) + (25.1\ x\ 78) + [(34.7 + 11.6 + 48.6)\ x\ (Ttotal - Tpreparation)]$
Ultimaker 3	$Etotal = (5.31\ x\ Ttotal) + (139\ x\ 181.1) + (16.7\ x\ 76.9) + [(47.8 + 1.37 + 35)\ x\ (Ttotal - Tpreparation)]$
Ultimaker 2 Go	$Etotal = (4.25\ x\ Ttotal) + (58.8\ x\ 67.8) + [\,74.8\ x\ (Ttotal - Tpreparation)]$

C. Parametric Models for Resource Consumption

An empirical equation (2) is used to predict the total amount of material used during the process. The total material consumption is the sum of the materials needed for the part and the support.

$$Mtotal = (\rho Part\ x\ VPart) + (\rho Support\ x\ VSupport) \quad (2)$$

where ρPart is the material density of the part, VPart is the volume of the part, ρSupport is the material density of the support, and VSupport the volume of the support. For these studied machines, there is no need of fluid consumption. Support material is removed manually from the part.

D. Technical and Economic Model

Technical model to predict the arithmetic roughness is the same used by Yosofi et al. [20]. However, for the economic model, we consider also the price of the electrical consumption that is 0.15 Euros/kWh.

Fig. 3 presents the studied part of 105 x 100 x 55 mm made in PLA polymer. This part represents a support for the surgical mask to move the mask away from the mouth. This part requires more support material than the part himself. The manufacturing angle of the top of the part is 90°.

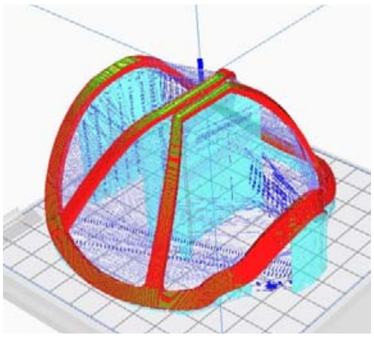

Fig. 3 COVID mask

E. Results

In order to compute all information about the different models obtained by data measurements or extracted from the literature, we designed a numerical tool. It allows the user to enter initial data and compare the results for each pair of machines in order to determine quickly the best one that suits them.

Table III shows the input values for the part studied. All the information is obtained thanks to the CAD and slicing software. Table IV indicates the estimated values by the models.

TABLE III
INPUT VALUES OF THE PART STUDIED

quipment	Part	Layer High (mm)	Infill (%)	Part volume (cm^3)	Support volume (cm^3)	Estimated time (min)	Real time (min)
Prusa i3 MK3S	COVID mask	0.3	100	10.4	14.6	238	253
Jltimaker 3		0.2		11.2	6.4	183	172
Jltimaker 2 Go		0.2		11.2	6.4	127	127

TABLE VI
OUTPUT VALUES (ESTIMATED VALUES)

Equipment	Energy (Wh)	Cost (euros)	Ra (µm)	Part weight (g)	Support weight (g)	SEC (kWh/kg)
Prusa i3mk3s	406	4.01	25.6	13.1	17.8	13.1
Ultimaker 3	248	6.79	17.2	14	8	11.3
Ultimaker 2 Go	169	3.41	17.2	14	8	7.7

Table V shows the estimated and the real values of the electrical energy consumption with de deviation for each machine.

Fig. 4 illustrates the combination of the estimated results for the three material extrusion machines. To have an exploitable result curve, we created a system of value scaling by calculating the percentage of each result related to the largest. Since the part studied is the same for the three machines, material consumption and arithmetic roughness are also the same.

TABLE V
DEVIATION BETWEEN ESTIMATED AND REAL ENERGY CONSUMPTION

Equipment	Estimated Energy consumption (Wh)	Real energy consumption (Wh)	Deviation (%)
Prusa i3mk3s	406	385	5
Ultimaker 3	248	223	10
Ultimaker 2 Go	169	153	8

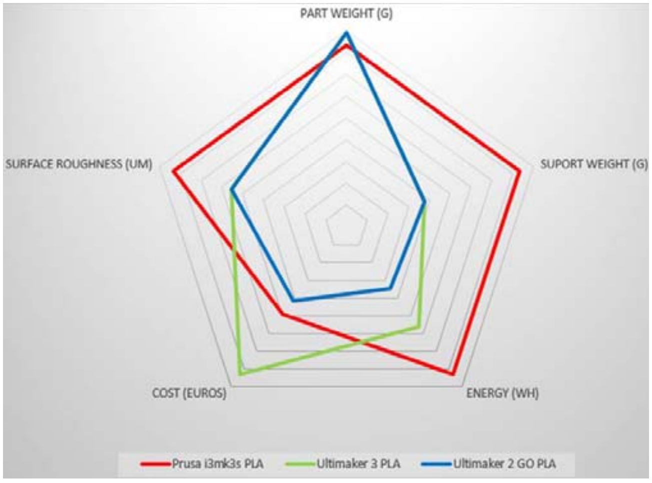

Fig. 4 Estimated results of the three machines

F. Discussion

Recording the energy consumption of the manufacturing process stage by stage, over several cycles of repetition made it possible to gain accurate models of electrical energy consumption. We measured the electrical energy consumption during the manufacturing of the part and the deviation between the model and measured values, as shown in Table V. We observe that deviation for the Prusa i3 MK3S and the Ultimaker 2 Go is less than 10%. The Ultimaker 3 has a deviation of 10% between the two electrical energy values. These deviations are due to the precision of the measuring device which has an impact on the precision of the models and in addition to the difference between the estimated time and the real manufacturing time. This way of presenting the results (Fig. 4) enables a user to make a choice of machine or process according to the criteria he wishes to highlight.

From an environmental point of view, the Ultimaker 2 Go is the ideal machine because it consumes less energy and support material. The difference of part weight between the two Ultimaker machines and the Prusa machine is 0.9 grams, which is negligible. This part made by the Ultimaker 2 Go will cost less than the other two.

Finally, the arithmetic roughness for the two Ultimaker machines is lower than the Prusa i3 MK3S. We can conclude that for this specific part, the ideal machine is the Ultimaker 2 Go. However, in order to have a more accurate study, it would be interesting to have a part quality indicator. Indeed, in our case, the model estimates that the Ultimaker 2 Go is the more appropriate solution. Nevertheless, parts printed with this machine have the poorest visual appearance of the three. Thus, future work will focus on adding indicators to support decision making, the study of other materials and include more technical indicators (yield strength, tensile strength).

IV. Conclusion

In this paper, the authors propose a technical, economic and environmental evaluation of three machines of the material extrusion process. The methodology used is based on both analytic models (validated by experiments) and experimental models. The work concerning the inventory data is not only focused on electrical consumption but also on resources consumption which also contributes to the environmental impact. These environmental aspects are then coupled with technical and cost properties in order to have a multicriteria evaluation allowing a user to have a global view of the consumption of a part according to its geometry. Furthermore, this methodology will be extended to other materials for the three machines studied, and more models will be investigated in order to evaluate these processes with new indicators.

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