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INTELLIGENT PATTERN RECOGNITION OF SLM MACHINE ENERGY DATA

Selective Laser Melting (SLM) is an additive manufacturing process, in which the research has been increasing over the past few years to meet customer-specific requirements. Different parameters from the process and the machine components have been monitored in order to obtain vital information such as productivity of the machine and quality of the manufactured workpiece. The monitoring of parameters related to energy is also realized, but the utilisation of such data is usually performed for determining basic information, for instance, from energy consumption. By applying machine learning algorithms on these data, it is possible to identify not only the steps of the manufacturing process, but also its behaviour patterns. Along with these algorithms, evidences regarding the conditions of components and anomalies can be detected in the acquired data. The results can be used to point out the process errors and component faults and can be adopted to analyse the energy efficiency of the SLM process by comparing energy consumption of one single layer during the manufacturing of different components. Moreover, the state of the manufacturing process and the machine can be determined automatically and applied to predict failures in order to launch appropriate counter measures.

1. INTRODUCTION

Saving and efficient use of energy are becoming more important since the awareness of the non-reuse of some energy resources such as fossil fuels. In order to decrease the use of non-renewable resources, several measures have been taken. For example, the search of renewable energy resources, the increase of the efficiency of combustion motors and the development of new strategies for decreasing energy consumption.

Meanwhile, the environment has been being damaged due to the consumption of energy and raw materials, as observed in the industrial production, transportation, among

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others. The gas emissions resulted from the combustion of fossil resources ensure several environmental problems. Some of these problems can be seen in form of acid rains, increase of the amount of greenhouse gas, climate changes, and worsening of the air quality. These can also influence negatively the everyday life. The efficient use of the energy is therefore urgently necessary and wise [1].

Thanks to the costs and those environmental concerns, the industry is interested in consuming more efficiently the energy inside the production. The potential for energy saving was estimated as 15% for manufacturing industries. However, several opportunities can be observed in the automotive and electro industry sectors [2].

For several years the Fraunhofer Institute introduced the concept of the E3 production, which represents a production with efficient and sustainable usage of energy and resources, as well as the reduction of the production emissions. The realization of this concept is performed through analysis and assessment of the production process [3]. One part of that concept is the monitoring of the energy consumption from machine tools. The measurement and analysis of energy data of such machine tools during the production is essential. The energy data are measured during a period of time and stored. With it, the data can be assessed from a server and evaluated.

By analysing the energy data stored, mathematical models can be described and methods developed. The use of intelligent algorithms can help the data evaluation and trends of the machine tools can be identified, as performed in [4-7]. Trends in energy consumption can be detected and used to identify possible failures, component wear, or even misuse of the machine.

Within this concept, this work aims at implementing an application to monitor the energy consumption of a selective laser melting machine. Models and methods were developed and inserted in this application. With it, the condition of the machine can be automatically recognized and the duration of a unique condition stored for a further analysis. By assessing the available data, it is possible to classify them using other developed algorithms. This supports an intelligent and rapid analysis of the energy data, which resulted in a model for an energy-efficient and resource-efficient production system. It also helps to react more quickly and adaptively to volatile energy offers.

2. SELECTIVE LASER MELTING

2.1. SELECTIVE LASER MELTING PRINCIPLES

Selective laser melting manufacturing technology (SLM) is a special technique of additive manufacturing. It is a manufacturing process that uses a metal powder bed and a thermal energy supplied by a computer controlled and focused laser beam to build a workpiece [8-11]. The layer thickness varies from 20 μm to 150 μm and the size of the metal grain has a range from 10 μm to 75 μm [12-13].

The main steps to complete the part manufacturing, starting from the design in Computer-Aided Design (CAD) software to the post-processing, are schematically demonstrated in Fig. 1. According to Zäh [13] and Gebhardt et al. [12], the manufacturing of a workpiece starts with the three-dimensional CAD model. After that, the model is digitally optimized in order to reach the dimensional tolerances and properties. Once these are reached, the CAD model is transformed into a Stereolithography (STL) model, which is a triangulated representation of the CAD model. By manipulating the data of the STL model, it is possible to define the desired position and angles that the part will be built, and the melting strategy can also be defined. With this characteristics determined, the thickness of a layer is specified and the STL model sliced digitally. The generated data containing the manufacturing details is then downloaded to the SLM machine in order to be able to manufacture the workpiece.

When the generated data is processed by the SLM machine, the manufacturing process can be started and a cycle begins. Firstly, a platform is lowered in order to give the desired thickness of the layer. Secondly, a thin layer of metal powder is deposited on the platform using a recoating system. Thirdly, a laser beam is used to melt the selected geometry in the top-most layer of this powder bed. This cycle is repeated until the last layer of the workpiece is built. The last step is the post-processing of the built workpiece. After manufactured, the part must be separated from the platform, and depending on the requirements of the customer, it must be polished and/or grinded to achieve customers specifications.

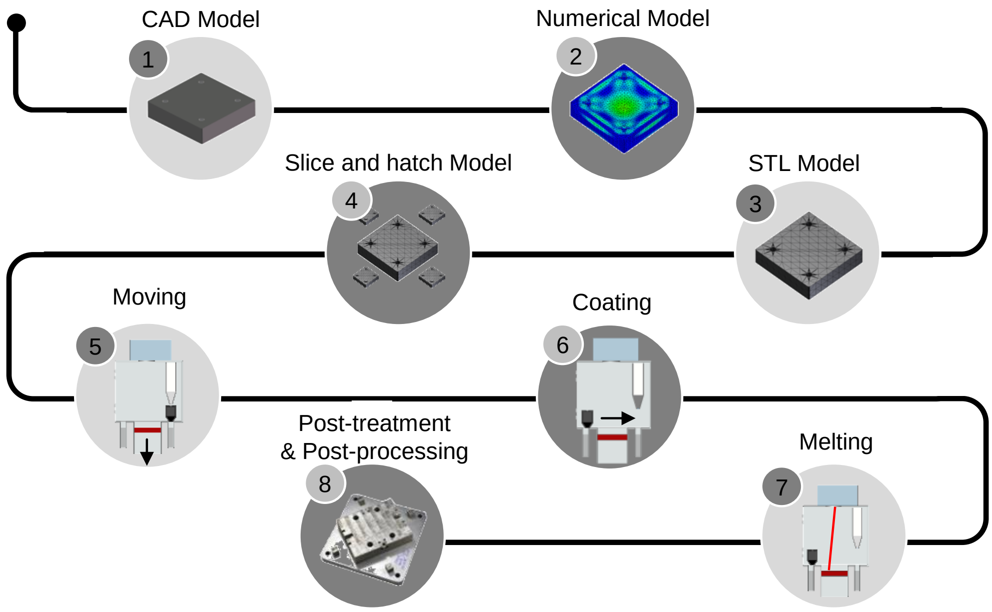


Fig. 1. Steps to manufacture a workpiece with SLM

2.2. SLM MACHINE AND MONITORED PARAMETERS

The SLM machine used in this work to acquire, to monitor and to analyze the energy data is the model SLM250^{HL} from the company SLM Solutions AG, Germany.

This machine is comprised essentially of a laser device, a cooling device, seven motors for the motion of internal components, and pumps for the protection gas and vacuum system. Besides, it also has a computer, used to gather the data, to input the workpiece design in layers and to configure the melting strategy.

The data acquisition and data transmission is performed using the schema shown in Fig. 2. The energy data is gathered using cable split cores sensors in each of the phases L1, L2 and L3 of the machine. Then, the data is transmitted to the cloud by using the Modbus device 'com.Tom' of the company Beck IPC GmbH, Germany. The access of the data is made through the web portal of the same company.

The consumption of the phases L1, L2 and L3 in the machine is dependent on which component is connected to each phase. The configuration of the used machine can be seen in Fig 2. The phase L1 supplies only the laser device. The phase L2 is responsible for providing energy for the motors, pumps and computer. The cooling device and the energy supply of the scanner are connected to the phase L3.

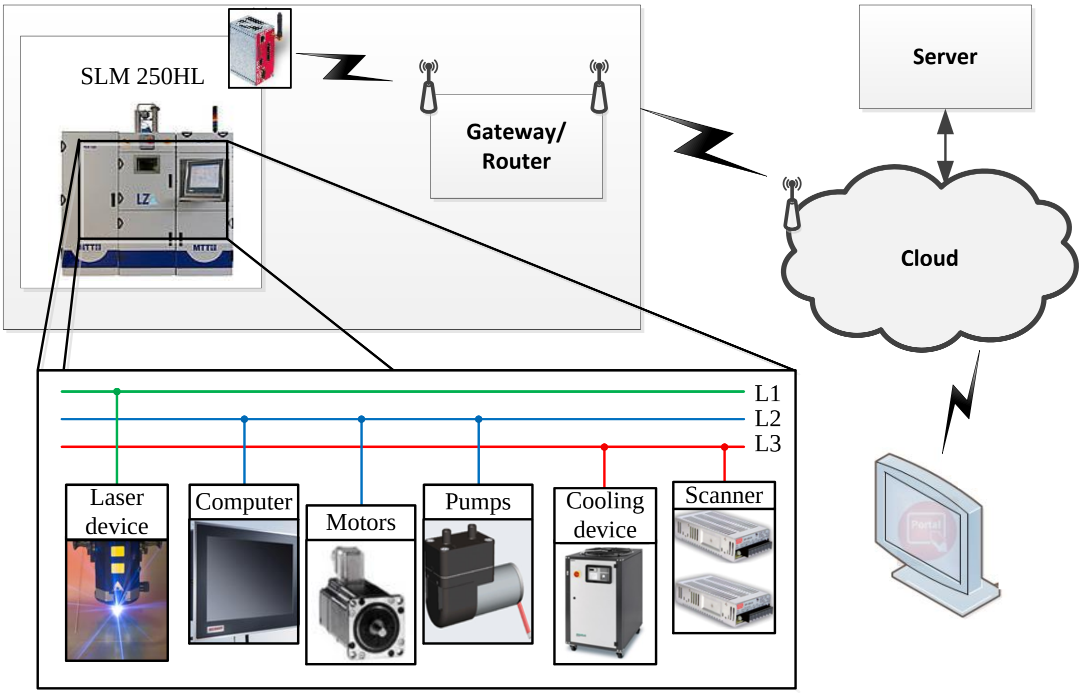


Fig. 2. Communication topology and monitored phases of the SLM machine with its components

3. METHODOLOGY

3.1. OVERVIEW

The performed methodology is shown in Fig. 3. At first, the data from the each phase of the machine were acquired. They were transmitted with the topology shown in Fig. 2 and explained in section 2.2. The data was stored in an internal server of the Fraunhofer Institute IPK in Berlin, where the data was accessed, visualized and extracted through the web portal ‘com.Tom’.

Once the data was stored, three paths were followed. The first path (symbol ‘I’ in Fig. 3) was performed to manually cross energy data and the process data in order to identify general machine patterns. For example, when the machine is on, or when a workpiece is being manufactured. With some patterns defined, the new data was extracted from the database to serve as input to the development of the algorithms and models in the application, used in the teaching process. This is the second path, or the path ‘II’ of the same figure.

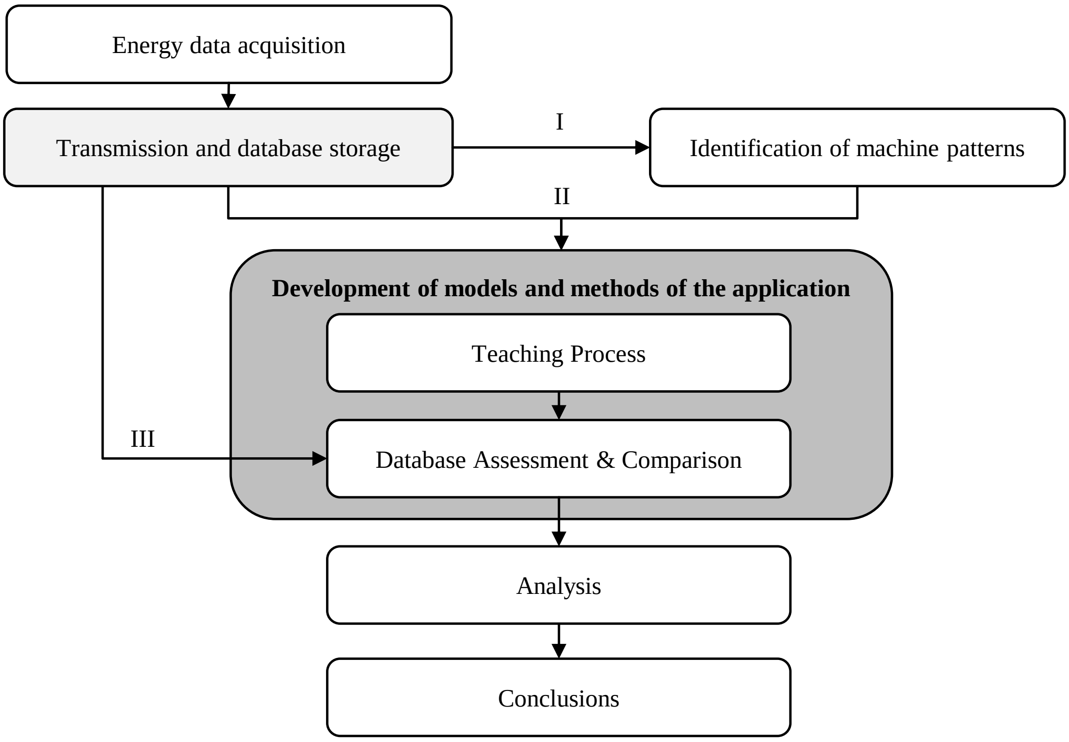


Fig. 3. Experimental approach

After the teaching process was finished, the third step (symbol ‘III’) was performed, which is the assessment of the rest of the database and new obtained data to evaluate and compare the result of the algorithms. Consequently, an analysis of the outcomes was executed and the final results of the work discussed and concluded.

3.2. DATABASE STORAGE

The storage of the energy data was performed by writing them in total of 13 columns. The first column is the timestamp of the acquired values. The time rate can be configured according to the needs. In the case of this work, the data was stored every 60 seconds. The second, third and fourth columns received the values related to the sum of each power: reactive, active and apparent powers. The next nine columns are related to the three types of power for the phases L1, L2 and L3. Except the first column, all data value was stored in Watt. An example of the extracted data related the active power can be visualized in Fig 4.

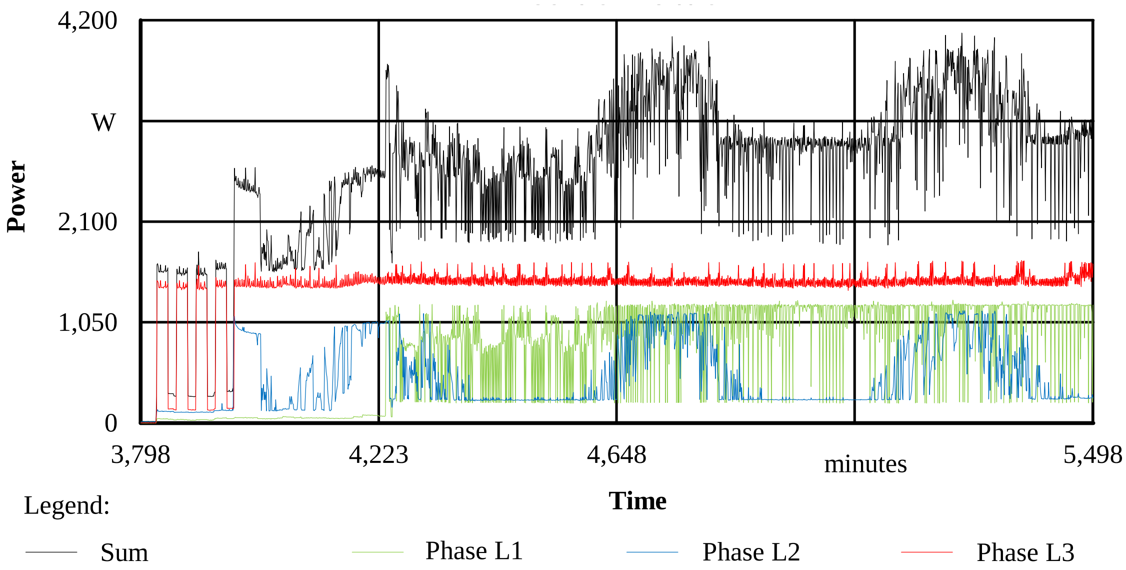


Fig. 4. Active power of each phase of the SLM machine and their sum

3.3. IDENTIFICATION OF THE MACHINE PATTERNS

The first step after the database storage was to know what kind of behaviour the machine develops, i.e., when a manufacturing process is being performed. The machine writes during a manufacturing process a log file containing the events and information that flew in this process. By using the log files it was possible to cross the initial and final dates of manufacturing processes within a period of time with the energy data. This can identify simple patterns from the machine by observing its characteristic curve.

From that curve, abnormal behaviours can be found such as idle situation of the machine. Moreover, a specific period of time can be chosen and analysed with more details by checking each phase separately. From the behaviour of each phase, it is possible to detect the influence on the energy total sum and where the influence comes from.

In order to observe such behaviours, to evaluate the curves and to build knowledge about those connections, data from a period of two weeks of were taken into account. Within this period, five manufacturing processes were realized. Their data regarding time are shown in Table 1. The considered information is the initial and final times, the total time of manufacturing, and the normalization with regard to the considered time period.

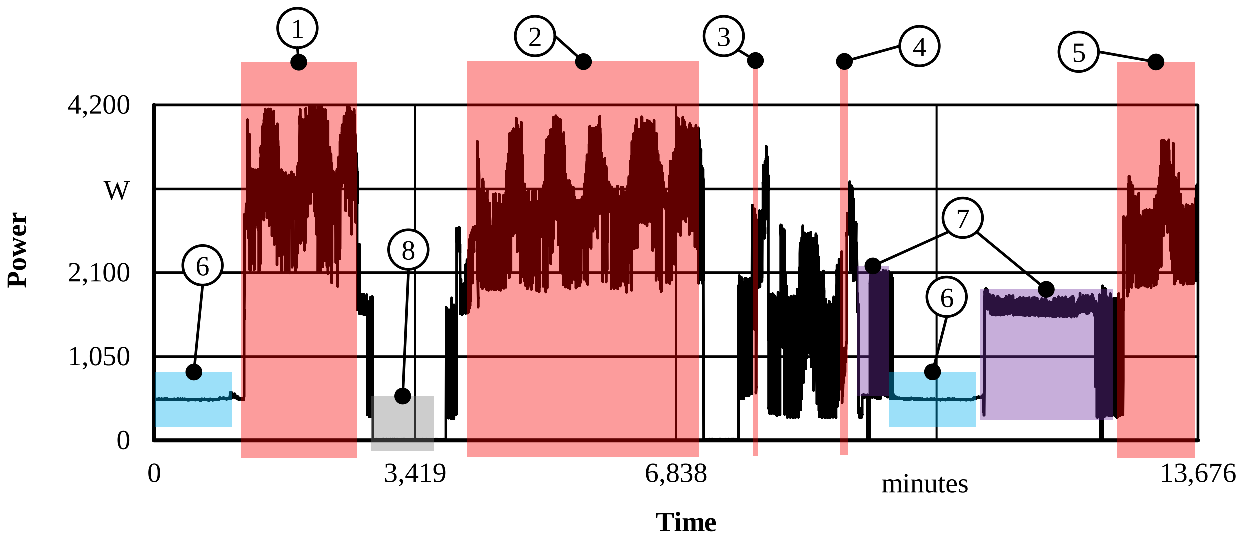
Fig. 5 brings the sum of the active power from each phase of the machine for the chosen period. In addition, the beginning and ending of the five processes from Table 1 are highlighted with the purpose of showing where each process fit in the diagram.

The numbers from 1 to 5 represent the manufacturing processes that occurred in the period. With this information, the pattern of the active power when a manufacturing process is performed is then identified.

Table 1. Information from manufacturing processes within the chosen time period

Process name	Start date	Finish date	Total time	Start point (normalized)	Finish point (normalized)
P1	07/20/15 14:40 hrs	07/21/15 16:42 hrs	26 hours	Minute 1,234	Minute 2,794
P2	07/22/15 16:42 hrs	07/27/15 09:08 hrs	112.5 hours	Minute 4,234	Minute 7,200
P3	08/11/15 13:03 hrs	08/11/15 14:33 hrs	1.5 hours	Minute 7,960	Minute 8,050
P4	08/12/15 08:15 hrs	08/12/15 09:57 hrs	1.7 hours	Minute 9,112	Minute 9,214
P5	08/14/15 21:12 hrs	08/17/15 09:43 hrs	60.7 hours	Minute 12,769	Minute 13,678

The numbers 6 to 8 illustrate the found patterns for different conditions. When the machine is on and it is not producing any workpiece, it needs around 500 W to maintain its components energized. This is represented by number 6 in the diagram from Fig. 5. When the cooling device is on, there are two possibilities of functioning. The first is to alternate, during no manufacturing process, the energy consumption in order to maintain the lubricant temperature. The second possibility is to maintain the energy consumption, represented by the number 7 of the same diagram.



1- P1
2- P2
3- P3
4- P4
5- P5
6- Standby
7- Cooling device
8- Machine off

Fig. 5. Active power for the chosen period and found patterns in the energy curve

Other behaviour can be detected. This last pattern is when the machine is switched off. This is recognized by the energy consumption near 0 W within a long period of time. The number 8 shows this behaviour.

3.4. IMPLEMENTED ALGORITHMS FOR INTELLIGENT PATTERN RECOGNITION

The three considered algorithms were Nearest Neighbour, Neural Network, and Support Vector Machine (SVM). The Nearest Neighbour algorithm is a simple method that can be used for classification of a feature vector to one of the known classes. This algorithm calculates the geometrical distance of the unknown vector (unknown measurement) to several next neighbours [14-15].

The use of Neural Network in the research environment is widespread. It is composed of three layers and each layer can include more than one neuron. A large number of training methods for neural network can be found and deployed for specific applications [16-19].

SVM is a modern approach in the field of machine learning, which the learn methods are based on the statistical theorems [20]. It is also a common method in condition monitoring field, as can be seen in [21-22].

The step after the calculation of the features is to use them as an input to train the classification algorithms. The output of the classification algorithms is the percentage of the correct classification of the unknown data to test the algorithms. The test data is part of the energy data, which was not used to train the algorithms, i.e., the rest of the database.

4. RESULTS

4.1. ENERGY DATA TOOL

The developed tool was implemented using MATLAB® 2014b and it is comprised of a graphical user interface (GUI) where it is possible to read energy data, to extract statistical characteristics, and to configure the single steps of a pattern recognition process. In addition, the tool allows the user to choose which algorithm can be used for a data analysis of a specific parameter.

4.2. CLASSIFICATION

As shown in section 3.3 it was possible to first identify visually four patterns by observing the curve of power. By taking the phases separately, one new pattern was identified: the laser process. For each pattern, the three mentioned algorithms were used in order to learn the pattern behaviours.

The evaluation of each pattern is performed by calculating the failure percentage of identification given in Formula 1 below:

$$F(\%) = \frac{NDI}{NI} \times 100 \tag{1}$$

where: *F* - failure percentage of identification, *NDI* – number of defect identifications, *NI* – number of identifications.

After teaching every algorithm of the tool the data from Table 1 as standard, new data were evaluated and the failure percentage of identification calculated.

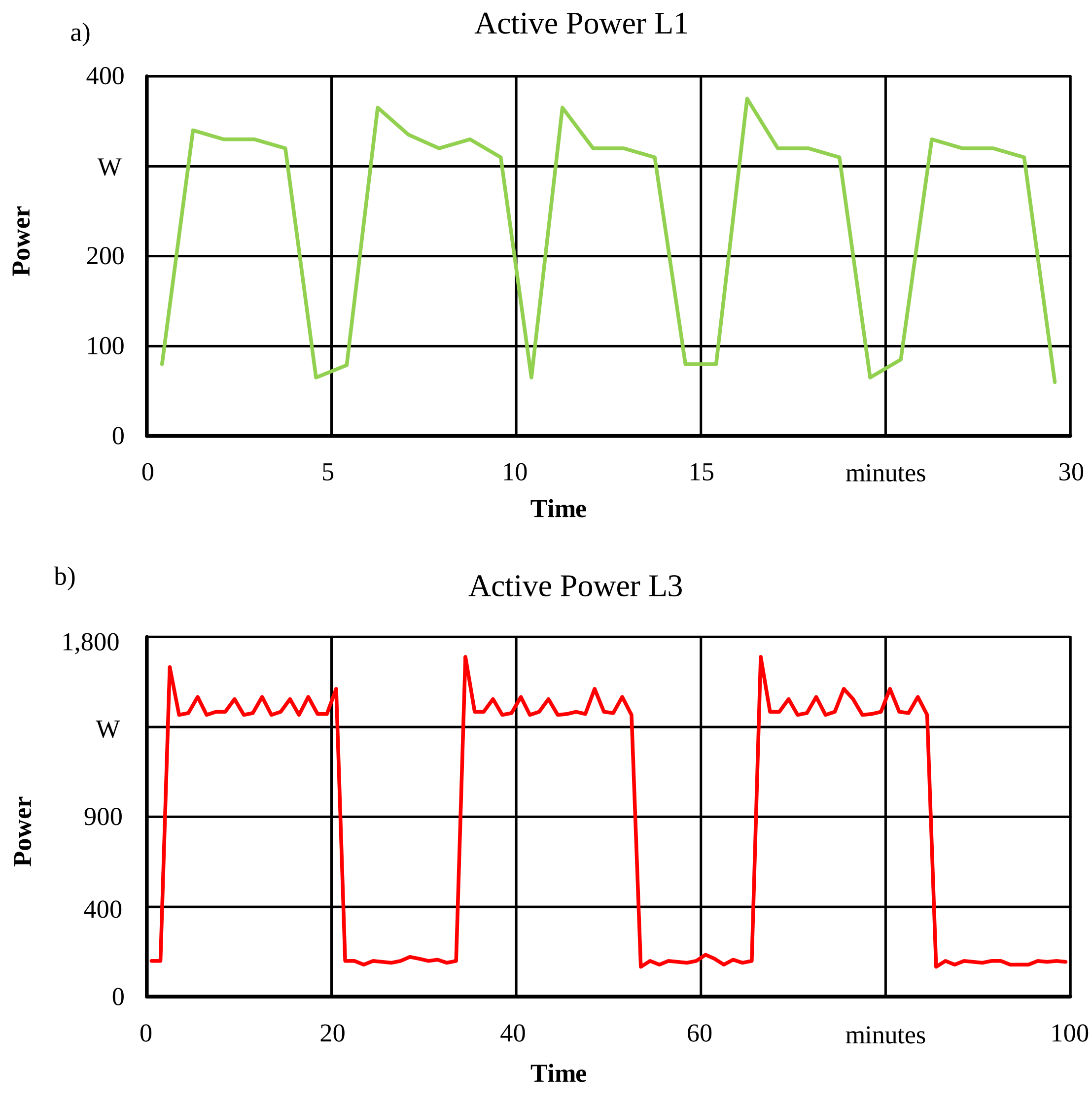


Fig. 6. Energy curve behaviours of the situations and systems from the SLM; a) laser device; b) cooling system

The first analysed system was the laser. Because it is connected directly to the L1 phase, only this phase was taken into account. The active power from L1 varies according to the needs of the laser device. The consumption will depend on the metal powder being used to manufacture the workpiece, once each material has different fusion point and, therefore, the laser device must be configured according to it. However, the teaching process did not take into account the type of material used, because the database contained information about different materials.

Then, the cooling system was analysed by using one single phase: the phase L3. The other situations, such as machine off and standby were analysed using the three phases and the sum of them. An example of the behaviours from the laser device and cooling system are shown in Fig. 6.

The Fig. 7 brings the results of the failure percentage of identification for four patterns of the machine and the algorithm with the lowest reached failure percentage of identification. Fig. 7a shows the outcome of each algorithm used for the patterns. The best recognizable pattern is the one of the cooling system followed by the machine off situation. The error percentages reached 0% and 0.01% respectively. In addition, the three algorithms reached a percentage error of 0.5% for the laser device energy curve.

For the case of the stand by situation, the algorithms had a percentage error higher than for the other cases. Nearest Neighbourhood and Neural Network achieved a percentage error under 1.00%, with 0.87% and 0.92% respectively. However, SVM had a percentage error of 1.21%.

In order to know which algorithm was proper for the machine, the entire dataset was considered and the results are shown in Fig. 7b. The best algorithm is the Nearest Neighbourhood with a total of 0.33 % of a percentage error, followed by Neural Network with a percentage failure of 0.35 %. The worst algorithm for this machine is considered the SVM, which had a percentage failure of 0.43 %.

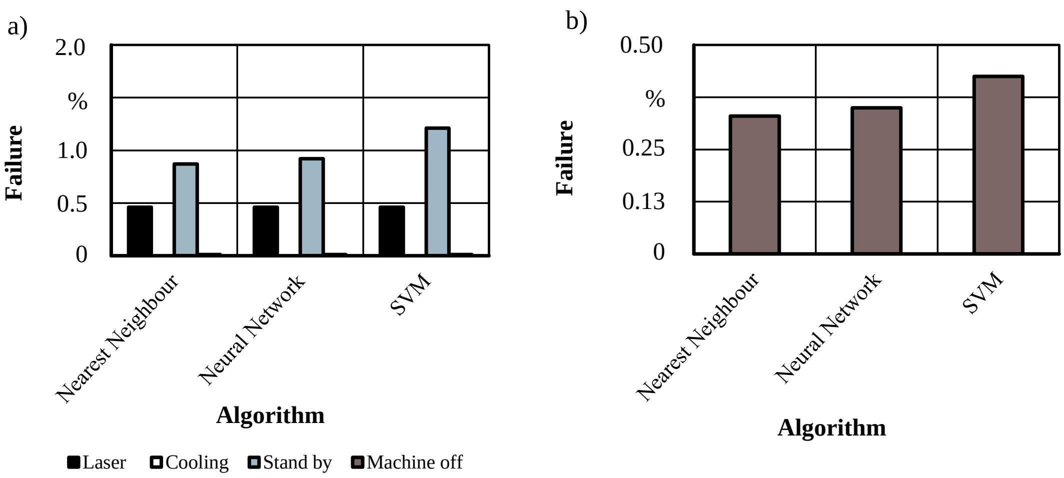


Fig. 7. Failure percentage of identification; a) errors of the algorithms per system and situation; b) total errors percentage per algorithm

5. CONCLUSION

This work showed the development of a tool to read, visualize and to recognize patterns through energy data from a selective laser melting machine. With this tool it was possible to extract information from the data about the conditions of the machine and process by using classification and clustering algorithms, such as SVM, artificial neural network and nearest neighbourhood. As a result, patterns of the use of the laser and the cooling device could have been identified. Furthermore, the standby situation of the machine was also detected. The choice of the algorithm is dependent on the characteristic under analysis.

By using the tool, the analyzed data and chosen algorithm is stored for further verification. Moreover, the identification and the calculation of the working period are also facilitated. However, in order to optimize the analysis of the energy consumption of the SLM machine, it is still necessary more detailed operation documentation. It should comprise further information regarding the type of material, protection gas and workpiece geometry.

Although pattern recognition was performed, the evaluation was made after the process has already occurred. Due to the closed architecture of the control system by the machine manufacturer, this evaluation is not implemented on the machine control software and a real time action by the machine controller is not possible. However, real time analysis can be realized by improving the developed tool in order to provide reports that contain the current machine situation during the manufacturing process. This real time analysis can provide a prior identification of failures and can improve the efficiency of the process by acting in a proactive manner. Furthermore, a stronger focus can be given on applying these models to the opportunities highlighted in [23-24] such as other machine types and different levels within the production system.

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