Abstract—Due to the growing demand to reduce the environmental impact, the manufacturing companies of today are encouraged to adopt new green methodologies, strategies and technologies for increasing the energy efficiency of their manufacturing production lines. These solutions have a great impact on several productivity metrics including availability and costs. The continuous pursuit of productivity and particularly of machine availability has led to an increase of the total energy consumption in production plants. However, productivity gains can also be achieved by reducing the life-cycle costs of the manufacturing production systems. The research currently done under the scope of Self-Learning Production Systems (SLPS) tries to fill the gap between availability and efficiency by providing an innovative and integrated approach for ensuring the efficient utilization of the resources in machine tools.

Index Terms—Machine Tool, Energy Efficiency, Data Mining, Context Awareness, Service Oriented Architecture

I. INTRODUCTION

The continuous pursuit of productivity and particularly of machine availability has led to an increase of the total energy consumption in production plants. Moreover, the increasing demand for new, high quality and highly customized products has led to very flexible production machines able to quickly react to new production conditions. However, the desired flexibility is often achieved by oversizing machine components in the design phase, what leads to a decrease of the overall energy efficiency. Although production machines have become more efficient in terms of accuracy, cycle time and flexibility, there are yet some deficits, like the efficient handling with resources [1]–[3].

Machine tools correspond to a significant part of the electrical energy consumers in manufacturing plants, since their work is almost completely done by converting electrical into mechanical energy. After the decision of the European Commission in the frame of the Ecodesign Directive (Directive 2009/125/EC) to include machine tools in the list of products to be analyzed, the European organization of machine tool manufactures (CECIMO) designed a concept for self-regulation of the sector. This reaction was anyhow not only caused by the political decision, but also because of the fact that energy efficiency is gaining more and more importance in the market of production machines.

II. BACKGROUND

The energy consumption of machine tool is a function of the temporal power demand which is not static but, on the contrary, dynamic during the machining process. The typical power demand of a machining process is shown in Fig. 1 and provides a basis to recognize states and/or actions during the machining process.

![Fig. 1. Machine tool typical power profile [4].](image-url)

The Fig. 1 confirms the idea that the power demand is basically constituted by a variable part and a constant part [1]. The variable and constant power represent together the minimal amount of power that is required to have the machine ready to run [5]. A more accurate distinction to the given power classification is also proposed in [4], where four power segments are considered, namely:

- **Fixed Power**: is the power demand to guarantee the readiness of the machine tool.
- **Operational Power**: is the power demand to operate the component during the machining phase.
- **Tool tip Power**: is the power demand at tool tip to remove work piece material.
- **Unproductive Power**: is the power converted into heat.

As stated in [4], acting on fixed energy consumption is highly relevant for improving the energy efficiency of manufacturing processes throughout the different machines states,
or in other words the effectiveness of energy usage throughout the different machines states is a necessary condition to energy efficiency.

Machine tools are extremely complex systems composed of several individual components/subsystems. In this scenario, machine tools of different type and category typically consist of different components/subsystems. Moreover, even in machine tools of the same type and category some components/subsystems could differ.

In the context of energy efficiency in machine tools it is important to distinguish between component level optimization and machine tool level optimization. The former leads to an increasing in the energy efficiency of overall machine by improving the efficiency factors of the components. The latter leads to an indirect increasing in the energy efficiency acting on components/subsystems demand during machine life-cycle.

As exposed in [6], along with the machining process, machine tools components/subsystems as energy converter are mainly responsible for the energy consumption in production. Consequently, in order to reduce the fixed power one strategy is to increase the efficiency at machine components level. However, the improvement of the energy efficiency at machine components level, i.e. the efficiency factor of machine components, is not enough. Therefore a new strategy that aims to look to the whole machine is needed. In this scenario, an improvement in the utilization degree of the whole machine [7] is reached by avoiding machine energetic disadvantageous working points and reducing the energy consumption of unavoidable idle time periods by shutting off or switching into more efficient energetic states the machine components.

Considering the machine structure presented in [7], the machine components can be separated into two main categories according to their functionalities main and auxiliary components respectively. A possible way to increase energy efficiency in machine tools can pass on the reduction of the machine fixed power demand acting on the auxiliary components according to the particular machine state.

The paper addresses the energy efficiency at machine tool level. An overview of different approaches that have been introduced and implemented to allow energy saving in machine tools is given. Finally, a novel approach based on machine tool behavioral modelling will be presented to improve the energy efficiency in machine tools.

1) Time-out Approach for Energy Management: The traditional approach to improve the machine utilization degree is represented by the so called **time-out approach** consisting in defining a *time-out* for each machine subsystem. In this case, the optimization results from shutting-down all the auxiliary services/components during the idle times identified by the time-out. Setting machine subsystems to energy optimal state is done by the machine controller that gathers all the necessary information about each subsystem and orders to switch to a particular state. The auxiliary services, i.e. the machine subsystems, are automatically turned on if a new production order is received. This approach improves the machine utilization degree, however the reactive nature of this behaviour implies an additional energy consumption and an extended execution time to achieve operational readiness due to the wake-up delay of the machine subsystems as stated in [8].

The Fig. 2 shows the **time-out approach** to raise the machine utilization degree in terms of energy consumption. In this case, a time-out is set for different machine subsystems, which can be shut off during idle-time (energy modes $σ_3$ and $σ_2$). There is no need to know, when a machine operation will be executed. The subsystems are automatically turned on (energy mode $σ_4$) after the incoming of a new operation. Nevertheless, because of this reactive behavior, the time needed to execute the planned operations is extended according to the wake-up delay of the subsystems ($ΔT_{Delay}$).

![Fig. 2. Machine energy mode development according to the time-out strategy.](image)

2) Industrial Network Profiles for Energy Management: Smart energy saving technologies such as SERCOS Energy [9] and Siemens PROFINenergy [10] have been implemented and introduced in the context of the manufacturing production processes and in particular in the context of machine tool to reduce the energy consumption. The SERCOS Energy and the Siemens PROFINenergy are profiles defined on top of the SERCOS-III and PROFINET Industrial Ethernet specifications. These profiles provide an interface for components to communicate information about energy consumption values in different energetic states. As stated in [11], for many components a suitable approach to model their energy consumption behaviour is based on a number of discrete states together with a set of continuous variables. Therefore, an energetic state of a component needs to be described by the following set of information: the average energy consumption, the necessary time needed to change from one energetic state to another, the energy needed for changing to and from the energetic states and the minimal time to stay. The Fig. 3 shows an example of a state machine using SERCOS Energy used to control operational and stand-by modes of a machine tool. The power demands (in the example $P_{Tare1}$, $P_{Tare2}$ and $P_{Tare3}$) provide information about the energy consumption in each one of the energetic states. The duration of the transitions (in the example $θ_1$, $θ_2$ and $θ_3$) called wake-up delays is fundamental to understand when the machine needs to be turned on into operation mode in order to be ready for the next operations just in time.

These protocols enable the setting of the machine during predictable idle periods such as lunch breaks and plant holi-
days. However, the short-term pauses and standstill times are not known in advance, which often reduces the usable potential as confirmed in [12].

III. SELF-LEARNING PRODUCTION SYSTEMS ARCHITECTURE

Focusing on the scope and challenges presented in previous sections, the SLPS reference architecture has been created by combining atomic components that can interact to improve the energy efficiency at machine tool level.

The reference SLPS architecture is constituted by two main components: the Extractor and the Adapter operating in a cooperative manner. These two together are responsible for identifying the current context under which the production system is operating (Extractor), and adapt the production system behavior with the purpose of improving its performance in face of contextual change (Adapter). The result of the context extraction process will be a standardized meta-model gathering all context relevant information obtained by monitoring process machines and devices. This standardized meta-model will be used by the Adapter to start an evaluation process (so called Adaptation Process) for improving production system productivity, efficiency and performance. Finally, the outcome of the adaptation activity, the Adaptation itself, is exposed to the system expert through the Expert Collaboration UI for a system expert evaluation.

Since the system response must take into account not only the particular context, but most important, the entire lifecycle behavior of both system and expert, a Learning Module has been provided, containing a set of machine learning algorithms capable for extracting patterns and regularities from gathered contextual data and operator decisions over time in order to create a representative model of the process used to predict its future behaviour. All processed data and knowledge generated are stored in Data Access Layer repositories for continuous evolution and evaluation. These components allow both Extractor and Adapter to access it when they need further information about current context.

An outline of the architecture with its main components is represented (see Fig. 4) [13]. The next subsections will present the main functionalities covered by the different components of this architecture.

A. Architecture Components

1) Extractor: is responsible for extracting, processing, filtering and finally storing actual manufacturing production process context.

Fig. 3. Example of a state machine using sercos Energy for the energy management of a machine tool with two stand-by modes.

2) Adapter: is the active component and is responsible for processing contextual data and adapting manufacturing process parameters, i.e. control parameters, maintenance/energy plans and/or scheduling/dispatching execution to face changes in process.

3) Learning Module: encapsulates machine learning algorithms and process explicit models to learn relying on data mining and operator’s feedback. Furthermore, is responsible to update process explicit models after human expert validation and/or feedback.

4) Expert Collaboration UI: is responsible to show Adapter suggestions about adjusted parameters allowing human expert validation, i.e. the human expert can accept or reject the Adapter suggestion. The result of validation is then sent to the Adapter and Learning Module.

5) Evaluator: Performance of the adaptation, context extraction and process models generalization capability are measured by the evaluator. Evaluation results are then sent to the Expert Collaboration UI to be presented to the human expert to assist him during the validation process.

6) Data Access Layer: wide range of data is available in Data Access Layer from the plant floor infrastructure. The Model Repository contains ontology based plant specific models for equipment, production processes and products. The Context Repository allows the updating and storage of extracted/processed contextual information for later retrieval. Information flow among the modules is event driven in some cases and time based in other cases.

7) Service Infrastructure: is responsible to ensure secure information flow between the SLPS solution and the existent manufacturing process equipments. The information flow is bi-directional allowing both the collection of relevant contextual information from the process and communication of adjusted manufacturing process parameters to the monitoring and control system.

8) Middleware: Information from ERP level, devices or plant data servers are brought to Data Access Layer directly

Fig. 4. Self-Learning Architectural overview [13]
or via middleware depending on plant specific equipment and communication protocols.

IV. APPLICATION SCENARIOS

This section illustrates one of the several industrial application scenarios from three distinct industrial partners directly involved in the design and development of the Self-Learning solution. A detailed description about the other application scenarios and the related business case can be found in [14].

A. Energy Management Application for Machine Tools

The presented scenario relates to the optimization of secondary processes on CNC machines during the machine tools lifecycle by integrating Self-Learning solutions to the existing service platform as introduced in [15]. The goal in this application scenario is to improve machine tool efficiency by using context aware and self-adapting solutions, provided by the SLPS approach, together with existent technologies.

B. Machine level energy control: Self-Learning approach

As an alternative to the common time-out strategy for reducing energy consumption and to improve the selection of energetic states for SERCOS and PROFIenergy machine compliant, the context sensitive self-learning approach is presented (Fig. 5).

![Fig. 5. Machine energy mode development according to the self-learning approach.](image)

During production line runtime, several machine control states are monitored by the Extractor in order to recognize idle-time patterns in different time domains. The entire list of recognized idle-times is sent to the Adapter in order to provide to the system expert a list of scheduling suggestions for energy saving tasks to be executed during idle-times depending on the their temporal dimension and on the entire lifecycle of the system, i.e. taking into account the different tasks executed in the past.

Although the production planning and control may not be available at process control level, the continuous observation of the production context makes it possible to model the machine tool behaviour in order to predict future machine utilization ($T_{Prediction}$). In this way, there is no need to set a time-out. The subsystems of the machine can be shut off directly after the advent of an idle-time. If the characteristic wake-up delay is known, it is possible to turn on the subsystems in advance, avoiding delays and productivity losses.

Moreover, the behavioral model of machine tool can be used to improve the scheduling of energy saving modes for SERCOS and PROFIenergy machine compliant, or in other words can be used to define the most appropriate energetic states according to the production context.

1) Extractor Activities: The continuous production context observation conducted by the Extractor will enable to collect information about machine idle-times during production operations. The extraction process is constituted by three main functionalities, namely context identification, context reasoning and context provisioning (see Fig. 6).

![Fig. 6. Extraction Process [16].](image)

Context identification receives raw-data from the Data Access Layer machine tool information classified in time domain (see Fig. 7). Context reasoning deduces high-level information (machine tool idle-times) from the received low-level raw data and checks the context consistency and reliability as well. Context provisioning encapsulates all identified machine idletimes in a standardized meta-model and notifies the Adapter that new context is available.

![Fig. 7. Example of detected machine idle times data](image)

2) Adapter Activities: After being notified by the Extractor, the Adapter will start an Adaptation Process. The Adaptation Process (see Fig. 8) refers to the execution of a sequence of tasks for evaluating received data consistency and computing a proposal of adaptation, i.e. for planning machine energy management tasks according to the machine tool contextual information.

After being notified about a change of context, the first thing the Adapter does is to retrieve all the available information related to this new context from the context repository and...
transform it into a generic data structure (Prepare Data task). The converted data is then analysed by exploiting supervised machine learning classification techniques. At this point current context information together with process knowledge comprising the entire lifecycle behaviour of the machine tool are used to calculate a list of energy modes scheduling suggestions for the machine tool (Analyse Data task). Finally, the result of the Analyse Data task (also called Adaptation) is shown to system expert using a graphical user interface (Fig. 9) in order to be validated (Adaptation Provisioning task). The validation task can consist of a positive validation, a negative validation or a mixed validation. In this way, the system expert can adjust, validate or refuse the Adaptation provided by the Adapter. The result of the validation task, i.e. the Adaptation validated, is sent back to the Adapter and used to improve its own knowledge about the particular machine, or in other words, to learn from system expert decisions (e.g. validation and refusal). Moreover, the validated Adaptation is sent to the machine using the OPC-UA connection and allowing to adapt its behavior to the incoming production activities.

Moreover, necessary information about the number of considered energetic states, the minimum time to stay in the target energetic state (break-even time) and the time needed to change from one energetic state to fully readiness state (wake-up time) can be configured by the system expert for each one of the energetic state using the Configuration UI (Fig. 10).

This information is then used by the Adapter to select the correct energetic state according to the dimension of the idle-time. However, the decisions of the system expert during the validation tasks (e.g. validation and adjustments) implicitly allow the Adapter to automatically understand the constraints between the different energetic states without any programming effort. This aspect represents a step forward in relation to the other approaches designed for energy management, since they are basically reactive approaches while the Self-Learning approach tries to learn in order to predict the correct points in time to switch on/off the machine components without waiting for operator notification improving, in such a way, the machine availability and the energy saving.

V. EXPERIMENTAL RESULTS

The SPLS prototype has been tested on data gathered from machines in the plant Lohr Werk 2 of the Bosch Rexroth AG in Lohr am Main, Germany. The system configuration is shown in Fig. 11.

The objective was to feed the SLPS solution with the provided data for testing the capability of the system to find patterns in idle times and schedule machine energy mode tasks. The selected energy mode tasks were then communicated to the existent shop floor machines using an OPC-UA connection. The SLPS solution has been tested for several hours along several days showing good levels of reliability, feasibility and
robustness. Finally, the results about the real energy saving together with the loss of machine availability obtained by using the SLPS provided prototype are shown in figure 12.

The figure clearly shows that the application of the SLPS prototype results in a real improvement of the energy saving for machine tools. However, looking at machine availability along time the figure shows the presence of an initial transient phase where the energy saving improves while the machine availability decreases due to the learning model of the machine that initially has not enough entries to correctly predict machine behaviour. After this transient phase, the system finally stabilizes, i.e. the SLPS Adapter learns with the system expert decisions along time and populates the learning model of the machine with new entries enhancing its capability to generalize. As a result, the loss of availability along time goes to the final zero value.

VI. CONCLUSION

Current work presents a contribution to the SLPS research domain, particularly regarding the Adapter part, by presenting a real application scenario where the major goal is to improve the energy efficiency of machine tools.

The proposed SLPS generic infrastructure addresses the need for adaptation of several process and control parameters envisioning the improvement of the overall system performance and achieves a smoother integration of control and secondary processes. This approach relies on context awareness allied to data mining technology to enable the system to adapt to contextual changes through learning over previous human expert inputs and monitoring data.

In the presented scenario, it is described how the extracted machine context is used for adapting the machine tool behaviour and improving its energy efficiency. This improvement is possible by reducing the energy consumption of unavoidable idle time periods and increasing the utilization degree of the whole machine. Through this scenario, the authors also expect to develop an educational aspect in matters of energy-conscious behaviour of operators while using machine tools. Moreover, as future work there are some aspects that still need to be further researched or refined, such as the reliability and the accuracy of the proposals produced by the Adapter during the operations in a real industrial environment.

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REFERENCES