Integrating uncertainty of available energy in manufacturing planning

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***Abstract*—Energy consideration in production planning is becoming more important due to concerns over the climate change. However, the uncertainty of energy availability hinders the optimisation of production. The proposed concept uses an iterative approach of adjusting production scheduling in respect to the available energy using a multi-criteria optimisation that not only includes factory utilisation but also the likelihood of the predicted energy availability.**

I. Introduction

Today, the planning of industrial production is primarily driven by the goal of optimal utilisation of production facilities. Considerations for optimised energy usage play only a minor role, if at all, e.g. in avoiding peak loads. However, the goal of changing Austria's energy supply to 100 percent renewables (*#mission2030*) changes the structure of energy production considerably. Many areas that currently still operate on fossil energy are gradually changed to electricity. This ranges from heating systems to process heat generation to mobility. A higher electricity demand together with the inevitable volatility of renewable energy means that production planning must take into account the availability of energy in order to achieve the primary goals of *#mission2030*. Under these circumstances, a fixed load profile is often no longer realistic; instead, the load should be adapted to the available energy. The Factories4Renewables concept aims to enable production plants to plan their manufacturing steps according to a predetermined yet dynamic energy availability in such a way that a given energy profile is maintained. This means that the given energy is not only not exceeded but also used as fully as possible while at the same time ensuring efficient utilisation of manufacturing resources. Production, therefore, becomes a plannable (electric) load for the power grid allowing to guarantee reliability and safety of the processes and to prevent negative effects up to possible instability of the energy system. The big challenge is in the handling of the inherent prediction uncertainty of the energy profiles, which increases with increasing planning horizon and production complexity. The goal is achieved by an iterative planning process, in which production planning is executed for energy profiles with different probabilities. The results are assessed and evaluated with respect to their compliance with the set of production constraints, and the best plan is successively adapted to the prediction uncertainty that is changing over time. Adaptive energy consumption models that are optimised using machine learning techniques increase the planning accuracy, and the inclusion of production-dependent energy storage and recuperation potentials improves the overall efficiency.

II. State of the Art

A. Production Planning

The current trends in manufacturing automation show, on the one hand, that the future of production systems will be characterised by a high degree of versatility in production systems, so that these factories have a high degree of flexibility in terms of time due to the redundancy of machines of such universal production systems [1]. On the other hand, Industry 4.0 factories will have to cope with a high level of complexity in the production environment and a highly dynamic order flow. Therefore, established Industry 4.0 factories are already relocating or distributing centralised functionalities of production planning systems (Manufacturing Execution Systems, MES) towards individual machines [2]. This trend of shifting decisions to lower levels is also becoming increasingly important on higher levels of enterprise resource planning systems (ERP systems) [3].

The distribution of control and planning functionalities is an established topic with an architecture based on the concept of orders and resources that work together to achieve a global optimum. This concept is still the core of modern approaches, which differ only in the level of the hierarchy introduced [4]. In addition, [5] proposes a cloud computing approach in which monitoring and control are distributed across independently running MES that are coordinated by a centralised ERP system. It makes the underlying manufacturing facility a highly flexible structure that is not limited by the physical layout of a single production line. [6] continues to point to blurring boundaries between a single physical factory and its enterprise management and multi-enterprise approaches. You can integrate multiple factories and management systems with a common supply chain and schedules.

Factories4Renewables does not aim to reinvent production planning systems, but rather defines interfaces to use existing systems and to be able to expand the aspect of energy optimisation. However, integration of energy constrains into existing production planning systems without redeveloping the entire automation pyramid is an open topic. Two possible approaches are to represent energy consumption as a special machine or operator [7],[8].

B. Energy Modeling

With the increasing importance of sustainability and digitalisation of industrial production, the detailed knowledge of a factory's energy consumption down to process-step level also plays a more important role. Two key-drivers stand behind the detailed modeling of energy consumption: benchmarking and increasing the energy efficiency on the one hand and adapting the energy profile of industrial production to a higher use of renewable, volatile energy sources on the other hand.

[9] developed a framework to model the embodied product energy. They categorised the manufacturing energy consumption into two groups: indirect energy is the energy needed to maintain the production environment, e.g. lighting and heating. Direct energy, on the other hand, refers to energy needed by the process itself and is further divided into theoretical energy (the minimum energy needed to carry out a certain process, e.g. cutting, drilling) and auxiliary energy (energy needed to prepare and support the process, e.g. compressed air, machine cooling, also machine start-up / idling / standby).

Proposing a soft sensing approach to determine the operational state based on the energy consumption, [10] abstracted the machine actions to a Finite State Machine (FSM) and assigned a vector (power, time) to each state transition. Based on the observed energy consumption, a sequence of machine states and a corresponding production state were deduced.

Like [10], [11] also implemented an FSM of the machine states and the corresponding power consumption, albeit with different purpose: they developed a mathematical model to optimise the production schedule in terms of energy cost. With the help of the FSM, the power demand of a given production schedule can be modeled to calculate the cost of energy.

[12] presented a modeling formalism to take into account design and operation of a machine when predicting the energy efficiency. In their most coarse model, which used an FSM-like abstraction of the machine operational states, energy consumption values of each operational state were determined empirically. It was emphasised that for this model parameterisation only a few measurements of basic states are sufficient to make meaningful predictions.

In their approach to calculate the energy costs of a production order, [7], in contrast to [12]'s empirical approach, presented a semi-analytical approach to determine a process step's energy. A process step is split into four parts (production, setup, shutdown, further resources) and the energy consumption is calculated with some machine- and material-dependent coefficients by differing between working time and break time. However, this model requires the power demand of the production resources to be known.

C. Energy consideration in production planning

According to the economic and environmental consideration, for many companies, energy efficiency is now an objective. Awareness of energy demands and available energy in the production and manufacturing facilities is gaining more importance. Especially the share of renewable energies is constantly growing. This means that considering the available renewable energy in production planning is a new constraint.

[13] categorise energy-oriented production planning into two main streams. The first stream considers the energy efficiency of the manufacturing processes in their objective function. In contrast, the second approaches consider cost efficiency as an objective function (by minimising the quantity of energy or minimising energy costs caused by peak loads).

[7] propose to consider the available energy as a resource "like an employee or a machine." Therefore, the available amount of energy is depicted as a resource in the MES software. To bring energy efficiency to the factory level, [14] proposes energy information should be integrated from device-level up to ERP. For optimising production and logistics, in addition to cost, energy-related information should be considered. [8] considers energy as a planning resource, which is equal to material and personal resources.

III. System architecture

The system architecture consists of three main components: Energy modeling, Entropy Regulator and Confidence Estimator (see Figure 1). The primary goal is to provide an infrastructure to integrate utilities' energy profiles and manufacturing planning systems in a seamless way without the need for redevelopment of either legacy systems.

A. System components and processes

The general process can be divided into five main steps:

1) Utility defines the energy profiles; The specified energy generation profile consists of several parts with different predictive accuracy. The day-ahead (1-day) profile is fixed by electricity trading with a (current) resolution of hours. Short-term daily forecasts (2-3 days) typically have a high level of accuracy, while the forecasts over a period of several weeks are significantly less precise. Forecasts of the availability of energy in several months are de facto only based on statistical data.
2) Energy modeling aggregates the energy profiles into a distribution range. The further in time, the wider the range becomes. Prior to the system operation, Energy Model analyses these historical measurements of the energy supply to define a distribution range that is used by the Entropy regulator to calculate likelihoods of energy profiles. It is assumed that the distribution of the energy generation does not change over time for a given point in time. In case there is no sufficient amount of measurements available, bootstrapping will be applied to define the distribution.
3) Entropy Regulator evaluates the distribution to define multiple profiles with a certain level of likelihood; Since the energy generation profile becomes less precise as the time horizon increases but production planning requires a "precise" energy profile, production planning is started

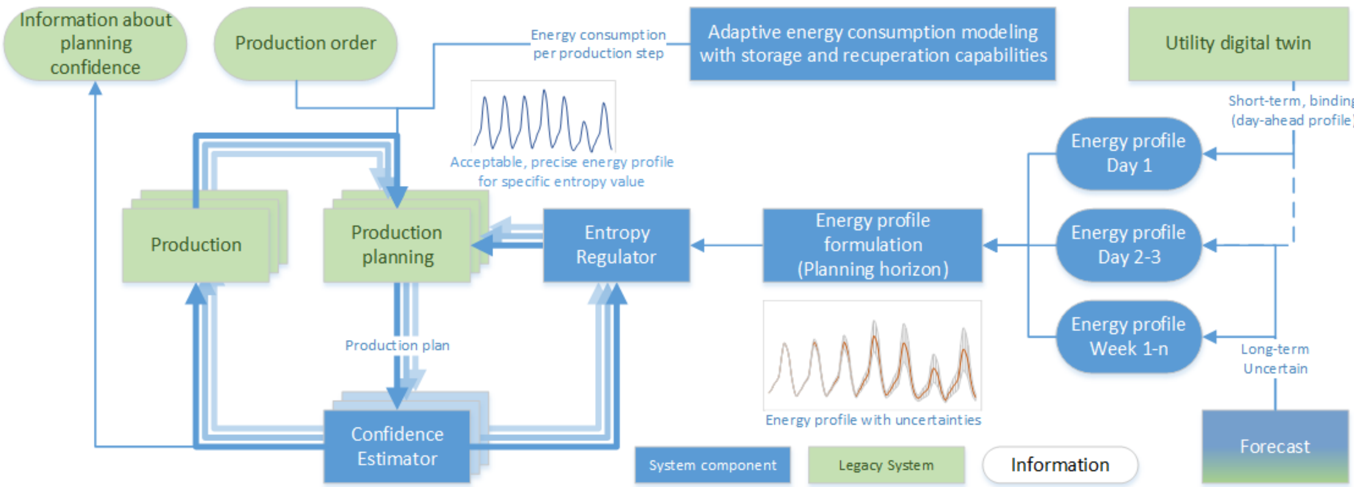

Fig. 1. System architecture

iteratively with different energy profiles, which convert the statistical uncertainty into a set of possible profiles for the scheduler. In case the range has the normal distribution, the most probable profile would be mean of upper and lower edges of the range. Realistically, profiles are not normally distributed especially with the large share of renewable sources. Therefore, given the known historical distributions (one per time slot of the the planning horizon) of the energy profiles, Entropy Regulator calculates the sum of the likelihoods of all the time steps in the planning horizon. During the initial step it calculates the maximum likelihood value for a given dataset.

4) Production planning with respect to the energy profile; The most probable energy profile is then sent to the MES system to plan production steps for a corresponding energy profile. It is assumed that the most probable profile will result in lower than desired factory utilisation. The system will use Overall Equipment Effectiveness (OEE) metric that accounts for Availability, Effectiveness, Quality of resources and provides a basic quantifiable result of planning [7]. The resulting output is the overall OEE value for the entire planning horizon as well as the OEE values of each time slot that indicate when the factory resources were not efficiently utilised.
5) Confidence estimator evaluates the overall results; The results of the production planning as well as the energy profile likelihood are used to calculate the Trust and Efficiency Level (TEL) that is a function of three types of variables: 1) Energy certainty level; How certain it is that the profile will actually happen, calculated by the Entropy regulator for a given energy profile 2) Manufacturing level; Efficiency of manufacturing utilisation; OEE value for a given energy profile and 3) Energy usage level; How closely energy consumption matches supply. If the TEL value is not satisfactory, Confidence estimator changes the energy profile to better match factory utilisation and requests the Entropy regulator to calculate the likelihood of that profile to happen.

The iterative process of steps 3, 4 and 5 continue until no improvement is possible or the overall TEL value is satisfactory. Entropy Regulator uses the probability range of the energy profiles defined by the energy model to limit the options for probably energy profiles. It cannot go beyond this range values because the likelihood of such a profile to happen is zero and hence will greatly decrease the overall TEL value. The entire cycle (steps 1-5) is repeated when the utility provides new profiles and therefore, the production planning may need to be adjusted.

B. *Energy modeling*

The purpose of the Adaptive Energy Consumption Model (AECM) is to determine the energy consumption per production step. This energy consumption will then be stored in the MES as an additional resource needed for the respective production step.

The indirect energy consumption must be measured and considered but will be regarded as not influenceable (despite the additional flexibility it would certainly provide to shift shares of the base load, but this goes beyond adapting the production itself and is therefore out of scope). The direct energy is planned to be modeled with an FSM for each machine in the manner of Figure 2. We plan to assess the power and energy values of the FSM states by combining the semi-analytical approach of [7] and the empirical approach of [12]: The findings of measurements basic machine states will be supplemented by coefficients which consider possible material- and production-order-dependent influences on the energy consumption.

The modeling results will be constantly compared with the measurements to refine the model and to discover big discrepancies, which might indicate machine failures.

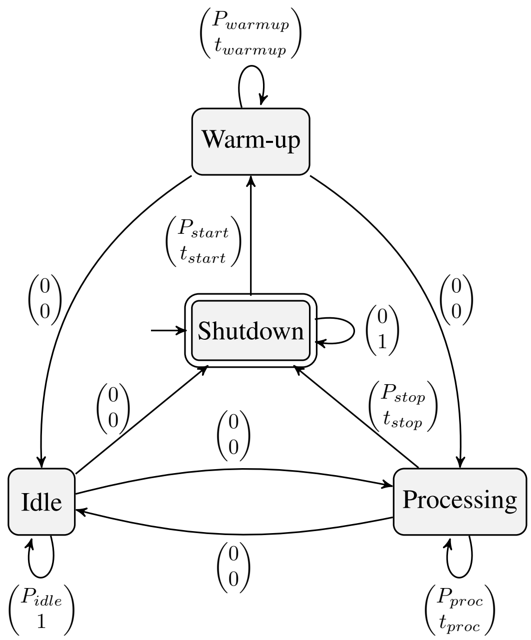

Fig. 2. FSM with assigned (power, time)-vectors, based on [10],[11]

C. Energy consideration in production planning

Classical power generation is replaced by renewable energy generation, and consequently, time-dependent energy is a constraint. So, production facilities are motivated to consume energy at low prices. Therefore consideration of time-dependent energy for production planning is a solid requirement. Accordingly, not only the cost but also the availability of the energy is time-dependent. Moreover, energy production by PV and wind is influenced by weather and seasons, which means strong fluctuations and uncertainty in supplying renewable energies. It seems that monitoring energy consumption just for avoiding peak loads or alerting the operators is not sufficient. It is required to integrate the energy demand in MES software.

In Factories4Renewables, the ideal solution for handling energy constraints is adopting and customising the existing MES system so that energy is considered as a limited resource in the process. MES systems inherently allocate, assign and control the resources like materials, production equipment, machines, and operators dynamically. Alternative to the ideal solution, defining energy as a special machine or specific operator makes it possible to introduce energy constraints to the legacy MES systems.

IV. Conclusion and Outlook

The above described concept provides a flexible way to integrate energy constraints in production planning as well as uncertainty of energy availability to improve performance reliability. Further work's focus will be on reducing the brute force approach in the iterative optimisation process as well as defining algorithms to tune the likelihood calculation to account for observed deviations between the predicted and actual measurement of energy supply during system run time. Although used in a different application area, [15] evaluates 8 different approaches in estimation of uncertainty of prediction that will be evaluated in the scope of the project to find the optimal solution for manufacturing systems scenario.

Energy modeling will be further automated to make dedicated measurements redundant. Instead of assigning amounts of energy to certain process steps in strict intervals, the self-learning aspect will be improved in order to refine the modeled consumption continuously.

Also, the function for TEL metrics calculation will be defined to reflect the weights of each of its three components.

Another aspect of research will focus on increasing transparency of energy constrains integration into production planning system to reduce the need for engineering changes of the well established manufacturing planning tools.

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