An Iot Based Approach For Energy Flexible Control Of Production Systems

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Abstract

Due to the increasing amount of renewable energy on the energy market resulting in a higher volatility of energy supply, manufacturing companies have an enhanced awareness of their energy demand in order to benefit from alternating prices. Energy flexibility is an opportunity to adapt manufacturing systems to the changing circumstances. The idea of energy flexibility follows the approach of synchronizing energy demand with supply, e.g. to exploit alternating weather conditions. This paper presents an energy-aware demand side management (DSM) approach to control manufacturing systems on the component level. The developed closed loop control is based on an algorithm fed with manufacturing, energy and environmental data and is realized at an Internet of Things (IoT) platform. Based on machine tool models the energy demand of a hypothetical factory is simulated. Taking on-site power generation data into account, the aim of the developed energy-aware control loop is to reduce the appearing residual power that must be balanced with grid-supplied power.

Keywords: energy flexibility; machine tools; on-site power generation; Internet of Things

1. Introduction

To achieve global climate agreements recently updated at the UN conference in 2015, new restrictions addressing the greenhouse gas (GHG) emissions were introduced by the German government. The Renewable Energy Law defines feed-in remuneration to increase the amount of renewable energy. As a result, the share of renewable energy has been increasing continuously to a rate of 29 % (188 GWh) in 2016[1].

The German climate protection plan 2050 [2] includes a holistic energy concept addressing the energy sector, buildings, transport, agriculture and industry. For the industry sector, a reduction of GHG emissions of 49 % is striven for. Both the changing energy market with an increasing share of renewable and the rising viability of on-site power generation for manufacturing companies lead to a volatile energy application of the most suitable methods are identified and the approach is realized on an IoT platform.

2. Energy flexibility in smart factories

The future factory

Due to environmental circumstances, the entire factory structure will change resulting in new challenges. The conventional goal triangle in manufacturing companies is evolving to a pyramid with the additional targets flexibility and sustainability [3] (figure 1).

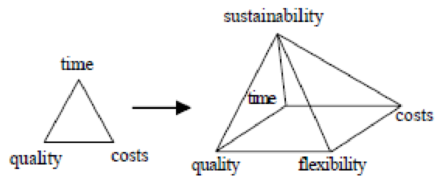


Fig. 1. Evolution of targets in manufacturing companies

Addressing sustainability, future factories should take social, economic and ecological aspects into account. A future concept of a sustainable manufacturing site is for example introduced by Stoldt et al. [4] with the key issues resource efficiency, zero emission and embedding people.

Besides the increasing awareness for sustainability, the digitalization influences the future factory significantly. The advantages of the implementation of IoT technology in the future are to be found in literature:

x Flexibility, compatibility, scalability, ubiquity [5-8]

x Resource, cost and operational efficiency [7,8]

x Real-time capability and robustness [6,7,9]

x Usability and transparency [6,9]

x Complexity and intelligence [6,9]

The above-mentioned advantages of interlinking based on innovative information technology accelerates the fourth industrial revolution. Therefore, it is assumed, that the conventional automation pyramid will evolve to CPS (cyber- physical system) - based automation [10].

The implementation of IoT technologies supports the adaptation of future factories to changing environmental circum- stances and can be useful for energy management in manufacturing companies.

Evaluation of energy flexibility in the research field of energy management in production systems

The research field of energy management includes different approaches and levels to face the challenges along with re- source scarcity. Both energy data acquisition and analysis as well as energy data monitoring are requirements for energy flexible production planning or control. Overall energy management includes all aspects regarding resource allocation and planning. The evaluation of energy flexibility is observed on all re-search field levels.

In general, Reinhart et al. [11] define energy flexibility as the capability of a production system to adapt quickly and with low financial expenditure to changes on the energy market. Based on this definition, dimensions to identify the energy flexibility on the machine level are introduced [12]. Accordingly, energy flexible machines have low switching times, high power change rates and short critical times. Popp et al. [13] determine the degree of technical energy flexibility based on the components¶ demand and their relation among each other quantified with the Energy Independency Indicator (EII). Furthermore, energy flexibility in- dices are defined to evaluate energy flexibility on the component and on the machine level [14]. Simon et al. [15] intro- duce a method for the technical and economical evaluation of energy flexibility regarding the identification and categorization of measures.

The introduced evaluation approaches strive for energy flexible production planning and control. Beier et al. [16] pre- sent a detailed literature review of related research by dividing the relevant energy flexible research approaches into planning and real-time execution. Whereas the planning approaches include organizational methods, the real-time execution targets technical energy flexibility. Relevant technical research approaches are to be found in [13,16-23].

Data communication in energy flexible production systems

The implementation of IoT technology is in progress, thus different levels are covered in literature. The OPC UA interface commonly used in industry can be expanded for energy data transfer. Especially due to the platform-independency, the use of OPC UA is widespread [24]. Bauer et al. [25] abandon the hierarchical automatization pyramid. The concept targeting the adaption of energy demand to supply includes a so- called energy synchronization platform consisting of a market-side and a company-side platform. On the company-side platform the communication model is based on the paradigm everything as a service. A factory within this concept is al- ready understood as a cyber-physical production system. Alternative approaches use wireless sensor networks to enable real-time energy monitoring [5,8]. Tan et al. [26] expand the approach of energy monitoring by a benchmark algorithm detecting advanced energetic statuses and conceptually intro- duce a totally IoT based approach. Shrouf et al. [27] develop an IoT energy management concept based on research, literature and expert interviews including both energy monitoring and a holistic integration of energy data into manufacturing.

3. IoT based closed loop control for energy flexible production systems

The introduced research works according to data communication in smart factories is currently on a conceptual level and not applied to energy flexible control approaches. Therefore, in the following an overall factory concept of an IoT based control loop is introduced and the simulation model structure, the control strategies and the model parameterization are defined and evaluated.

Overall concept of IoT based energy flexible factories

Figure 2 shows the overall factory model for the closed loop control for energy flexible production systems. Both on the component and on the factory level, demand data is measured and communicated to the cloud. Within the cloud, a database includes relevant energy information, e.g. the EII of all components. Furthermore, supply data from on-site generation and the power grid is provided to the cloud. To realize short-term prediction further data could be included, e.g. from weather or energy market forecasts. The implemented control strategy at the cloud computes the control commands from the given information according to the control strategy.

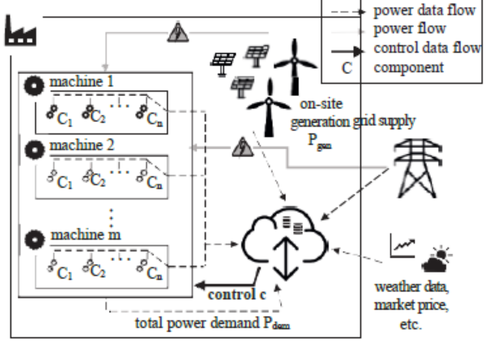


Fig. 2. Overall concept of IoT based energy flexible factories

Simulation model structure

To identify the impact of the closed loop control a simulation model was built up in Matlab Simulink. That model can be executed locally or on the IoT platform Thing Speak in an extended version. The modeling assumptions and simplifications were defined to detect relevant information only. The components¶ behavior is simulated with the following different modules (figure3).

Functional storage module: Each component is modeled with a so-called functional storage, which is (un)loaded during the component ¶VDFWLYH(passive) state. Based on the mean state time of the component, the storage size and the filling(emptying) gradient can be determined. The internal control switches the component to active (passive), when the storage reaches the bottom (top) dead center SOCbottom (SOCtop).

Convergence module: This module balances the compo-QHQW¶VVWDte of charge(SOC)1attheendofthesimulationto the start value (50 %) to avoid faults during the evaluation.

Reference component module: As a reference component module, a one-to-one copy of the introduced modules only with internal control was used to determine the differences between the only internal (storage-based) and the externally controlled (cloud-based) component.

To avoid inefficient control commands and high frequency switching, the external control is allowed in the following SOC range:

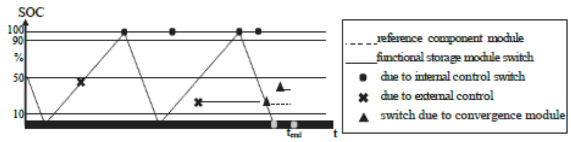


Fig.3.62&WLPHFRXUVHZLWKVLPXOD WLRQPRGXOHV¶IXQFWLRQV

In addition to the component subsystem, the model includes a determination subsystem, which computes the relevant key figures based on the input parameters

x mean power demand in active state pdem,a, x mean power demand in passive state pdem,p,x component or machine status s

x and the absolute SOCabs.

The resulting key figures for the different control strategies are defined within formulas (1) to (3).

To evaluate the impact of the developed energy flexible control strategies, present data were considered, whereas fore- casts were neglected initially.

Control Strategies

To adapt the energy demand to the supply, three different control strategies are developed. All considered control strategies are based on the total power demand data (Pdem) and on-site generation data (Pgen). The difference between the two parameters is defined as the residual power (Pres), which is used to describe the interaction of the factory and the power grid (formula4).

$P_{res} > 0$, if $P_{dem} > P_{gen}$ Æ grid supply

Pres
< 0, if Pdem

<Pgen

Æ grid feed-in (4)

Pres = 0, if Pdem = Pgen Æ grid neutrality

As third input, component data indices were used, whose specifications depend on the specific control strategy.

Strategy 1: power difference: The simplest decision rule is based on the FRPSRQHQW¶VPHDQSRZHUGLIIHUHQFH .The

mean power differences of all regarded components are sorted by sign and by value. At first, all components with a mean power difference with the same sign as the residual power are excluded. Secondly, the largest remaining power difference is selected and the related component is switched (c = 1). Fig- ure 4 shows the control strategy starting with the component with the maximum value of mean power difference.

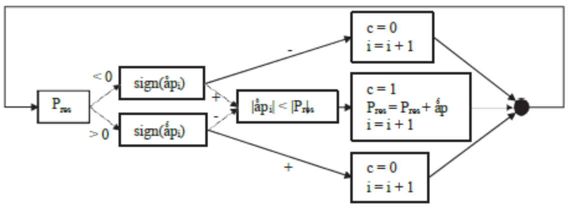


Fig.4.SchemeofCS1(start:max_¨S_)DQG&62 (start:max/minSOC)

Strategy 2: state of charge: The SOC-control strategy follows the same scheme as strategy 1 (figure 5), but differs in iteration order. Whereas strategy 1 starts with the component i with the largest value of mean power difference, strategy 2 starts with the component holding the smallest/largest SOC.

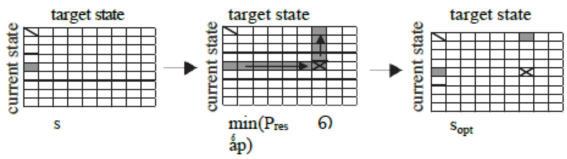
Strategy 3: best fit: The third control strategy takes an additional static database into account, which includes all possible configurations of the system. For an exemplary five-component-system the corresponding database with all pos- sible current states (rows) and all possible target states (columns) is computed resulting in a matrix with the dimension

'p pdem,a–pdem,p

–,s active
+,s passive

SOC
SOC abs
SOC top – SOC bottom

25 x 25, since each component has two different states (active and passive). The matrix contains between one current and one target state. Based on the value of the residual power the best fitting is chosen to determine the target state. The method of control strategy 3 is shown in figure5.



Model implementation

The simulation model represents a virtual factory consisting of machines of three different types M1 (4x), M2 (2x)

and M3 (4x) and their energy independent components C11, C12 (both M1), C2 (M2) and C3 (M3). Measured power data of those components are provided in the component model. To consider all machine components, the total power demand on the factory level is based on measured data of five days and scaled regarding the installed amount of flexible energy. The on-site generation data is based on real measured data of radiation and wind during five days in November and scaled by the installed renewable power in the model.

4. Simulation procedure and method evaluation

The simulation model was used with different parametrization to analyze and evaluate the closed loop control considering three different purposes, explained in the following.

Simulation parametrization

Selecting the influencing parameters and configurations, the simulation model should lead to the identification of

x the performance of the control loop regarding the control strategies, the simulation step size and the delay time,

x the most suitable factory configuration considering the amount of energy flexible components and the dimensioning of installed on-site generation and

x the impact of the IoT environment.

Therefore, the simulation model ran according to the parameters shown in table 1.

Table 1. Simulation parameters

Parameter	Characteristics
database	average of a five-day-measurement of demandand on-site generationdata
controlstrategy	CS1,CS2,CS3,CS12(½CS1,½CS2), CS 23, CS 13, CS 123 (1/3 each)
stepsize	0.1 s, 0.5 s, 1s
delaytime	0.1 s, 15 s, 60s
energyflexibility	10 %, 18 %, 25%
Dimensioning of the on-site generation	1:0.5; 1:0.75; 1:1, 1:1.25, 1:1.25, 1:1.5, 1:2
model execution system	local,IoT

The introduced control strategies were applied individually (e.g. CS 1) or in combination by equal weight (e.g. CS 12). The step size is a simulation parameter considering the size of simulation time steps and can be varied manually in the simulation. To ensure model plausibility the parameter specification for the step size was chosen in a certain range. The delay time describes the time lag within the system which in KPI1 KPI2 KPI3

general occurs in closed control loops. The values for this parameter were considered regarding the minimal delay time (due to the model at least as high as the chosen step size) and expected delays within the IoT simulation (higher, not exact computable delay due to communication interfaces). The amount of flexible energy was initially set to 18 % (common value for machine tools [13,28]) and varied up-/downwards. The dimensioning of the on-site generation (DOG) was realized regarding the amount of energy demand, i.e. in case of 1:0.5 the generated amount of energy of five days is half of the energy demand over the same period.

Definition of key performance indicators (KPI)

To evaluate the closed loop control, three different key performance indicators were defined. The determination of all KPIs is based on the resulting residual power with and with-out application of the developed control loop.

KPI 1: reduction of CO2 emissions: KPI 1 determines the impact of the control method regarding CO2 emissions. Grid supply is weighted with the German CO2 emission factor of 527 g/kWh (power trade balance) [29], whereas on-site generated power is assumed to be renewable and is therefore emission-free.

KPI 2: additional time of grid neutrality: This KPI evaluates the influence of the closed loop control on the time of grid neutrality, i.e. all simulation time steps with Pres = 0.

KPI 3: cost reduction: KPI 3 considers the economic evaluation concerning the running costs. Due to the newest development within the EEG legislation towards market regulated feed-in remunerations and the decreasing production costs of renewable energy, the consumption of own-generated power will get more viable in the future. To weight on-site generation and grid supply power, future prices are used according to scenario B in [28] (table 2).

Table 2. Future scenario for energy price development

	FutureScenario	Unit
Mean energy price (grid supply)	0.16	¼/N:K
Feed-in-rewards	0.06	¼/N:K
Ownenergyproductioncosts	0.05	¼/N:K

Future Scenario Unit

Mean energy price (grid supply) 0.16 ¼/N:K

Feed-in-rewards 0.06 ¼/N:K

Own energy production costs 0.05 ¼/N:K

Performance of the closed loop control

The performance was evaluated considering three parameters: step size, delay time and control strategy. To analyze and compare their influences, a sensitivity analysis was carried out.

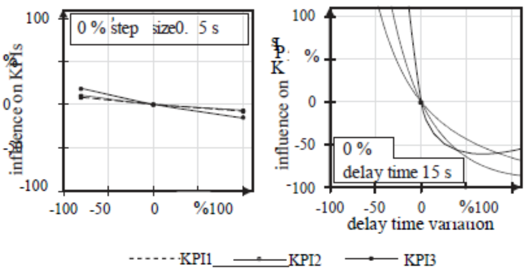


Figure 6 shows the sensitivity of the three KPIs

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Dimensioning of the on-site generation for the step size (left) and the delay time (right). model execution system local,IoT

The introduced control strategies were applied individually (e.g. CS 1) or in combination by equal weight (e.g. CS 12). The step size is a simulation para-meter considering the size of simulation time steps and can be varied manually in the simulation. To ensure model plausibility the parameter specification for the step size was chosen in a certain range. The
-100 -50 0 %100
delay time describes the time lag within the system which in KPI1 KPI2 KPI3 general occurs in closed control loops. The values for this parameter were considered regarding the minimal delay time (due to the model at least as high as the chosen step size) and expected delays within the IoT simulation (higher, not exact computable delay due to communication interfaces). The amount of flexible energy was initially set to 18 % (common value for machine tools [13,28]) and varied up-/downwards. The dimensioning of the on-site generation (DOG) was realized regarding the amount of energy demand, i.e. in case

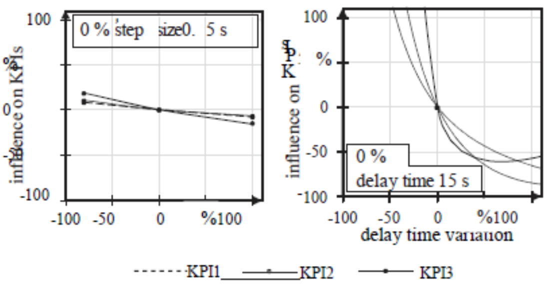


Fig. 6. Influence factors step size (left) and delay time (right)

Both parameters show an inversely proportional influence on the KPIs. Whereas the impact of a changing step size is very small, the variation of delay time shows a more distinct effect. The sensitivity for step size is approximately linear, i.e. in case of further increasing (decreasing) the step size, the effect on the KPIs gets equally smaller (higher). The highest sensitivity against the step size can be observed for KPI2(additional time of grid neutrality). In contrast, the observed impact declines very fast for increasing delay time. Nevertheless, a saturation is observed for KPI 2 and KPI 3, which means that delay times higher than a certain threshold do not further decrease the influence. The variation of the delay time changes the flexibility of the whole system, and therefore has a significant influence on all KPIs.

The results concerning the control strategy are shown in figure 7. The control strategies (x-axis) are sorted by their impact on the KPIs. Control strategy 2 shows the highest influence on all KPIs, whereas the lowest influence is observed for strategy 3. CS 1 is in the same range as CS 2. The insufficient results for control strategy 3 are explicable by the unconsidered input data SOC. In case of external control commandintheEORFNHGFRPSRQHQW¶V62 &range,the computed best fit combination of the FRPSRQHQWV¶VWDWes is not achieved. Both, CS 3 and CS 1, do not consider SOC as decision value. Nevertheless, the impact for strategy 3 is higher due to sequential formation of control commands. Executed simulations with combination CS23 and CS123 result in between the individual control strategies and are neglected in the presentation to ensure clear presentation. energy flexibility is rising with increasing amount of flexible energy regarding KPI 1 and KPI 3. The influence of the energy flexibility on KPI 2 (additional time of grid neutrality) is very low in comparison. This can be explained by the variation of energy flexibility just based on the flexible energy and neglecting the flexible time of use, i.e. the period, the flexible energy is available. Therefore, increasing (de- creasing) energy flexibility does not affect time parameters. Concerning the influence of DOG, the same effect was observable. Its impact on KPI 2 is lower than on KPI 1 or KPI 3, due to the dimensioning according to the energy amount only. The impact on the reduction of costs (KPI 3) shows a maximum at the dimensioning of 1:1.15. Based on the determination of the cost reduction a maximum close to a 1:1 was expected. The influence on KPI 1 (reduction of CO2 emissions) is increasing with rising on-site generation. The differences in impact on KPI 1 and KPI 3 can be attributed to differences in their determination. Whereas KPI 1 (reduction of CO2 emissions) weights grid-supplied power only, the determination of KPI 3 (reduction of costs) includes grid and self supplied power. To compare the parameters, the average of all KPIs was used to identify differences. Figure 8 shows the delay time with the largest impact on the KPIs.

100

%

0

-50

Fig. 9. Influence factors energy flexibility (left) and DOG (right)

4.5. IoT environment

To analyze the impact of the IoT environment, the local model was modified and partly implemented at the cloud. One of the main improvements of cloud-based closed loop control is the centralized accumulation of flexibility information, which is significant for decision making and developing control strategies for all different flexible components in a system of production machines to exploit all given energy flexibility potentials in an optimized way. The cloud-base simulation was executed with the following parameters:

influencing parameter variation

delay time control strategy

control strategy 1, step size 0.1 s, delay time 0.1 s, energy flexibility 18 %, DOG 1:1. Figure 10 shows the result range of the locally conducted simulations and the IoT result range.

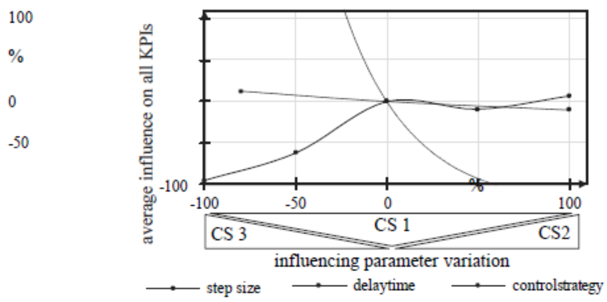
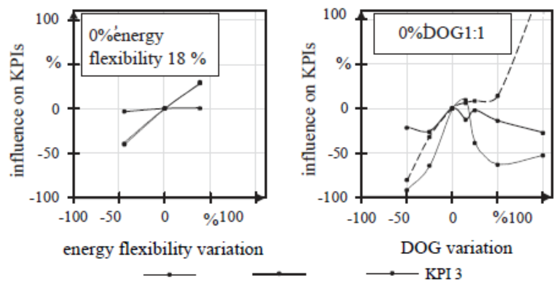


Fig. 8. Comparison of influence parameters

The control strategy cannot be treated as a continuous parameter. Comparing control strategy 1 and 2 the impact on the KPIs is as high as the influence of the step size. Strategy 3 shows an effect in the range of the delay time¶ VLQIOXHQFH.

4.4. Factory configuration

The factory configuration was analyzed by regarding the parameters energy flexibility and dimensioning of on-site generation (DOG) as shown in figure 9.



The impact of the. The results of the IoT simulation show conformity with the ORFDOVLPXODWLRQ¶VUHVXOWVUHJD UGLQJKPI1andKPI3.TheIoT model outcome is approximately located in the middle for KPI 3, whereas the results for KPI 1 are in the lower edge. In case of KPI 2 the IoT simulation results do not reach the local simulation results. In IoT-based simulation the occurring delay times are higher than in locally execution and results in less sufficient performance regarding the KPIs. Nevertheless, the developed IoT model is applicable for the desired use case. Further analyses are in progress.

KPI3

KPI2

KPI1

influence on KPIs

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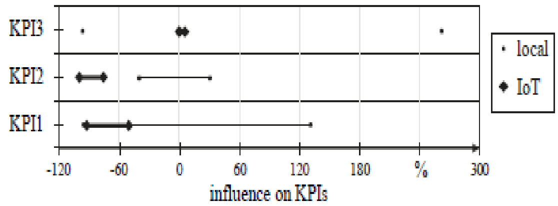

Fig. 10. IoT simulation results versus local simulation results

5. Conclusion and Outlook

The performance analysis indicates that the influence of the parameters differs. It is possible to deduce certain requirements for data communication in general. The delay time has a major influence on all considered KPIs. Therefore, it is important to provide data very fast, whereas the topicality of the data is less important. The results show that data conduction plays a significant role compared to data computing. The control strategies are able to reduce costs and CO2 emissions and increase the time of grid neutrality. Nevertheless, control strategy 3 shows weak results compared to control strategy 1 or 2. The factory configuration has a higher input than the regarded influencing parameters. Therefore, it is important to implement energy flexibility and on-site generation in early planning steps and apply the closed loop control in addition to ensure most sufficient results. In addition to the conducted simulations further analyzes will be carried out with the IoT model to detect barriers and advantages of the cloud environment. Furthermore, the introduced IoT control loop will be integrated into machine tools to analyze the behavior under real conditions. An IoT communication system is already implemented and will be completed with the closed loop control for flexible production machines.

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