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APPLICATION OF THE NON-LINEAR OPTIMIZATION ALGORITHM DIFFERENTIAL EVOLUTION FOR OPTIMIZATION OF MANUFACTURING SYSTEMS REGARDING THEIR ENERGY EFFICIENCY

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ABSTRACT

Due to the increasing importance of energy efficiency in manufacturing systems, this work analyzes the use of two optimization algorithms, which allow an optimization of production systems. These two algorithms are the brute force method and the Differential Evolution which is based on evolutionary strategy. The objective value for the optimization is the energy efficiency, which is described by an innovative indicator system. This is applicable to any hierarchical level of a production system and considers the interdependencies between the individual processes. An exemplary production system is modeled as an event discrete simulation to analyze the functionality of the optimization algorithms. that the Differential Evolution is able to calculate the results in less time compared to the brute force method. But the Differential Evolution is not able to identify the global optimum in any case. Its reliability depends on the parameterization of the three available control variables.

1 INTRODUCTION

Due to social and political changes, the consideration of energy efficiency is becoming increasingly important. This development includes political objectives to reduce CO_2 emissions and primary energy demand. The European Union aims to reduce emissions by 40 % and primary energy demand by 50 % until 2050 (Ferderal Ministry for Economic Affairs and Energy. 2014; Ferderal Ministry for Environment, Nature Conservation, Building and Nuclear Saftey. 2014a; May et al. 2015). These objectives will be achieved by the transformation of energy systems. This transformation is based on the increasing use of renewable energy sources and on increasing energy efficiency. This applies in principle to all sectors (industry, commerce, households and transport), but industry has the greatest potential for improving efficiency (Bunse et al. 2011). Exploiting this potential has the direct advantage for companies that costs are decreased, which refers to the reduction of energy and emission certificate costs. An indirect advantage is that the image of a company is improved by efficiency increases. This in turn has a positive effect on sales, as customers prefer to buy their products from environmentally friendly companies (Dombrowski et al. 2014).

The following analysis investigates to what extent optimization methods are suitable for improving energy efficiency in the context of new planning, adaptation planning and production planning of factories. These investigations focuses on the computation time of the optimization methods, because in future the production planning will have to make decisions in real time. The time requirements arise from future applications, which may include fluctuating energy prices or electrical demand side management. These two applications enable the industry sector to support the energy system transformation. In particular,

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flexible load shifting can assist the stability of the electrical power grid (Graßl and Reinhart 2014). Today's energy market operates in time slots of 15 min, which is why the optimization algorithms have to achieve outcomes below this time. For new planning and adaptation planning, significantly longer time periods are available, which is why the computing time is less relevant for this purpose.

In general, two prerequisites are necessary for the optimization. First, all necessary information of the production system have to be available and usable. This is not the case by default in the current manufacturing systems. However, the ongoing industrial development (industry 4.0, digitization, internet of things) shows that this information will be available in future adaptive production systems (Schuh et al. 2013). Second, the energy efficiency has to be represented by a suitable key performance indicator system. This indicator system should be able to represent different process types (material transforming, energy converting, logistic processes) and provide an indicator that serves as an optimization objective.

In order to use optimization methods for production systems in the context of new planning, adaptation planning and production planning, the basics are first addressed in section 2. These basics include the representation of energy efficiency by an innovative indicator system, the definition of the state space of production systems and the description of the optimization algorithm Differential Evolution. Subsequently, an exemplary manufacturing system is presented in section 3, which serves to analyze the optimization procedures. Section 4 presents the optimization results, whereby the performance of the Differential Evolution is related to the brute force optimization. Finally, section 5 summarizes the results and provides an outlook on further research opportunities.

2 BASICS

The following section gives an overview about the basics, regarding the energy efficiency of manufacturing systems in section 2.1, the state space of production systems in section 2.2 and the operating principle of the non-linear, global optimization algorithm Differential Evolution in section 2.3.

2.1 Energy Efficiency

Energy efficiency is not a physical quantity and is therefore represented by key performance indicators. Basically, the energy efficiency of a production process is defined as ratio between the usable output and the energy used to produce it (Pérez-Lombard et al. 2013; Patterson 1996). Different types of indicators can be developed depending on the consideration of inputs and outputs of a production process. Thus, thermodynamic, thermodynamic-physical, thermodynamic-economic or economic indicators can be defined (Patterson 1996). But the main problem of indicators for the shop floor level, as exemplary the specific energy consumption, is that only one input and one output variable are set in relation. Most processes have indeed more inputs and generate more than one output. Typically, a process and its operating resource requires input workpieces and electric energy and manufactures products and exemplary waste heat. Due to this, an innovative indicator system was developed in Meißner et al. (2018) to represent the efficiency in more detail.

The indicator system consists of the Process Status Indicators (PSI) and the Process Interdependency Indicators (PII). The PSIs are able to represent the efficiency of separate processes with an arbitrary number of input and output variables. Furthermore, different types of inputs and outputs can be considered, as exemplary the material flow or electric energy. Thus it is also possible to describe different process types, such as material transforming, energy converting or logistic processes. Due to the fact that the PSIs are designed to represent processes, it can be applied to all hierarchical levels of a production system. Based on the PSIs, the Process Interdependency Indicators represent the interdependencies between processes regarding energy efficiency (Meißner et al. 2018).

The PSIs consist of three indicators to describe different relations between the input and output values. Therefore, Figure 1 shows an overview about the PSIs. The first indicator is the **Energy Performance**

Indicator (EPI) which is defined as

$$EPI_{PP_k,In_i,Out_j} = \frac{Out_j}{In_i}.$$

The EPI describes the efficiency relation between one separate input In_i and one separate output Out_j of one production process PP_k and is similar to the specific energy consumption. The indices i and j are the counting variables for the input and output values respectively. The indice k counts the production processes (PP) within one production system or process chain. Consequently, the number of EPIs depends on the number of inputs and outputs. Further, each EPI has an individual unit which depends on the combination of the considered input and output values (Meißner et al. 2018).

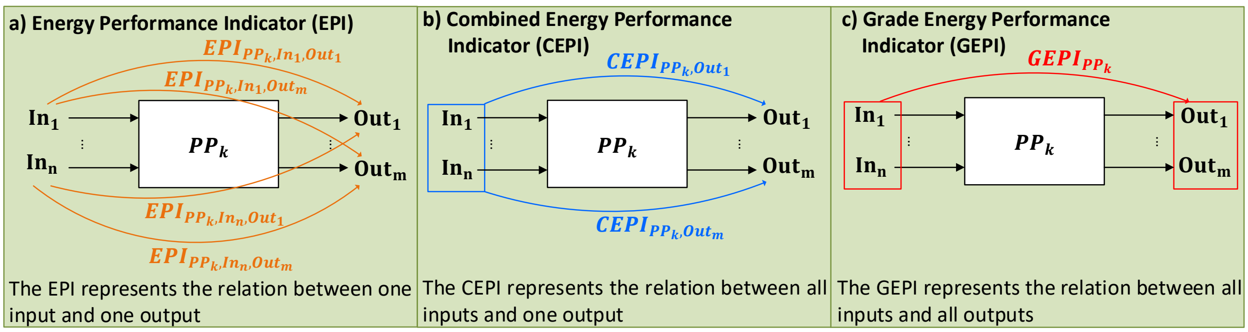

Figure 1: Overview of the three Process Status Indicators.

Based on the EPI, the **Combined Energy Performance Indicator (CEPI)** represents the relation between one output variable and all input variables of one process and is calculated as

$$CEPI_{PP_k,Out_j} = \frac{1}{\sum_{i=1}^{n} \frac{b_i}{EPI_{PP_k,In_i,Out_j}}}.$$

The variable n represents the maximum number of input variables of the considered production process. The complexity for this indicator is to determine the individual rating factors b_i for assessing the different input variables. Objective of this rating is to assess the different impact of the inputs on the efficiency (Meißner et al. 2018). Exemplary, the use of compressed air has a higher influence on the energy efficiency of a production process compared to the use of electric energy, because the generation of compressed air is more expensive (Meißner et al. 2018). Due to the fact that the economic consideration of manufacturing systems is the most important one for companies, the assessment of input variables is done by economic rating factors. Exemplary, the electric energy is rated in $€/kWh$ and the input material in $€/part$. Also other assessment methods are possible as the rating regarding CO_2 emissions (Ferderal Ministry for Environment, Nature Conservation, Building and Nuclear Saftey. 2014b).

Finally, the **Grade Energy Performance Indicator (GEPI)** describes the energy efficiency of one production process regarding all inputs and outputs. It is defined as

$$GEPI_{PP_k} = \frac{\sum_{j=1}^{m} \frac{Out_j}{CEPI_{ref,Out_j}}}{\sum_{j=1}^{m} \frac{Out_j}{CEPI_{Out_j}}}. \tag{1}$$

As written in (1) the calculation of the GEPI depends on two CEPI values. First, the $CEPI_{Out_j}$ represents the actual state of the production process and is therefore calculated by measurement data. Second, the $CEPI_{ref,Out_j}$ describes the reference state of the considered production process. This reference state corresponds to an ideal manufacturing process which means that no idling occurs, processing times are fixed, energy consumption is fixed, no stochastic influences occur, no errors regarding the material flow occur, technical equipment and employees are available to 100 %. Consequently, the value for the $CEPI_{ref,Out_j}$ has to be determined before the indicator system can be used for monitoring manufacturing processes. The advantage of the use of such a reference system is that the GEPI has no unit. In this way, different processes, as material transforming, energy converting and logistic processes, can be represent by the same indicator (Meißner et al. 2018). Furthermore, the GEPI can also be used to represent the energy efficiency of processes at different hierarchical levels of a factory system.

Based on the GEPI the **Sum Grade Energy Performance Indicator (SGEPI)** is defined. The SGEPI is able to represent the energy efficiency of a process chain and considers the interdependencies between the single processes. The indicator is calculated as

$$SGEPI = \frac{\sum_{k=1}^{o} GEPI_{PP_k}}{o}.$$

The SGEPI summarizes the individual GEPIs of single processes of a process chain and standardize them depending on the maximum number of processes o. The objective of this indicator is to create one value which serves as an objective value for an optimization algorithm. For the SGEPI it has to be considered that each process of the considered production system has the same influence on the energy efficiency of the system. In the following, the SGEPI is used as optimization objective.

2.2 State Space of Production Systems

For an optimization algorithm it is necessary to define the state space of the considered optimization problem. Regarding production systems the main characteristic is, that the various processes have discrete operating points and not a continuous state space. Figure 2 shows a schematic manufacturing system with five production processes. Each process has an individual number of discrete operating points (OP) which represent different processing of material. The operating points can represent different products which are processed or different possibilities to process one product. So, each process dispose about a operating point quantity Z_{PP_k} that includes all operating points of the production process. Exemplary, the process PP_1 in Figure 2 has the operating point quantity $Z_{\mathrm{PP}_1} = \{1,2,3\}$. Further on, each operating point quantity disposes about a lower bound LB_{PP_k} and an upper bound UB_{PP_k}. The state vector $\vec{X}$ contains the information about all individual operating points of the various processes within the manufacturing system and is defined as

$$\vec{X} = \begin{pmatrix} OP_{\mathrm{PP}_1} \in Z_{\mathrm{PP}_1} \\ OP_{\mathrm{PP}_2} \in Z_{\mathrm{PP}_2} \\ \cdots \\ OP_{\mathrm{PP}_o} \in Z_{\mathrm{PP}_o} \end{pmatrix}.$$

To represented the combination of operating points simplified, the operating state is defined as $OS = OP_{\mathrm{PP}_1}.OP_{\mathrm{PP}_2}.\ldots.OP_{\mathrm{PP}_o}$. The operating state is subsequently used to name the respective state of a manufacturing system.

2.3 Differential Evolution

Besides the brute force optimization the algorithm Differential Evolution is used as an optimization method. This is a non-linear, global optimization algorithm based on evolutionary strategies. The Differential Evolution is explained in detail in Price et al. (2005) and Figure 3 a) provides a general overview of its functionality, which is briefly explained below. For the first investigations regarding the optimization of production systems the *DE/rand/1* algorithm of Price et al. (2005) is used. This is the classical Differential Evolution, whereby Price et al. (2005) presents five more variants and their implementations.

First, the three control variables have to be defined by the user. These are the population size N_{P}, the step size F_{Weight} and the crossover constant C_{R} (Price et al. 2005; Storn and Price 1997; Das and Suganthan

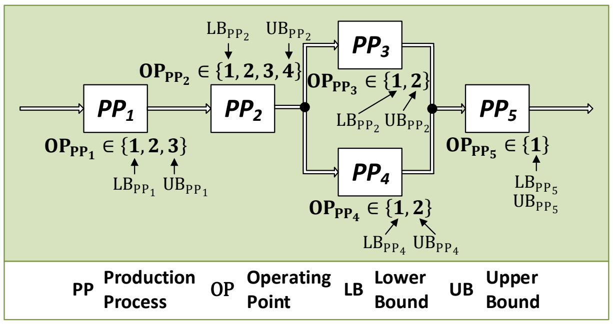

Figure 2: Discrete state space of production systems.

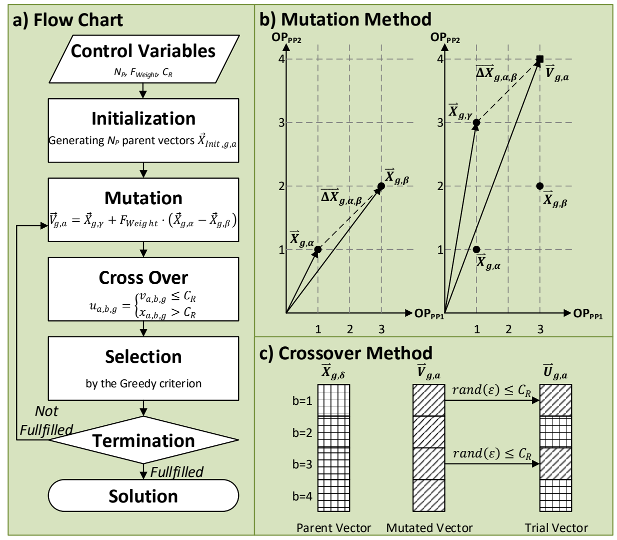

Figure 3: Overview of the basics of the optimization algorithm Differential Evolution.

2011). The definition of the control variables are discussed in more detail in the following explanations with respect to the state space of manufacturing systems.

The next step is the initialization, which generates N_{P} random parent vectors $\vec{X}_{g,a}$ within the state space. These initialization vectors cover the complete state space, so that the starting problem of global optimization is solved. The index g describes the generation of vectors and consequently the initialization vectors are the first generation why $g = 1$ apply. The generated vectors are numbered starting by zero up to $N_{\mathrm{P}} - 1$ and this numbering is represented by the index a. For the algorithm, the population size must be at least $N_{\mathrm{P}} = 5$ (Price et al. 2005; Storn and Price 1997; Das and Suganthan 2011).

After the initialization, the optimization loop starts with the steps mutation, crossover and selection. The mutation calculates N_{P} mutated vectors as

$$\vec{V}_{g,a} = \vec{X}_{g,\gamma} + F_{\mathrm{Weight}} \cdot (\vec{X}_{g,\alpha} - \vec{X}_{g,\beta}).$$

Figure 3 b) shows the mutation, whereby first two parent vectors $\vec{X}_{g,\alpha}$ and $\vec{X}_{g,\beta}$ are chosen randomly. The difference of these two vectors $\Delta\vec{X}_{g,\alpha,\beta}$ is multiplicated with the step size F_{Weight} and summarized to a third randomly chosen parent vector $\vec{X}_{g,\gamma}$. By this calculation it is important that the three randomly selected parent vectors are different, why

$$\begin{cases} \alpha \neq \beta \neq \gamma \neq \delta \\ \alpha, \beta, \gamma, \delta \in a \end{cases}$$

apply (Price et al. 2005; Storn and Price 1997; Das and Suganthan 2011). The step size can only assume values between zero and two. Due to the state space of production systems, the use of non-integer values is not meaningful. For this reason, only the step sizes zero, one and two are reasonably.

The fourth step is the crossover to determine the trial vector $\vec{U}_{g,a}$, which is shown in Figure 3 c). Thereby single elements of the mutated vector $\vec{V}_{g,a}$ are replaced by elements of a parent vector $\vec{X}_{g,\gamma}$, which is also selected randomly. If an element b is replaced, depends on the crossover constant C_{R} and the randomly determined value $rand(b)$ and the calculation therefore is

$$u_{g,a,b} = \begin{cases} v_{g,a,b} & rand(b) \leq C_{\mathrm{R}} \\ x_{g,a,b} & rand(b) > C_{\mathrm{R}} \end{cases} \quad .$$

The crossover constant C_R can assume values between zero and one. An individual analysis must be carried out to determine, which value range can be used to achieve the desired result. In general, the crossover constant should be rather larger, whereby in the literature initialization values of 0.9 or 1 have proven successful for most optimization problems (Price et al. 2005; Storn and Price 1997).

Next, the selection is done, which decides if the trial vector $\vec{U}_{g,a}$ or the original parent vector $\vec{X}_{g,a}$ remains for the following generation. The Greedy criterion is used, which means that the vector with the better objective function value is transferred to the next generation of parent vectors (Price et al. 2005; Storn and Price 1997; Das and Suganthan 2011).

Finally, the termination criteria is evaluated to determine if a solution is sufficient. Five different procedures or even a combination of these are available. These include the variants listed in the following: objective met, limit the number of generation, population statistics, limited time, human monitoring. If the termination criteria is fulfilled the optimization loop ends and the solution is determined. Otherwise the optimization loop starts again with the mutation (Price et al. 2005; Storn and Price 1997; Das and Suganthan 2011). Within the framework of the termination criteria, the determination of the maximum number of iterations I_{Itermax} or the limitation of the number of generations is of interest. It has to be ensured that the combination of the population size N_{P} and the maximum number of iterations is smaller than the number of operating states r_{OS}. Accordingly,

$$N_{\text{P}} \cdot I_{\text{Itermax}} \leq r_{\text{OS}} \tag{2}$$

applies so that no operating state is calculated more than once.

Another characteristic of Differential Evolution is that several optimization objectives can be considered, so that a multi-criteria optimization is achievable. This enables the inclusion of further objectives in addition to energy efficiency, such as throughput time or on-time delivery. The following studies focus on the optimization of energy efficiency. For this reason, the previously introduced indicator SGEPI is selected as the objective value for the optimization.

3 EXEMPLARY PRODUCTION SYSTEM

As an example application a production system is used which was developed in Delbrügger et al. (2019) for an innovative multi-level simulation concept. A 3D visualization of this system is shown in Figure 4 a). The original manufacturing system consists of two milling machines, two conveyor belts and four robots. This production system is extended by the compressed air requirements of the two machining centers and the generation of compressed air (Meißner et al. 2018). Furthermore, the logistical integration of the production line to the receiving warehouse and outgoing warehouse of the factory is taken into account. These two transport processes are carried out by a forklift truck which covers a distance of 45 m during each transport. The schematic representation of these two extensions is shown in Figure 4 b) and the technical properties of the operating resources are listed in Table 1.

The main characteristic of the production system is that the two milling machines dispose about six different operating points to produce the workpiece in Figure 4 c). The features of these operating points are listed in Table 2. The operating points differ in their electric energy consumption and processing time. Furthermore, each machine is able to use compressed air or a combination of compressed air and cooling lubricant for cooling and chip removal. In case that the combination of compressed air and cooling lubricant is used, the compressed air requirements of both milling machines are lower. The choice of these two options is independent of the previously mentioned operating points in terms of electric energy consumption and processing time. This results in twelve operating points for each milling machine and 144 operating states for the manufacturing system, which can be selected for machining the workpiece. The operating points 1 to 6 of each milling machine represent the use of cooling lubricant and compressed air, while the operating points 7 to 12 only use compressed air. Requirements of compressed air are covered by a typical compressed air system which simulation model is presented in Meißner et al. (2018). The generation, storage and distribution are taken into account and the control is carried out by a two-point control.

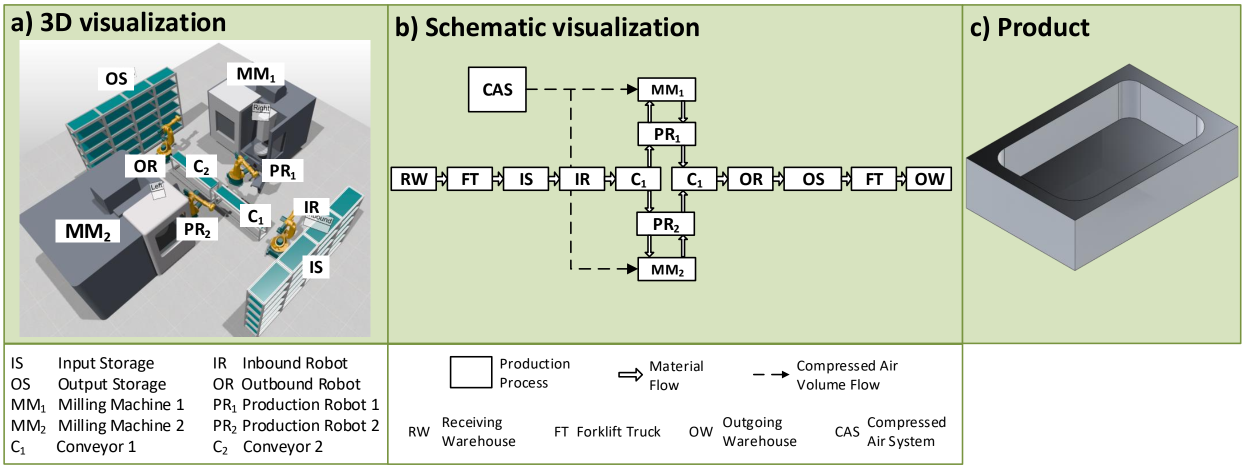

Figure 4: Visualization of the exemplary production system and the manufactured product.

The simulation model of the presented production system is implemented in the simulation environment Matlab / Simulink, using the toolbox SimEvents. A discrete event simulation is implemented, which has the advantage of a shorter computing time. The electrical power requirements and the required volume flows are represented by state flow diagrams. Each state therefore describes an operating point of the respective operating resource. Both of the machining centers and their operating points are characterize by the power values in Table 2. The other operating resources are modeled by their nominal values in Table 1 as they only have one operating point. For the following analyses, a time interval of 7.5 hours is considered and simulated in order to investigate the efficiency of the production system over one work shift. The implementation of the Differential Evolution for Matlab is taken from Price et al. (2005) and applied. The corresponding control variables are adjusted and the simulation model of the manufacturing system is used as the objective function. The *DE/rand/1* variant of the algorithm is used, as mentioned before. To realize the brute force optimization, a loop construction is implemented, which runs through all combinations of operating points of the two milling machines.

4 OPTIMIZATION RESULTS

In the following section, the two optimization methods will be tested on the production system presented above. On the one hand, the aim is to show that optimization is possible in terms of energy efficiency and energy flexibility. On the other hand, it is analyzed which optimization algorithm can be used for which application purpose (new planning, adaptation planning, production planning).

4.1 Brute Force Results

In order to identify the most energy efficient operating state of the manufacturing system using brute force, all 144 possible operating states are simulated and evaluated. Figure 5 and 6 show the resulting objective values regarding the number of produced pieces, electric energy consumption and SGEPI. The consideration of the physical objectives leads to a Pareto front, which is shown in Figure 5. Problematic is that only two influencing factors on the efficiency are considered. Accordingly, only one input and one output variable are considered. So, no exact statement can be reached which operating state works most efficiently. The SGEPIs of the separate operating points shown in Figure 6 allow a more detailed approach because all variables and their economic rating are considered. It appears that the operating state 8.7 is the most efficient. According to Table 2, the energy requirements of both machining centers are the lowest in this operating state and the machining times are the shortest. At the same time, the compressed air requirement is higher compared to the operating state 2.1, which means that the compressed air system

Table 1: Technical characteristics of the operating resources.

Parameter	Value	
Forklift Truck FT:		
Speed	1.667 m/s	
Distance	45 m	
Rated electric power	1 kW	
Machine hour rate	22.45 €/h	
Conveyor belts C_1 and C_2:		
Length	1 m	
Rated electric power	0.09 kW	
Machine hour rate	0.061 €/h	
Robots IR, PR_1, PR_2 and OR:		
Number of axis	6	
Rated electric power	8.8 kW	
Machine hour rate	2.96 €/h	
Machining centers:	**MM_1**	**MM_2**
Speed range	0-28000 rpm	0-18000 rpm
Maximum torque	48 Nm	130 Nm
Rated electric power	55 kW	35 kW
Machine hour rate	36.26 €/h	36.26 €/h
Compressed air system CAS:		
Rated volume flow	72 Nm^3/h	
Maximum pressure	8 bar	
Reservoir volume	1.5 m^3	
Rated electric power	6.7 kW	
Machine hour rate	15.01 €/h	

Table 2: Characteristics of the different operating points of the two machining centers.

Operating Point	Processing Time	Electric Power	Electric Energy
Milling Machine MM_1:			
1 / 7	115.4 s	13.49 kW	0.431 kWh
2 / 8	109.5 s	13.45 kW	0.408 kWh
3 / 9	134.4 s	12.57 kW	0.468 kWh
4 / 10	145.5 s	12.27 kW	0.495 kWh
5 / 11	294.6 s	9.87 kW	0.807 kWh
6 / 12	189.6 s	10.93 kW	0.566 kWh
Milling Machine MM_2:			
1 / 7	115.4 s	5.88 kW	0.187 kWh
2 / 8	127.6 s	5.57 kW	0.197 kWh
3 / 9	131.1 s	5.72 kW	0.207 kWh
4 / 10	145.6 s	5.27 kW	0.212 kWh
5 / 11	325.5 s	8.02 kW	0.721 kWh
6 / 12	168.1 s	10.34 kW	0.477 kWh

Chip removal and cooling	**Volume Flow**
Milling Machine MM_1:	
Cooling lubricant and compressed air	3.19 m^3/h
Compressed air	4.44 m^3/h
Milling Machine MM_2:	
Cooling lubricant and compressed air	1.87 m^3/h
Compressed air	3.59 m^3/h

is more utilized. As a result, both the compressed air system and the entire production system are more efficient using the operating state 8.7 compared to the state 2.1.

Especially the computation time has to be considered for the optimization method. In this case the calculation needs 2.44 h. The detailed saving of simulation result data is included in this time which is not mandatory for the application in a company. Due to this, there is potential to save time. But the computation time is still high so the brute force algorithm cannot be used efficiently in production planning because there is not enough time available. For new and adaptation planning, the computation time is acceptable.

4.2 Differential Evolution Results

In order to investigate the functionality of the Differential Evolution and at the same time the possible value range of the three control variables, various simulation analyses are performed. The control variables are varied in order to determine which combinations work most reliable for the presented optimization problem. Each combination of control variables is simulated ten times to obtain a statistically relevant result. The crossover constant C_{R} varies between 0 and 1 with an increment of 0.25. The step size F_{Weight} is discreetly varied between the values 0 and 2. For the population size N_{P} the values 5 and 10 are applied, resulting in the maximum number of iterations I_{Itermax} from (2) to 28 and 14. A mathematical rounding down to an integer value is always carried out so that the multiple calculation of operating states is avoided. Apart from the limitation of iterations, no other termination criteria is considered, so that the algorithm always runs through the maximum number of iterations in the following.

Table 3 gives an overview of the results obtained, with the main focus on identifying the most energy-efficient operating state 8.7 and how often it is determined. It turns out that a crossover constant C_{R} smaller than 0.5 and greater than 0.75 generally fails to yield good results. The same applies to a step size F_{Weight} of 0. For the population size N_{P}, it is shown that both investigated values can provide good optimization

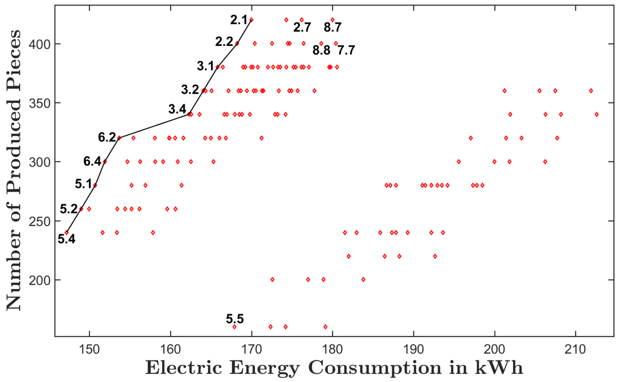

Figure 5: Brute force results regarding the physical quantities of electric energy consumption and produced pieces. Only the operating states of the Pareto front and those mentioned in the text are labeled.

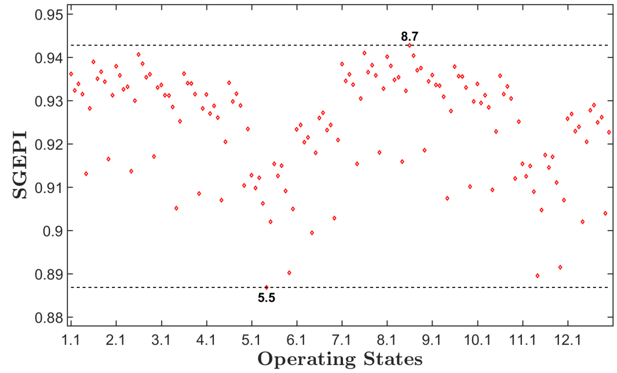

Figure 6: Brute force optimization results regarding the process interdependency indicator SGEPI.

results depending on the other two control variables. For a crossover constant of 0.5 and a step size of 1, both population sizes yield good results. In contrast, for a step size of 2, only a population size of 10 provides good results. With a crossover constant of 0.75, only the combination of a step size of 1 and a population size of 10 yields good results.

The Figures 7 to 9 show the evaluation of the control variable combinations which yield the best results from Table 3 as box plots. Figure 7 shows that the combination of $C_R = 0.5$, $F_{\text{Weight}} = 1$ and $N_P = 5$ provides the best results for the application of Differential Evolution. In the two cases where the operating state 8.7 is not identified, the state 2.7 is returned as optimization result. This is the second most efficient operating state, as shown in Figure 6. Therefore, this combination of control variables can be considered as most reliable. Figure 8 shows the control variables $C_R = 0.5$, $F_{\text{Weight}} = 2$ and $N_P = 10$. This combination also yields good results. However, the states 7.7 and 8.8 are identified as deviations. Therefore, the control variable combination from Figure 7 is more reliable. The same applies to the control variable combination $C_R = 0.75$, $F_{\text{Weight}} = 1$ and $N_P = 10$ in Figure 9.

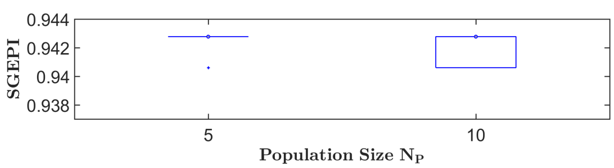

Figure 7: Evaluation of the optimization results for the control variables $C_R = 0.5$, $F_{\text{Weight}} = 1$ and $N_P = \{5, 10\}$.

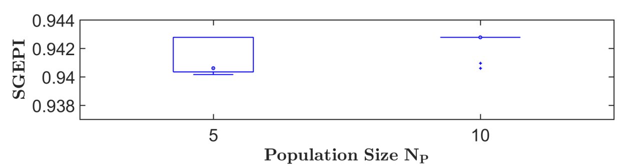

Figure 8: Evaluation of the optimization results for the control variables $C_R = 0.5$, $F_{\text{Weight}} = 2$ and $N_P = \{5, 10\}$.

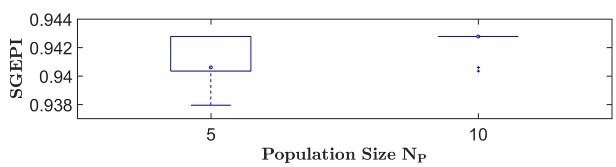

Figure 9: Evaluation of the optimization results for the control variables $C_R = 0.75$, $F_{\text{Weight}} = 1$ and $N_P = \{5, 10\}$.

Table 3: Reliability of the Differential Evolution depending on the control variables.

Crossover constant C_R	**Step size** F_{Weight}	**Population size** N_P	**Number of correct result**
0	0	5	0
0	0	10	1
0	1	5	0
0	1	10	2
0	2	5	0
0	2	10	3
0.25	0	5	0
0.25	0	10	2
0.25	1	5	6
0.25	1	10	6
0.25	2	5	1
0.25	2	10	3
0.5	0	5	2
0.5	0	10	5
0.5	1	5	8
0.5	1	10	7
0.5	2	5	4
0.5	2	10	8
0.75	0	5	0
0.75	0	10	2
0.75	1	5	4
0.75	1	10	8
0.75	2	5	5
0.75	2	10	5
1	0	5	0
1	0	10	0
1	1	5	4
1	1	10	7
1	2	5	6
1	2	10	4

The average computation time for one optimization run is 0.49 hours. Accordingly, there is a significant reduction compared to the brute force algorithm. In the context of production planning, it must be analyzed individually, whether such a computation time is sufficiently short so that Differential Evolution can be applied. For new planning and adaptation planning, the computation time is as acceptable as the computation time of brute force optimization. In this case, it has to be evaluated, if it is acceptable that the most energy efficient operating state is not always identified.

5 CONCLUSION AND OUTLOOK

Due to industrial and political developments, the consideration of the energy efficiency of manufacturing systems is an important factor for companies. Therefore, it is analyzed how optimization algorithms can be used to improve efficiency. For this purpose, a universal performance indicator system is presented. This can be applied at any hierarchical level and is able to handle different process types, as material transforming, energy converting or logistic processes. Based on this indicator system, the Sum Grade Energy Performance Indicator is used as optimization objective because the interactions between the processes are included in this efficiency representation. The use of simulation models for factory planning is becoming increasingly important, as various planning options can be tested before operation. Using a modeled production system as an application example, two optimization algorithms are compared with each other. In optimization methods, simulation models can be used as objective functions so that no mathematical objective functions have to be determined. The optimization of the efficiency by the brute force method is the reference basis, in which all operating states of the production system are simulatively evaluated. Due to the time required for this calculation, this procedure is only suitable for new and adaptation planning. For production planning, the application of Differential Evolution is investigated. This is a non-linear, global algorithm based on evolutionary strategies. For the application of Differential Evolution an investigation is carried out, how the three control variables (population size, crossover constant and step size) have to be chosen to realize a reliable optimization. The background is the discrete state space of production systems, which is composed of the operating points of the individual operating resources. It shows that the Differential Evolution delivers reliable results when parameterized correctly. But it does not always identify the global optimum. For future investigations, it is advisable to analyze the determined range of control variables in more detail, so that the reliability of the algorithm can be verified more precisely. The application of other implementations of Differential Evolution from Price et al. (2005) is also of interest, since this paper focuses on the classical variant of Differential Evolution. The consideration of other optimization algorithms is also of general interest. This paper limits itself to the use of Differential Evolution to show that the energy efficiency of production systems can be increased by optimization algorithms. Another result is that the computation time for the use of Differential Evolution is clearly reduced compared to brute force optimization. However, it must be checked whether the computation time is sufficiently short for the individual application of production planning in companies. Especially for short-term changes (e.g. flexible energy prices or demand side management) real-time decisions are necessary, which are not realizable with the two presented optimization methods. A feasible solution is the application of machine learning algorithms for further research. For example, in Zhang et al. (2017) Neuronal networks are used to enable real-time job scheduling decisions. In addition to considering the energy efficiency of production systems, other objectives, such as logistical aims, should be considered in future studies. This way, the multi-criteria optimization of Differential Evolution can be tested. For this purpose the application of a more complex production system respectively its simulation model is of interest.

Summarizing, both optimization algorithms are suitable to treat manufacturing systems. However, the brute force algorithm is only suitable for new planning and adaptation planning because of its long computation time. The Differential Evolution significantly reduces this computation time, but does not always identify the global optimum depending on its parameterization.

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