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Risk Treatment for Energy-Oriented Production Plans through the Selection, Classification, and Integration of Suitable Measures

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Abstract: With rising electricity prices, industries are trying to exploit opportunities to reduce electricity costs. Adapting to fluctuating energy prices offers the possibility to save electricity costs without reducing the performance of the production system. Production planning and control play key roles in the implementation of the adjustments. By taking into account the price forecasts for the electricity markets in addition to machine utilization, work in process, and throughput time, an energy-oriented production plan is set up. The electrical energy is procured based on this plan and the associated load profile. Deviations from the forecast and the purchased amount of electricity lead to high penalties, as they can destabilize the energy system. For manufacturing companies, this means that machine failures and other unexpected events must be dealt with in a structured manner to avoid these penalty costs. This paper presents an approach to selecting, classifying, and integrating suitable measures from existing risk treatment paths into the production schedule. The selection of measures is based on a hybrid multi-criteria decision-making method in which the three relevant criteria, namely, cost, energy flexibility, and risk reduction, are weighted by applying both an analytic hierarchy process and entropy, and they are then prioritized according to multi-attribute utility theory. In the following, the subdivision into preventive and reactive measures is made in order to choose between the modification of the original plan or the creation of backup plans. With the help of mathematical optimization, the measures are integrated into the production schedule by minimizing the cost of balancing energy. The approach was implemented in MATLAB® and validated using a case study in the foundry industry.

Keywords: production planning and control; scheduling; energy flexibility; risk management; fault management; multiple-criteria decision-making

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1. Introduction

Industries are facing the challenge of rising costs for electrical energy. The average electricity price for new contracts for the industry in Germany increased from €0.1207 per kWh in 2010 to €0.2138 per kWh in 2021. During this period, bulk buyers with an annual consumption of 70 million kWh or more had an increase from €0.0863 to €0.1149 per kWh with occasional drops [1]. Both small and medium-sized as well as energy-intensive industrial companies are therefore encouraged to take advantage of opportunities to reduce their electricity costs in order to maintain their competitiveness in the long term.

A promising approach to reduce these costs is adjusting the electricity demand to the variable prices on the energy markets. In the day-ahead market, the number of hours with negative electricity prices rose from 134 in 2018 and 211 in 2019 to 298 h in 2020. The mean value of the negative prices ranged in these years between −€13.70 and −€17.30 per MWh. Averaged over the respective year, the maximum daily price spread was around

€30 per MWh [2,3]. This price volatility in the electricity markets is significant for potential cost reduction.

The prerequisite to take advantage of these favorable prices and to comply with the restrictions on annual peak load and deviations is so-called energy-oriented production planning and control (PPC), which considers variable price forecasts for the electricity markets in addition to machine utilization, work in process, throughput time, and other criteria in a production system [4]. PPC is also responsible for dealing with unforeseen events such as machine failures and the corresponding adjustment of the order sequence in order to achieve the specified production targets as cost-effectively as possible [5]. With regard to electricity consumption, it is particularly important to avoid exceeding the annual peak load and deviations from the amount of electricity procured. These lead to higher grid charges or penalty costs for the imbalance caused between the available and used electrical energy in the electricity system. In order to avoid these costs, approaches within the energy-oriented PPC are required to evaluate potential risks within a production plan and to integrate suitable measures.

Roth et al. [6] introduce an approach for developing and evaluating risk treatment paths in energy-flexible production systems based on interpretive structural modeling and the calculation of conditional probabilities using Bayesian networks. Figure 1 depicts the idea of the approach in which a risk treatment path and the measures contained therein are integrated into the production plan in order to obtain a risk-treated production plan. The advantage of these paths compared to a situational reaction is that all the effects and possible interactions can be considered in advance. The approach creates a multitude of paths, as all identified risks and measures are linked based on their interactions and conditional probabilities.

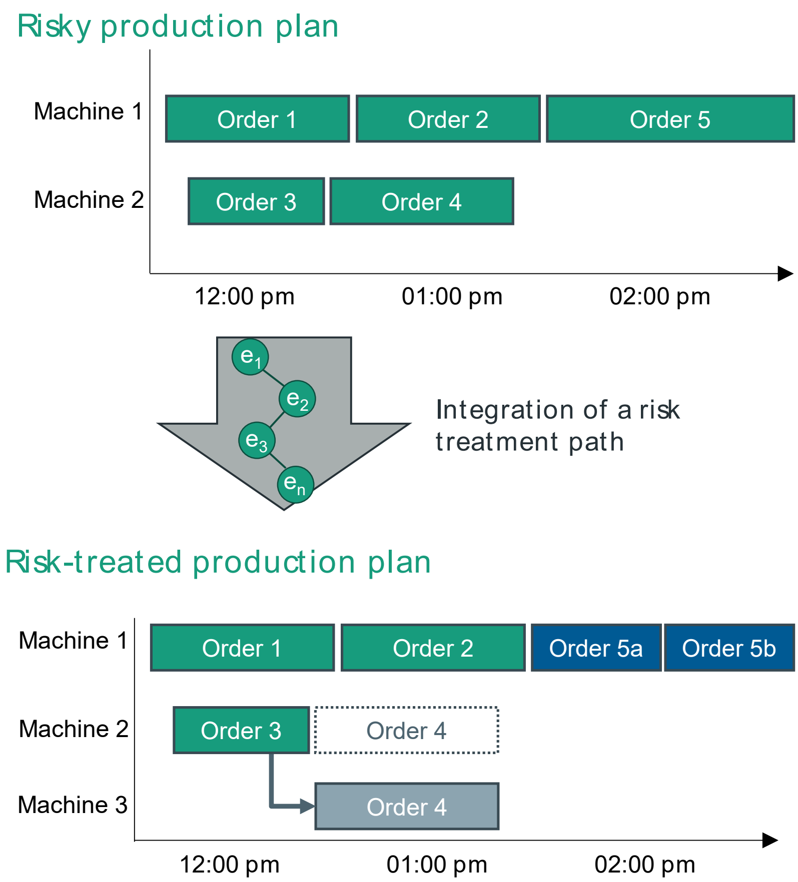

Figure 1. Integration of a risk treatment path into a production plan [6].

The approach thus leaves a need for further development with regard to the selection of a suitable path and the classification and integration of the measures it contains. In the literature, a large number of methods exist for the selection of alternatives, but there is no adaption to energy-oriented PPC. Furthermore, the state of the art offers no subdivision of energy flexibility measures into preventive and reactive, which is necessary for forward looking direct adjustments to the plan and alternative strategies if faults occur.

It is assumed that this should also follow a specific and structured approach in order to reduce the effort required for risk treatment and thus increase the acceptance of its implementation in companies. This article presents an approach that responds to these requirements. It starts with the paths shown in Figure 1 and presents how a preferred path can be selected and how the measures contained can be integrated into the production plan.

In the following, Section 2 first presents the state of the art in the relevant areas and the resulting need for action. Section 3 then introduces the scientific concept of the approach, which is described in detail in Section 4. The application based on a use case in a foundry is depicted and discussed in Section 5. The article closes with a conclusion and outlook in Section 6. The key notations are listed in Table 1.

Table 1. Notations.

Parameter	Description
A	Weighting decision matrix
a	Elements of the weighting decision matrix
$\Delta C_{tot}{}^{M}$	Change in measure-induced total costs
$\Delta C_{tot}{}^{R}$	Change in risk-induced total costs
ΔC_{tot}	Change in total costs
$cons_t$	Energy consumption in time unit t
D	Decision matrix
$duration_{ks}$	Duration of job k on station s
e	Entropy
EF	Energy flexibility
EF_{states}	Energy flexibility states
EF_t	Energy flexibility time
EF_{tech}	Energy flexibility technologies (e.g., storage facilities)
end_{ks}	Due date of job k on station s
i	Alternative
j	Criteria
k	Job
P	Probability of occurrence of risks and measures
P_{risk}	Probability of occurrence of risks
$peak_{max}$	Maximum peak load
Δpow_t	Deviation of the actual energy consumption from the forecasted load profile
$Power_{ks}$	Power consumption of job k on station s
$Power_t^{planned}$	Planned power consumption in time period t
QDC	Quantity deviation cost
r_{ij}	Rating for alternative i with criterion j
s	Station
$start_{ks}$	Start time of job k on station s
t	Time unit
u_{ij}	Marginal utility score for alternative i with criterion j
U_i	Final utility score for alternative i
$\vec{v}$	Eigenvector
w	Weighting
w_{AHP}	Subjective criteria weighting by analytic hierarchy process (AHP)
$w_{Entr,j}$	Objective criteria weighting by entropy
w_j^{final}	Final weighting for a criterion j
λ_{max}	Largest eigenvalue

2. State of the Art

This section first describes the state of the art in the field of risk management and energy-oriented PPC. Since various criteria have to be taken into account in risk management, common methods for solving complex decision problems are presented. In the following, methods for the categorization of measures are introduced. The need for action on which this contribution is based is then derived from these key areas.

2.1. Risk Management and Energy-Oriented PPC

Since failures, in general, can have far-reaching negative effects on the performance of a production system as well as on the manufacturing costs of the products, many articles offer a structure for the causes and effects of malfunctions as well as approaches for situational fault management. According to Schwartz and Voß [7], faults are events that have an effect on a process with a deviation from what was intended to occur. Greve [8] distinguishes between those faults which originate from the process and those that influence the process from outside. The causes are often used to further classify faults. A distinction is made between equipment-related, personnel-related, material-related, information-related, and order-related causes of failure by various authors [9–13]. Every cause of failure can be linked to its effects on a production system. An allocation of causes and effects, which also takes into account deviations in the electrical load profile, was worked out by Schultz [13]. In his contribution, a system is presented with which deviations in energy-flexible production systems can be counteracted with situational measures. Rösch et al. [14] introduce an approach for cost-based online scheduling to enable reactions to short-term changes and thus makes a contribution to fault management in energy-flexible production systems.

Risk management is characterized in particular by the fact that it also takes into account the probability of occurrence of the event when dealing with faults [15]. Many risk management approaches in the field of production systems are mostly based on the risk management process described in DIN ISO 31,000 [15] with risk identification, risk analysis, risk assessment, and risk treatment, whereby individual process steps are partially combined or sub-processes are supplemented. Various frameworks and approaches were developed specifically for the manufacturing sector. For example, the framework for risk management developed by Oduoza [16] enables key risk indicators in the manufacturing sector to be searched for and identified. Specific approaches can also be found in the area of PPC, such as Klöber-Koch et al. [17], who add production risks to a classic PPC system in order to make predictions about impending risk situations and to take these into account in the planning process.

If the energy consumption and energy costs in the production environment are to be considered in particular, specific work can also be found for this. Abele et al. [18] simulate disruptions in order to investigate their effects on the energy flexibility and costs of an energy-optimal production plan. The energy-optimized plan serves as an input variable for the subsequent simulation of faults. The changes in the production plan caused by disruptions lead to changed load profiles and thus also to changed electricity costs. The influence of disruptions is ultimately examined on the basis of the change in electricity costs and serves as a basis for decision-making for future investments in energy-oriented production.

Schultz et al. [19] integrate energy as a limited resource within the framework of energy-oriented production control. Exceeding the available energy resources is possible, but it is associated with disproportionately high costs. Taking into account the predominant goal in production control of adhering to delivery deadlines, the authors consider the fluctuations in energy consumption associated with the production process. The aim is to minimize the deviations from the planned load profile.

Golpîra [20] introduces smart energy-aware manufacturing plant scheduling. By proposing a new multi-objective robust optimization for a factory microgrid, the approach can be considered risk-based, as it considers the conditional value-at-risk. Coca et al. [21] illustrate the simultaneous evaluation of sustainability dimensions, containing environmental and occupational risks with an industrial case from the metal-mechanic sector. Energy flexibility in production systems is specifically considered in the work of Simon et al. [22]. The authors discuss the relevance of risk evaluation with regard to energy flexibility measures and present an approach to assess energy flexibility in production systems in terms of their risk potential on production goals, such as quality, costs, and throughput times.

2.2. Solving Complex Decision Problems

One difficulty in risk management is the different, sometimes conflicting, target values that need to be taken into account when making decisions. In the context of energy-oriented production planning, one example is that the capacity of stations should be utilized to fulfill the delivery time and that machine costs are reduced. On the other hand, the station utilization should be reduced in time windows with high electricity prices and be shifted to times with lower or negative prices.

In the literature, there are different approaches for multi-criteria decision-making (MCDM). A large number of articles in this field distinguishes between work on the development of new MCDM methods and detailed descriptions of their functioning (including Saaty [23], Ishizaka and Nemery [24], and Alinezhad and Khalili [25]), and comparative work that analyzes known MCDM methods (including Vujicic [26], Wang et al. [27], and Zanakis et al. [28]). Zavadskas et al. [29] give an initial overview of the relevant literature within the categories mentioned.

Zavadskas et al. [29] emphasize the increasing importance of hybrid MCDM methods for solving complex decision problems. An MCDM problem is generally divided into the steps of weighting the criteria and prioritizing the alternatives. Some MCDM methods are suitable for both weighting and subsequent prioritization, while other MCDM methods require a weighting of the criteria and do not offer a methodical approach for this.

For the selection of environmentally friendly technologies, Doczy and Razig [30] combine the analytic hierarchy process (AHP) and multi-attribute utility (MAUT) to give decision-makers in construction projects a method for a comprehensive assessment of sustainability without neglecting the conventional goals of construction planning. The evaluation is based on four criteria tailored to the construction sector. Şahin [31] conducts a comparative study of an MCDM problem in the context of sustainable energy generation in Turkey. The author compares the results of 42 decision problems resulting from a combination of different MCDM and weighting methods. The individual results are then summarized in an overall rating. Şahin concludes that a combination of several MCDM methods can compensate for the disadvantages of individual methods and thus enable a more accurate selection of the best alternative. Feizi et al. [32] combine a weighting based on AHP and Shannon entropy with a technique for order of preference by similarity to ideal solution (TOPSIS) to find an optimal mining location. The enormous number of 260,400 alternatives should be emphasized here. Ren et al. [33] compare the results of three different hybrid MCDM methods in the context of the planning of sewage treatment plants in consideration of the sustainability aspects. It is found that the technology selection is method-dependent. Consequently, they recommend not basing a decision on a single MCDM method but comparing the results of different methods. In addition, the authors consider both hard, easily quantifiable, and soft, only qualitative, decision criteria.

Muqimuddin and Singgih [34], among others, deal with the risks resulting from disruptions in the production process. The authors carry out a failure mode and effects analysis (FMEA) with three different risk priority numbers, which are weighted using an AHP. Identified faults are then prioritized with the help of TOPSIS. By combining the methods, risks are prioritized depending on the subjective assessments of the decision-maker. Turskis et al. [35] also place their method for risk assessment in the context of disruptions that endanger the information technology (IT) security of critical infrastructure. This is a holistic risk management method, which includes both risk identification and risk assessment. Wang et al. [36] consider service risks in hospitals with the aim of increasing service quality. Since service quality is primarily measured using non-quantifiable parameters, the combination of FMEA and fuzzy MCDM developed by the authors is particularly suitable in this context.

2.3. Categorization of Measures

Risk treatment requires suitable measures to compensate for the effects of risks. Since production systems usually have very specific characteristics, various approaches to the generalization and categorization of measures can be found in the literature. Pielmeier [12] assigns measures that have a direct influence on production control to the levels of in-house production planning and control of the Aachen PPC model, which is described in Schuh and Stich [5]. The author emphasizes that event-specific control strategies can be selected through the classification. Furthermore, the classified measures are linked with target values using a cause–effect matrix. VDI 5207 Part 1 [37] assigns previously introduced energy flexibility measures to the level model of production. The energy flexibility measures cover a broad time horizon from a few seconds to several hours. The classification enables a targeted consideration of individual measures, depending on the current state of knowledge, and thus an efficient implementation of the measures.

Verhaelen et al. [38] consider reactive fault management in the context of global production processes. The methodology developed by the authors enables a flexible and quick response in the event of a malfunction. Faults are classified into a three-level categorization system based on their causes and linked to appropriate measures. Furthermore, a protocol for the description of the fault is developed that facilitates the prioritization of faults and the associated initiation of measures. Schwartz and Voß [7], on the other hand, clearly differentiate in their work between prevention strategies and reaction strategies for fault management in production. The use of the two strategies is tested using a simulation model, and the effects of the measures are assessed using efficiency and instability measures. The methodology is assigned to machine utilization planning. Hernández-Chover et al. [39] do not consider the planning of preventive and reactive measures directly, but they also weigh up between predictive maintenance and repairs that become necessary due to malfunctions. In doing so, they consider the critical infrastructure in an empirical case study and identify the proposed method as the optimal relationship between forward-looking investments and subsequent repairs.

2.4. Need for Research

The investigation of the relevant scientific subject areas led to the following research gaps, on the basis of which the need for action for the creation of the approach is derived:

1. Energy-oriented PPC mostly neglects operational fault and risk management or is based on complex algorithms with little practical suitability. In order to implement the selected measures, a sensible method of integrating measures is required.
2. A large number of methods exists for the individual weighting of alternatives, but there is no adaptation of MCDM to energy-oriented PPC. Furthermore, no approach offers the consideration of risk-specific criteria in energy-flexible production systems.
3. In the literature, there is either a subdivision into preventive and reactive measures or an assignment of measures to the Aachen PPC model. The process views of the Aachen PPC model are not divided into preventive and reactive sub-steps, which would enable both forward-looking direct adjustments to the plan and alternative strategies if faults occur.

In summary, an approach must be developed that selects relevant risks and measures to be considered in a structured manner. In addition, it should enable the subdivision into the preventive and reactive treatment of risks and finally contain the planning of the measures on the basis of the target values of the energy-oriented PPC.

3. Scientific Concept

The presented approach builds on the development and evaluation of risk treatment paths following Roth et al. [6]. It is based on the determination of interactions through interpretive structural modeling and the calculation of conditional probabilities using Bayesian networks. The result is a multitude of risk treatment paths that contain risks and measures that can occur in a production system under consideration.

The generation of the risk-treatment paths in Roth et al. [6] is subject to several assumptions, the most important of which are:

1. The regarded area of application is limited to the use of electrical energy in production systems,
2. Processes are formalized in discrete production timetables,
3. Experts are available to supply the necessary information to generate the Bayesian networks.

Any further limitations named in Roth et al. [6] equally apply to the approach in this paper. The following assumptions apply specifically to the approach presented in this paper:

1. A discretized, energy-optimal production schedule is available,
2. For the risk-treated energy-oriented PPC, the planned energy schedules including the maximum allowances for peak loads are available,
3. A detailed risk inventory including measures is available, wherein process-specific parameters in the dimensions of time and energy consumption are known for every risk and every measure.

Figure 2 depicts a graphical overview of the approach proposed in this paper. The boxed numbers in Figure 2 additionally show in which section one can find details on the respective process step. The main process steps of the approach are:

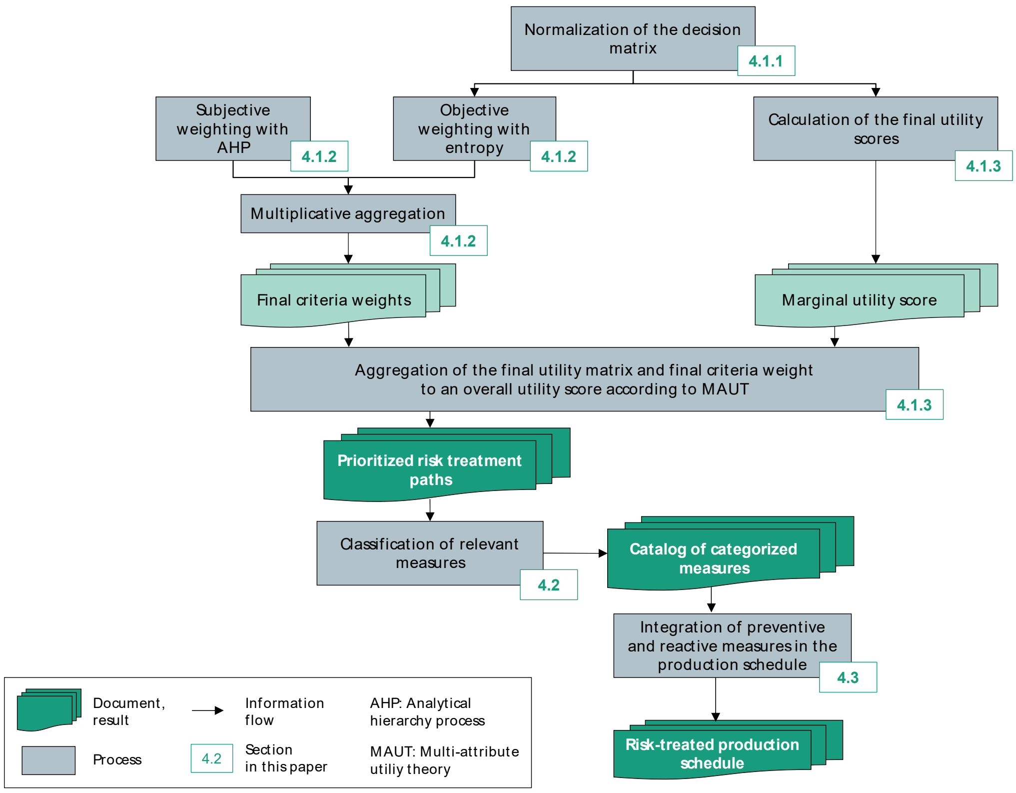

Figure 2. Overview of the approach.

1. Calculation of the final criteria weights by combining AHP and Shannon entropy,
2. Calculation of the marginal utility scores according to the problem-specific utility functions,
3. Calculation of the final utility score and subsequent prioritizing the risk-measure path profiles in descending order,

4. Classification of the relevant measures into preventive, reactive, and non-distinguishable in accordance with [37],
5. Integration of the measures into the process schedule depending on the prior classification, resulting in a risk-treated process schedule.

The application of the approach produces three overarching results: the prioritized risk treatment paths, a catalog of categorized measures, and as the final result, the risk-treated production schedule.

4. Description of the Approach

This section introduces the details of the developed approach. Section 4.1 summarizes the measure selection process, which is based on a hybrid MCDM approach with AHP and entropy for criteria weighting and MAUT for the prioritization of the paths. Then, Section 4.2 outlines the process for measure classification into preventive and reactive by utilizing the categorization of energy flexibility measures in the VDI 5207 standard [37]. Finally, Section 4.3 integrates the selected measures in the production schedule with the help of a mixed-integer linear problem (MILP) and a branch-and-bound optimization, minimizing the cost of additionally purchased energy. The integration of measures is understood as the creation of new, risk-treated scheduling that, through preventive measures, contains less risk potential. In addition, reactive measures are integrated so that backup schedules are created that are used when faults occur.

4.1. Prioritization of the Risk Treatment Paths with a Hybrid MCDM Approach

For the risk treatment, measures must be integrated into the existing production schedule. To identify which measures to integrate, the risk treatment paths that contain different measures are ranked, and, subsequently, measures are extracted from the chosen path. As the risk treatment paths are evaluated in multiple dimensions, the resulting decision problem is a multi-criteria decision-making problem and thus requires complex decision-making methods to identify the best alternative from all the available paths. This paper introduces a hybrid MCDM approach that weights the criteria combining AHP [23] and Shannon entropy [40] and subsequently ranks the alternatives according to the rules of MAUT [41].

4.1.1. Normalization of the Decision Matrix

The model developed by Roth et al. [6] evaluates each path according to the trilemma of cost, energy flexibility, and a risk priority number. In this research paper, the trilemma is modified to fulfill the requirements of criteria selection in MCDM problems, as stated by Wang et al. [42]. The authors define five principles to be obeyed when identifying suitable criteria: (1) the systemic principle, (2) the consistency principle, (3) the independency principle, (4) the measurability principle, and (5) the comparability principle. The systemic principle demands a holistic assessment of the regarded problem. In every PPC system, costs are one of the key decision factors [12] and therefore need to be considered in the decision problem, hereinafter referred to as cost. Reinhart and Schultz [43] propose energy flexibility as a key indicator in the energy-oriented PPC, as it incorporates several energy-related variables in one indicator, hereinafter referred to as energy flexibility. Furthermore, this research is positioned in risk and fault management, and thus a risk-related dimension needs to be added to the problem to describe it holistically. The risk-related indicator is hereinafter referred to as risk reduction. The expert weighting of the three criteria additionally ensures that the criteria of the decision problem are in line with the decision-maker's goals; thus, criteria (1) and (2) are considered fulfilled. To demonstrate that principles (3) to (5) are fulfilled, a closer look at how the criteria are calculated is necessary.

The costs are calculated according to the cost model introduced by Roth et al. [6], which distinguishes between, e.g., production costs, logistic costs, and delay costs, and it divides these in turn into respective sub-categories, such as material or personnel costs. Costs are defined as the change in costs in the modified production schedule in relation to the unmodified production schedule. The deviation is the sum of deviations in the above-mentioned cost categories. For every cost component, only measure-induced costs are regarded, resulting in the measure-induced change in costs $\Delta C_{tot}{}^{M}$, where $\Delta C_{tot}{}^{M}$ is negative for cost savings, positive for increased costs, and "0" for unchanged costs [6]. Thus, for $\Delta C_{tot}{}^{M}$, the lower the better. The cost thus indicates the costs incurred through the integration of the measures on the path. In practice, they therefore often correspond to the deviation from cost-optimal scheduling, which does not consider any risk effects.

The energy flexibility indicates the remaining flexibility available in the system to react to disruptions influencing the production system's energy consumption. The regarded dimensions of energy flexibility are the potential to change loads or so-called energy flexibility states EF_{states}, the potential to shift the time of consumption EF_t, and the potential of energy-flexibility technologies, e.g., the use of storage facilities and flexible on-site generation EF_{tech}. The overall energy flexibility EF is then calculated by multiplying the three dimensionless components:

$$EF = EF_t \Delta EF_{states} \Delta EF_{tech} \tag{1}$$

A value higher than one indicates the desired high energy flexibility, whereas a value lower than one indicates undesired low energy flexibility.

Risk reduction indicates how much the risk is reduced by the integration of the measures into the production schedule, such as a change in production sequence or a shift of production starts. Risk reduction can thus be understood as the added value of the risk treatment approach and is defined as the absolute difference between the risk potential of the original plan and the resulting risk in the risk-threatened plan:

$$Risk\ reduction = |risk\ potential - resulting\ risk| \tag{2}$$

The risk potential of a path, on the other hand, is defined as the product of the probability of occurrence of the risks P_{Risk} it contains and the costs caused by the risks $\Delta C_{tot}{}^{R}$, i.e., the damage [44–46]:

$$Risk\ potential = P_{Risk} \cdot \Delta C_{tot}{}^{R} \tag{3}$$

The resulting risk considers all path elements and thus consists of the product of the probability of occurrence of the risks and measures P and the total risk and measure costs of the pathΔC_{tot}:

$$Resulting\ risk = P \cdot \Delta C_{tot} \tag{4}$$

A high rating for the risk reduction is desired whereas the worst possible outcome is a risk reduction of zero, implying that no measures were integrated, and thus no potential risk was reduced.

Thus, all three criteria are in line with criteria (3), namely, independency. As for costs, a differentiation between measure and risk-induced costs is introduced, and the energy flexibility only considers cost-independent factors. Furthermore, all three criteria are quantified evaluations of the regarded system and thereby fulfill principle (4). To achieve comparability across the criteria that utilize different scales, normalization of the criteria ratings r_{ij} is necessary (criteria (5)). Depending on the direction of the criteria, Equation (5) or Equation (6) is applied [25], resulting in a normalized rating r^*_{ij}, with a value of one corresponding to the best possible alternative i and zero being the worst possible alternative i for the respective criterion j:

$$r^*_{ij} = \frac{r_{ij} - \min(r_{ij})}{\max(r_{ij}) - \min(r_{ij})},\ for\ maximizing\ criteria \tag{5}$$

$$r^*_{ij} = 1 + \frac{\min(r_{ij}) - r_{ij}}{\max(r_{ij}) - \min(r_{ij})},\ for\ minimizing\ criteria \tag{6}$$

The cost indicator $\Delta C_{tot}{}^{M}$ is to be minimized, and the energy flexibility indicator EF and the risk indicator risk reduction are to be maximized. The three criteria can now be graphically represented in a trilemma and are summarized in the decision matrix D with r^*_{ij} being the normalized rating for alternatives $i = 1 \ldots n$ with respect to the criterion $j = 1 \ldots m$:

$$D = \begin{bmatrix} r^*_{11} & \cdots & r^*_{1m} \\ \vdots & \ddots & \vdots \\ r^*_{n1} & \cdots & r^*_{nm} \end{bmatrix} \quad (7)$$

4.1.2. Subjective and Objective Criteria Weighting

For the subjective expert weighting, the three trilemma criteria AHP is applied. The AHP [23] is widely used in the literature and practice due to its straightforward application and high reliability, even in uncertain decision situations [47]. It is based on the principle of pairwise comparison, usually done by experts, and it serves as the subjective weighting method in the approach. The pairwise comparison results in an $n\ x\ n$ decision matrix A with the elements a_{ij}, each of which indicates the relative weighting of two criteria, i and j. Values on the diagonal are equal to one. The remaining comparisons are filled with values from one to nine, and their inverse fractions for opposite dependencies [48]:

$$A = \begin{bmatrix} 1 & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ \frac{1}{a_{1n}} & \cdots & 1 \end{bmatrix},\ a_{ii} = 1,\ a_{ji} = \frac{1}{a_{ij}},\ a_{ij} \neq 0 \quad (8)$$

The following applies for the pairwise comparison: the higher the chosen value for criterion i, the higher the preference of criterion i over criterion j. For the comparison, a scale from one to nine is introduced, as it is effective in expressing preferences with sufficient precision and does not overwhelm the human decision-maker [49]. A verbal explanation of the nine levels is given in Table 2.

Table 2. Descriptive explanation of the AHP pair-wise comparison scale [49].

Intensity of Importance on an Absolute Scale	Definition	Explanation
1	Equal importance	Two activities contribute equally to the objective
3	Moderate importance of one over another	Experience and judgment slightly favor one activity over another
5	Essential or strong importance	Experience and judgment strongly favor one activity over another
7	Very strong importance	An activity is strongly favored and its dominance demonstrated in practice
9	Extreme importance	The evidence favoring one activity over another is of the highest possible order of affirmation
2, 4, 6, 8	Intermediate values between the two adjacent judgments	When compromise is needed
Reciprocals	If activity i has one of the above numbers assigned to it when compared with activity j, then j has the reciprocal value when compared with i.	

The choice of the exact preference level within the range is the decision-maker's. As outlined in Section 4.1.1, the three relevant criteria to compare are cost, EF, and risk reduction. The regarded factors, which influence the pairwise comparison, are, e.g., a client's importance, sustainability goals, risk attitude, and time criticality. Some examples of decisions are listed below:

- Risk reduction is more important than cost: the orders are particularly time-critical and for particularly important customers. Additional costs are therefore accepted for the reduction of risks.

- Energy flexibility is more important than risk reduction: the information available in the planning period is vague because rush orders could arrive. High remaining energy flexibility is required in the system.
- Cost is more important than risk reduction: the forecasts for penalties for deviations are low, and load peaks are not expected in the period under consideration. There is no great need to incur costs for risk reduction measures.

These comparisons can serve as a guide for decision-makers. Individual preferences may exist in a specific production system, and thus individual decisions must take into account the circumstances and requirements of the production system in question.

The calculation of the criteria weights w_{AHP} for the decision matrix A is carried out by multiplying its largest eigenvalue λ_{max} by the respective eigenvector $\vec{v_i}$:

$$w_{AHP} = \lambda_{max}\,\vec{v_i},\;\; with\;\lambda_{max} = \max_i \lambda_i \tag{9}$$

Finally, the consistency of the expert judgments is checked with the consistency ratio (CR). The inputs are assumed to be consistent if CR ≤ 0.1 hold true; otherwise, the expert inputs must be revised. The CR is the fraction of the consistency index (CI) and random consistency index (RCI) as shown. The value of the RCI depends on the number of alternatives and was introduced by Dong [50]. Small inconsistencies are accepted, as human inputs are subject to error, especially with an increasing number of alternatives. Furthermore, if inconsistencies are small, they do not have a decisive influence on the result of the AHP.

In addition to the subjective weighting with AHP, an objective weighting takes place using the entropy (information theory) according to Wang et al. [42]. The aim of the entropy is to calculate a weighting that reflects the information and uncertainty contained in an individual criterion. The entropy e_j is calculated using Equation (10) and is based on the normalized decision matrix D (Equation (7)).

$$e_j = -k\sum_{i=1}^{n} r_{ij}^{*} ln\left(r_{ij}^{*}\right),\; j = 1\ldots m \tag{10}$$

where $k = \frac{1}{\ln(n)}$ and n the number of alternatives per criterion. The higher the entropy, the higher the uncertainty of the criterion, and the lower the weighting w_j should be. This relationship is represented in the calculation of the objective weighting $w_{Entr,j}$ [32,40,42]:

$$w_{Entr,j} = \frac{f_j}{\sum_{j=1}^{m} f_j}\text{ with } f_j = 1 - e_j \tag{11}$$

The final weighting w_j^{final} for a criterion is generated by multiplying the objective weighting $w_{Entr,j}$ and subjective weighting $w_{AHP,j}$ similar to [32,42]:

$$w_j^{final} = \frac{w_{Entr,j}\cdot w_{AHP,j}}{\sum_{j=1}^{n} w_{Entr,j}\cdot w_{AHP,j}} \tag{12}$$

The final weighting w_j^{final} combines the possibility of mapping individual preferences with the AHP and at the same time reduces the distortions by entropy due to the consideration of the contained information value of the different options. Since in this case there is sufficient data to calculate the entropy and an expert familiar with the use case is available, both weightings can easily be determined and combined.

4.1.3. Calculation of the Final Utility Scores and Aggregation into an Overall Utility Score

The MAUT assumes that every decision is based on maximizing one's own utility [24]. The normalized decision matrix D (Equation (7), Section 4.1.1) forms the basis for calculating the marginal utility score of alternative i with criteria j $u_{ij}\left(r_{ij}^*\right)$. A universal utility function does not exist, but rather the chosen functions highly depend on the decision-maker. In general, the distinction between linear and exponential utility functions is widespread [24,25,51]. Figure 3 shows a depiction of the different utility functions. If small changes in the criteria values in the lower third are rated as significant, a concave utility function should be selected. If small changes in the upper third of all values are rated as significant, a convex utility function should be selected.

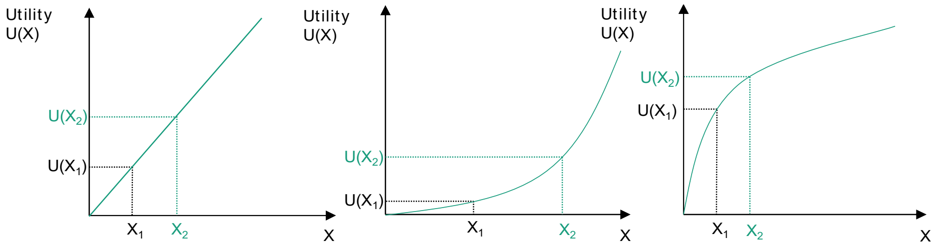

Figure 3. Utility functions (linear, convex, concave).

Equation (13) depicts the generalized form of the exponential utility function for the marginal utility score u_{ij}, where x depends on the decision-maker's utility with $x < 1$ for a concave function and $x > 1$ for a convex function [25].

$$u_{ij}\left(r_{ij}^*\right) = \frac{exp\left(\left(r_{ij}^*\right)^x\right) - 1}{exp(1) - 1} \tag{13}$$

If the distribution is even, a linear utility function should be selected:

$$u_{ij}\left(r_{ij}^*\right) = r_{ij}^* \tag{14}$$

To identify a decision-maker's underlying utility function, direct methods or indirect methods can be applied [24]. With direct methods, the decision-maker answers direct questions about his or her preferences through ratings or preferences on lotteries, etc. Indirect methods can be versions of additive utility methods, which are based on linear programming [52]. If it is not possible to define the decision-maker's risk preference for a trilemma criterion, a neutral utility function should be chosen. As a result, a new decision matrix containing the marginal utility scores is created:

$$U_{ij}\left(r_{ij}^*\right) = \begin{pmatrix} U\left(r_{11}^*\right) & \cdots & U\left(r_{1m}^*\right) \\ \vdots & \ddots & \vdots \\ U\left(r_{n1}^*\right) & \cdots & U\left(r_{nm}^*\right) \end{pmatrix} \tag{15}$$

Eventually the final utility scores U_i are calculated for each risk treatment path, i.e., each alternative, with the marginal utility scores $U_{ij}\left(r_{ij}^*\right)$ and the final weighting w_j^{final}:

$$U_i = \sum_{j=1}^{m} U_{ij}\left(r_{ij}^*\right) \cdot w_j^{final}, \quad i = 1 \ldots n \tag{16}$$

Arranging the risk treatment paths descending from $U_{i,max}$ to $U_{i,min}$ results in a prioritized list of all paths and thus in the selection of measures that in the next steps are categorized and integrated into the production schedule.

4.2. Classification of Relevant Measures

To integrate the identified measures into the production schedule, it is first necessary to distinguish between preventive and reactive measures in order to create a catalog of categorized measures. The literature suggests that the main differentiator is the timing of the measure considering the occurring damage [7,25,29].

- Reactive measures are only used when damage has already occurred. The aim is to keep the resulting damage and the associated costs as low as possible. Due to the immediate implementation, short-term changes in the production schedule must be expected.
- Preventive measures are used to avoid potential damage and its financial impact as well as the reduction of the likelihood of occurrence. They are implemented at an early stage before the fault occurs. This excludes the possibility of changes to the production schedule with short notice.

In addition to differentiation according to the time of implementation of a measure, economic aspects must be considered. Preventive measures should generally be preferred in the case of high expected costs for reactive measures [53]. The advantage of taking both categories of measures into account in this approach is that the preventive measures reduce the impact and likelihood of potential faults. At the same time, the planning of reactive measures creates an information base for the reactions if faults still occur, so that a solution does not have to be sought under time pressure.

A generalized and thorough overview of relevant measures for energy-flexible production is given in VDI 5207 Part 1 [37]. The distribution of the measures within the three implementation levels of the energy-flexible factory serves as a reference point for selecting relevant measures for operational risk management (Figure 4).

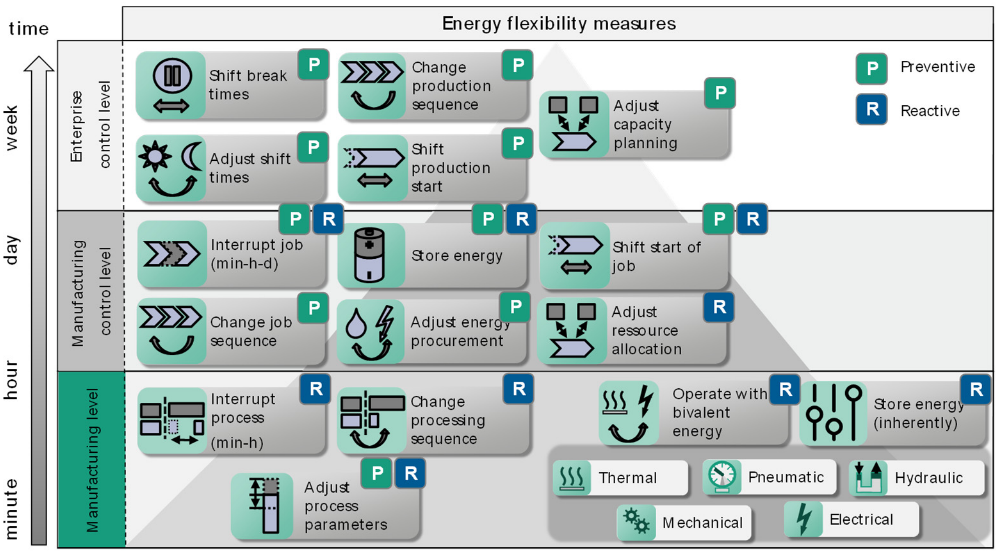

Figure 4. Energy-flexibility measures and their classification into preventive (P) and reactive (R) measures. Figure based on VDI 5207 Part 1 [37]. Reproduced with permission of the Verein Deutscher Ingenieure e. V.

The different implementation levels in Figure 4 imply different time horizons that serve as orientation for dividing the measures into preventive and reactive. Still, for some measures it is not possible to assign them to only one category without knowing the specific production context. Thus, these measures are marked as preventive and reactive. At the short-term manufacturing level, all measures are considered reactive except for the adjustment of process parameters, which can also be an activity planned in advance. At the manufacturing control level, most of the measures available are preventive, as the regarded time horizon ranges from hours to days and thus implies longer advance planning. The manufacturing control's measures further influence the measures at the lower level, and preventive planning of these should be done whenever possible. Nonetheless, in the event of severe disruption, a job may be interrupted reactively, and, if available, energy storage will be used. The enterprise control level only consists of preventive measures due to the necessary longer planning horizon of days to weeks. Finally, it should be noted that this division into preventive and reactive measures is a general orientation because in the wide variety of different industries with specific planning and production systems, the respective measures may differ.

4.3. Integration of Preventive and Reactive Measures in the Production Schedule

Once measures have been successfully divided into reactive and preventive, implementation of the measures into the production schedule needs to be planned. The rescheduling of reactive measures is considered to be segment-based rescheduling, similar to Toba [54]. This means that for reactive measures, only the segments after the potential risk occurrence are affected and rescheduled, whereas for preventive measures, the measure execution must be prior to the expected time of disruption to be effective. Therefore, the implementation of preventive measures may affect the entire production schedule.

The production schedule needs to be modified so that the previously selected measures are integrated as well as they can be, taking into account the logistical goals of the production system and the boundary conditions for the planned energy consumption. Due to the differentiation into preventive and reactive measures, new production schedules must be generated. These are the modified production schedule with all preventive measures, which replaces the original plan. Furthermore, a backup plan is drawn up for each reactive measure implemented, as the reactive measures only come into effect when a disruption occurs.

The integration of measures is formalized as a MILP, which can be solved through branch-bound-and-cut optimization, e.g., in MATLAB® [54,55]. For the present problem, it is important to aim for short computation times to ensure the applicability of the approach in operational practice. This can be achieved by reducing complexity wherever the problem setting allows it. The goal of this optimization is to integrate the measures energy optimally and thereby create a risk-treated, energy-optimal production schedule by the addition of preventive and reactive measures.

In the course of this section, the term *production* schedule refers to a plan that aggregates all relevant jobs on all workstations for the respective production period under consideration of resources and sequence restrictions, whereby one *job* contains a product's production steps, i.e., the necessary workstations including durations, sequence restrictions, and resource consumptions. The workstations come with capacity restrictions, and not every job is necessarily processed on every workstation. The initial production schedule prior to risk treatment is assumed to be available and energy-optimal, hereinafter referred to as energy-oriented PPC.

Measures are thus either treated as jobs and are fixed in their allocation to one workstation or modify the load and time dimensions of jobs scheduled by the energy-oriented PPC. When scheduling the measures, the risk-treated energy-oriented PPC must still comply with logistical and energy-consumption target values. Consequently, two options remain for the risk treatment:

1. An extension of the original energy-oriented PPC by risk-specific target values and constraints leading to a detailed and comprehensive optimization problem.
2. Setting the results of the initial energy-oriented PPC as an input variable for an optimization problem that is limited to the implementation of measures.

Option (1) results in correspondingly higher computing times due to increased complexity. This also leads to more difficulties in understanding the solution process and thus lowers the acceptance of the approach for the end users. Option (2), on the other hand, results in a non-optimal solution, but with expected significantly shorter calculation times, thus increasing flexibility in the application of the approach. It is also advantageous that the energy-oriented PPC is not redesigned but expanded. This increases understanding and acceptance if the generated solution fulfills the end user's standards. Due to the predominant advantages of option (2), this will be pursued further below.

Thus, the optimization problem consists of an energy-optimal production schedule as input that can be generated using different approaches, e.g., those described in Section 2.1. In addition, the measures of the chosen risk treatment path need to be scheduled to create the risk-treated production plans.

In order to meet the logistical goals and to avoid delays, the end times of the jobs scheduled in the energy-oriented PPC are fixed and block the workstations for the scheduling of measures in these time periods.

Usually, when creating an energy-oriented production plan, a cost-optimal result is sought after the variable price forecasts. The electricity demand planned and procured in this way should be consumed within tolerances in order to avoid high penalties. As part of the risk treatment, price fluctuations in the markets are no longer of central importance, as the plan is already generated, but the time-dependent penalties for deviations from the originally purchased electricity consumption have to be focused on now.

Thus, the objective function of the optimization problem minimizes the quantity deviation cost (QDC) QDC_t for each time unit t that arises from a deviation of the actual energy consumption from the forecasted load profile Δpow_t.

The QDC is substituted by the forecast for reBAP, which stands for "regelzonenübergreifender einheitlicher Bilanzausgleichsenergiepreis" and assigns a uniform price to the balancing energy that was necessary in the past. The reBAP is calculated in retrospect for every quarter-hour of a day. If no suitable forecasts are available for the reBAP, intraday market forecasts can also be used, as the amount gives an impression of the energy availability and the demand and thus the level of the penalty costs caused by deviations.

The objective of the optimization is to minimize the QDC, which arises due to the deviations from the planned load profile. This is shown in the target function with the deviation Δpow_t and the QDC_t at the respective point in time t.

$$Minimize \sum_{t \in T} (\Delta pow_t \cdot QDC_t) \tag{17}$$

To ensure logistic targets are met, a job must start early enough to not miss any due dates:

$$start_{ks} \leq end_{ks} - duration_{ks}, \ \forall i \in I, \ k \in K\,, \tag{18}$$

where $start_{ks}$ describes the start time of job k on working station s and end_{ks} the due date of the job k on station s. The duration of job k on station s is described by $duration_{ks}$.

To calculate the actual energy consumption $cons_t$, the binary x_{kit}, that is, one if job k is allocated to workstation s in time unit t and zero otherwise, is multiplied by the workstation and job-specific power consumption $Power_{ks}$:

$$cons_t = \sum_{i=1}^{m} \sum_{k=1}^{l} Power_{ks} \cdot x_{kst}, \ \forall t \in T \tag{19}$$

Additionally, it must be ensured that the measure integration does not lead to the peak loads being exceeded; thus, the total consumption $cons_t$ must be smaller than the maximum allowed peak load $Peak_{max}$ for every time unit

$$cons_t \ \leq \ Peak_{max}, \ \forall \ t \in T. \tag{20}$$

Finally, the deviation in energy consumption is calculated as the total consumption minus the planned consumption $Power_t^{planned}$.

$$\Delta pow_t = cons_t - Power_t^{planned}, \ \forall t \in T \tag{21}$$

The optimization is performed twice—once to generate the modified production schedule and once to generate the backup plan. Figure 5 depicts schematically how the optimization improves the handling of disruptions. In the above production schedule without prior risk treatment, a disruption leads to a spontaneous decision to post-process. This leads to the annual maximum load being exceeded, as shown in the adjacent diagram of the load profile. With the risk treatment shown in the lower area of Figure 5, the possible disruption is considered in advance with a backup plan, containing reactive measures for the case of the occurrence of the fault. The pause on station 4 enables post-processing to compensate for the disruption without exceeding the peak load. To create the risk-treated plan in the above-mentioned approach, only the affected jobs are rescheduled.

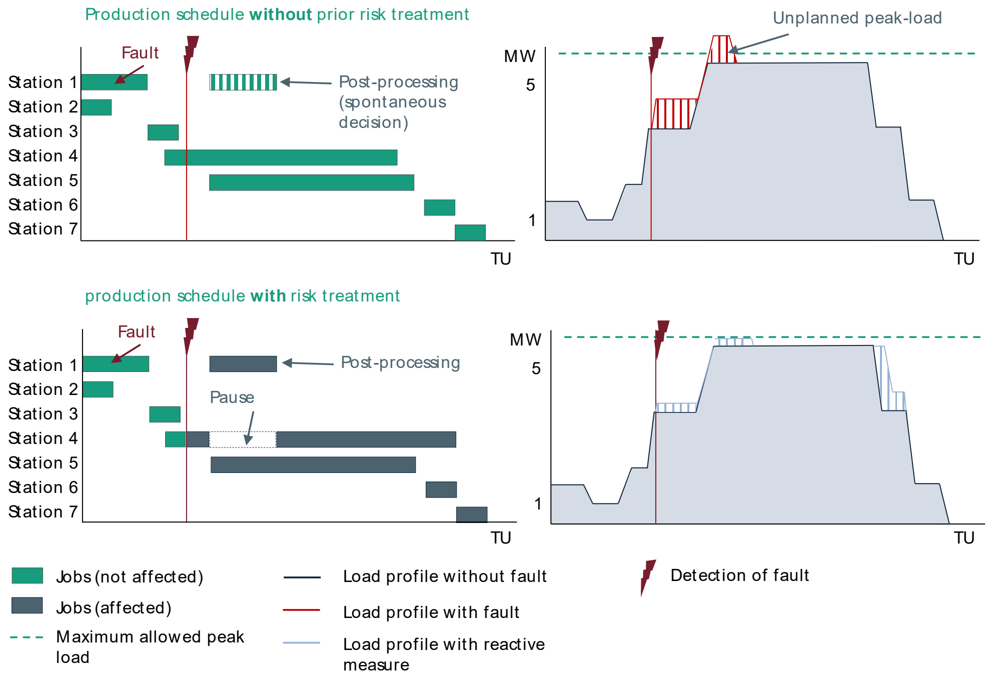

Figure 5. Schematic initial production schedule and the effects of disturbances on the load profile.

5. Application of the Approach

The use case for demonstrating the approach is located in the foundry industry. As the melting processes are considered especially energy-intensive, the foundry industry can significantly influence the power grid [56]. In the use case, four furnaces are used to melt raw iron, iron ore, and scrap iron. The ladles are transported to the casting fields via forklifts. Molds and cores are produced on site. The whole process of melting, molding, core preparation, casting, and post-processing is considered for a time period of 65 time units (TU), which is equivalent to 16.25 h. A detailed description of the use case can be found in Roth et al. [6].

The approach requires the risk treatment path profiles obtained in Roth et al. [6] as well as process-specific risk and measure data, which are gathered with the help of expert interviews and failure mode and effects analysis (FMEA). Six risks with their potential extents of damage and probability of occurrence were identified and are listed with the related nine different measures in Table 3. At this point, it is important to note that risks that are directly related to quality management processes were not considered, as they are not in the sphere of influence of the PPC.

Table 3. Risk inventory with the frequency of occurrence, extent of damage, and the related measures.

ID	Risk (Frequency)	Extent of Damage	ID	Measure
R1	Mold for a small part is faulty—exchange of mold pattern is possible (1 per week)	Time delay to casting and subsequent processes	M1	Switch to casting panel with identical material requirements
		Additional post-processing	M2	Casting with increased post-processing effort
R2	Mold for a small part is faulty—exchange of mold pattern is not possible (1 per week)	Additional order to be planned; changed load profile	M3	Preparation of an additional mold
		Additional post-processing	M2	Casting with increased post-processing effort
R3	Core for a small part is faulty—exchange of core box is possible (2 per week)	Time delay to casting and subsequent processes	M1	Switch to casting panel with identical material requirements
		additional post-processing time	M2	Casting with increased post-processing effort
R4	Core for a small part is faulty—exchange of core box is not possible (2 per week)	Additional order to be planned; changed load profile	M4	Preparation of an additional core
		Additional post-processing	M2	Casting with increased post-processing effort
R5/R6/R7 *	Furnace failure (2 per year)	Delay melting	M5	Adjust furnace utilization if an unoccupied furnace is available
		Delay melting	M6	Adjust process start
		Delay melting; changed load profile	M7	Adjust parameter melting temperature and duration
			M8	Interrupt melting process (only possible for small TUs)
R6	Forklift failure (5 per week)	Time delay in follow-up processes	M9	Provision of a spare forklift
			M10	Switching to transport trolleys

* This risk applies to every furnace individually.

The measures are further subdivided into process-altering and supplementary process measures, e.g., M2: casting with increased post-processing effort alters the post-processing, and M3: preparation of an additional mold is a supplementary process to be planned in addition to the scheduled mold preparation processes. For every process-altering measure, the measure-induced deviation in duration and load profile, and for every supplementary process measure, the absolute duration and load profile is filed.

Additional input parameters for the scheduling are the planned load profile, the QDC, and the initial energy-optimal production schedule, including production-specific requirements.

In the following, the application of the approach is described. The section is structured based on the three main steps of the approach, with the calculation of the final criteria weights, the classification of the relevant measures, and, finally, the integration of the measures.

5.1. Prioritization of the Risk Treatment paths

For the measure selection, the AHP periodization matrix and utility functions for the three criteria of cost, risk reduction, and energy flexibility are needed. An interactive MATLAB® Live Script is created as the user interface. For optimization, MATLAB® offers an Optimization Toolbox™ that can solve MILPs efficiently. The approach is implemented in MATLAB® version 9.6.0.1472908 (R2019a). All input data are stored in Microsoft® Excel® and can therefore be easily modified.

Firstly, all ratings for the paths created in advance using the approach in Roth et al. [6] are normalized, resulting in trilemma criteria for every path. In Figure 6, the trilemma for three exemplary paths is depicted. To compare the three paths, their criteria are shown in the diagram below on the right.

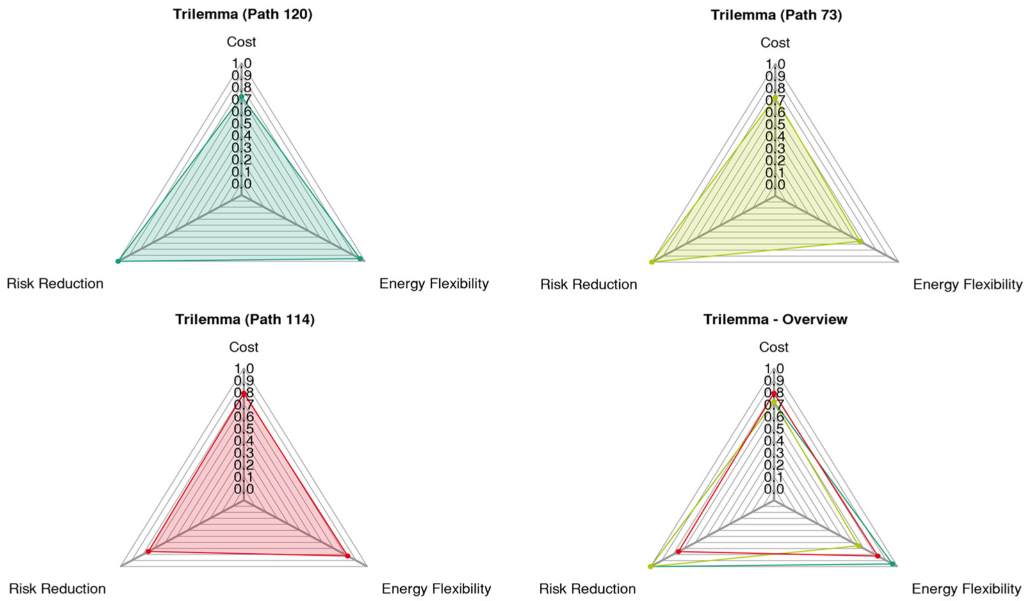

Figure 6. Trilemma of three risk treatment paths including an overview.

With the involvement of the experts from the production system, the approach to weighting the trilemma criteria was then carried out in order to be able to categorize the paths according to their suitability. For the decision matrix in Table 4, the principal eigenvector according to the AHP [23] determines the weighting of 0.0679 for cost, 0.7703 for energy flexibility, and 0.1618 for risk reduction, according to the assessment of the experts. This is due to a high need for the remaining energy flexibility in the system for reactive measures, since the orders are particularly tightly timed in the period under consideration, and failure to meet deadlines is associated with high penalties. Risk reduction is also given a higher weighting than cost; additional costs for measures are therefore accepted in favor of risk reduction.

Table 4. Decision matrix for the AHP.

	Cost	Energy Flexibility	Risk Reduction	Final Weighting
Cost	1	1/9	1/3	0.0679
Energy flexibility	9	1	6	0.7703
Risk reduction	3	1/6	1	0.1618

The objective weighting, applying Shannon entropy, results in a weighting of 0.0245 for cost, 0.0710 for energy flexibility, and 0.9044 for risk reduction, assuming all values are normalized according to Equation (5) or Equation (6). The proportionally high weighting of risk reduction in comparison to the two remaining criteria highly influences the final weighting obtained by multiplicative aggregation. The large deviation in values is not uncommon, as subjective and objective weighting are generated independently. Thus, the final weighting results in 0.0082 for cost, 0.2700 for energy flexibility, and 0.7218 for risk reduction.

For this use case, the utility functions based on the underlying data structure were selected, so that differences in ratings are amplified. This is achieved by choosing a convex utility function when most data points lie within the upper third of the scale. When most date points lie within the lower third of the scale, a concave utility function is applied. For the remaining third, a linear function was utilized. Thus, for cost and energy flexibility, a convex utility function was chosen and for risk reduction a linear utility function.

$$u_{ij}\left(r_{ij}^{*}\right) = \frac{exp\left(\left(r_{ij}^{*}\right)^{2}\right) - 1}{exp(1) - 1} \tag{22}$$

Applying the respective utility function to the decision matrix results in marginal utility scores for every alternative and every criterion. The final utility scores are calculated by weighted sums, and the paths, i.e., the alternatives, are ranked in descending order. Table 5 depicts the top three paths with their marginal and final utility scores under the assumption of the previously generated final weighting.

Table 5. Marginal and final utility scores of the three best performing paths.

	Marginal Utility Score			
Criteria	**Cost**	**Energy Flexibility**	**Risk Reduction**	**Final Utility Score**
Weight	**0.0082**	**0.2700**	**0.7218**	
No. 120	0.3930	0.8689	1.0000	0.9596
No. 73	0.3930	0.3107	1.0000	0.8089
No. 114	0.5028	0.5677	0.7507	0.6992

The top three paths contain the following measures: Path 120 contains R4 (core for a small part is faulty) and M4 (preparation of an additional core), path 73 contains R7 (delay melting) and M5–7 (adjust furnace utilization, adjust process start, adjust parameter melting temperature and duration), and path 114 contains only M7 (adjust parameter melting temperature and duration).

The selection of paths that contain little or no risk can be explained by the fact that the risk reduction criterion shows a strong accumulation in its assessments and is therefore generally avoided. The selection is therefore shifted to the criteria costs and EF, which are then rated higher. The distribution of the risk reduction depends crucially on the input variables of the extent of the damage and the probability of occurrence of the damage. During the application, the conscientious collection of this data is therefore of high relevance for the reliable selection of suitable paths. Furthermore, the measures contained in the prioritized paths must be compared and selected for integration into the production plan.

5.2. Classification of Relevant Measures

To showcase the potential of the risk reduction measures, the four measures (Table 6) from the prioritized paths were selected for the measures catalog to be integrated into the production schedule. The division of the measures into preventive and reactive is based on the allocation of the presented categorization of energy flexibility measures. For example, M5 can be assigned to the energy flexibility measure "adjust resource allocation" and is, therefore, a reactive measure.

Table 6. Catalog with four categorized measures.

ID	Description	Type	Effect on the Process
M4	Preparation of an additional core	Reactive	Altering
M5	Adjusting furnace utilization if an unoccupied furnace is available	Reactive	Supplementing
M6	Adjust process start furnace	Preventive	Supplementing
M7	Adjust parameter melting temperature and duration of furnace	Preventive	Supplementing

M7 is assigned to the energy flexibility measure “adjust process parameters” for which a decision must be made depending on the production situation. In the application, the process parameters should only be adjusted if a fault actually occurs and is therefore defined as a reactive measure.

5.3. Integration of Preventive and Reactive Measures in the Production Schedule

Figure 7 shows the result of the scheduling in the form of a risk-treated production plan for the allocation of orders on the workstations.

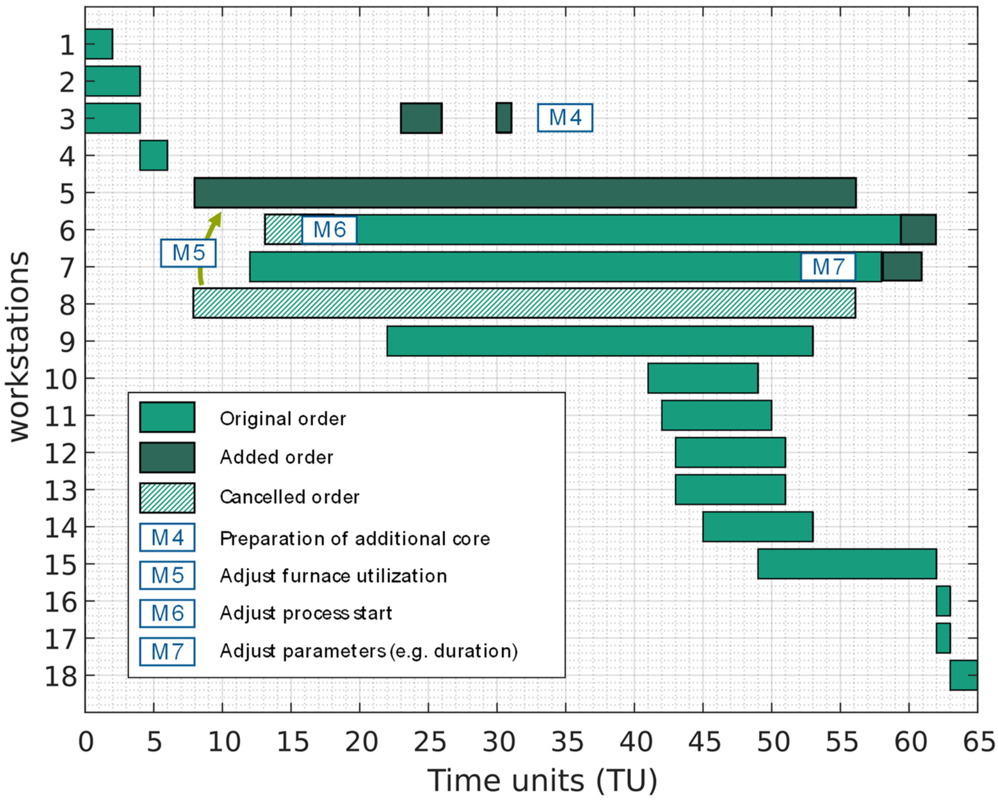

Figure 7. Risk-treated production schedule Gantt chart with marked reactive and preventive measures.

In order to counter R7, the failure of furnace 4, causing a delayed melting, the reactive measure M5 was implemented in the backup plan, which is only used when the risk arises. Measure M5, the utilization of another unoccupied furnace, can then be implemented by the switch from furnace 4 (workstation 8) to furnace 1 (workstation 5) if R7 occurs.

In addition, M6 and M7 were implemented in the plan as preventive measures, which means that they replace the original production plan.

1. M6 (adjustment of the process start) is implemented in the melting process on furnace 2 (workstation 6). This avoids possible warm-up times in furnace 2 due to a delayed casting time in the event of the occurrence of R7, as furnace 2 is used for the pre-melting for furnace 4.
2. M7 is implemented by the adjustment of temperature (decreased) and thus an extended duration of the melting process on furnace 3 (workstation 7). This is necessary in order to synchronize the termination of the melting processes on the furnaces for the casting.

As a reaction to a faulty core, which was identified as R4, the reactive measure M4, the preparation of an additional core, was scheduled in the backup plan to create a replacement core on workstation 3. Since the core creation can be carried out flexibly in a longer time interval, it was placed at times with lower reBAP prices.

Figure 8 shows the electrical load curve across the TU. The yellow dashed line shows the original load profile. The reBAP forecasts, which affect the timing of measures, are shown in red for orientation. The green load profile represents the risk-treated load. The short-term peaks for the creation of the additional core (M4), as well as the reduction of the load by adjusting parameters (M7), are the effects when the reactive measures are used. With the preventive measure M6, the load profile changes as an effect of the delayed start. Measure M5 with the changed utilization of the furnaces has no effect on the electrical load profile.

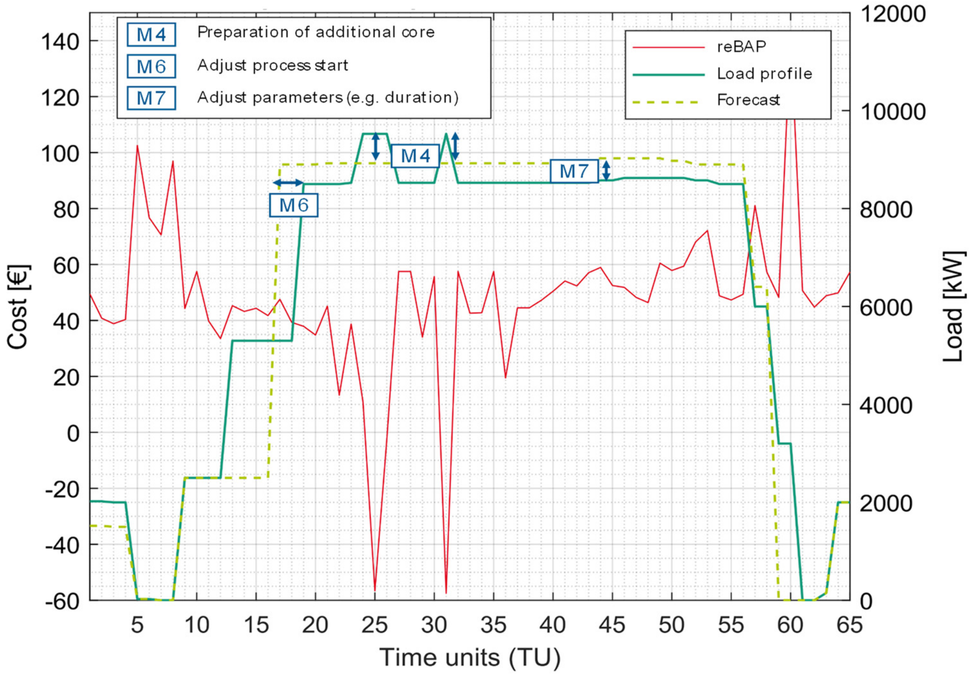

Figure 8. Load profile before (light green dashed line) and after the measure implementation (dark green line). For reference, the reBAP price is included.

5.4. Discussion

The application of the approach for the use case of a foundry resulted in a suitable risk treated energy-oriented production plan. The advantages over a situational decision in the event of faults as described in the state of the art lie in the consideration of the interactions of all known risks and measures in advance. In addition, preventive measures to reduce the probability of occurrence or the extent of damage are made possible.

The prerequisite for applicability is an acceptable level of effort in carrying out the risk treatment, especially since experts from different areas must be involved. By the introduction of this specific approach for the energy-oriented PPC, the effort required to select and adapt general approaches from the literature is reduced. Furthermore, the adaption to the energy-oriented PPC offers the possibility of automating the individual steps by the future development of software. The approach first requires a weighting of criteria for the selection of paths. Some manual steps are necessary here, which was supported by convenient graphical user interfaces for inputs. In addition, this weighting is only required occasionally, for example, if there have been changes in the production program or customer requirements. The classification of measures, which is also done manually, rarely needs to be adjusted after an initial assignment in most cases. The selection and integration of paths are then required more frequently, which is why these processes were more automated through the scheduling.

The approach was applied using the representative use case of a foundry. In further applications to use cases of other companies and sectors, the transferability of the approach should be tested and increased in order to take into account the inhomogeneity of the industrial sectors. In a long-term study, the effort of the application of the approach should be compared with the overall benefit through savings from avoided or reduced damage in the event of disruptions. This has remained open in the present use case due to a short period of application.

6. Conclusions and Outlook

As described in the introduction, industry is facing major challenges due to increasing energy prices. Energy flexibility measures can lead to cost reductions by adapting the load to the available energy. Faults in the often complex production system lead to high additional costs, so that risk treatment of production schedules is recommended.

This approach can offer significant added value with manageable effort through the structured and reliable consideration and treatment of risks. Applied in industrial practice, this can encourage the willingness of industry to be energy-flexible. Furthermore, risk treatment leads to the better handling of faults and lower subsequent costs for the company. Thus, planning security for the operation of the energy system with a high proportion of volatile feed-in increases.

To improve the approach in terms of ease of use and reliability, the following options have been identified:

- The approach assumes that the final selection of measures is monitored by a human decision-maker. It is also assumed that a manual definition of risk preferences and classification of measures is desired. As a result, the approach cannot be carried out fully automatically. This would require AHP, as well as the selection of the utility function to be replaced by data-based processes and machine learning.
- The optimization considered uses constraints to describe the restrictions of the production system. In the case of more complex production systems, it may be necessary to use meta-heuristics such as genetic algorithms in order to be able to map all boundary conditions and interactions.
- After the reactive measures have been carried out, the effects should be put in a feedback loop in order to take the findings into account when developing reactive measures in risk treatment. The approach should be expanded to include this functionality. The results of the feedback loop can, i.e., be used for the calculation of Bayesian networks described in Roth et al. [6].
- The input and output data of the approach can be adapted in such a way that interfaces to the common systems in industrial companies can be implemented more easily. For example, order data for scheduling can be transferred from enterprise resource planning systems and load profiles of workstations from the energy management system, and the risk-treated production plans can be visualized by the manufacturing execution system. Thereby, the effort required for the application can be further reduced.

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