# INTEGRATING MACHINE TOOL CONDITION MONITORING AND PRODUCTION SCHEDULING IN METAL FORMING

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## Abstract

*The state of the art literature of condition monitoring (CM) and predictive maintenance does not reflect adequate industry-oriented approaches, which address the integration of CM within production scheduling in production management systems. Addressing this problem, the present paper proposes a novel approach for a machine tool condition based production scheduling. This approach provides a categorization model for grouping different products by their unique demands and wear-effects concerning the machine tools' conditions, which is applied in the use-case of metal forming machine tools.*

**Keywords**: maintenance, condition monitoring, scheduling, categorization, condition based scheduling;

## 1. INTRODUCTION

Today's industry is facing economic pressure due to increasing customer demands concerning a product's uniqueness as the individualization of products can be seen as one of the current megatrends dominating various industries [1, 2]. However, this trend is not only limited to the consumer goods industry but is present along the whole supply chain [3]. Even low-tier industries like the metal forming industry notices an upsurge of product variants. Maintenance processes and strategies are not sufficiently prepared to meet this expectations and therefore need to be optimized [4]. Furthermore, customer demands such as on-time delivery and product quality need to be met as they are essential for not losing the customers [5]. This combination of a widening product portfolio and constant basic needs is leading to an increased complexity within the production planning and scheduling systems of companies in the production sector [6]. In the case of a flexible job shop, those two disciplines are in usual separately examined. A production plan is, generally speaking, a long-term plan that tries to fulfill certain time and capacity restrictions as well as to utilize some synergies within the overall production system. The outcome is in most cases a schedule that is fixed within a flexibility corridor (i.e. some flexibility is left over for short-term planning) [7]. Within production scheduling the flexibility corridor is used to utilize short term synergy effects such as set-up-optimization, or for catching up delays [cf. 8]. This can be achieved, for example, by changing the production sequences or reassigning production orders to production equipment. While doing so, the question arises whether a specific product can be produced on a certain production equipment or not. However, in the case of metal forming, this is limited by the prevailing production equipment's technological capabilities. These capabilities can be dimensional-restrictions, temperature-profiles or even the capability of producing within certain tolerance-levels. Moreover, the latter one depends on the current condition of the production equipment's components. If the aforementioned assumptions hold at a production system with varying products, the production sequences become condition dependent. In most cases it can be assumed that similar products (or similar components of a product) can be produced at the same equipment. However, it also has to be assumed that a product's (or a product's component's) unique features such as physical quality attributes differ compared to more or less related products (or components) within the product family. While some products (or components) have comparatively low-tolerance-levels, others are less sensitive. Furthermore, in the case of metal forming, the equipment's wear-rate depends on the product's material characteristics. As a result, the capability of producing a product depends on an equipment's condition, on the one hand, and the change of the equipment's condition depends on the products produced, on the other hand. This paper lays the foundation for such a condition dependent production sequencing by describing a categorization model for grouping different products by their unique demands and wear-effects concerning condition monitoring by applying an industrial use-case. Furthermore, a method for utilizing this categorization within the decision-process for production scheduling is presented.

The remainder of this paper is structured as follows: In section 2, an overview of current research in the fields of production scheduling and condition monitoring is given. In section 3, condition based scheduling is reviewed, discussed and the concrete research problem is derived which is answered in section 4 using a brief case-study. Therefore, a categorization method for integrating condition monitoring and scheduling is presented and then applied at a bottleneck machine of a high-grade steel plate manufacturer. Finally, the results are summarized and concluded in section 5.

## 2. LITERATURE REVIEW AND DISCUSSION

As the aim of this paper is the integration of condition monitoring and production scheduling, the literature review is subdivided into two short overviews about the topics respectively.

### 2.1 Production scheduling

Production planning and scheduling is a major discipline in practices as well as in research within industrial engineering and production management, as it can influence the effectiveness and efficiency of a whole production system. Scheduling aims at solving the job-shop problem, where *"… a set of jobs needs to be processed on a set of machines"* as Abedinnia et al. describe [9]. It can be dependent on several problem specific influence factors and is often short term oriented. For a long period of time production scheduling has been done manually with simple tools like spreadsheets or just pen and paper by applying sequencing methods such as First-In-First-Out, or Slack. However, due to an increase of customer demands accompanied by an increase in the production planning and scheduling complexity, manual scheduling becomes more and more challenging. To ensure profitability of a production system the use of computer-enabled optimization is often inevitable, as potential cost savings are enormous. [8, 10, 11]

Especially the area of operations research focuses on this topic, as for example the authors Zhang et al., who summarize a wide variety of different algorithms and mathematical models for solving the job-shop problem (JSP) [12]. The authors Abedinnia et al. conducted a tertiary study and analyzed current research streams within production scheduling. Their findings suggest that there is a research gap within the practical application of optimization in production scheduling [9]. In theory, scheduling problems are mathematically difficult combinatorial problems. One might think of the set-up optimization within the schedule of $n$ products. If the set-up matrix is considered as being not symmetrical there are $n!$ possible schedules. As the number of products within the schedule grows, the factorial $n!$ increases faster than all polynomial and exponential functions. Hence, scheduling problems are commonly known to be NP-hard, which means that they are not globally solvable to optimum in polynomial time. Therfore, mostly approximate algorithms such as genetic algorithms are mainly applied on the JSP [9, 11, 13]. Once the necessary data for the scheduling task is gathered, it is computational complex to solve towards optimum, but, as mentioned before, there do exist various methods to do so. Gathering the necessary data is crucial, as the solution will only be as good as the optimization model itself. Hence, in practice it is important to use high quality contemporary data, as scheduling is acknowledged being a reactive process, which is dependent on the current state of a system. Moreover, the authors Oulhadj et al. emphasize, that there is a lack of research within scheduling, which considers such contemporary shop floor data and refer to it as dynamic scheduling [14].

### 2.2 Condition monitoring

Condition monitoring is commonly known as a process where the status or *the condition* of a component is evaluated by a combination of sensor signals and evaluation software. As mentioned in the introduction, the conditions of a production equipment's component are not binary (sufficient or not sufficient). Conditions are regarded as being continuous; while they are good (no wear) at the beginning of a component's lifetime, they unceasingly decrease over time. At the end of a production equipment's lifetime, the condition is at a level where certain quality standards cannot be kept anymore and the equipment has to be maintained or even replaced. Condition monitoring is a topic which is not entirely new at all and its origins date back to the 1980s [15]. However, with the upraise of the topics smart factory, predictive and prescriptive maintenance, condition monitoring has become more popular lately [16–20]. Hence, research moved from manual analogous measurements towards digital on-line condition monitoring. Moreover, it is not limited to the most important parts of production equipment anymore as the prices of the used sensors are at a historical minimum nowadays and data warehousing of these gathered data in a significant scale is economically viable [21]. Additionally, there is a broad variety of sensors, which can be used for condition monitoring tasks. Vibrations (physical and / or acoustic) are fairly often used in condition monitoring, as a production equipment's wear is almost always accompanied by vibrations. Also temperature, electrical current and power consumptions as well as flow, humidity etc. can be appropriate signals used within a condition monitoring system. Besides the sensor signal itself, the data processing is a crucial step towards calculating an equipment's conditions. Mainly time-domain analyses and frequency-domain analyses are distinguished [19]. While the first one gives insight to tendencies (e.g. continuous temperature rise of a component over the past hours), the latter one is used for the detection of wear-effects of rotatory equipment (e.g. detection of a certain bearing default by its frequency signature) [19]. Condition monitoring systems are often not only limited to show the current condition of an equipment but are also used for statistical analysis and machine learning approaches to predict future conditions as, for example, shown in [22–24]. As mentioned before, vibration monitoring is a very common way of condition monitoring. The authors Delgado-Arredondo, for example, combine sound and vibration analysis to detect faults within an electrical motor [18]. It is also possible to monitor a machine tool's condition with vibration monitoring as Dimla et al. show in their paper, where they use a multi-layer perceptron in addition for classifying the tool states of a cutting tool [24]. While Agdham et al. also use vibration signals for estimating wear of a machine tool with high precision [25], Ruiz-Cárcel et al. even enhance their approach with process data for an improved condition monitoring [26]. Besides vibration analysis, a very popular form of condition monitoring is motor current signature analysis (MCSA), where the current of an electrical motor is measured, transformed into frequency domain and used to predict certain conditions such as stator faults, broken rotor bars, or even bearing defaults [27, 28]. In addition to this broad variety of use-cases, there also exist some literature reviews such as [19, 29].

It can be summarized that there has been extensive research concerning condition monitoring the past few years. However, according to the literature analyzed, research is often restricted to laboratory settings and the information about the condition is not integrated within the production planning systems most of the time.

## 3. CONDITION BASED SCHEDULING

As mentioned above, the current literature on production scheduling is lacking industrial use-cases which utilize computer-enabled optimizing. In addition, the practical use-cases that do exist, often fail on utilizing contemporary shop floor data (such as data originating from the condition monitoring systems).However, little literature exists which is integrating those two disciplines. [30]

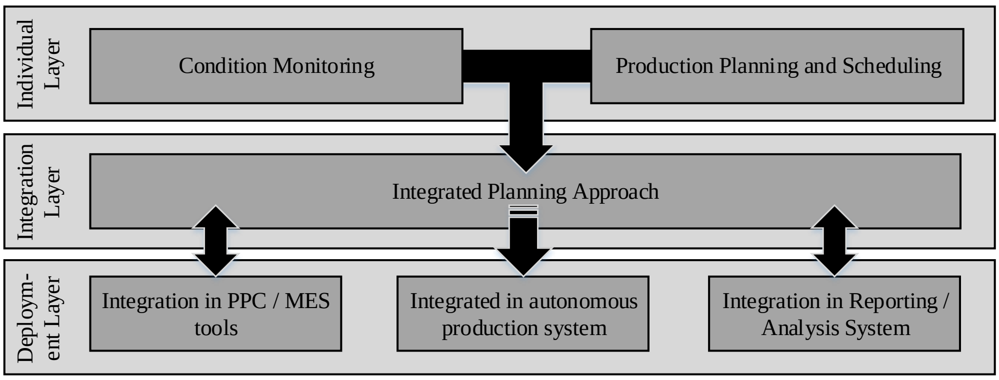


**Figure 1** –Integration and Deployment of CMS and PPC

In spite of the different research, the applicability of existing models often do not provide realistic results and are, consequently, not applied in the operational praxis. Especially the interaction between condition monitoring of machine components and tools, the scheduled production plan and current quality measurements of the products is not considered. Furthermore, many of those models lack a validation in industrial environments, as they are often based on idealized assumptions [30]. When focusing on the integration of condition monitoring systems (CMS) within a planning approach, theoretical methods are usually used to calculate maintenance schedules. In order to enable the deployment of such an approach, it is important for the responsible planners and domain experts to understand the algorithms' planning results. Therefore, the achieved results need to reflect the actual situation as close as possible. This can be achieved by using state of the art knowledge regarding predictive / prescriptive maintenance such as industrial data science methods. Based on multimodal maintenance records, shop floor and production planning data, prescriptive maintenance models are able to predict future events and prescribe optimal maintenance measures. In order to do so, predictive data analysis, machine learning, expert domain knowledge and semantic reasoning is considered together to improve decision-making by selecting suitable strategies and measures in regards of the whole maintenance management [31]. The deployment of an integrated planning approach can be, for example, a scheduling algorithm implemented in the company's IT landscape such as enterprise resource planning (ERP), production planning and control (PPC) or manufacturing execution systems (MES). Another possibility is the integration within an autonomous production system, or within appropriate reporting and analysis systems used as a decision support system for the planner (cf. Figure 1).

To enhance research in this area, it is the aim of this paper to provide a categorization method for enabling the integration of production scheduling and condition monitoring, which is shown as "Integration Layer" in Figure 1.

### 3.1 Novel perspective on condition based scheduling

As briefly described in the introduction, the capability of a production equipment to produce a certain product can be dependent on its condition. Especially in industries like the metal forming industry, correlations between a product's material characteristics and the machine tool's condition often exist [20]. While some products (or components of a product) need to fulfill narrow tolerance-levels, others are less critical. Hence, for the production of the latter ones the equipment's condition does not need to be at its best level. However, when producing a critical product or component, a good condition is essential. One might imagine the milling process of a product's component as a thought experiment. If a certain component has to be assembled (e.g. a press fit) in a later production step, not exceeding the defined tolerances during milling is crucial for the product's mountability. For maintaining certain tolerance levels, the machine tool (milling head) has to be at a good condition. If the same production equipment is also used to manufacture other, less critical components, it seems obvious to adapt the sequence (manufacture the critical product first and others later). However, the correlation between an equipment's condition and product quality is bidirectional, as varying material properties (hardness, ductility, etc.) cause distinct wear-effects at the production equipment and therefore lead to diverse changes within the equipment's condition. In addition to milling, other processes like heat treatment (temperature profile dependency), pickling and etching (acid condition dependency), or other cutting processes like drilling, metal shears cutting and turning are affected by an equipment's condition dependent sequencing.

Summarizing, it can be concluded that there is a bidirectional correlation between product quality and an equipment's condition. Hence, this correlation can be utilized within production sequencing in order to optimize the effectiveness of a production system.

## 4. INDUSTRIAL USE-CASE AND SOLUTION CONCEPT

Within existing research, a concept for a tool condition monitoring based production planning was proposed [cf. 30]. Based on this concept, the current chapter presents a method for a condition dependent production categorization which is applied at an industrial use-case in the metal forming industry as well as its utilization as a decision-making process within production scheduling.

A crucial step towards integrating machine tool condition monitoring and production scheduling is an appropriate categorization method for describing their correlations. As discussed before, the correlations are bidirectional: (i) The production scenario influences the production equipment's wear over time (especially its machine tool's wear) and (ii) using a particular equipment for manufacturing certain products relies on the equipment's capabilities which are affected by its current conditions. As a condition can be multidimensional and difficult to imagine, for its description the term "healthpoints" ($HP$) is introduced. The term is derived from gamification, as it suggests to use *"...game design elements in non-game contexts to motivate and increase user activity..."* as well as their acceptance [32]. A high HP indicates a good condition of a machine's equipment and a low HP symbolizes a worn equipment. Since the conditions can be intuitively described, it is possible to categorize a set of products (produced at the same equipment) according to their condition dependencies and wear-effects. This is done reciprocally, as the underlying correlations between product quality and an equipment's condition are bidirectional. Therefore, the minimal condition requirements a particular product has on its production equipment are referred to as minimum HP ($HP_{min}$). If the current state of an equipment is beneath this minimum level, the respective product cannot be manufactured. If manufacturing is possible, each product produced at the production equipment reduces its HP, which is modelled by a HP difference ($\Delta HP$). The latter one can be condition dependent too, as for example, the wear-rate of an equipment itself [33]. This is the case if an increase of the wear leads to a progressive (more wear implies a higher wear-rate) or degressive (more wear implies a smaller wear-rate) change of the wear-rate.

| product ID | $HP_{min}$ | $\Delta HP$ |
|---|---|---|

**Table 1** – condition dependent product categorization

This method for a condition dependent product categorization was applied at an industrial use-case of a high-grade steel plate manufacturer. The identified bottleneck of the manufacturer's value stream is a tall industrial shears, which is characterized by a high number of product variants. About 18,000 variants were produced during the past three years. The respective product variants differ in their properties such as in their dimensions and material attributes. Furthermore, there is a narrow correlation between the products' cut-qualities and the plate shear's blade-condition, which was already identified by the operators. In order to fulfil the quality standards, they had developed a subjective product classification. As there were no electronic measurements of the blade-conditions in place, the operators had to estimate the conditions themselves manually, which implied fault-prone, varying and subjective estimations.

To enhance the production planning at the bottleneck machine and utilize the condition dependency within production scheduling, a condition monitoring system was introduced at first. Since it has proven to be viable within literature, a vibration sensor was chosen initially for on-line data generation during the ongoing production process. The sensor was directly attached onto the shears' blade and generated a point of measurement every 125 milliseconds. As the movement of the blade is comparatively slow, the frame rate was sufficient. The raw sensor data was analysed within time domain and statistical values (mean and maximum oscillations) were derived from the raw signal representing the intensity of each distinctive cut. If there is much wear, the oscillations are increased compared to an intermediate cut. For modelling this behaviour oscillation data was combined with a cut-counter, together representing the wear-rate. After some observations the maximum and minimum condition levels could be derived in order to normalize the wear-rate and fitting it into the proposed HP-scale, enabling a sufficient an understandable visualization of the blade-condition. Finally, the condition can be modelled as shown in Figure 2. At the beginning (new blade) the HP are at their maximum value and each cut decreases the HP dependent on the oscillation level. While some cuts (with a high oscillation index) lead to an increased wear-rate, other cuts do not have such dramatic effects.

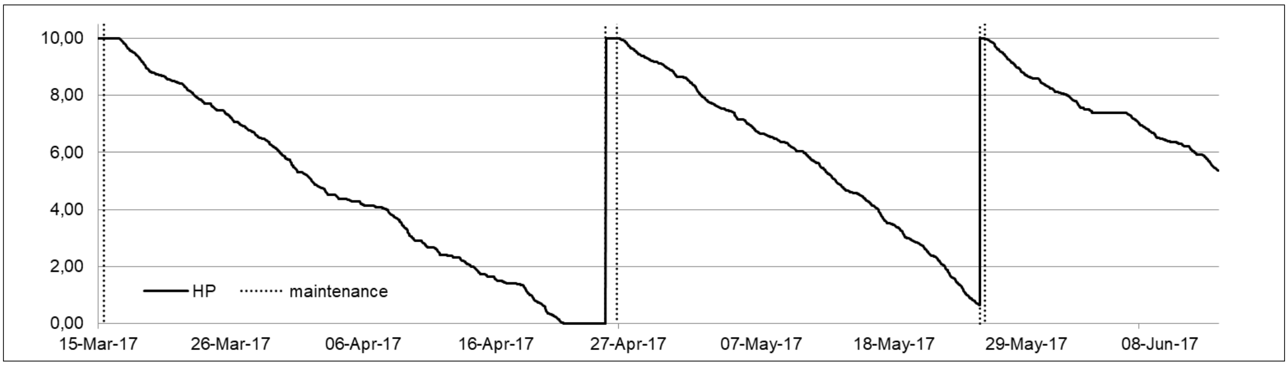


**Figure 2** – CM of the blade condition

For validating the results of the CM system, the sensor-based condition calculations were compared to the subjective condition estimations of the machine's operators. Validations' results show that the combination of the vibration sensor with a cut-counter for calculating the blades conditions is sufficient.

As soon as an understanding concerning the term HP was developed by the operators of the bottleneck machine, it also became possible to do a product classification of the products within the portfolio of the high-grade steel plate manufacturer. With the help of process experts, the minimum HP needed for producing a distinctive product were derived. The products were aggregated to more than 470 distinctive product groups and then those product groups were classified according to Table 1. It was concluded that the $HP_{min}$ mainly depends on the product's material properties (e.g. hardness and ductility). However, as described above, the correlation between product-quality and an equipment's condition is bidirectional. In order to model this bidirectionality, each product category was assigned with its individual wear-effects $\Delta HP$, which were derived from a statistical aggregation of the product groups' wear-effects shown within the CM system (cf. Figure 2). Finally, the following dependency could be derived:

$$\Delta HP = f(T, C) \tag{1}$$

Thereby, the functional interrelation between the wear-effect and the product's thickness (T) as well as its category (C, which inherently contains the material properties) is described. It is quite intuitive that a thicker as well as a more ductile product leads to increased wear-effects. However, a dependency of the current condition (HP) and the wear-effect ($\Delta HP$), as briefly described above, could not be observed within the use-case. This eased the product classification as it became linear. Furthermore, it is important to note that $\Delta HP$ describes the wear-effect per cut. So if there is more than one cut within a production order (e.g. n cuts), the total HP decrease is also cut-quantity-dependent ($\Delta HP_{total} = n \cdot \Delta HP$). With the classification of the product's minimal HP and their unique wear effects, the condition dependent product categorization was finished and a table, based on the structure shown in Table 1, was mapped with the necessary information.

Subsequently, this condition dependent product categorization can be used within production planning and scheduling in order to optimize the decision-making process concerning product sequencing. A method to do so is shown in Figure 3, which is, subdivided into the condition monitoring system (CMS) shown on the left hand side and the production schedule shown at the right hand side of the Figure. While the CMS (based on a vibration sensor as described above) measures the current condition (HP) of the equipment at time i, the production schedule shows that product x is the next production order. Hence, product x can be described by its condition dependent product categorization (cf. Table 1).

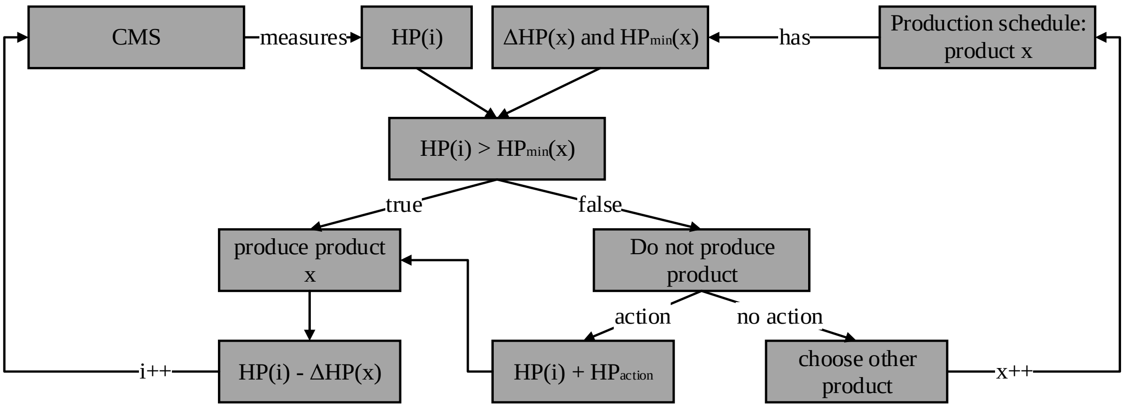


**Figure 3** – Condition dependent scheduling process

As shown in Figure 3, a product x has a product dependent minimum condition $HP_{min}(x)$ and a product specific wear-effect $\Delta HP(x)$. In order to produce product x, the current condition must be greater than the minimum condition needed. If this prerequisite is true, product x can be produced which leads to a reduction of the equipment's HP by $\Delta HP$. However, if the prerequisite cannot be met, an immediate production of product x is not possible, but there are two new possibilities. On the one hand, an action (e.g. maintenance, setup etc.) can be carried out in order to increase the equipment's HP by an action dependent amount $HP_{action}$ and hence enable production of product x. On the other hand, the decision-makers may modify the schedule and change the product in order to avoid time-consuming actions like maintenance. A change of the production sequences influences economic indicators and may affect neighboring production steps. Which one of the two possibilities is carried out depends on other inherent conditions of the production system such as work-load, capacities or even delivery dates. For a proper consideration of these multiple criteria, a fitness function has to be developed in order to support the decision maker.

In a nutshell, the method shown in Figure 3 provides a decision-making support system within short term scheduling of the bottleneck machine by advising whether the production of a particular product is possible or not. This method for condition dependent scheduling is a further step towards enabling an autonomous production scheduling as it represents the decision module of such a system.

## 5. CONCLUSION

This paper introduced a categorization method for integrating machine tool condition monitoring and production scheduling and applied this method at an industrial use-case of a steel plate manufacturer. Thereby, the identified research gap of utilizing contemporary data within production scheduling was addressed.

It is shown that there is a bidirectional dependency between product-quality and an equipment's conditions. This is, especially true in the case of metal forming where the material properties of tools and products have narrow correlations. Although it is assumed that these correlations are not only existing within metal forming the findings of the present paper are limited to the metal forming industry as there is no empirical evidence in other areas. Hence, further application-oriented research is needed within other industrial areas.

The paper further proposes a method for utilizing correlations between product-quality and an equipment's condition for the decision-making process within product scheduling. The proposed method for a condition dependent scheduling has general applicability and can be used wherever these aforementioned correlations do exist and, consequently, a condition dependent product categorization is possible. The method shows a decision-making process, which supports process owners in deciding whether producing a particular product is possible, or not.

However, it does not affect the whole production schedule as it is limited to a single decision. Consequently, as a next step, the method has to be integrated within a scheduling algorithm that considers planning aspects affecting the whole value stream such as delivery dates, productivity, stock levels or overall production costs. Therefore, the method also represents a first step towards an application-oriented autonomous production planning system but further research needs to be done in order to integrate the proposed method for condition dependent product scheduling. Finally, the impact of the different deployment strategies and especially its economic benefits needs to be validated in industrial use-cases.

## 6. ACKNOWLEDGEMENT

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