# Production Disturbances Handling: Where Are We and Where Are We Heading?

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## Abstract

Half of manufacturing companies' production capacity is estimated to be compromised due to disturbances. With the upcoming Industry 4.0, this problem is expected to be minimized through technological solutions. The aim of this article is to propose alternatives to handle production disturbances by means of technological support, to minimize their occurrence and impacts. To this purpose, we conducted a literature review and a series of interviews with five companies. We distinguish six stages for handling production disturbances: detection, diagnosis, mitigation/correction, root cause analysis, prevention, and prediction. Our results indicate that all these stages are expected to benefit from Industry 4.0 technologies significantly. Furthermore, our results point out that practitioners perceive the stages of prevention and prediction with the highest potential for improvement. However, focus on the diagnosis and root cause analysis stages is also necessary since those stages are coupled to the prevention and prediction. The contributions of this article are twofold. Firstly, it provides a holistic view of the stages and technologies to handle production disturbances in Industry 4.0, from which practitioners can extract directions for implementation. Secondly, the paper provides focus for further research in the field of disturbance management with the identification of the current challenges.

## Keywords
Production disturbances, Industry 4.0

## 1. Introduction

With the advent of Industry 4.0, production systems are envisioned with nearly zero disturbances (Eleftheriadis & Myklebust, 2016; May & Kiritsis, 2019). Different technologies support the Industry 4.0 era to become a reality. Among the leading technologies are smart sensors, smart devices, big data, data analytics, internet of things (IoT), cloud computing, additive manufacturing, augmented and virtual reality (Posada et al., 2015; The Boston Consulting Group (BCG), 2015). These technologies will provide the means for developing self-adaptable, self-optimized, and self-maintained production systems (Lee et al., 2015).
However, there is a long way to go until we reach a disturbance-free system. The overall equipment effectiveness (OEE) of manufacturing companies is only around 50% (Ylipää et al., 2017). In other words, about half of the manufacturing capacity is not utilized, primarily because of disturbances. Therefore, the reduction of production disturbances causes a significant impact on financial performance. Furthermore, it also affects the environmental and social aspects of sustainability. It is possible to achieve more efficient resource utilization in a production system with fewer disturbances, as well as safer working conditions.
But what is a production disturbance? There are different definitions in the literature, ranging from "unexpected and unplanned events" to "all events that affect quality, operational performance, security or working conditions" (Stricker & Lanza, 2014; Bokrantz et al., 2016; Kaya & Bergsjö, 2018). In this paper, we consider that a production disturbance is "an undesired and unplanned event that causes the production system not to perform as planned".

To achieve the vision of Industry 4.0 of a system with the minimized occurrence of disturbances, it is both important to detail how disturbances are expected to be handled in the future and how practitioners are currently dealing with them. The aim of this article is to propose an approach to handling production disturbances by means of technological support. Two research questions led our investigation:
RQ1) How are production disturbances expected to be handled in the context of Industry 4.0?
RQ2) How do manufacturing companies perceive their performance towards handling production disturbances?
In order to answer RQ1, we conducted a literature review, whereas a series of interviews were conducted with five Swedish companies to answer RQ2.

## 2. Methods

The methods used in this work can be divided into two steps: a literature review and a series of interviews. For the literature review, we collected articles through a search on the academic database Scopus using the keywords ("industry 4.0" OR "digital industry" OR "smart factory") AND (disturbance OR failure OR downtime OR loss OR fault OR anomaly OR incident) AND ("production system") applied to the titles, abstracts, and keywords. We excluded papers not written in English, and the ones not related to production systems nor production disturbances. In total, 101 papers were selected and their content analyzed. The papers were classified into six different categories regarding detection, mitigation/correction, diagnosis, root cause analysis, prevention, and prediction. It was our aim to answer RQ1 from the literature review, since it would allow us to examine how production disturbances are expected to be handled in Industry 4.0 and the supporting technologies for each stage according to the academic publications.
In the second step, we performed a multiple-case study with five Swedish companies. To select the companies, we looked for those that monitor the production disturbances. As our potential interviewees, we looked for people working directly with handling production disturbances in those companies.
Semi-structured interviews with open-ended protocols were conducted individually with the five companies, in two rounds. The respondents belong to different departments in the companies (production, maintenance, quality, and engineering) and have different positions (line leaders, production managers, coordinators, and engineers). At least one person representing the production department (usually the production manager) and one person representing the maintenance department were interviewed in each company. A total of 14 people were interviewed.
At least two of the authors of this paper participated in each of the interviews. After the second round of interviews, the respondents were asked to self-assess their company's performance in the different stages of handling production disturbances, from one (being the poorest performance) to five (high performance). In this stage, we aimed to answer RQ2, since the interviews provided data regarding the perceived performance in the different stages of handling production disturbances.
The results of this paper were presented to the companies after compilation and analysis. The objective of this presentation was to verify the agreement from the companies, regarding the results.

## 3. Results

### 3.1 The stages for handling production disturbances in Industry 4.0

Different stages for managing production disturbances are proposed in the literature. Ylipää (2000) considers the actions taken for correction, prevention, and elimination of disturbances. Fleischmann et al. (2016) present four stages: detection, diagnosis, comparison, and action. Reis & Gins (2017) consider three stages, being detection, prognosis, and diagnosis. In contrast, May & Kiritsis (2019) present a framework based on prediction, detection, management, prevention, and repair.
In this paper, we distinguish six stages complementing those already proposed in the literature: detection, diagnosis, mitigation/correction, root cause analysis, prevention, and prediction. Figure 1 shows these different stages and how they are related to each other. Detection, diagnosis, and mitigation/correction are stages that refer to *fighting* the disturbance and its impacts. They take place when a disturbance occurs and they are necessary so the system returns to its normal condition. Root cause analysis, prevention, and prediction relate to *avoiding* the disturbance and its impacts. These stages ensure that the disturbance do not reoccur, or, in case of an unavoidable disturbance, that its impacts are minimized.

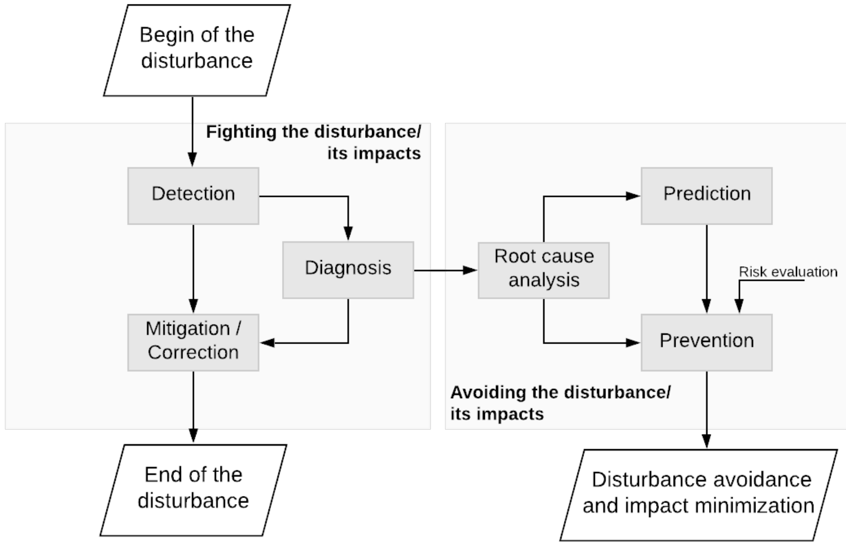


Figure 1. Stages of handling the production disturbances

We analyzed and classified the collected articles into the six different stages of handling disturbances. Figure 2 presents the total distribution of the articles throughout the years of publication. The year 2019 was not finished when the papers were selected and our analysis was performed. Figure 3 shows the distribution of the articles classified in each of the different stages. Some articles were classified simultaneously in two or more stages. Articles about detection, mitigation/correction and prediction occurred more often than articles about prevention, root cause analysis and diagnosis.

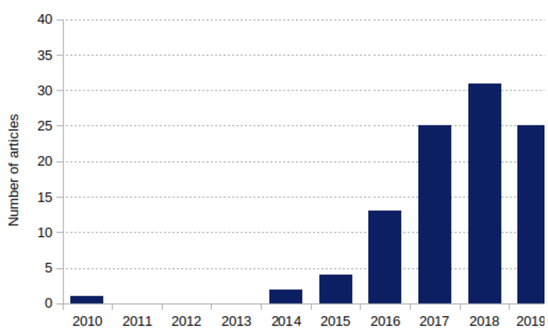


Figure 2. Distribution of the papers along the years

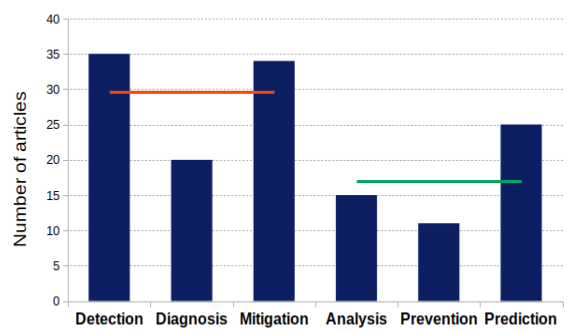


Figure 3. Classification of the papers in the different stages

In the following paragraphs we describe the definition of the different stages, the current practices observed in the multi-case study, the vision for Industry 4.0, and the supporting technologies according to the examined articles. These findings are summarized in Table 1.

Table 1. Summary of the different stages of handling production disturbances

| | | What it is | General current practices observed in the companies | Vision I40 according to the reviewed articles | Main supporting technologies according to the reviewed articles |
|---|---|---|---|---|---|
| **Fighting the disturbance / its impacts** | **Detection** | The recognition of the disturbance | Detection is supported by alarms and based on human senses | Fast, precise, automatic detection based on different types of process data | Smart sensors, IoT, Big Data |
| | **Diagnosis** | The identification of the immediate cause of the disturbance | Diagnosis is based on the operator experience and knowledge | Automatic complex diagnosis considering the correlation of different types of data | Smart sensors, IoT, Big Data, data analytics |
| | **Mitigation / correction** | The necessary actions to fix the disturbance and/or minimize its impacts | Mitigation is based on the operator experience and knowledge. In some cases, there are written procedures to be followed | Assisted mitigation, fast communication, order supplementation | Smart devices, IoT, digital twin, additive manufacturing |
| **Avoiding the disturbance / its impacts** | **Root cause analysis** | The identification of the root causes of the disturbance | Analysis is based on the team experience and knowledge. Simple methods are used such as 5 whys and fish-bone diagram | Data-driven and collaborative analysis | Cloud, data analytics |
| | **Prevention** | The necessary actions to avoid the disturbance and/or to minimize its impacts | Prevention is based on risk evaluation, and analysis of the previous disturbances; not performed to a large extent | Data-driven and collaborative prevention, with simulated scenarios | Cloud, data analytics, simulation |
| | **Prediction** | The indication of the probability that a disturbance occurs in the future | Prediction is based on experience and knowledge; not performed to a great extent | System self-prediction leading to self-adaptable process | Smart sensors, data analytics, Big Data, digital twin |

### 3.1.1. Detection

Detection is the recognition of the presence of a disturbance. Detection is usually an inference done by the comparison between the current and the normal state (Reis & Gins, 2017). This is possible by monitoring production variables. After recognizing the disturbance, its immediate cause can be identified, and the necessary actions can be taken to reestablish normal conditions. In other words, the detection stage leads to both the mitigation/correction and the diagnosis stages (see Figure 1).
In the companies studied in this work, the operators usually detect the disturbances by themselves. In some machines, some sensors and alarms might indicate a problem, such as the production's interruption. The operators also utilize their experience and senses to detect the disturbances. For example, this can happen when they recognize an unfamiliar sound or an unfamiliar smell in the production system.
In the context of Industry 4.0, detection is expected to be fast and precise. Moreover, detection should be automatic, meaning the minimization of human supervision. In this scenario, smart sensors technologies connected to products, machines, and people through the internet of things (IoT) play an essential support role (Wang et al., 2018). The utilization of 3D scanning, image processing, and RFID technologies for quality control are examples of how detection can be supported by smart sensors (Zhong et al., 2015; Yetis & Karakose, 2018; May & Kiritsis, 2019). Furthermore, the use of a complex and diverse set of data, the big data, offers a new approach to the detection stage (Gavrilovska et al. 2017).

### 3.1.2. Diagnosis

Diagnosis is the identification of the immediate cause of a disturbance. While detection can be quite fast (in the order of seconds or minutes), diagnosis can take longer, ranging from minutes to hours or even days (Reis & Gins, 2017; Schneider et al., 2019). The diagnosis stage takes place after the detection stage and leads to assertive mitigation and root cause analysis (Figure 1). However, diagnosis can be bypassed if the disturbance gets fixed but the immediate cause remains unknown.

In the companies we studied, the operators use their experience and knowledge to identify the disturbances' immediate causes. When the operator alone cannot make the diagnosis, it is common that other departments get involved, such as maintenance and quality. Once the immediate cause is identified, the disturbance is classified in a system for the record. However, mistakes in the classification of disturbances are quite common. Additionally, not much technology is used to support the diagnosis stage.

Diagnosis might not be a simple task because it requires an understanding of the correlation and the causality of the different production variables. In Industry 4.0, a complex and precise type of diagnosis is expected to be automatically performed, with diverse sets of data. As in the case of mitigation/correction, smart sensors, big data and IoT are also supporting technologies. They will create the means for diversification of data (Fleischmann et al., 2016; Lee, Jin, & Bagheri, 2017; Morales et al., 2019). Nonetheless, there is one technology that differs from the mitigation/correction stage and plays a central role in diagnosis; that is data analytics (Reis & Gins, 2017). Through data analytics, it will be possible to learn new patterns of correlation and causality based both on past data and expert knowledge leading to the identification of the immediate causes of disturbance.

### 3.1.3. Mitigation/Correction

The mitigation/correction stage refers to the actions that need to be taken to minimize the impacts of the disturbance. It also includes the necessary actions for repair, correction, and reestablishment of normal conditions (Eleftheriadis & Myklebust, 2016; May & Kiritsis, 2019). Once a disturbance is detected and diagnosed, proper and specific actions should be performed with the minimum time, effort, and impact to the production line (May & Kiritsis, 2019).

In the companies studied in this work, the mitigation starts with the operator. Depending on the type of disturbance, there are written instructions on how the operator should proceed. If the disturbance is related to another department, such as maintenance, the operator might request additional support. To reduce the disturbance's impacts, it is possible, for instance, to reschedule the production by utilizing a different production line.

Mitigation/correction is expected to be fast, assisted, and complemented in the context of Industry 4.0, where different technologies are expected to support the mitigation/correction stage. Smart devices provide the means for fast notification of the involved people, and support for troubleshooting takes place through the connectivity offered by IoT technologies (Wieland et al., 2010; Kong et al., 2018). Augmented reality supports expert assessment and assistance by remote access to the factory (Aschenbrenner et al., 2016; Mourtzis et al., 2017). Simultaneous simulation in digital twin models assists decision making regarding the rescheduling of the production (Weyer et al., 2016). Furthermore, in cases where an urgent order must be fulfilled to the customer, additive manufacturing can be applied as a solution (Hochreiner & Waibel, 2016).

### 3.1.4. Root cause analysis

The objective of the root cause analysis stage is to find out the root causes of the disturbance. The root cause is the one that, once eradicated, hinders the recurrence of the disturbance (Mourtzis et al., 2016). To identify the root cause, it is necessary to know the immediate cause of the disturbance. Hence, there is a link between the diagnosis and the root cause analysis stages (see Figure 1). Additionally, the root cause analysis stage is also related to both the prediction and prevention stages. The correct root cause analysis of a disturbance leads to assertive actions for prevention and provides the required knowledge for prediction.

Root cause analysis requires a deeper understanding of how the different variables in the process affect each other and how they are related to managerial practices. These variables regard the production department and correlated departments such as maintenance, procurement, and quality. There are different methods to identify the root cause of a disturbance, such as a fish-bone diagram, five whys, and fault tree analysis (Bokrantz et al., 2016). The root cause analysis demands an in-depth investigation, usually with the participation of a cross-functional team.

Among the investigated companies, the root cause analysis stage is performed to a limited amount of disturbances, depending mostly on their impacts on production output. In most of these companies, a cross-functional team is formed in order to investigate the root cause of a specific disturbance when necessary. The analysis is based on the experience and knowledge of the people involved, using methods such as five whys and fish-bone diagram. Lack of documentation is a common issue among the companies, especially because they mostly use "paper and pen" in this type of investigation.
The root cause analysis stage is expected to be a data-driven and collaborative stage in the Industry 4.0 context. Cloud technology offers a platform for knowledge sharing and discussion among different production sites (Mourtzis & Vlachou, 2018). Furthermore, it offers applications to the management of documentation, which can guarantee adequate registration, classification, and follow-up of the disturbance (Bauer et al., 2014; Scheuermann et al., 2017). Accordingly, the cloud technology allows data analytics to extract knowledge from past events and their root cause analysis (Mourtzis et al., 2016, Brundage et al., 2017), leading to effective prevention and prediction stages (Figure 1).

### 3.1.5. Prevention

Prevention is the stage in which actions are taken to avoid a disturbance to occur (or reoccur) and to minimize its impacts in the case of an unavoidable disturbance. There are three different types of prevention: through root cause analysis (see the root cause analysis stage), through prediction (see prediction stage), and through risk evaluation (see Figure 1). Methods for risk evaluation include failure mode and effect analysis (FMEA), hazard and operability study (HAZOP), and what-if analysis (Bokrantz et al., 2016). The study of different probable scenarios leads to the necessary countermeasures to avoid the disturbance, such as preventive maintenance, inspection, the establishment of new procedures, and redundancy of critical machines.
Not all companies investigated in this study perform risk evaluation in their plants regarding production disturbances. In some of the companies, actions for prevention are taken after the root cause analysis of a past disturbance. Except for one company, maintenance is mainly reactive, and a fire-fight culture is predominant. Technological support was not identified in the studied companies.
The prevention stage, similar to the root cause analysis stage, is expected to be a data-driven and collaborative process in the context of Industry 4.0. In this case, cloud technologies also offer a possibility for sharing knowledge among different factories, providing a field for disseminating information about the disturbances. One nuclear technology regarding the prevention stage is simulation. Simulation techniques can be applied in order to verify possible disturbance scenarios, their impacts, and the effects of countermeasures (May & Kiritsis, 2019). Furthermore, through simulation it is also possible to evaluate the robustness and resilience of a production system (Himmiche et al., 2018; Müller et al., 2018), and to improve preventive maintenance and inspection planning (Upasani et al., 2017). Virtual reality and digital twins also provide the means for simultaneous what-if analysis (Lomte et al., 2018).

### 3.1.6. Prediction

Prediction is the indication of a likely disturbance in the future. Prediction can lead to prevention insofar as counteractions can be taken in order to hinder the disturbance (May & Kiritsis, 2019). If the disturbance is unavoidable, prediction can lead to the minimization of the impacts since the disturbance can be known in advance.
In the context of Industry 4.0, production systems are expected to self-predict the remaining useful life of the machines through degradation and health monitoring of the individual machines and prediction of the behavior of the entire production line. Predictive maintenance (Rivas et al., 2019), line bottleneck prediction (Huang et al., 2019), and line and machine performance prediction (Cisotto & Herzallah, 2019) are different possibilities to perform this stage.
Among all the different stages, prediction is the one with the most limited practice among the five companies investigated: there was a predictive stage in only one of them. In this company, at the end of each day, a scheduled meeting takes place in order to discuss the potential disturbances in the following day. This is based on the experience and knowledge of the participants from the different departments, such as production, maintenance and quality, with no technological support.
Smart sensors, big data, data analytics, and twin models are central technologies for continuously monitoring the system, for recognizing patterns, and for calculating the remaining life of the machines through health monitoring (Lee et al., 2015; Chiu et al., 2017; Peres et al., 2017). In Industry 4.0, not only production data is considered to be

critical for prediction, but also a combination of logistics, maintenance, inventory, and quality data (Reis & Gins, 2017).

### 3.2 Companies' self-assessment

Table 2 presents a brief description of the companies investigated in this paper regarding the type of industry, number of employees, and our observation about the different stages of handling production disturbances. Except for company A – which operates in a batch process –, all companies have a job shop type of production. The number of employees in the plants investigated ranged from 25 to 900 employees.

Table 2. Description of companies

| Company | Industry | Type of process | N. of employees in the plant | Current practices in the different stages |
|---|---|---|---|---|
| **A** | Cider and beer brewery | Process batch-based | 460 | Utilization of sensors and alarms in the machines for detection. Diagnosis is based on operators' and technicians' knowledge and experience, and there is a high level of wrong classification of the disturbances. Mitigation is based on written procedures, when the operator is not able to handle the disturbance autonomously, other departments are involved. For specific disturbances, a cross-functional investigation team is created, and the analysis is based on historical data. To some extent, preventive maintenance and risk evaluation are performed. On a daily basis, based on the knowledge and experience of the operators, potential disturbances for the coming days are discussed. |
| **B** | Damper manufacturer focused on the automotive industry | Job shop production | 166 | Utilization of sensors and alarms in the machines for detection. Diagnosis is based on operators' and technicians' knowledge and experience. For mitigation, there written instructions for the operator and checklists. When the operator is not able to handle the disturbance autonomously, other departments are involved. For specific disturbances, a cross-functional investigation team is created, and the analysis is based on "paper and pen". Preventive maintenance is performed to some extent. Prediction is not performed to a great extent. |
| **C** | Steel bars manufacturer for building structures | Job shop production | 25 | Utilization of sensors and alarms in the machines for detection. Diagnosis is based on operators' and technicians' knowledge and experience. Do not experience problems with wrong or lack of classification. For mitigation, when the operator is not able to handle the disturbance autonomously, the supervisor is called. Analysis is based on "paper and pen", and on operators' knowledge and experience. Prediction and prevention are not performed to a great extent. |
| **D** | Tool steel manufacturer | Job shop production | 900 | Utilization of sensors and alarms in the machines for detection. Diagnosis is based on operators' and technicians' knowledge and experience.Problems with wrong and lack of classification of the disturbances are experienced. For mitigation, there are written instructions and checklists. For specific disturbances, a cross-functional investigation team is created, analysis being based on historical data. Preventive maintenance is performed to some extent. Prediction is not performed to a great extent. |
| **E** | Polymer component manufacturer focused on the automotive industry | Job shop production | 114 | Utilization of sensors and alarms in the machines for detection. In some cases, there is late detection in the process regarding quality issues. This leads to late diagnosis and mitigation. Diagnosis is based on operators' and technicians' knowledge and experience, and there is a high level of no classification of the disturbances. For mitigation, when the operator is not able to handle the disturbance individually, other departments are involved. For specific disturbances, a cross-functional investigation team is created, and the analysis is based on "paper and pen". Prevention and prediction are not performed to a great extent. |

Figure 4 presents the results of the self-assessment of each of the companies (a-e) and the average result (f). The scale ranges from 1 to 5, and it represents their perception from low to high performance, respectively. The red and green lines are the averages for the "fighting the disturbance" and "avoiding the disturbance" phases, respectively.

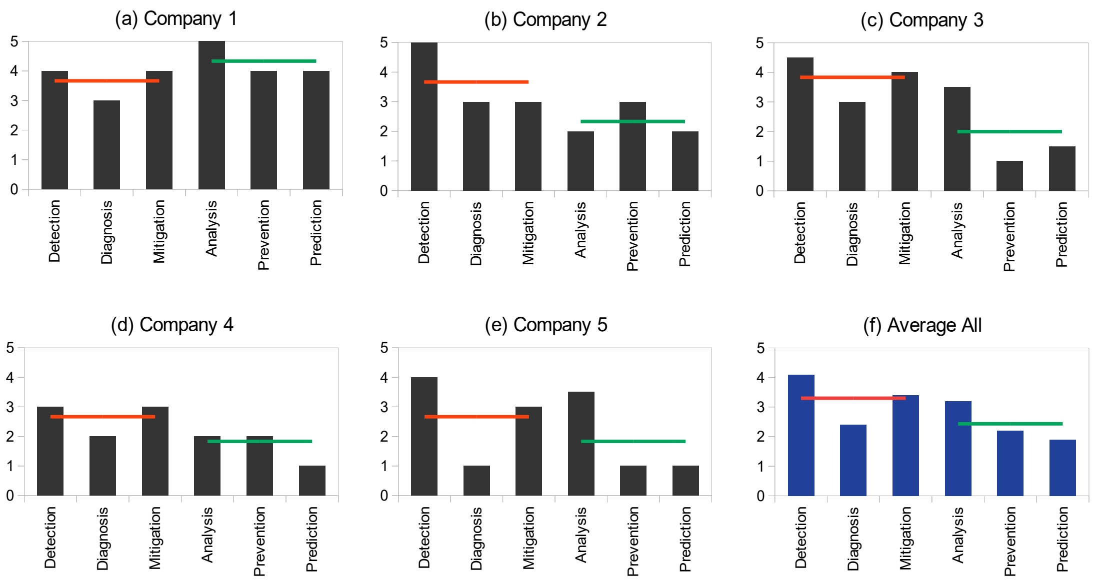


Figure 4. Self-assessment for each company (a-e) and average (f)

The phase of fighting the disturbance was better ranked than the phase of avoiding the disturbance, on average. Individually, the stages of detection, mitigation/correction, and root cause analysis were better ranked, whereas the stages of prediction, prevention and diagnosis were lower-ranked by the companies. Detection was considered as the stage with the highest performance, and prediction as the stage with the lowest performance, on average.

## 4. Discussion

The literature review indicates that all the stages presented in this work can benefit from the support of Industry 4.0 technologies. The main supporting technologies to handle disturbances identified in this paper are smart sensors, smart devices, the cloud, IoT, big data, data analytics, simulation, digital twin, and additive manufacturing. The future of handling production disturbances is expected to be a faster, precise, automated, assisted, and collaborative environment.

Regarding the current situation, the investigated companies perceive a bigger room for improvement regarding the phase of avoiding the disturbance compared to fighting the disturbance (see Figure 1). This finding is in line with the low OEE values that Ylipää et al. present (Ylipää et al., 2017), reflecting the difficulty of the companies in preventing disturbances to happen. Regarding the literature (see Figure 3), there are relatively more papers focusing on the stages of fighting the disturbance rather than the stages of avoiding it.

Practitioners perceive their practices in the detection and mitigation/correction stages as the ones with the highest performances, even though simple technological support is used in the detection stage, and almost no technological support is used in the mitigation/correction stage. This might indicate that detection and mitigation/correction can still achieve better results through human supervision compared to the other stages.

In the case of the stages of prevention and prediction, the companies perceive their performance as less satisfactory than the other stages. In this case, technology has a higher potential impact on the companies' results regarding the handling of production disturbances. The prediction stage has received some attention among academics (see Figure 3), but this is not the case for the stage of prevention. To create a disturbance-free system, the prevention stage should be further and deeper investigated by the academic community.

The companies' self-assessment indicates that diagnosis and root cause analysis are intermediate stages with respect to performance. The diagnosis stage is the one, among the stages of fighting the disturbance, with the lowest ranking

among the companies. Diagnosis is the stage that connects the phases of fighting and avoiding the disturbance (see Figure 1), through the root cause analysis stage. On the other hand, finding the root cause of a disturbance in the root cause analysis stage is a necessary condition for both prevention and prediction. However, not much focus in the literature has been given to either stages of diagnosis and root cause analysis (see Figure 3), and practitioners still report low levels of overall equipment performance (Ylipää et al., 2017). In that sense, the diagnosis and root cause analysis stages should also be deeper investigated in further research.
Other variables that were not analyzed in this work also affect the perceived performance among the companies. Among these variables, we consider that managerial practices and philosophies, culture, strategies, and available resources should be investigated in future works.

## 6. Conclusion

In this work, through a literature review and a series of interviews, we investigated both how production disturbances are expected to be handled in Industry 4.0 and how they are currently handled by practitioners. Furthermore, we proposed an approach on how to handle the disturbances so their recurrence and consequences are minimized. Two research questions were outlined:

RQ1) How are the different stages of production disturbances handled in the context of Industry 4.0?
RQ2) How do Swedish companies perceive their performance towards the different stages?

Regarding RQ1, we proposed an integrated view of six different stages for handling production disturbances in the context of Industry 4.0. The stages are detection, diagnosis, mitigation/correction, root cause analysis, prevention, and prediction. Different technologies are expected to support each of the stages, such as smart sensors, smart devices, the cloud, IoT, Big Data, data analytics, simulation, digital twin, and additive manufacturing. In Industry 4.0, the process of handling production disturbances is expected to be faster, precise, automated, assisted and collaborative, leading to minimization of occurrence and impacts of the disturbances.
In order to answer RQ2, we conducted a multiple case study with five Swedish companies, based on interviews and a self-assessment of their current performance in the stages of handling production disturbances. Our results indicate that the companies perceive their performance to be higher in terms of the stages of detection and mitigation/correction, and lower in the case of prevention and prediction. On the one hand, academics have given focus on prediction in the last years. On the other hand, there is still a need for research focusing on the prevention stage in order to support practitioners. The results indicate that the companies also perceived room for improvement regarding the stages of diagnosis and root cause analysis. Root cause analysis is closely related to prevention, and diagnosis to analyses, and for this reason, those stages also deserve more focus on the academic field.
The contributions of this article are twofold. Firstly, it provides practitioners with the direction of how the stages for handling production disturbances are expected to take place in Industry 4.0, and the main supporting technologies in order to minimize their occurrence and impacts. Secondly, the paper also suggests focus for further research regarding the handling of production disturbances.
As future work, we suggest a more in-depth exploration of the impacts of different practices regarding change management on the different stages, in order to support the implementation of the different technologies. The right technologies together with the right management practices pave the way for the establishment of the Industry 4.0 vision: a production system free of disturbances.

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