PDCA Protocol to ensure a Data-Driven Approach for Problem-Solving

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Abstract

Problem-solving based, as much as possible, on real data, expert knowledge, and on-field observation are quite desired objectives. However, it creates several difficulties on deployment in real situations. In this work, a data-driven version of the well-known PDCA cycle is proposed for continuous improvement within a general class of problems represented by key performance indicators (KPI). Such class is wide enough to accommodate several real problems but still has a controlled level of complexity that allows defining a general data-driven protocol that covers all the (sub)steps of the cycle. New approaches and alternatives in the literature are discussed. A brief example of one of the steps of the protocol is given with real data from a company that adopts many of the new Industry 4.0 technologies.

Keywords
Continuous improvement, PDCA cycle, Data-driven protocol, Problem-solving methodologies, KPI tree.

1. Introduction
In the continuous improvement area, when practitioners and researchers face a new project, frequently they revise one of the first successful practical examples known in the literature, the Toyota case. Renowned for its transparent working culture, Toyota's philosophy has still being replicated in many companies across the globe (Makwana & Patange 2021).

It all started with the Toyota Way, a document published by Toyota Motor Corporation (2001), that aimed to clarify the five work line principles that the company employees needed to embrace throughout their work activities. The two major pillars of the Toyota Way are Continuous Improvement and Respect for People - both intrinsically intertwined with each other. After almost two decades of social, economic, and cultural changes worldwide, adding the challenges of the industry 4.0 brought by the increase in knowledge, Toyota renewed its underlying philosophy, bringing a more refreshed and modern Toyota Way 2020. The revised model of Toyota Motor Company (n.d.) is based on ten major premises. In this work, with a careful examination of the primary division of the Toyota Way 2001 premises, a similar allocation was done for the newer model (see Figure 1).

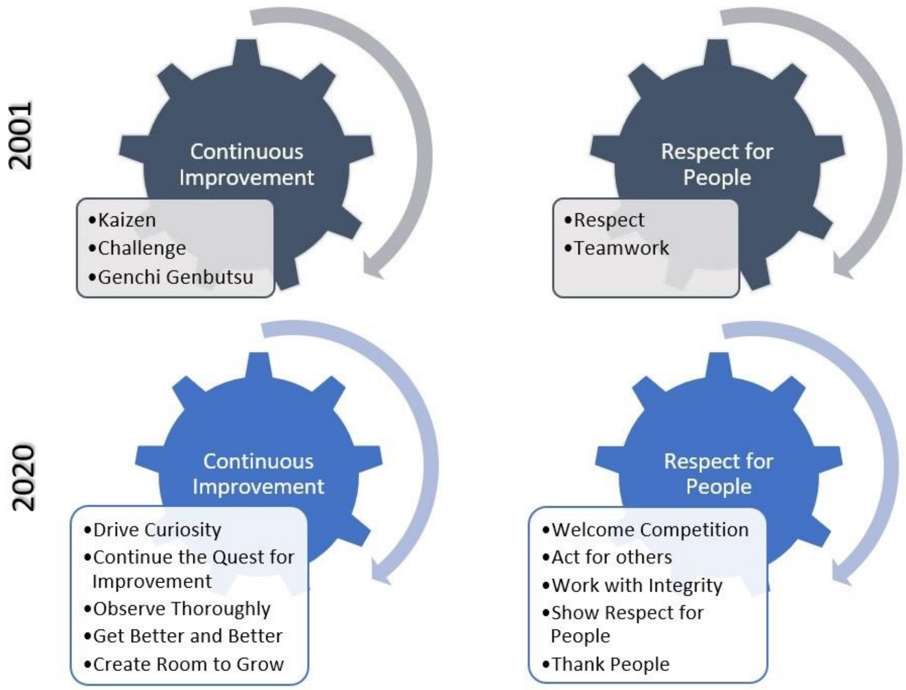

Figure 1 - Toyota Way 2001 vs Toyota Way 2020. Adapted from Toyota Motor Company (n.d.) and Toyota Motor Corporation (2001).

As a complement to the Toyota Way, through the hands of Fujio Cho, the company presented a set of work actions named the Toyota Business Practices (TBP). Serving almost as a framework, this grounded set of practices was designed to help develop the initial Toyota Way, and it has remained until nowadays as a structured methodology to act on real-world problems (K. Liker 2020). At its first publication, by Liker (2004), the TBP was composed of seven steps, and later on, K. Liker (2020) evolved to what can be seen on the surface, as an eight-step problem-solving process, based on the so-called Plan-Do-Check-Act cycle (see Figure 2).

In some regard, Toyota was able to combine a continuous improvement culture with problem-solving thinking and problem-solving methodologies (e.g., the PDCA cycle). In the same alignment, the Japanese term Kaizen also arose and became a widespread term used in the scope of performance leverage in Asia and the rest of the world. Nowadays, the literature offers a fuzzy conceptualisation of the term where between many concepts, “problem-solving” (Itoh, 2004a, 2004b) or “continuous improvement” (Imai, 1986) have been addressed under the same circumstance. Thus, researchers have connected these three terms very closely.

Here, we assume that continuous improvement (CI) is understood as an ongoing effort driven by the underlying philosophy of Kaizen, that is made about trial and error, where people are permanently learning and moving forward to improve something. Considering the definition, throughout this article, the word Kaizen is used interchangeably with CI. Additionally, problem-solving is seen as a Kaizen procedure that may be conducted before or after perceiving a problem, or any type of disturbance from normality, in a given product, service, or process. In the next section, different problem-solving methodologies that have emerged in the literature are presented, according to the nature of the Kaizen study purpose.

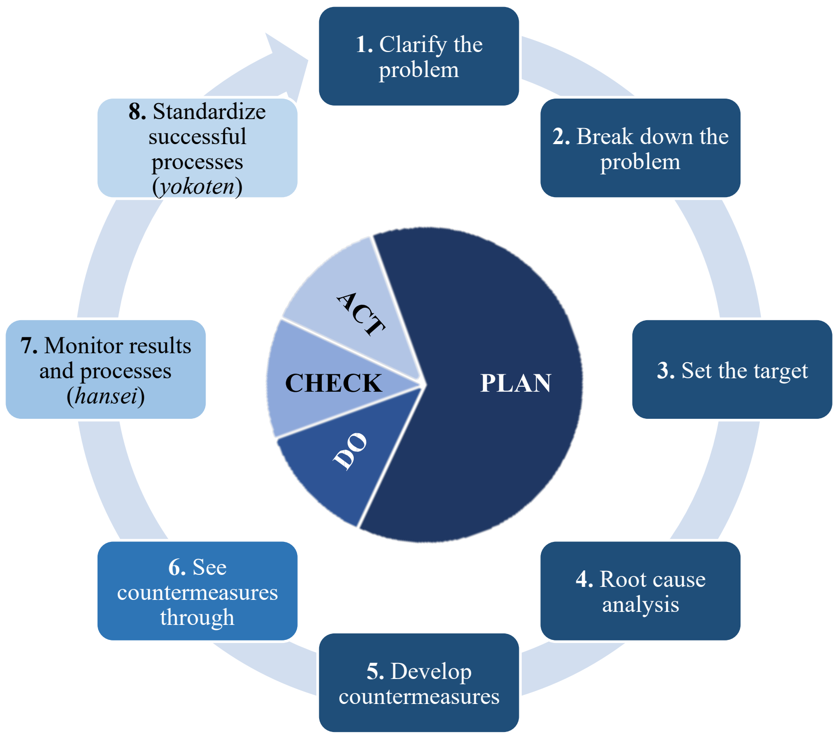

Figure 2 – Eight-step PDCA cycle based on the Toyota business practices. Adapted from Richardson & Richardson (2017).

The article is organized as follows. An introduction of the work is presented in Section 1. Section 2 shows the literature review: subsection 2.1 displays the most used problem-solving methodologies found in the literature and their nature, subsection 2.2 explains the emergence of the new PDCA 4.0 concept within the urge of digital transformation in companies, and subsection 2.3 presents the distinct problem-solving approaches based on the PDCA cycle and the need of a "data-driven" protocol. Section 3 describes the protocol design methodology, and Section 4 provides its full description. By the end, Section 5 introduces some of the previous and ongoing work relating to the protocol presented in the paper and Section 6 concludes the work.

2. Literature Review

2.1 Problem-Solving Methodologies and Nature of Use

In the literature, several problem-solving methodologies have been presented, which can be grouped according to their nature and purpose (see Table 1). Some of them are variants of others to either meet more specific needs of certain CI procedures or even because of the area of studies where the methodology had to be implemented.

Table 1 - Problem-solving methodologies and nature of application – a review based in Escobar et al. (2021).

Nature	Methodology	Reference
Managerial	PDCA (Plan, Do, Check, Act)	Imai (1986)
	PDSA (Plan, Do, Study, Act)	Deming (2000)
Reactive	DMAIC (Define, Measure, Analyse, Improve, Control)	Yang & El-Haik (2008)
	8D Cycle (**8** improvement **d**isciplines, see reference for full detail)	Bicheno & Holweg (2009)
Proactive	DMADV (Define, Measure, Analyse, Design, Verify) - the most used proactive method according to Francisco et al. (2020)	Shahin (2008)
Predictive	IADLPR[2] (Identify, Acsensorize, Discover, Learn, Predict, Redesign, Relearn)	Escobar et al. (2021), a refinement of Abell et al. (2017)

A CI project may pertain to one of four distinct approaches: managerial, reactive, proactive or predictive. In the managerial scope, the PDCA cycle (1951) is referred to as the more comprehensive and well-established problemsolving method (Jones et al. 2010) that became the foundation of Kaizen in Japanese manufacturing (Moen & Norman 2009). Within the same scope, the PDSA cycle (1993) is a slight update from the previous one, and it has been largely favoured by healthcare organisations - some examples are Hazwani et al. (2022) and Sullivan et al. (2022). For a reactive approach, the DMAIC methodology strives to improve existing processes, and it has been commonly used in the field of Lean Six Sigma; so the 8D cycle known as a team-oriented method focused on solving critical manufacturing process problems (Delgadillo et al. 2022). Belonging to the innovative spectrum of Kaizen methodologies, the DMADV method is the most used in the area of Design for Six Sigma (DFSS) (Francisco et al. 2020), where the literature addresses 13 alternative strategies, all of them emphasizing the design process, and a proactive intent. Recently, Escobar et al. (2021) developed the IADLPR^2 method, a CI technique that aims to increase the chances of successfully deploying Quality 4.0 initiatives in high-complexity manufacturing systems.

The number of different methodologies that exist for problem-solving is quite revealing. The thematic has already been so explored and revised over time. Nevertheless, the PDCA cycle remains the preferred one: it is simple, it is founded in four basilar stages, according to the Kaizen perspective, and it is a proven effective approach for CI - see recent work of Franco-Quispe et al. (2022), Ghatorha et al. (2022) and Lerche et al. (2022). For the mentioned reasons, the PDCA cycle is the chosen methodology for what follows.

2.2 The Urge for Digital Transformation and the Raise of the PDCA 4.0 Concept

The demand by the market for faster delivery times, automated and efficient processes, higher quality and customised products are driving companies towards the I4.0 phenomenon (Zheng et al. 2020). Since its early days, the topic has raised several research questions in the problem-solving and CI areas: “Is it possible to develop an automatic CI platform to help decision making?” or “Can a dataset be automatically processed by a program, revealing which processes should be improved, what countermeasures could be taken, and which standardization procedures should be followed, accordingly?”.

Even with the increasing number of data-driven solutions during the last years, companies still utilise conventional methods to conduct CI projects. In a comprehensive survey carried out by Peças et al. (2021), six major aspects were identified as the biggest limitations of conventional CI methods:

1. Obeya Rooms are the only place for consulting the project status information.
2. There is a lack of information about the current status of actual and previous problem-solving projects.
3. Data collection and analysis are done manually.
4. The means for communicating and spreading best practices are very inefficient.
5. Basic analytics tools are used.
6. Simulation and optimization techniques have been missing.

Nowadays, various companies already detain a manufacturing execution system (MES) where data is easily available. However, the problem of how to transform data into information is still a reality. Considering these limitations and challenges, Peças et al. (2021) developed a holistic and structured framework towards an approach that combines I4.0 and CI: the PDCA 4.0. Thus, a systematic study was conducted, providing an extensive and comprehensive overview of the technological elements that can be addressed in each step of the PDCA cycle, to help problem-solvers start their technological journey (see Figure 3).

Considering the holistic framework as the general big picture, currently, the authors of this work are working on the development of a PDCA 4.0 approach based on the case study of KPI trees. The goal is to develop a data-driven problem-solving methodology that follows the PDCA cycle structure, where managerial KPIs are analysed according to its relationship tree (see Section 4 for further detail).

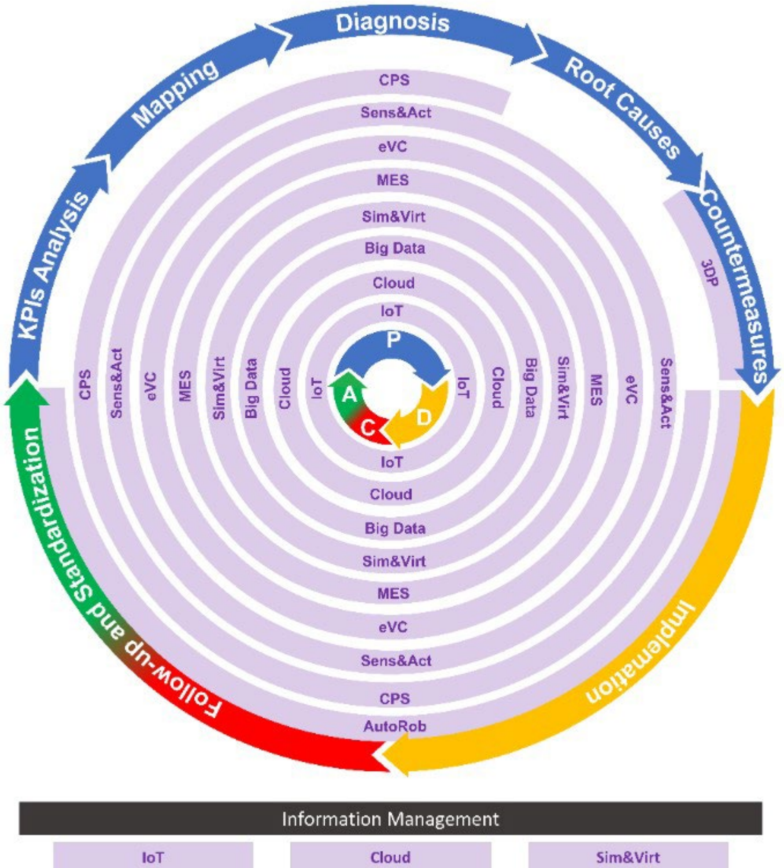

Figure 3 – The PDCA 4.0 concept with the available I4.0 technologies (Peças et al. 2021).

To accomplish this, and as a first step, it is imperative to clarify and understand the chosen methodology to be easily adapted to a data-driven problem. Thus, how could we convert a conventional CI project into a data-driven one that uses the PDCA cycle methodology? To this extent, the Plan-Do-Check-Act phases must be unfolded and scrutinized.

2.3 PDCA Cycle Approaches in the Literature – The Necessity of a "Data-Driven Protocol"

With its roots in Japan, by the time through the lessons of Dr W. Edwards Deming (1950), the PDCA cycle was presented as a functional tool to stimulate learning and innovation. According to Toyota, the PDCA methodology emerged to progressively improve system performance by either doing small/incremental improvements, often called *Kaizen* (Womack et al. 2007), or innovative/radical changes for breakthrough improvements, also known as *Kaikaku* (Nicholas 2018). Looking into the literature for problem-solving "steps", "phases", or "stages" within the PDCA cycle methodology, a variety of approaches can be found (see Table 2).

Looking closely at these approaches, overall, they seem a bit generic, lacking a higher level of detail that is expected to develop a data-driven problem-solving guide. Besides, comparing them side-by-side, a perceived lack of consistency can also be noticed, in terms of the number of "steps", as well as its order of occurrence. Gathering these aspects, the authors of this work conclude that to design an endorsed data-driven approach for problem-solving based on the underlying philosophy of the PDCA cycle, there must exist a guide or a protocol that describes a set of detailed steps and corresponding accountable entities. To this extent, a so-called "data-driven protocol" is described in Section 4.

Table 2 - State of the art regarding in-depth problem-solving approaches based on the PDCA cycle.

	References				
	Imai (1986)	Nicholas (2018)	Sobek & Smalley (2014), K. Liker (2020) and Peças et al. (2021)	Imai (2012), Liker & Trachilis (2011)	Richardson & Richardson (2017)
Plan	1.(What) Definition of the problem 2.(What) Analysis of problem 3.(Why) Identification of causes 4.(How) Planning countermeasures	1. Grasp the current situation 2. Identify the root cause 3. Devise countermeasures and visualize the future state 4. Create implementation plan 5. Create follow-up plan 6. Discuss with affected parties 7. Obtain approval	1. Collect data to understand the current situation 2. Define the problem 3. State the goal 4. Analyse and solve the problem 5. Develop the plan	1. Clarify the problem 2. Break down the problem 3. Target Setting 4. Root cause analysis 5. Develop countermeasures	1. KPI analysis 2. Mapping 3. Diagnosis 4. Root Causes 5. Countermeasures
Do	5. Implementation	8. Execute the implementation plan	5. Implementation of the plan	6. See countermeasures through	6. Implementation
Check	6. Confirmation of result	9. Execute the followup plan	6. Collect and analyse data to assess results	7. Monitor both results and processes	7. Follow-up
Act	7. Standardization	10. Establish process standard	7. Institutionalize successful planned	8. Standardize successful processes changes	8. Standardization

3. Protocol Design Methodology

To design the protocol, a preliminary search of the most relevant publications addressing CI, kaizen, and problemsolving was first carried out for a better understanding of the concepts, the most used underlying methodologies, and the reason for being the most utilized compared to other known methods (Section 2 of this work). Then, within the scope of industry 4.0, a more specific search was conducted, circumscribing studies adopting the PDCA cycle for problem-solving (Abell et al. (2017), Buer et al. (2018), Xu & Dang (2020), Ma et al. (2021), Guo et al. (2021)). The final picture of the protocol was obtained based on the analysis of the mentioned studies, in parallel with some of the authors' work outcomes of a manufacturing case study. The intention was to answer the following question: *How do we design a protocol based on the PDCA cycle structure, that details the fundamental tasks, variables, and elements to be considered for the easy and quick development of a data-driven problem-solving platform?*

4. The "Data-Driven" PDCA Protocol

HSE (2012), as cited by Bettal Quality Consultancy (2020), defines a protocol as: "…a written plan that specifies procedures to be followed in defined situations (…) are more explicit and specific in their detail than guidelines (…)". Structured within its four main stages, the data-driven PDCA protocol aims to provide a checklist of tasks, elements, variables, and human resources for an effective problem-solving activity, based on data (see Table 3). Unfolding the Plan-Do-Check-Act phases, eight big milestones are intended to be met. For each milestone, a detailed description is given, and the accountable people for the CI project are known: data managers (people who receive and manipulate data to generate information) and process experts (people who deal with real-world problems on a daily basis and have a bigger practical and on-the-field view of the problem).

Beginning on the **Plan** phase, usually the longest, an extensive and careful study of the problem is performed, and five big milestones are outlined:

1. **Clarify the problem:** Here is where the problem is approached for the first time. A general explanation of the problem and its location needs to be given, so as the current reference value ($Pref$). Additionally, previous CI procedures conducted for the same problem need to be evaluated. Knowing what has been done previously can significantly help the preparation and development of more considered countermeasures, where non effective actions can be avoided.

2. **Break down the problem:** This is the part where we map the problem, and the datasets are first explored. Mapping is very important to visually analyse the relations and dependencies between elements that define the problem, so the variability contributions are displayed. Therefore, the general parameters and sub-parameters are first identified to detect the relevant metadata and necessary datasets for analysis. Then, once these datasets are extracted from manufacturing execution systems of companies, data managers proceed with the study and validation of them, doing data cleaning and statistical evaluation. In addition, three data functions (trend, seasonality, and noise) are determined, so as the influence level of the general parameters, to help accurately choose the target ones for the next phase. These functions are also very important to determine study periods for root cause analysis in milestone 4.

3. **Set the target(s):** Here, we define the parameters to target and the general value of the problem. An optimization problem study is performed to help find the optimal target values.

4. **Root cause analysis (RCA):** With a current full picture of the problem's state, we can now determine the RCA direction based on the target parameters. An extensive set of steps is now expected to be explored by the process experts.

5. **Develop countermeasures:** By developing countermeasures for each of the identified problem causes, the person or team in charge of the Kaizen event is not simply trying to find potential solutions, but also to formulate the full implementation plan. This includes knowing the necessary human resources and their role in the process, the execution timeline, monitoring periods and projected costs.

Moving to the **Do** phase, the countermeasures are now being tested, and the plan is put into action.

6. **See countermeasures through:** During the testing period, process experts will be responsible for doing the implementation follow-up, making sure that the plan is being correctly implemented.

In the **Check** phase, the final implementation results are analysed and compared:

7. **Monitor results and processes:** Similar to milestone 2, data managers gather the datasets from the testing period for validation, data cleaning and statistical evaluation. Then, pre- and post-implementation parameter values are compared to check if the targets were reached. Next, the process experts evaluate and decide what are the effective countermeasures and/or which should proceed to further revision or rejection. As preparation to the final stage, the difficulties faced during implementation are put under evaluation to determine if the effective countermeasures can easily be standardized and spread throughout.

At the final **Act** phase, the process experts need to plan the standardization and spreading activities so the first CI countermeasures are well received, and the problem can evolve to a new improvement cycle.

8. **Standardize and spread:** In agreement with the people involved in the **Do** stage, the process experts design, describe and assign the activities necessary to standardize and spread the effective countermeasures throughout the company, checking its effectiveness with control parameters in defined monitoring periods.

Table 3 - Problem-solving protocol.

	Milestone	*Protocol Description*	*Responsible HR*
Plan	1. Clarify the problem	1: Explanation of the general problem. 2: Identification of the problem's location. 3: Definition of the problem's current reference value $(Pref)$. 4: Analyse of previous CI procedures: 4.1: Period of occurrence and undertaken countermeasures. 4.2: Defined target parameters and achieved improvements. 4.3: Major difficulties towards implementation. 4.4: Major difficulties towards standardization and spreading.	1-4: Process experts.
	2. Break down the problem	5: Identification of the parameters and sub-parameters that define the general problem. 6: Identification of relevant metadata. 7: Acquisition and validation of the datasets: 7.1: Verification of parameter units and formatting. 7.2: Merge dataset tables from different files, according to key parameters. 7.3: Identification of empty fields or "NAs" for each parameter.	5: Process experts. 6-9: Data managers.
		7.4: Removal of irrelevant parameters (redundant and/or irrelevant to the study). 8: Statistical analysis of the "good" parameters: 8.1: Statistical characterization of each parameter (mean, median, standard deviation and/or others). 8.2: Statistical characterization between parameters (relationship index, e.g., Pearson's correlation coefficient). 9: Decomposition of the parameters time series: 9.1: Determination of data trend functions. 9.2: Determination of data seasonality functions. 9.3: Determination of data noise functions. 9.4: Determination of the influence level of different data parameters.	
		10: Definition of the general target value of the problem $(Ptarget)$. 11: Definition of the target parameters (k). 12: Optimization problem study to determine the target values of the parameters, according to: 12.1: The cost/objective function. 12.2: Problem constraints. 13: Definition of the target values of the parameters (K_k).	10: Process experts. 11-13: Data managers.
	3. Set the target(s) 4. Root cause analysis	14: Analysis of the underlying processes that influence the parameters: 14.1: Value stream objects and classes. 14.2: Sub-processes and respective steps. 14.3: Resources (internal and/or external). 14.3.1: Resource requirements. 14.3.2: Resource availability restrictions. 14.3.3: Resource characteristics of quality, economic, ecological and of usability. 14.4: Responsible actors for each resource. 14.5: External phenomena (not controllable by the process expert).	14: Process experts.
	5. Develop countermeasures	15: Design and description of the countermeasures. 16: Definition of the responsible human resources for each countermeasure. 17: Definition of the implementation timeline (start/finish dates). 18: Definition of the monitoring periods. 19: Determination of the implementation costs.	15-19: Process experts.
Do	6. See countermeasures through	20: Follow-up of the implementation status of each countermeasure.	20: Process experts.

Check	7. Monitor results and processes	21: Acquisition and validation of the datasets from the testing period. (Repetition of steps 7.1 to 7.4). 22: Statistical analysis of the "good" parameters of test. (Repetition of steps 8.1 and 8.2). 23: Comparison of pre- and post-implementation parameter values. 24: Process variability comparison between pre- and postimplementation. 25: Evaluation of effective countermeasures (solutions). 26: Definition of countermeasures for revision or rejection. 27: Analysis of implementation difficulties, and evaluation for the following stage.	21-24: Data managers. 25-27: Process experts.
Act	8. Standardize and spread	28: Design and description of activities for standardization and spreading of the effective countermeasures. 29: Definition of the responsible human resources for each activity. 30: Definition of monitoring periods and parameters.	28-30: Process experts.

5. Protocol Step Nine - The Time Series Decomposition

Step 9 in the protocol described above suggested looking, along time, to the parameters as time series and proceeding with a time series decomposition into three component functions: seasonality, trend, and noise. This step is somehow a continuation of previous work from the authors, where a benchmark study relative to the performance of manufacturing line workers was conducted using multi-directional efficiency analysis (Rocha et al. 2022). Driven by data, this study allowed the benchmark of human-related factors (experience time, wage, delay time and response time) that had a major impact on a manufacturing line performance, namely the number of reworks and bottleneck occurrence. To complement the influence of the human factor in manufacturing, the authors of the present article are currently working on the development of a data-driven problem-solving platform. This platform is necessary to study and analyse one of the most relevant performance metrics for top management, the Overall Equipment Effectiveness (OEE). As defined internationally, this KPI results from the multiplication of three major factors: Availability (A), Performance (P) and Quality (Q). Nevertheless, these factors also result from the direct influence of other production metrics and variables. In the case of a Portuguese company in the manufacturing sector, the OEE KPI is influenced by a very large number of production metrics (above 100). Considering the complexity level associated, the company engineers have been addressing this issue as a *KPI tree problem*. The goal of the data-driven platform based on the PDCA cycle is to help engineers continuously study and analyse this complex problem to gradually improve the OEE factor. As can be seen from the plot of Figure 4, the KPI value is quite nonstationary over time, which reinforces the importance and pertinence of developing the CI platform.

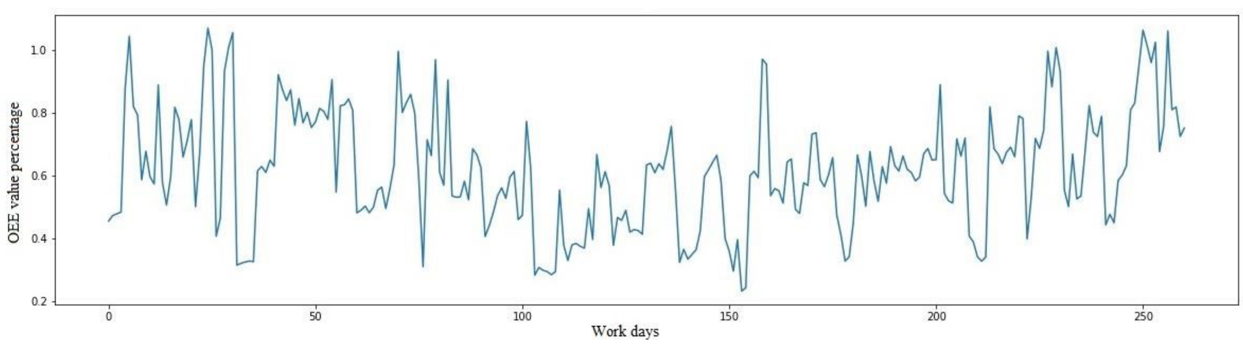

Figure 4 - OEE value fluctuation on a full work year.

It is also clear that some standard statistics, such as averages, will not provide enough information about the problem. To this extent, the data-driven PDCA protocol presented above has been followed, and results are shown in Figures 5-7.

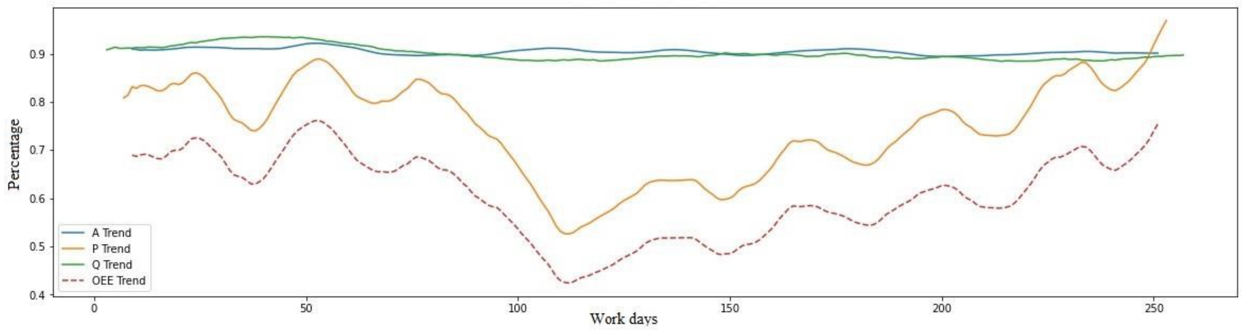

Figure 5 - Trend components of the OEE factors and the OEE itself.

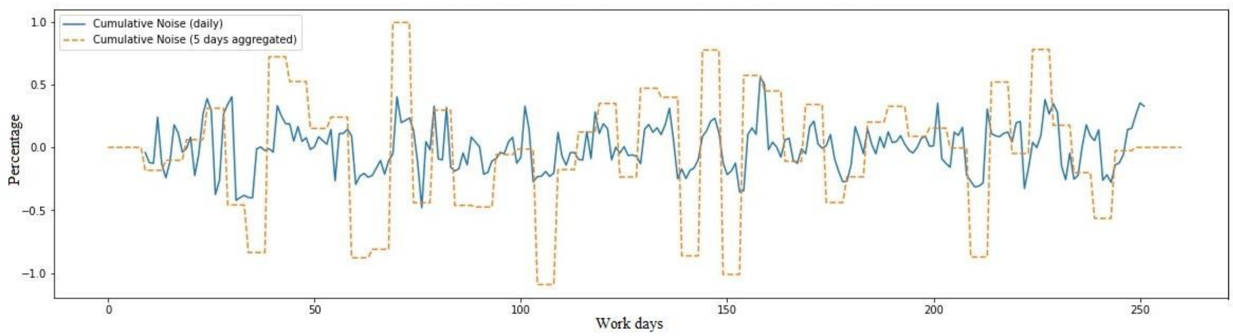

Figure 6 - The cumulative noise functions and their cumulative influence in the seasonality and trend.

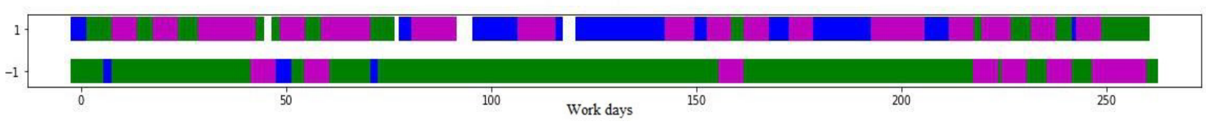

Figure 7 – Influence level of the OEE factors throughout the workdays - (blue) is the positive/negative Availability influence; (green) is the positive/negative Performance influence; and (purple) is the positive/negative Quality influence. Positive influence has the value +1 and negative the value -1.

Having a glance at the protocol, these graphics are the outcome of milestone 2. They show the tendency values of the three parameters that compose the OEE value, the cumulative noise, and the parameters level of influence (negative or positive) in the OEE. Due to lack of space, these images will be analysed and explained in further detail in the following work. Further milestones are also expected to be reached and shown at that time.

6. Conclusion

Nowadays, numerous companies already detain an efficient manufacturing execution system, where data is consistently and easily available. However, there is still the problem of transforming all such (big) data into valuable information. Additionally, regularly companies conduct continuous improvement and problem-solving activities, so it becomes imperative the correct and effective use of data. To this extent and motivated by the new concept of the PDCA 4.0, from Peças et al. (2021), a PDCA Protocol is presented with the main focus of applying recent algorithms and mathematical techniques over real data to support an informative implementation of the PDCA cycle.

The protocol is a novel contribution to the literature that aims to provide an extensive data-driven methodology for problem-solving. It has already been used in recent works of the authors, and technical/mathematical details of the protocol steps will be presented in future publications, using data from real companies in the manufacturing and logistics areas.

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