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OPTIMIZATION OF THE LOGISTIC "FILL RATE" KEY PERFORMANCE INDICATOR THROUGH THE APPLICATION OF THE DMAIC APPROACH

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Abstract

Measuring and monitoring the performances of supply chains over time is a primary interest factor for companies. In this way, it is possible to determine the effectiveness and efficiency of strategies for being competitive in global markets, verify the achievement of the predetermined targets, and establish intervention and improvement measures. In this context, key performance indicators (KPIs) are widely used to measure the numerous activities performed across a supply chain. Numerous KPIs are available in the literature, and they are often customized by each user to make them more suitable for their reference context. This paper analyzes the logistic "fill rate" KPI that characterizes the shipping phase of goods by evaluating the fill rate of the transport unit used. A case study analyzes the fill rate indicator used by a multinational corporation that produces and markets food packaging. Through the DMAIC (Define, Measure, Analyze, Improve, and Control) approach, the criticalities of the current formulation of the index are highlighted, and a new model for calculating the index is proposed and applied experimentally at a plant in northern Italy.

Keywords: Key performance indicators (KPIs); Fill rate; Supply chain management; DMAIC approach

1. Introduction

The extremely dynamic global market has significantly increased competition between companies that must continually find the best ways to lower the price of products and continuously improve their characteristics [1]. The tools and approaches of supply chain management practices support improvements in organizational performances and the competitive advantages of companies in global markets [2], [3].

Hence, logistics are treated as part of supply chain management, ensuring that the various corporate functions involved in planning, implementing, and controlling the material and information flows occur efficiently and effectively [4]. This integration roles between the various business functions can be identified from the definition of logistics provided by the Council of Logistics Management. In particular, the logistic function can be distinguished in different macro-activities that correspond to different phases but are integrated [1], [5]. These are inbound logistics, stock management, outbound logistics, and return logistics. When so framed, the role of logistics for a company represents the link between internal operations and the surrounding ecosystem. The choices made in a certain area of the logistics activities impact all other areas, generating mutual conditioning [6]. Logistics management significantly affects the overall direct and indirect costs of a company that are necessary for moving products, from sourcing raw materials to delivering goods to customers, including all of the intermediate steps. Logistics have a strong impact on earnings [7]. These costs could be divided into numerous components, including: transport, warehousing, stock management, administration, packaging, and indirect logistics costs. Marotta et al. [8] divided the first four components into percentages and a temporal evolution. The incidence of logistic costs changes among companies in different industries since they pertain to various business areas (e.g., sales, purchasing, and manufacturing). Rantasila and Ojala [9] and Škerlič and Sokolovskij [10] quantified the share of sales revenues that is linked to logistics costs as being at least 6%, but they may also reach a share of 25% [7]. The evolution of the effectiveness and efficiency of the processes that characterize a supply chain (also from an economic point of view) can be monitored through performance measurement systems (PMSs). These are tools that integrate measures that support the decision-making process. This information is analyzed through appropriate key performance indicators (KPIs), which are financial and non-financial measurable values that estimate how effectively a company achieves its key business objectives [11]. These company data in which metrics, ratios, and percentages are conveyed form the basis of the decision-making process for planning improvement actions [12]. Organizations use KPIs at multiple levels to evaluate their success in reaching targets. KPIs analyze performance dimensions; in particular, asset management, time, cost, productivity, and quality of service [13]. Considering the strong impacts of logistics activities on the performance of a company (including economics), having suitable and adequate KPIs is a primary objective. This work describes a specific case study represented by a company that deals with producing and marketing packaging products. The paper describes the current formulation of the FR indicator. It suggests an optimized formulation that will increase the effectiveness of the logistics processes and the methods for monitoring performance.

2. Literature review

Organizations search for KPIs that are aligned with their specific targets. A widespread solution, especially by software vendors who have tried to include the greatest possible choice of KPIs in their products, is to favor the custom development of KPIs. In this study, a novel approach was developed for the automated prediction of relevant KPIs for organizations to favor the indicator customization process. The problem of the number of KPIs describing the performance of a supply chain was also addressed in a study by Brint et al. [14], where they highlighted difficulties in the collection and management of the many data necessary for the quantification of the indicators and the overlaps between the indicators. To overcome this problem, they used principal component analysis (PCA) to reduce the number of KPIs, followed by TOPSIS (technique for order performance by similarity to an ideal solution) for validating the results, reducing the initial dataset of their case study by 28 KPIs to a set of only 8 KPIs. The same problem has been described in numerous review papers available in the literature, aimed at both the study of the entire supply chain and, specifically, the aspects of logistics and transport. Karl et al. [15] analyzed the influence of non-financial KPIs on supply chain resilience and identified which ones had greater impacts as order and delivery lead times, on-time deliveries, supplier delivery efficiencies, and customer satisfaction. Maestrini et al. [16] summarized the reference context of supply chain performance measurement systems through a life cycle perspective. Qorri and Mujki [17] focused on measuring the sustainability performance of supply chains, supported using numerous multi-criteria decision-making methods.

Oriented to measures of logistics management, the studies by Domingues et al. [11] and Wudhikarn et al. [6] focused on reviewing third-party logistics providers and the tangible assets and intellectual capital (IC) of organizations, respectively. Several logistics indicators have been selected as those most used in the literature, such as on-time or out-of-date delivery performance, order fill rate (FR), inventory level and condition, delivery time or speed, and information and documentation accuracy. Larrea [18] evaluated several KPIs applied to logistics management during humanitarian operations. Domingues et al. [11] evaluated the representative indicators of third-party logistics providers through a multi-level approach (decision level, activities, and actors) and provided a comprehensive and innovative performance measurement framework. Dornhofer et al. [19] developed a framework of KPIs for evaluating the effectiveness and efficiency of current logistics processes through a lean perspective, evaluated in an automotive context. Dumitrache et al. [20] evaluated the KPIs applied in large Romanian transport companies to improve their fleet utilization, average daily trips, and transport capacities. Kucukaltan et al. [21] integrated the balanced scorecard (BSC) model and the Analytic Network Process (ANP) method to provide a novel way to evaluate logistics performance indicators from a logistician's perspective. The specific aspect of the reverse supply chain has also been analyzed using KPIs [22], [23]. Another aspect of considerable interest is using KPIs for sustainability assessments. Numerous aspects have been analyzed, including energy, emissions into the atmosphere, and the use of resources. Often, these assessments involve the three traditional pillars of sustainability: environment, economy, and society [24], [25], [26].

3. Methodology and case study

The methodology adopted in this study applied the principles of Lean Six Sigma as a combination of the speed inherent in the Lean production method with the statistical rigor of Six Sigma approaches. Specifically, the define, measure, analyze, improve, and control (DMAIC) approach represented the operational framework, which, through different tools, was used to fix problems with existing processes [27]. The description of phases that formed the Six Sigma DMAIC approach is reported in Table 1, identifying the objectives, activities, and main outputs that characterized this approach. The DMAIC approach was applied sequentially to the case study using different operational tools.

The case study described in this paper refers to a company that develops, transforms, and distributes packaging solutions such as packaging materials, machinery, and accessory products packaging. The multinational company operates in various countries around the world through numerous production plants and trading companies divided into clusters according to the geographical distribution. The case study supported the analysis of a specific plant located in Italy responsible for producing packaging materials and its marketing, especially to Italian customers. The logistics transport was the focus of this study.

The company monitors the deployment of logistics losses and costs through appropriate KPIs. It applies indicators to monitor the following aspects: logistics cost, inbound cost, outbound cost, warehouse cost, savings from co-loading, and fill rate. The goal of the distribution of the loss of the logistics costs was to control the end-to-end flow from the supplier to the customer, grouping the elements belonging to the same category and measuring their influence on inbound and outbound costs. For all the indicators used, the activities carried out at the plant considered in this paper guaranteed the achievement of the reference targets. The only exception was related to the FR, which reached a score below the reference target. This performance was confirmed for several past years. The FR was an outbound KPI included in the transportation losses that evaluated the space maximization of the transportation by a vector (truck for inland transportation and container for sea transportation). It was used for the inbound transportation of base materials and outbound transportation of the packaging materials and additional materials. The FR was the KPI target of the present study. The actual formula of the FR calculation of a shipment was based on the partial occupation of the additional material expressed in volume, added to the partial occupation of the packaging expressed in weight. Its formulation is reported in (1). This KPI calculation considered the additional material and packaging material separated because additional the materials grew in volume, thus decreasing the potential total “full” truck weight. In the case of the packaging materials, the maximum weight limitation of the truck or container was reached before the truck/container was filled up. For light additional materials, the truck or container was filled up before the weight limitation was reached. The FR losses considered the cost loss derived from the space not used in a vector for a shipment. It considered the actual shipment cost, and so it was evaluated on the contract prices with the carriers and the unplanned freight cost less extra charges such as cancellation, express charge, and waiting time. Its formulation is reported in (2).

DMAIC approach	Objectives	Activities	Possible tools	Outputs
Define the problem	Identification of the purpose of the work to clarify to everyone what improvements you want to make to the process under review	- Identification of team members - Selection the process under investigation - Definition of the project’s objectives	- Benchmarking - SIPOC method - Gantt Charts - Project charter - Voice of Customer - Stakeholders’ analysis - Quad-Chart - Multigenerational plans - ROIC analysis tools	- Project charter - Gantt chart - SIPOC map
Measure the baseline performance	Collection of useful data to characterize and analyze the objectives of the project	- Process flowcharts - Data collection - Data assessment	- Process flowcharts - Benchmarking - Value stream map - Gage reproducibility and repeatability - Pareto chart - Capability analysis	- Process Sigma value - First conclusion and/or observation on collected data
Analyze the root causes	Identification of the root causes of the business inefficiencies	- List of potential causes - Sort the causes	- Brainstorming - 5WHY technique - Modell expectation maximization - Diagram cause-effect - Hypothesis testing - Multi-vari chart - Root cause analysis (RCA) - Failure mode and effects	- - Identification of the gaps between the actual and goal performances, the causes, and the opportunities for improvement

			analysis (FMEA)	
Improve the process	Improvement in the process by determining potential solutions and ways to implement them	- Identification of possible improvement solutions - Analysis of improvement solutions	- Brainstorming - Expectation maximization model - Process flow improvement - Risk analysis - Lean tools - Simulation software - Mistake-proofing (Poka Yoke) - Prototyping	- Evaluate whether the solution is effective and financially viable
Control the improved process to prevent regression	Develop metrics that help leaders monitor and document continued success	- Process monitoring - Process analysis	- Statistical process control - Quality control plan - 5S - Mistake proofing (poka-yoke)	- Process control plan to mainstream gains

Table 1. Operational framework of the DMAIC approach

$$\text{FR KPI} = \frac{Shipment\,Weight\left(PM, Strips, Lid\ Mat, Tab\ Mat, Film\right)(kg)}{Truck\ weight\,capacity(kg)} + \frac{Shipment\,Volume\left(Straws, Closures\right)(m^3)}{Truck\,Volume\ capacity(m^3)} \tag{1}$$

$$\text{FR Losses} = [100\% - \text{Fill Rate of the vehicle}] \times \text{Shipment cost or Actual truck cost} - \text{Pro-rated full truck cost} \tag{2}$$

4. Results and discussion

This section describes the results obtained by applying each step of the DMAIC approach to the case study, and it provides some discussion.

4.1 Define the problem

To properly define the problem, the project charter was created, as reported in Table 2. This approach allowed us to characterize the main elements that defined the problem, identifying the objectives, the times, and the ways to proceed. Furthermore, the project team was created, involving members from different logistics areas to provide knowledge on the topic. Each was assigned a role in the project activities, such as manager, operational support, or action support.

Problem statement	Project scope	Objectives	Key process measurement
All the KPIs used by the company to assess the efficiency and effectiveness of the logistics losses and costs are consistent with the expected objectives, except for the FR, which has unsatisfactory performance	Understand the reasons for the failure to achieve the target set for the FR and establish the approach to achieve it	- Understanding the causes - Establish the necessary interventions - Monitor post-modification results	- FR target = 58% - Approximately 72% of the local shipping destinations and 28% of the export destinations - Approximately 1530 trucks/year
Timeline	**Deliverables**	**Leveraging opportunities**	**Project team**
D June M July A September I October–November C December	- Process data - Document plan - Reports and information	- Tools - Test results - KPIs - Improvements in operational management	- Director - Project coordinator - Logistics coordinator - Logistics export coordinator - Shipping team

Table 2. Project charter

4.2 Measure

To analyze the reference context, data about the FR and shipment details (cost and material quantities) were collected.

The maximum weight and volume restrictions and destination country were also analyzed.

Factories	**Factory 1**	**Factory 2**	**Factory 3**	**Factory 4**	**Factory 5**	**Factory 6**	**Factory 7**	**Factory 8**
FR Adjusted	80%	65%	65%	63%	59%	56%	55%	54%

Table 3. FR indices of the eight factories for the year 2019

We used benchmarking to analyze the performances of the FRs at different plants that formed the cluster to which the case study of this paper also belonged. Table 3 shows the annual value (for the year 2019) of the FRs for the eight cluster factories. Factory 8 had the poorest performance. Considering only the system that had the worst performance for the FR, the assessment of the "number of shipments" and "destination country" made it possible to isolate the highly frequented and lowly frequented destinations (Fig. 1). The highly frequented destinations were Spain, Portugal, Switzerland, France, Slovakia, Slovenia, Finland, and Germany. The lowly frequented destinations were Armenia, Bosnia and Herz, Bulgaria, China, Malaysia, Macedonia, Turkmenistan, and Uzbekistan.

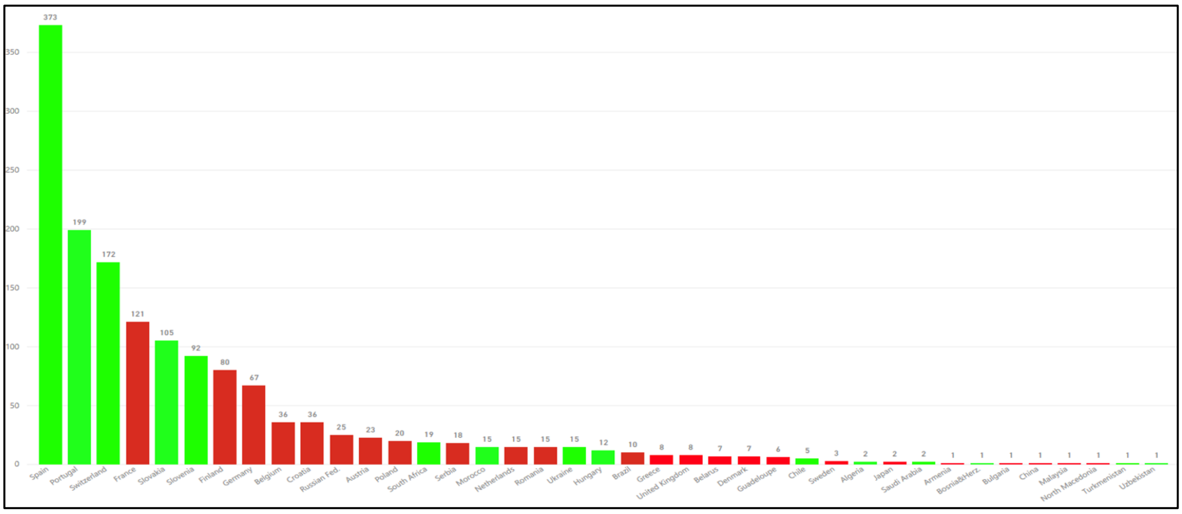


Fig. 1. FRs for the year 2019 per country (the numbers indicate the annual shipments to that country)

Fig. 1 indicates the destinations with an FR that met the company's target (in green) and those that did not reach the threshold (in red). The most popular destinations met the target (except for France, which was very close to the threshold), while the insufficient values refer to the countries served less frequently. It was interesting that those below the threshold were mainly European countries close to the plant that was the subject of this study, with an average number of 27 shipments per year. The most distant destinations (e.g., those outside of Europe) usually reached the FR target, and in any case, they were characterized by a limited number of shipments per year (approximately eight). This information allowed us to understand how, for distant shipments, more significant transport consolidation and optimization were always sought to reduce logistical costs. The second analysis concerned the composition of the shipments, verifying the frequency of the combined loads (packaging materials and additional materials). Only 4% of the total shipments to the market included additional materials in the order, while most of the loads (96%) were made up of packaging materials only. The conclusions were: first, separating the dimensions of the items' volumes and weights in the formula was not influential. The formula had its best scenario with 100% of the weight maximization plus (+) 100% of the volume maximization. However, this assumption did not reflect the reality because it was physically impossible to fix all of the trucks' spaces with the pallet combinations. Second, it was impossible to fill all the trucks' spaces because there were technical limits and constraints, such as the spaces next to the trucks' doorways, special palletization, and special requests, such as the prohibition of stacking. Third, the most frequent condition was that the items' weights for a single shipment influenced the FR.

4.3 Analize

Statistical tools and brainstorming were used to study the phenomenon. The 5WHY tool was the first method applied to delineate which variables were impactable (or not) in our study. This tool allowed us to analyze the emerging problems and explore their cause–effect relationships. From its application, four main elements that caused a low FR emerged (Table 4), providing useful indications that allowed for the evaluation of possible improvement interventions. In particular, the estimated time of arrival (ETA) comparability, the destination comparability, the unique delivery requests, and the numerosity of the items in a shipment and their space combinations were the aspects that were analyzed.

Problem: FR decreased due to a lack of delivery order consolidation				
Why	Why	Why	Why	Why
Completed the order with the same destination (or next) and different date ETAs	The customer did not accept the change to the ETA	It was assumed that the customer would not be satisfied	Lack of cooperation	Procedure not focused on the consolidation saving or there was no collaboration with the planning material
Problem: FR decreased due to not enough truck space for consolidation				
Why	Why	Why	Why	Why
Completed the order with the same destination (or next) and same date ETAs	Not enough space in the truck to merge the two orders	No collaboration between the CSRs during the DO planning	Satisfaction of the customer quantity requested	Procedure not focused on the consolidation saving or there was no collaboration with the planning material
Problem: FR decreased due to special palletization				
Why	Why	Why	Why	Why
There was more space booked in the truck to satisfy the special palletization or special request	It was assumed that it was possible to load 22 pallets in one truck regardless of the characteristics of the pallets	It was not possible for shipping to consider all of the special requests	There was no procedure defined	The formula did not take it into consideration
Problem: FR decreased due to not enough truck space and volume combination				
Why	Why	Why	Why	Why
There were items that could not fill the full truck space	The pallet configurations and reel weights	Each type of reel in the order had different weights and volumes	It was a problem of backpack optimization	We did not have the power to modify the items

Table 4. 5WHY tool

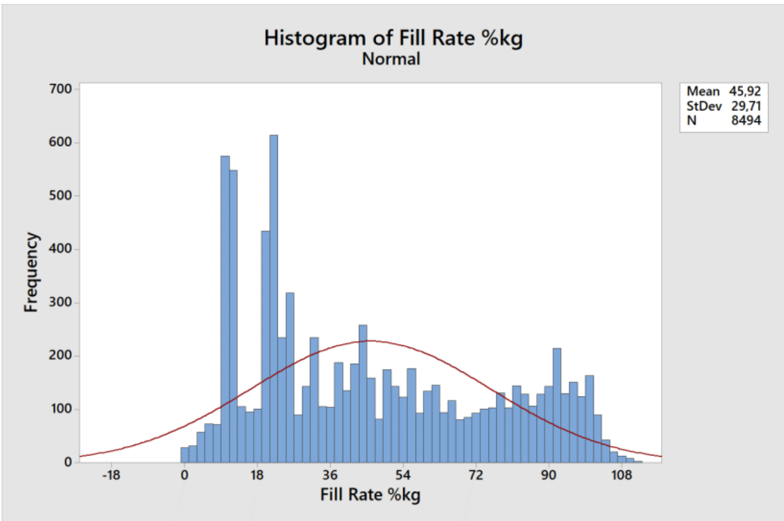


Fig. 2. FR Histogram of the plant analyzed in the case study

These elements were crucial for achieving merged transportation and, thus, improving the FR of a transport. The brainstorming showed that the main problems were caused by actions and decisions that did not directly depend on the logistics departments. Therefore, with these elements, it was assumed that to have a KPI that correctly evaluated the efficiency of the transport from the logistics side, it should not consider any elements that the logistics departments could not modify or those elements for which the logistics departments had no decision-making power.

Therefore, only data directly representative of the actions directly related to the logistics functions were considered. An analysis of the representative data of FRs considering all the shipments together is shown in Fig. 2, and it is evident that it was impossible to obtain a normal distribution of the index using the current formulation. This meant that the values were not concentrated around a single average value and grouping the data in any bell shape was impossible.

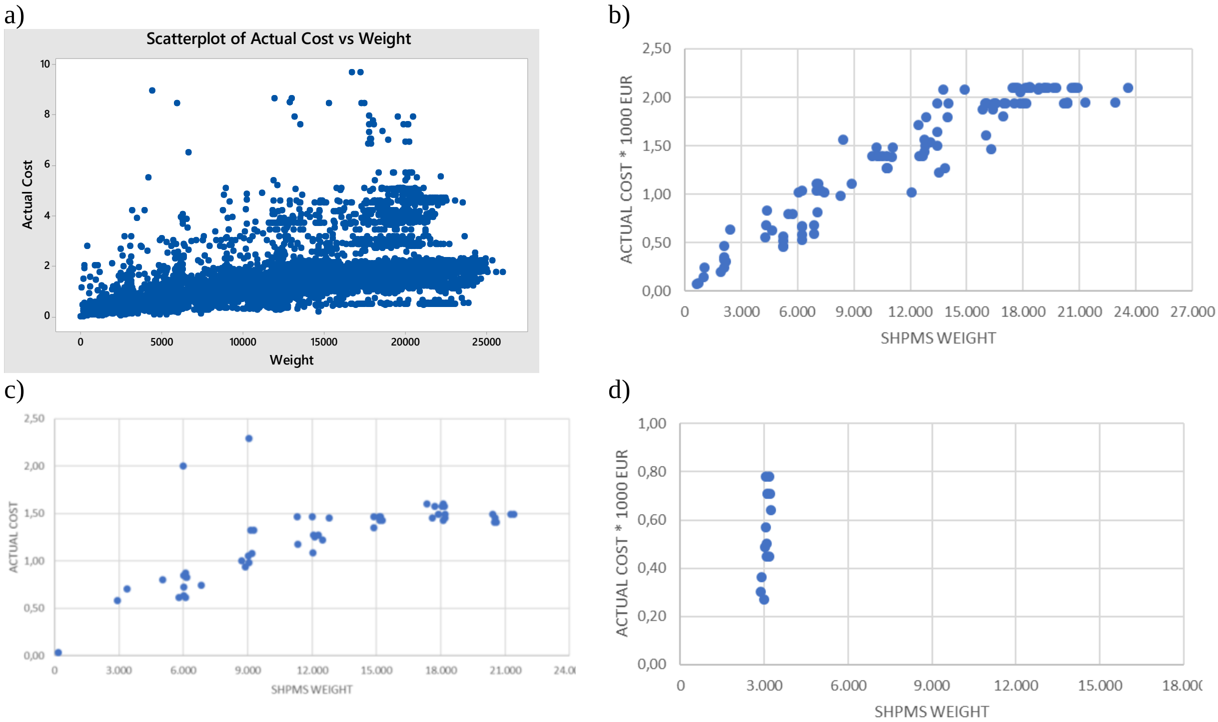


Fig. 3. Overall actual situation (cost vs weight): a) representation with all the distinctions without distinction; b) example of a destination where the trend was easily identifiable; c) example of a destination where the trend was identifiable, though with some anomaly; and d) example of a destination where the trend was unusual

Fig. 3 shows the scatter plots of the cost of shipping versus weight. Considering all the shipments together, Fig. 3a shows that there were no trends or behaviors because all the weights ranging up to 25 tons were exploited, and that was correct since we delivered the CSRs' orders that (most of the time) were randomly made without considering transport optimization. This result evidenced that every shipment's goods and weights were unpredictable. Instead, correlations were detectable if the shipments were divided by destination to cluster the data considering the 172 destinations where the analyzed site shipped. A total of 95% of the destinations are shown in 3b, 3c, and 3d, illustrating examples of destinations where the trends were easily identifiable, destinations where the trends were identifiable (though with some anomaly), and destinations with unusual trends, respectively. The costs increased with the weights of the loads in an almost constant trend up to a threshold, where the shipments were paid as full trucks loaded, regardless of the loads. The straight line had a slope that depended on a cost increase coefficient per pallet. A threshold represented the situation where the cost did not increase with the weight but remained constant within an error. There was not necessarily a point of discontinuity. The data analysis showed that 20% of the actual cost per shipment was larger than the full truck cost. This meant that these were cases with extra costs. A total of 7% of the shipments were paid as full trucks.

4.4 Improve

The improvement phase was divided into two main activities: developing a new formulation of the FR indicator and experimental application to the case study. The Expectation Maximization machine learning algorithm was applied to cluster the data for each destination. The algorithm allowed for defining a new formulation of the FR that was more representative of the analyzed context. A formulation capable of analyzing the most effective cost that each shipment had referred to the specific destination, and the weights of the goods were defined. In this way, the new FR was able to assess how much the real cost of shipping deviated from the best-expected cost. The new index was called pay weight. The developed model was based on general Bayes' rule, shown below in (3):

$$P(z|y,\theta)=\frac{P(y|z,\theta)\cdot P(z|\theta)}{P(y|\theta)} \Leftrightarrow P(y|\theta)=\frac{P(y|z,\theta)\cdot P(z|\theta)}{P(z|y,\theta)} \qquad (3)$$

$$P(A_1 | B) = \frac{P(A_1 \cap B)}{P(B)} = \frac{P(B|A_1)\cdot P(A_1)}{P(B|A_1)\cdot P(A_1) + P(B|A_2)\cdot P(A_2)} = \frac{P(B|A_1)\cdot P(A_1)}{P(B \cap A_1) + P(B \cap A_2)} = \frac{P(B|A_1)\cdot P(A_1)}{P(B)} \rightarrow CVD \qquad (4)$$

where A_1 and A_2 are the two models that the universe is divided into and B is the probability that the event observed belongs to model A_1 or to model A_2. Applying the model to the case study, its formulation became the following:

$$\begin{aligned} P(Model1 | y_i \cap x_i) &= \frac{P(Model1 \cap y_i | x_i)}{P(y_i | x_i)} = \frac{P(y_i | x_i \cap Model1)\cdot P(Model1 | x_i)}{P(x_i \cap Model1 | x_i) + P(y_i \cap Model1 | x_i)} \\ &= \frac{P(y_i | x_i \cap Model1)\cdot P(Model1 | x_i)}{P(y_i | x_i \cap Model1)\cdot P(Model1 | x_i) + P(y_i | x_i \cap Model1)\cdot P(Model2 | x_i)} \end{aligned} \qquad (5)$$

$$\begin{aligned} P(Model2 | y_i \cap x_i) &= \frac{P(Model2 \cap y_i | x_i)}{P(y_i | x_i)} = \frac{P(y_i | x_i \cap Model2)\cdot P(Model2 | x_i)}{P(x_i \cap Model2 | x_i) + P(y_i \cap Model2 | x_i)} \\ &= \frac{P(y_i | x_i \cap Model2)\cdot P(Model2 | x_i)}{P(y_i | x_i \cap Model2)\cdot P(Model1 | x_i) + P(y_i | x_i \cap Model2)\cdot P(Model2 | x_i)} \end{aligned} \qquad (6)$$

where *Model*1 is event 1 (the linear trend with a slope factor in the clustering), *Model*2 is event 2 (the linear trend without a slope factor in the clustering), *Model*1 ∩ *Model*2 is the universe, x_i is the weight of a shipment and an input (derived from the master data), y_i is the actual cost of a shipment and an input (derived from the master data), and, in general, P(*Model*1 | x_i) = P(*Model*1) and P(*Model*2 | x_i) = P(*Model*2).

The iterative algorithm calculated the probability that a data point x_i belonged to a specific cluster (*Model* 1 or *Model* 2) and converged to a local maximum. The model was also formulated through MATLAB code to make it operational. The results indicated a situation in which, first, the shipment had a good performance because its actual cost was equal to the prediction; second, the shipment had a good performance because its actual cost was lower than the expected; and third, the shipment had a bad performance because its actual cost was greater than expected. All the destinations were applied to evaluate the goodness of the new pay weight indicator.

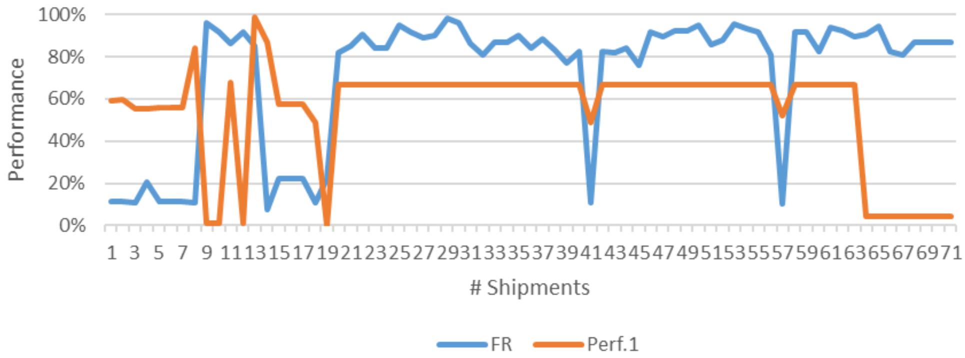
4.5 Control

The calculation of the FR was conducted through both formulations (the initial and the new one) for some key destinations that were selected with a significant number of shipments. Table 5 reports the percentage of similarity between the evaluation results, intended as a percentage difference between +/- 5% between the results. The two formulations produced results that were not very similar in all destinations, with values between 18% and 44%. Only one destination in Spain had a high level of similarity that reached 70%. Graphically, Fig. 4 reports the trends for two destinations, i.e., number 1 in Fig. 4a and number 13 in Fig. 4b. With the new formulation, the level of the FR for the structure analyzed had achieved the performance objectives established by the company's management.

Destination	**Number of shipments**	**Similar results between the two formulations**
Destination 1: Spain	71	70%
Destination 2: Portugal	53	44%
Destination 3: Germany	131	28%
Destination 4: France	109	29%
Destination 5: Switzerland	349	23%
Destination 6: Spain	151	29%
Destination 7: Belgium	175	29%
Destination 8: Portugal	125	28%
Destination 9: Portugal	391	19%
Destination 10: Spain	342	22%
Destination 11: France	75	31%
Destination 12: Germany	262	19%
Destination 13: Belgium	109	18%
Destination 14: Spain	187	36%
Destination15: Spain	181	30%

Table 5. Project charter

a)



b)

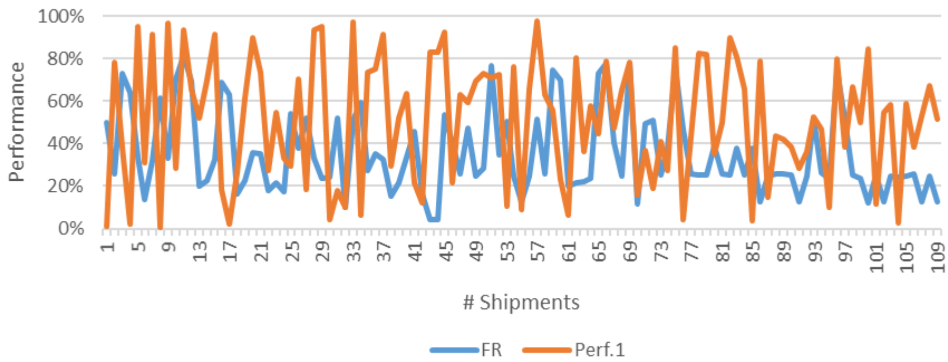


Fig. 4. Similarity trends between the two KPIs for two specific destinations

5. Conclusions

This paper proposes a novel approach for improving the understanding and control of logistics performances using optimized KPIs. The approach is an integral part of Lean Six Sigma, which is applied in production and process management as a method of improvement. With a specific case study, we evaluated its application to an improvement in the formulation of the FR applied to the monitoring of the performance of distribution logistics. The result was as follows: the company, with specific reference to one of its structures located in Italy, had improved the performance of the FR by reaching the reference targets set by the company and aligning the results with the performance of the other plants. The analysis showed that it proposed a formulation that was more suitable for understanding the phenomenon's complexity and overcoming the identified limitations. Based on the existing process used in Six Sigma, this paper improves the DMAIC approach. Due to the complexity of logistics, a new process was needed. Therefore, we can extend the define, measure, analyze, design, and verify (DMADV) approach to new processes in the future.

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