IEOM Society International

International Journal of Industrial Engineering and Operations Management (IJIEOM)
Volume 2, No. 1, October 2020
pp. 1 - 13

Analysis of Cargo Release Services with Process Mining

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https://doi.org/10.46254/j.ieom.20200101

ABSTRACT

Process Mining (PM) uses event logs extracted from process-oriented IS in order to uncover, analyse, diagnose and improve processes. However, the number of studies demonstrating PM applicability is limited, particularly in the field of logistics. This paper presents a methodological framework for a multi-faceted analysis of real-life event logs based on PM and the usefulness of its techniques, combined with traditional IE&M methods, thus offering an innovative approach on multiple levels by combining the use of PM and more traditional methods; using PM to demonstrate the actual movement of goods and generate a physical map of movements inside the warehouse; and enabling continuous tracking. A case-study, implemented on the cargo release process of a large Israeli logistics company, demonstrates this approach. Results reflect a major gap between the actual and the described processes, as an automatic creation of the process from logs shows that 64% of the customers received their goods after 4.5 hours (instead of 90 minutes, as service standard requires). Practical implications include detailed steps and a recommendation for additional analyses. Research value analysis shows that PM techniques constitute an ideal means to tackle organizational challenges by reflecting real-time situations, suggesting process improvements and creating companywide process awareness.

ARTICLE INFO

Received
April 29, 2020
Received in revised form
June 10, 2020
Accepted
June 25, 2020

KEYWORDS

Process Mining, Cargo Handling, Service Standards, Process Conformance, Logistics Operations

1. Introduction

During the last decades, information systems (IS) have developed from simple systems with limited functionality to complex, integrated structures. As a result, it has become harder to understand and monitor how these systems impact the execution of everyday processes in organizations. Process Mining (PM) (W. M. P. van der Aalst, 2011) offers a solution based on the extraction, analysis, diagnosis, and visualization of the data recorded by an IS during process execution. Although in the past, major contributions to the PM literature were predominantly technical in nature, these techniques have proved their usefulness in practice as well. Nevertheless, application-oriented studies have only received modest attention (De Weerdt et al., 2013). This study demonstrates the benefits and challenges of applying PM techniques by implementing a multi-faceted analysis of business processes within the cargo release process of a major logistics company. PM goes beyond the process analysis capabilities of traditional business intelligence tools (Golfarelli, Rizzi, and Cella, 2004). Accordingly, it can be considered a proficient means of helping organizations understand their actual way of working, thereby serving as a foundation for process improvement. This results from the fact that the cornerstone of PM is real data that demonstrates how business operations are carried out *de facto* in an organization, an approach that is significantly different from other techniques of process improvement, such as interviews with key stakeholders. In order to examine the performance of this approach, a methodological framework based on existing literature was developed, describing the PM study as implemented in a logistics services company. While this framework is similar to earlier research (Bozkaya, Gabriels, and Werf, 2009; Rebuge and Ferreira, 2012; De Weerdt et al., 2013), it is also unique

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in many ways, as it examines warehouse locations rather than activities. The novel interpretation of this study was to use physical locations instead of process activities, while using PM techniques to analyse Big-Data log files. This enabled the formulation of different analyses, combining them with traditional IE&M methods. Consequently, this study clarifies the benefits as well as the challenges of conducting a real-life PM study focusing, for example, on service standards, and substantiating that other data collection methods are unreliable. The importance of Services Standards Analysis is self-explanatory, yet it usually done based upon customer feedback (Stelzer, Englert, Hörold, & Mayas, 2016). This research approach, which is backed by theoretical background (Kedem-Yemini, Mamon, & Mashiah, 2018; Ruschel, Santos, & Loures, 2020; Van Cruchten & Weigand, 2018), is novel and does not require feedback from customers.

The following section will outline the development of the field in the last decades and the reasons that the application of PM techniques in services organizations faces distinctive challenges, as well as introduce a case study. Section 3 will elaborate on the research methodology. Section 4 is dedicated to the case study, and section 5 will report on the results. Finally, conclusions will be presented, as well as recommendations for future implementation and research limits.

2. Process Mining (PM)

As PM is a relatively new discipline, some background is required to evaluate the research. Dumas et al. (2005) discuss one of the most influential trends of the past decades: the shift from data-orientation to process orientation. The changing context stimulated the progression of process-aware information systems (PAISs) which can be found along the entire value chain: ERP (Enterprise Resource Planning), WfM (Workflow Management), CRM (Customer Resource Management), case handling, B2B (business To business) and SCM (Supply Chain Management) systems.

As stated above, PM goes beyond the process analysis capabilities of traditional business intelligence tools (Golfarelli, Rizzi, and Cella, 2004). Accordingly, as De Weerdt et al. (2013) claim, it can be considered as a proficient means of assisting organizations in understanding their actual manner of working, thereby serving as a foundation for process improvement. This is mainly because the cornerstone of PM is real data that demonstrates how business operations are carried out in an organization *de facto*. This is significantly different from other approaches to process improvement, such as interviews with key stakeholders or artifact collection (W. van der. Aalst, 2016). Besides the availability of event logs, there is an increased interest in monitoring business processes. On the one hand, legislation and increased emphasis on corporate governance are forcing organizations to follow their business activities more closely. On the other hand, there is constant pressure to improve the performance and efficiency of business processes. This requires the development of additional tools and methods to analyse the data (Ruschel et al., 2020). PM discipline (W. M. P. van der Aalst et al., 2007) is based on model-driven approaches and data mining. It proposes to provide methods, techniques, and tools for the construction of models that adapt to concrete situations by examining system execution traces (i.e., logs). Although some PM techniques have been proposed and a few tools are available, their usage still requires expertise in formal modelling and analysis. Therefore, they cannot be considered straightforward solutions.

Because contemporary information logistics systems record business events, it is possible to analyse those event-logs in this methodology. However, even though much research has examined PM algorithms, there is a major gap regarding applications of PM (W. van der. Aalst, 2016; Mahendrawathi, Astuti, & Nastiti, 2015; Van Cruchten & Weigand, 2018). Among these papers, a significant proportion are based on data collected from hospitals and healthcare systems (Kurniati, Rojas, Hogg, Hall, & Johnson, 2018; Rebuge & Ferreira, 2012; Rojas, Munoz-Gama, Sepúlveda, & Capurro, 2016), some relate to education and training fields (David et al., 2015; Juhaňák, Zounek, & Rohlíková, 2017), and very few discuss industrial applications (Greyling & Jooste, 2017; Stelzer et al., 2016; Suriadi, Wynn, Ouyang, ter Hofstede, & van Dijk, 2013). A Careful examination of the published works reveals that among those, it is rare to find an example involving logistics services (Stelzer et al., 2016; Van Cruchten & Weigand, 2018). This is surprising since, as quoted before, the entire value chain is well established with PAISs. Prominent publications on this subject include Stelzer et al.'s paper on the improvement of service quality in public transportation systems using automated customer feedback (Stelzer et al., 2016), Van Cruchten & Weigand's proposal of data preparation methods that apply logistic domain knowledge for PM (Van Cruchten & Weigand, 2018), Lee, Lv, Ng, Ho, and Choy's proposal of an IoT-based warehouse management system with an advanced data analytical approach using computational intelligence (Lee, Lv, Ng, Ho, & Choy, 2018) and Ruschel et al.'s application of PM techniques in developing a probabilistic model in Bayesian Networks integrated to predictive models (Ruschel et al., 2020). However, none of these papers deal with the lacuna of real logistics cases, ready to implement in logistics firms. The goal of this paper is to demonstrate the applicability of PM in the field of logistics domain, particularly in combination with traditional tools.

2.1 PM Tools

In the early nineties, with the emergence of management techniques such as process re-engineering, the modelling of processes began to gain prominence. Most of these systems keep track of the execution of the business processes by

logging large amounts of data that form the input for process analysis techniques (De Weerdt et al., 2013). Nowadays, PM is being mentioned time and again in the literature as the most appropriate methodology for modelling processes based on the data recorded in an information system (W. M. P. van der Aalst, 2011). PM is typically used to uncover the process model, determine its compliance with the standard model and identify the potential for process enhancement. Table 1 presents an investigation of some of the current PM tools that perform this type of analysis.

Table 1. Vendors and Products for Process Mining (PM)

Tool	Producer	Description	Reference	Web Site
PROM	Non-Commercial Tool	Aims to help practitioners as well as academicians to implement PM techniques based on various algorithms such as genetic algorithm, heuristic miner, et cetera. This tool enables evaluators to demonstrate business processes and analyse the model in great detail. Requires expertise in the field.	(Verbeek H.M.W., Buijs J.C.A.M., van Dongen B.F., 2011)	http://www.promtools.org
DISCO	Fluxicon	Technology that can automatically create smart flow diagrams of log files. High level of visualization, including process simulation. Filtering ability, variants analysis, and statistics. A product that is suitable for the use of managers. Supports a well- developed academic initiative.	(W. van der. Aalst, 2016)	www.fluxicon.com
Celonis Process Mining	Celonis GMBH	Claims to combine PM with Machine Learning and Artificial Intelligence to achieve highly intelligent and fully automated insights from data logs.	(W. van der. Aalst, 2016)	www.celonis.com
Minit 3	Gradient ECM	Automatically analyses business processes and highlights paths and variants. It focuses on banks, insurance, and manufacturing.		www.minitlabs.com
Lana	Lana Labs GmbH	PM automated, pulse visualization. Open API, ability to export process to dashboards or R analysis.		www.lanalabs.com

2.2 Challenges when Performing PM

In order to utilize all the advantages of PM, efforts have been made to create project methodologies that are tailored toward supporting PM projects, as methodologies such as CRISP-DM and SEMMA are very high-level and provide little guidance for PM specific activities (W. M. P. van der Aalst, 2011). In the past, two well-known PM methodologies prevailed: Process Diagnostics Method (PDM) (Bozkaya, Gabriels, and Werf, 2009), which has also been adapted for healthcare environments (Rebuge and Ferreira, 2012), and the L* life-cycle model (W. M. P. van der Aalst, 2011). PDM is designed to quickly provide a broad overview of a process, while L* covers many different aspects of PM and touches on broader topics, including process improvement and operational support. Unfortunately, these methodologies are not suitable for every project (van Eck et al., 2015). Some of their main problems include a limited scope of PDM, which covers only a small number of PM techniques and emphasizes avoiding the use of domain knowledge during the analysis (Bozkaya, Gabriels, and Werf, 2009), thus deeming it less applicable for larger, more complex projects (Suriadi et al., 2013). L* covers more techniques but was primarily designed for the analysis of processes and aims at discovering a single integrated process model. Neither L* nor PDM explicitly encourage iterative analysis, which proved vital for both this case study and the case study performed by Suriadi et al. (2013). Van Eck et al. (2015) presented a new methodology, known as PM2: PM Project Methodology. PM2 is designed to support projects targeted at improving process performance or compliance with rules and regulations. It covers a wide range of PM and other analysis techniques and is suitable for the analysis of both structured and unstructured processes. The research presented in this paper utilizes the PM2 methodology and tools.

3. Research Methodology

Aiming to maximize the benefits generated by the research analysis, data collection was performed by traditional methods (interviews, observations and document collection), followed by the collection of data from the WMS system. The data were analysed first by forecasts, process simulation, Lean and Pareto analysis, and then shifted to PM by using the PM2 framework. This methodology consists of six stages: (1) planning, (2) extraction, during which initial research questions are defined and event data are extracted. After the first two stages, one or more analysis iterations are performed.

Each analysis iteration executes the following stages one or more times: (3) data processing, (4) mining & analysis, and (5) evaluation. An analysis iteration focuses on answering a specific research question by applying PM related activities and evaluating the discovered process models and other findings. Such an iteration may take anywhere from minutes to days to complete, depending mainly on the complexity of the mining and analysis. If the findings are satisfactory, they can be used for (6) process improvement and support. Unlike literature review, the PM analysis was aimed to warehouse physical locations rather than process activities. This approach enabled different type of analysis and conjunction of IE&M analysis to PM maps.

The tool selected for the PM was DISCO (vendor Fluxicon), as Sapir Academic College belongs to its academic initiative and is a tool adapted for managers. Therefore, all the illustrations presented in this paper were generated by DISCO. This tool has been adopted by other publications as well (W. van der. Aalst, 2016; Juhaňák et al., 2017; W. M. P. van der Aalst, 2011). Additional explorations were implemented with PROM, similarly to (Bezerra & Da Silva, 2019; Greyling & Jooste, 2017; Suriadi et al., 2013; W. M. P. van der Aalst et al., 2007b).

Three types of PM methods were employed (W. van der. Aalst, 2016):

1. Discovery – This technique takes an event log and produces a process model without using any a-priori information.
2. Conformance -The existing process model described in interviews was compared to the event log of the same process. Conformance checking was used to check if reality, as recorded in the log, conforms to the model.
3. Enhancement - Intended to generate added value to the Maman Group by changing or extending the a-priori model, demonstrating the process's improvements.

4. Case Study

As the purpose of this paper is to demonstrate the usefulness of PM analyses in practice, it is best demonstrated by a case study in the logistics services industry. This industry is of main interest for PM since it includes many computed business processes that are suitable for event log analysis, yet not reported as worthwhile. The case at hand involves a large Israeli logistics company, the Maman Group, which uses WMS system to provide services.

4.1 Maman Group

Maman Cargo Terminals & Handling Ltd. is the leading provider of logistics services in Israel, offering comprehensive services to government bodies and the foremost companies in the market. Maman's cargo operations, based at the cargo terminals located at Ben Gurion International Airport, provide a full range of cargo handling services for all international air cargo imported or exported from Israel. Although as of 2008 the Maman terminal is no longer the sole service provider in this field, it handles a cargo capacity of up to 300,000 tons per year, which is about 56% of all the cargo that entered Israel via air in 2017. Macro-economic data for 2018 indicates an increase of 8% in the incoming air cargo in Israel. The terminal is open around the clock, seven days a week. It employs about 450 people in three daily shifts and serves all airlines and courier companies operating at BGIA, all in a one-stop shop including the airlines' representative offices, customs, customs agents, cargo agents, transport companies, economic and relevant governmental bodies. The terminal is also comprised of various types of storage options that meet the needs of the incoming and outgoing cargo, a crane system, pallet systems, and free shelving.

Our research focused on the cargo release process, where three central entities are involved in the work process: the customer, customer services, and the cargo release department. The process begins with the arrival of the customer at the customer service centre with a batch form and a release form (Get Pass). Once the forms are approved by customer services and scanning barcodes, the customer receives an operational permit to enter the premises with the truck and approach a ramp. The customer service clerk determines the ramp according to the type of cargo to be released. When the truck reaches the release ramp, the customer hands the forms to the release officer, who sends the forklift operators to pick up the cargo. When the batch and all cargoes have been collected, the release officer checks the cargo and scans its barcodes, and the forklift operators move the cargo to the appropriate truck.

4.2 Research Objectives

The team's research goal was to discover and validate the actual process model of cargo release and check if the company performed according to the service standard of 90 minutes, as promised to customers. If not, one of the objectives was to suggest methods that would enable the Maman company to achieve this goal. This would be achieved by utilizing combined methodology – traditional IE&M methods and new data science methods, particularly PM.

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5. Results

5.1 Traditional Methods

In order to determine the levels of effort (LOE) for the next year, the team first employed observations and forecasting techniques, which enabled the prediction of next year's demands. The results presented here are based upon 228 observations (α=0.05) and upon all the data collected in 2017 (January to October) in the WMS system. For the task of gathering the prediction data for Jan-Oct 2017, the team used three different forecast methods (simple average, moving average with k=4 and exponential smoothing), which were compared with 4 measures (NAPE, MSE, MAD, ME) as per Nahmias (2009). The results are presented in Figure 1, and Table 2 shows the error measure values. According to the results, the best method to predict cargo releases was a simple average, and the forecast is for more than 10,000 cargo releases per month for 2018.

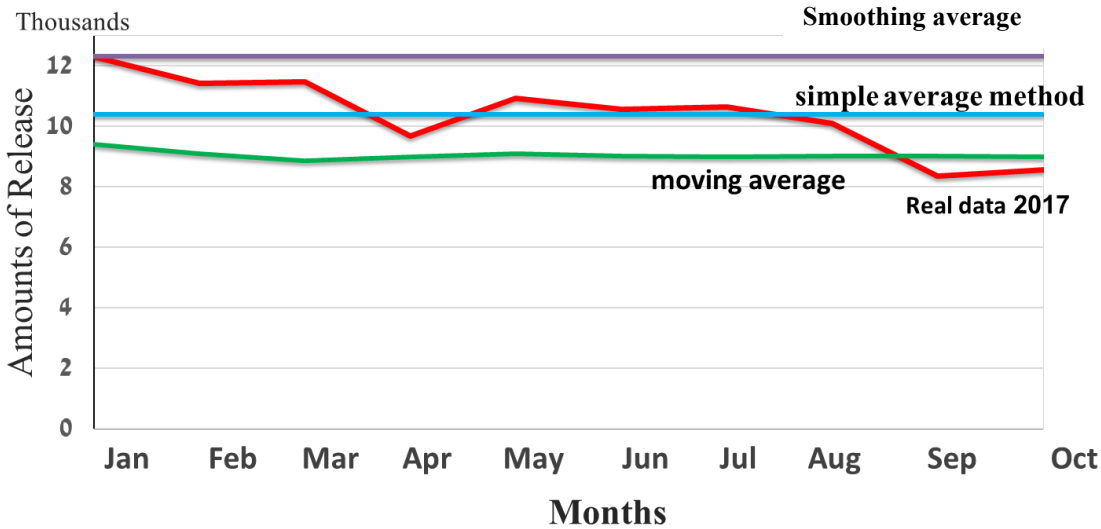

Figure 1. Forecasting demands – anticipated cargo releases.

Table 2. Comparison of forecast measures

ME	MAD	MSE	NAPE	Prediction Method
$\frac{\sum_{t=1}^{n}(F_t - D_t)}{n}$	$\frac{\sum_{t=1}^{n}\lvert F_t - D_t\rvert}{n}$	$\frac{\sum_{t=1}^{n}(F_t - D_t)^2}{n}$	$\frac{\sum_{t=1}^{n}\left\lvert\frac{F_t - D_t}{D_t}\right\rvert}{n} * 100$	Formula
-1,357	1,579	2,825,893	14.53	Moving average K=4
-0.2	987	1,448,862	6.63	Simple average method
1,137	1,137	1,574,708	11.94	Exponential smoothing

Field research was based on a 20-day sample. During those days, the research team visited the site and the warehouses and spoke informally with employees and customers. The main customers' complaint was regarding the time consumption, as many of them stated, "If I have to come here it takes me the entire day". This indicated that the management service standard of 90-minute cargo release was not implemented in the field, although the company indicators that were provided showed only a minor problem regarding cargo release time.

5.2 Data Log

Creating a real model from a log data file using PM requires a focus on the desired processes and the ability to filter "noise" activities. This research focused on main release activities, and therefore the log file was filtered by main locations, main customs codes and all carriers but two (that had a different release agreement). This process excluded

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activities that affect performance indicators but are irrelevant to the research (such as handling corpses, different types of hazards, food, etc.).

Figure 2 shows some statistics on the main log after filtering, summarizing the events overtime (based on the filtered log). It reflects the main issue-related cargo handling release time – a mean duration of 10.8 days and a median duration of 2 hours (compared to the 90-minute service standard) and reflects 72% of the original log cases. After converting the log to a process map, it can be presented by a fuzzy logic diagram (W. van der. Aalst, 2016) of the cargo release process.

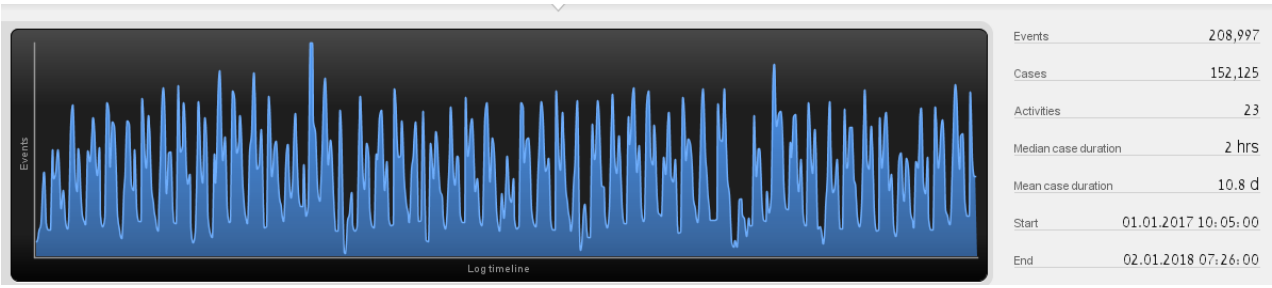

Figure 2. Data summary, events overtime as filtered from the original log file.

5.3 Process Discovery

Regular PM data load relates to "case ID" versus "activity". Usually, the “case ID” when applying this technique would be a form, such as a purchase order or an insurance policy (Mahendrawathi, Astuti, and Nastiti, 2015; Rebuge and Ferreira, 2012). DISCO utilizes Activity-Based Decomposition (W. van der. Aalst, 2016), and due to the research team's definition of warehouse location as "activity" and the "case ID" as the Bill of Lading, the process discovery map is quite different than usual. These definitions allow the process to begin when the customer arrives to pick up the goods, creating a flow in the process by moving the goods in the warehouse connected to the same Bill of Lading. Therefore, the representation in Figure 3 is innovative, as it shows a physical map of movements inside the warehouse in the form of a “Spaghetti Diagram” created by the research team with DISCO. While a client receives a Bill of Lading that is comprised of many lines, which are in different locations in the terminal warehouse, the following diagram is presented in low resolution detailing in order to simplify it. It shows clearly that the Automatic Storage Area is the most active area, where most of the warehouse locations exist. It should be clarified here that PM utilizes all the available data rather than just sample data. Figure 3 is based on over 205,000 records, with frequencies. This accomplished the first goal – determining the actual process as per the real data log.

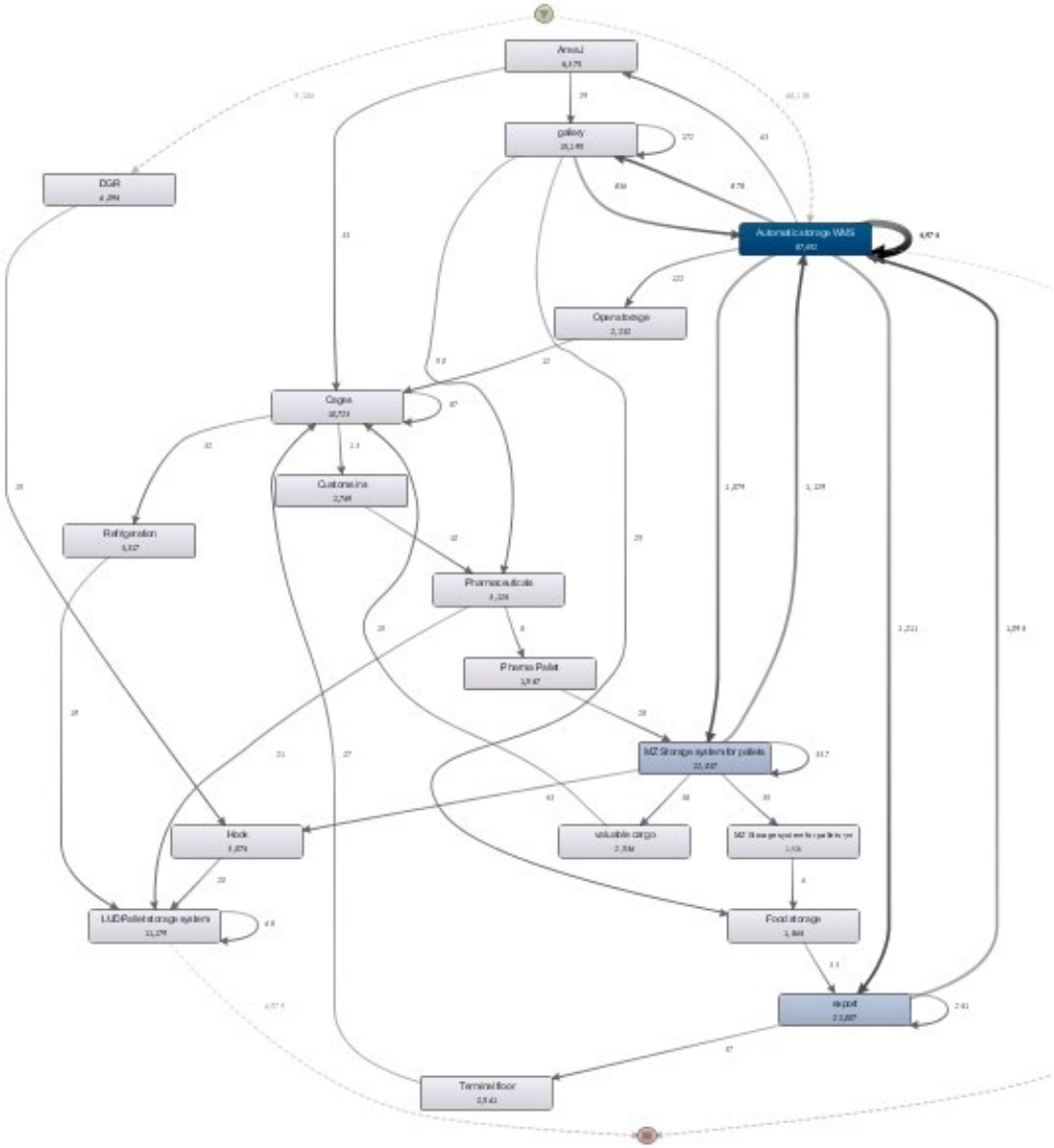

Figure 3. Handling cargo layout with frequencies as built from the filtered log file**.**

5.4 Conformance

Conformance checking compared the release cargo process as described in interviews to the actual process as found in PM. It revealed new facts, such as rework and attributes affecting it. Figures 4 summarize this. Thus, it was found that the actual process was somewhat more complicated than expected by the managers, that cargo was moved around the crane area frequently and that some locations acted as bottlenecks in the release process.

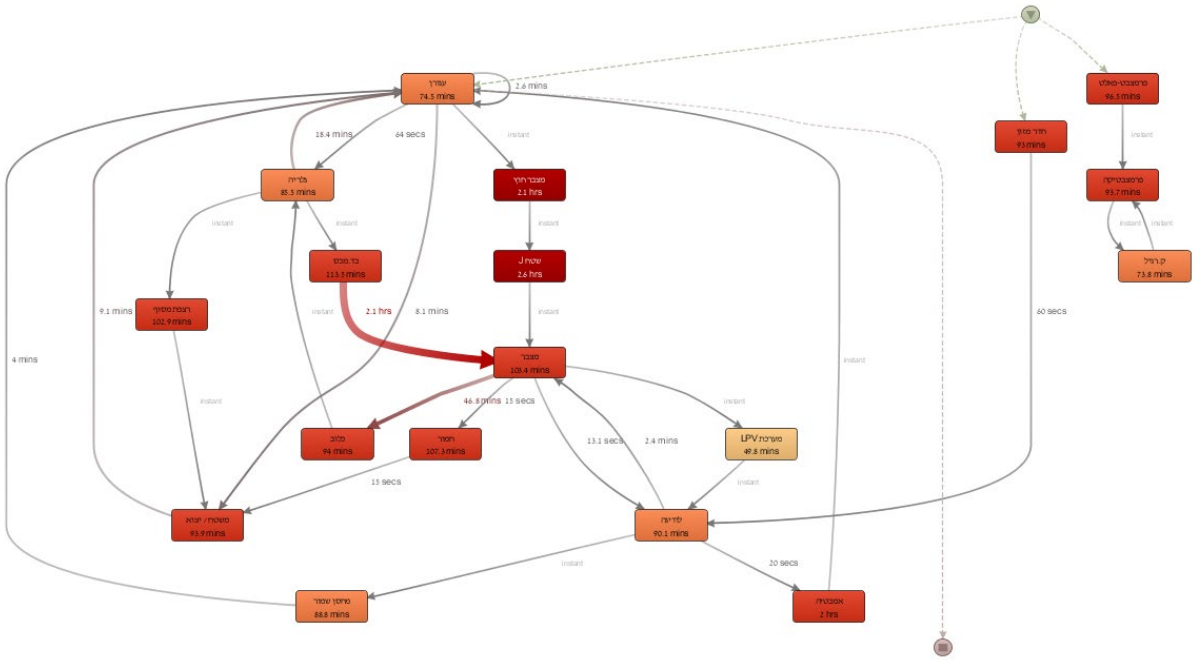

Figure 4. Handling cargo release layout with mean time, based on the filtered log file.

5.5 Enhancement

The third component, enhancement, was examined in three steps – analysis, improvements, and evaluation. First, for the analysis, the focus was on the cases that took up to 9 hours, as other cases were defined as exceptions. This enabled the research team to perform statistics on over 120,000 events that are 45% cases of the original log file. In figure 4 (mean time) the darker red indicates the locations in the warehouse that consumed more time for the release process to be implemented. These were identified as 'problematic locations', including, for example, the free storage area. Similar analysis was performed on median times. Figure 5 shows the map created from this filtered log file with mean time. The total release time at each location is indicated by the darkness of the item's background colour.

The analytics on the data log file revealed valuable information regarding the work processes of the Maman Group. Based on these analytics, the second step was improvements. Process research showed a map with the actual release process, including all the paths of the process, defined as the variants of the process. Data analysis found 4,594 variants of the original process, with eight of the variants representing 67% of the cases. Analysis of the frequent variants identified four problematic locations, where the cargo handling release process lasted more than 90 minutes by median time and mean time. The release handling time for each of the 23 locations in the warehouse was determined, and statistics were produced for each agent and carrier (including rework, idle time and bottlenecks). This analysis of the handling process revealed that preplanning while unloading the planes and storing according to the Bill of Lading would dramatically improve the release time. In order to complete the enhancement goal, the team combined other methods, in particular 5S methodology and job scheduling (during the unloading process), so that single Bill of Lading locations could be improved, consequently reducing the time consumed by the cargo release process. The consequences of this improvement were estimated by using the Arena simulation model, presented in Figure 6. The model was run twice, once without changes (mean time 267 minutes to release, median time 112 minutes) and then with the suggested enhancement (mean time of 79 minutes).

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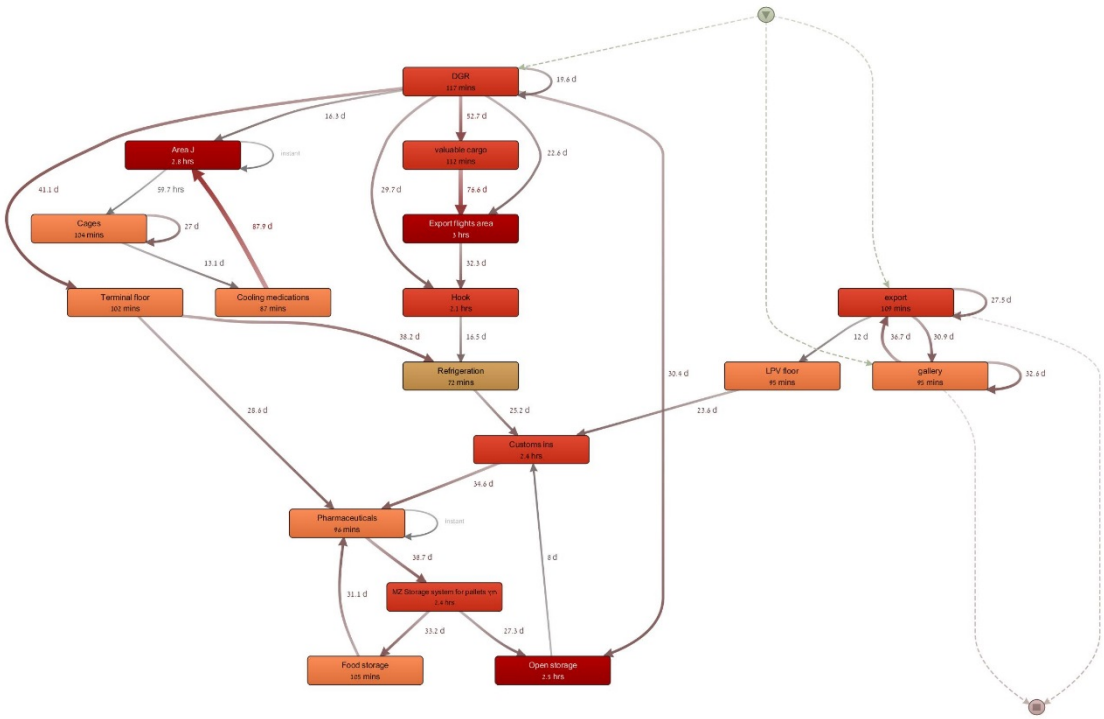

Figure 5. Handling cargo release layout median time, focusing on the "free storage" area.

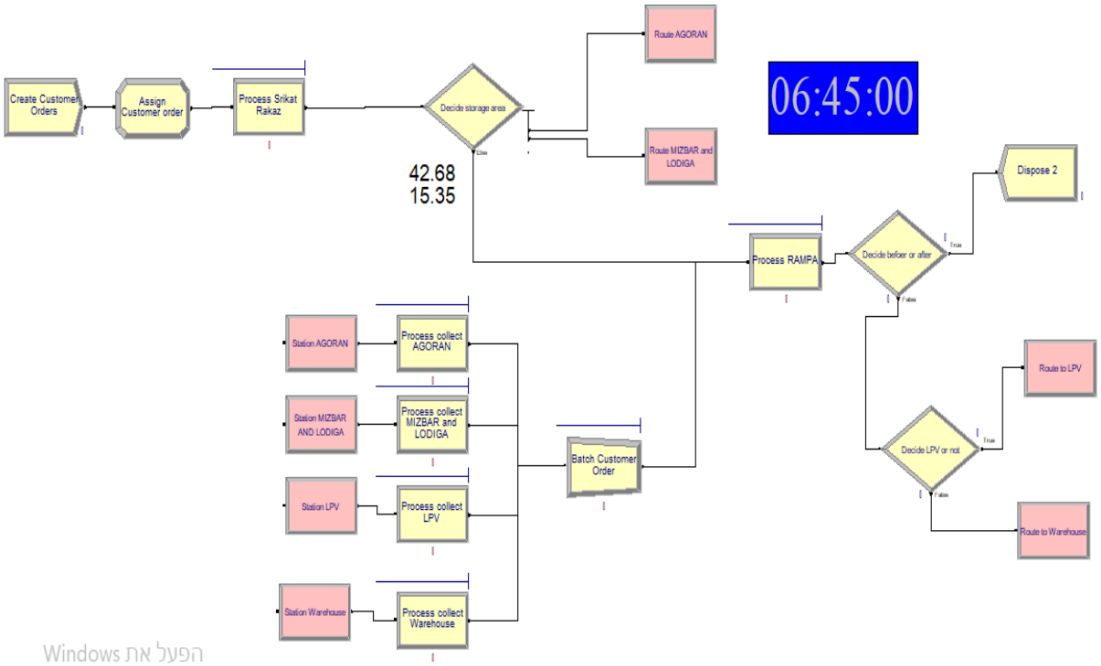

Figure 6. Arena simulation model for cargo release time after improvement estimation.

6. Conclusions

As the results of this research produced many conclusions, they will be divided into two main types: specific and general. Among the specific conclusions, four will be discussed following.

First, a major gap was discovered between the actual process and the described process, especially obvious in the time analysis. It was determined that most of the customers did not receive their cargo after 90 minutes. In fact, 64% of the customers received their goods after 4.5 hours (!). Based on these findings, it was suggested that the Maman Group

change their storage procedures so that goods are stored according to the Bill of Lading, as the research data recorded major delays on long releases, resulting from the current location of different stations. According to research estimations, it can be assumed that the release time may be cut by approximately half.

The **second** recommendation also relates to warehouse location. It is recommended that three remote storage areas (such as Pharmaceutics) be shifted to areas closer to the loading area. Analysis of the distances and the impact of the distance on release time resulted in faster release time for each location.

The **third** conclusion was based on the fact that many releases required rework. For example, shipments were moved from one crane area to another 4,974 times. This usually meant that the cargo was in the wrong location, which caused both a delay in release time and a waste of resources and funds. A detailed review was completed, assessing the implications of the relatively large amount of required rework with Maman's management.

The **fourth** conclusion is related to quality. This analysis displayed the company exceptions in quality (error) as prohibited cargo mobility that occurred over the entire year. Moving cargo to improper storage stations can cause quality issues. An example of quality issue research showed pharmaceutical cargo on an export platform as irregular action. It can result in cooling issues that may damage the cargo, thus exposing the company to various risks. This issue was presented to the management so that they could improve procedures and avoid mishaps.

As for general conclusions, it should be emphasized that this research performed PM on a field that had not been previously examined, Logistics Services, using existing tools, designed for other purposes, in an innovative manner. This method generated a visual representation of the activities taking place in the warehouse, clarifying it for both the management and the workers. In addition, it revealed hidden problems and encouraged the development of release process recommendations, aiming to improve service. Finally, this paper demonstrates that it is not only feasible, but extremely advantageous, to use PM techniques in order to analyse Big-Data log files.

7. Process Observations

Case study observations can be useful for generalizing the methodology; Following are a number of observations deriving from this research that can ease planning implementation of the findings in other organizations or processes.

First, intensive work was required to export the log files. The research assumptions did not include the human resources component; thus, its implications were not considered. Obstacles resulting from internal political issues are often found in research performed in working organizations, especially involving data from information systems and private ownership of data. As top management was very interested in the results of the research, it was concluded successfully. Yet the human component must be taken into consideration in future implementation. Related to this, the second observation is that exporting the log files was technically quite easy (except for the issue of big data), as expected.
Third, the methodology does not emphasize enough the need to understand every detail of the process. While creating the map is not difficult, without a deep understanding of the terms in use, habits, and methods, they are quite difficult to interpret. This was solved during the field research that took place prior to the log analysis, in which the research team visited the site and the warehouses and spoke informally with the employees and customers in 20 different instances. Another factor was the "open door" approach enabled by the Maman Group, which allowed the researchers to conduct unrestricted interviews.

The fourth and final observation is that the visualization created by the process maps generated in this research clearly show the physical movement of cargo items inside the warehouses, in a way that is easily understood and communicated to the management and employees. This is a major advantage of the methodology.

8. Discussion and Conclusion

This paper presents the application of PM in a new field, cargo release processes. It proposes an applicable framework that reveals actual processes, stressing conformance and possible quality issues that the company can improve upon. The framework of this research can be implemented regardless of the information systems in use, as it relies on actual data and statistics and produces clear maps of actual processes, including all their variants. This research demonstrates a combination of well-known IE&M techniques (such as observations, forecasting, 5S and simulation) with a new data science technique (PM) and used a variety of computerized tools (Arena, Disco, Excel, WMS System) in order to achieve the research goals. The Maman Group embraced the results and recommendations and immediately began to change their company's work processes for both received packages and cargo release.

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Usage of PM as a research methodology in logistics services is exceptional. The need for it is described on literature (Stelzer et al., 2016; Van Cruchten & Weigand, 2018), and it is a great achievement for this research showing that it can be done. Furthermore, it can create substantial benefits to the organization. Based on the findings, it is clear that the Maman Group needs to change their storage procedures so that the release time is improved. The suggested change, storage by Bill of Lading, is logical, but without clear proof and clear time-consuming averages, had not been implemented to date. As the results are clearly visual, they can form the basis for the commencement of the improvement process in this major organization. The most interesting part is that the company's systems (as WMS) showed different release time averages. Management referred to those times and saw a decreasing percentage of cargo that met the service standards, thus initiating this examination. Further investigation shows that cargo release time was calculated using false perceptions of the process, not taking errors and unallocated cargo into account, and based on a small sample of goods. This research enables logistics companies to follow the actual path of all goods, rather than basing their information on sampling or possibly incorrect assumptions.

The results initiated another recommendation - a change of some warehouse locations. Again, this was based on the actual movements of cargo during the entire year. Assuming next year's prediction, regarding the same blend of cargo, is found to be correct, this recommendation will save the company time, as it will bring frequent items closer to ramp. This is an excellent example of a "Spaghetti Chart" perception as per Chiarini's suggestion, whereby the most important wastes were detected using tools derived from lean thinking (Chiarini, 2013). These costs, often related to cargo handling transportation inside warehouses, are usually not effectively traced. PM methodology enabled its trace and estimation. The usage of PM combined with traditional IE&M methods (such as forecasting, simulation, and warehouse location and layout) was proven efficient, easily comprehended and communicative. Consequently, the problems of rework and quality issues were quickly demonstrated and both management and employees could foster the research recommendations.

This leads to a discussion of another accomplishment of this study; It not only demonstrates a real-life case usage of PM, but it uses PM in a unique manner. The PM maps, unlike the examples in literature review (David et al., 2015; Greyling & Jooste, 2017; Kurniati, Johnson, Hogg, & Hall, 2016) show the actual movement of goods, thus acting in similarly to the SLP-based "from-to" charts (Chen, 2016). As opposed to these charts, PM maps are created automatically and can be changed on ongoing basis, reflecting a novel use and approach to PM tools.

The research limitations are clear. First, the recommendations presented here are generalized – there is a need for more demonstrations regarding other logistics companies, so that the results may be more comprehensive and appropriate implementation methods may be developed. Second, PM is a relatively new method, and therefore the existing tools are limited to existing algorithms and not yet common to all users. However, new tools are rapidly developing, and vendors are facilitating their use in organizations. There is a special need to "re-Play" the data, combining simulation with process discovery (W. van der. Aalst, 2016).

This paper demonstrates the potential of PM techniques in the field of Logistics, particularly service level measures and reduction of waste with PM techniques (implemented in DISCO and ProM 6.3) combined with IE&M established methods. Future work will continue in several directions. The first path offered is to combine the approach proposed in this paper with other PM tools, thus enabling the discovery of interaction patterns in order develop and propose new measures for existing processes. The second is to create a comparative study between various methods utilizing Big-Data event logs, such as the comparison of PM techniques to traditional IE&M results. The third proposed path is to implement an approach that will be deployed and tested on other companies with diverse environments, and will allow more generalized results. furthermore, it will allow calibration and amelioration of the measures and propose solid methodology to monitor Logistics Services. In order to enhance the usability of the measures it is suggested that an intuitive graphical interface for non-experts be designed, including such features as automatically setting parameters and suggesting suitable types of analysis. Finally, another important step would be to further investigate techniques in event log decomposition so that typical paths on specific performance may be extracted.

Acknowledgements

I would like to acknowledge Mr. Naor S. Mamon and Mr. Gal Mashiah for their support and help in the research process.

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Biography

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