Analyzing Process Execution Time for Evidence-Based Policy Making in Information Systems Using Process Mining

Mohsen Mohammadi
Assistant Professor in Computer Engineering;
Esfarayen University of Technology; Esfarayen, Iran;
Email: Mohsen@esfarayen.ac.ir

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Abstract: Enterprises employ information systems to carry out their day-to-day business operations. Organizations implement business policies to enhance their competitive edge through efficient process management. This paper aims to propose a method that combines two approaches: evidence-based policymaking and process mining, to facilitate process reengineering. While numerous evidence-based approaches utilizing process mining techniques have been employed to assess process performance through measurements, these methods often focus on individual process instances. This is in contrast to Business Process Redesign (BPR) assessments, which encompass more comprehensive performance measurements, including overall process performance. This study proposes a method for analyzing process execution time, which includes Cycle time, Lead time, and Activity time. The aim is to support evidence-based policymaking in information systems through the use of process mining. Several key performance indicators (KPIs) have been defined for evidence-based management of business processes to identify process bottlenecks. The results of this paper demonstrate the application of process mining in analyzing the execution time of business processes. Using a real-world dataset, the study identified time-consuming activities and provided key performance indicators (KPIs) to guide process optimization. These findings demonstrate the effectiveness of process mining in identifying bottlenecks and inefficiencies within operational processes, ultimately leading to improved process performance and efficiency.

Keywords: Evidence-based Approach, Process Mining, Process Performance, Key Performance Indicators, Execution time

1. Introduction

Information systems play a crucial role in helping enterprises execute their operational business processes (Mohammadi & Muriati, 2012). To gain a competitive edge through streamlined process oversight, organizations rely on implementing business policies. These policies are instrumental in effective management as they outline the standards, procedures, and regulations governing day-to-day business activities (Wang et al., 2009; Mohammadi, 2017). Several comprehensive organization-wide policies, such as Business Continuity Plans, Records Management, and Performance Management, are highlighted as examples in Peltier (2004).

Supporting the execution of business processes is commonly facilitated by process-aware information systems. These systems encompass both traditional workflow management systems (WFMS) and modern Business Process Management Systems (BPMS). They collect and retain significant data on business events, which are stored in event logs for later analysis and process improvement purposes (Van Der Aalst, 2007). The availability of such detailed event logs has driven the shift towards an “evidence-based” approach in designing and improving business processes. This evidence-based management approach is typically achieved through the use of various indicators that effectively capture important aspects of business processes and their associated stages throughout the process management lifecycle (Wetzstein et al., 2008; Wang et al., 2009).

In the context of Business Process Management (BPM), management approaches such as Lean Six Sigma and Business Process Reengineering (BPR) primarily focus on enhancing operational efficiency. This includes minimizing flow time and reducing defects (Cho et al., 2017). However, numerous analytical methods have emerged to enhance the efficiency of the model, based on specific performance measures. For example, techniques such as integer programming or Markov decision problems have been employed to determine optimal policies.

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While Lean Six Sigma and Business Process Reengineering (BPR) primarily focus on improving operational efficiency by reducing flow time and defects, Process Mining has emerged as a data-driven approach that utilizes event logs and process models to thoroughly analyze process execution. Process Mining's distinctiveness lies in its ability to identify bottlenecks, inefficiencies, and optimization opportunities, ultimately enhancing operational performance and efficiency. Recently, process mining has primarily been utilized as an approach to thoroughly analyze and assess the performance of various processes within an organization (Van der Aalst, 2016). Therefore, there is a significant need for solutions that can help business process users and owners analyze process policies efficiently and effectively using process mining techniques.

In this paper, a method is presented for analyzing process execution time, specifically focusing on Cycle time, Lead time, and Activity time metrics, to support evidence-based policymaking within information systems using process mining. These interconnected metrics reflect the efficiency and effectiveness of processes. Process policies can influence these metrics by driving changes in resource allocation, process design, and workflow optimization to achieve shorter cycle times, lead times, and activity times, while maintaining or enhancing overall process quality. For clarity, let's consider two practical process policies. Firstly, a manufacturing process aims to minimize cycle time, ensuring that products move through all stages within 24 hours. Process mining helps to identify bottlenecks and streamline production. Second, in e-commerce, it is essential to shorten the lead time from order placement to delivery to within 48 hours. Process mining pinpoints delays, enabling targeted workflow improvements to meet customer expectations while maintaining product quality. These examples illustrate how process policies directly shape these metrics, promoting efficiency and process quality.

The paper's structure is as follows: the subsequent section examines the relevant literature, while Section 3 outlines the technique and its implementation in a specific case. Section 4 provides a discourse, and Section 5 ultimately presents the conclusions.

2. Literature Review

When assessing process or organizational performance, three primary dimensions come into focus: time, cost, and quality. These dimensions are measured using specific Key Performance Indicators (KPIs). Executable process models play a crucial role in analyzing projected performance, encompassing metrics such as response times, waiting durations, flow durations, resource utilization, costs, and more. Additionally, timing information is often embedded in event data, with events being timestamped chronologically to facilitate performance evaluation. Focusing on the aspect of time, the resulting performance indicators include:

Lead Time (Flow Time) encompasses the overall duration from the beginning of a case to its completion. Within this context, Service Time represents the duration dedicated to actively working on a case, often constituting a fraction of the lead time. Additionally, waiting time refers to the duration during which a case waits for the availability of a resource, which can be measured either per activity or as a whole. Finally, Synchronization Time refers to the period during which an activity remains incompletely enabled, awaiting an external trigger or parallel branch activation (Van der Aalst, 2013; Li et al., 2019).

Cycle time represents the total time it takes for a case (or a process instance) to complete from start to finish. This includes the time that the case is actively being processed, as well as any waiting time in queues or due to delays. Lead time is the duration from the initiation or entry of a new case into the system to its completion. It provides insights into the duration of time customers or stakeholders have to wait before their requests are fulfilled. The ratio is defined as (Cycle time / Lead time). These three steps collectively aim to identify cases where delays occur, corresponding to process policy 1. For example, one aspect of this policy is to ensure that the ratio for each case is not less than 0.2.

Numerous research endeavors have been undertaken within both academic and industrial domains to evaluate process performance through measurement. (Kueng & Krahn, 1999) introduced a comprehensive framework for measuring process performance, which encompasses stages ranging from identifying process objectives to improving business processes through the use of performance metrics. (Kueng, 2000) further outlined a stepwise approach for establishing performance indicators and delineated six criteria for effective process performance indicators: quantifiability, sensitivity, linearity, reliability, efficiency, and improvement-oriented aspects. Other scholars, such as Wetzsteing et al. (2008) and Popova & Sharpanskykh (2010), have focused on proposing methodologies for creating individual process indicators. Wetzsteing et al. (2008) utilized a KPI ontology, while Popova & Sharpanskykh (2010) used an indicator modeling framework.

An approach is proposed in (Wang et al., 2009) for process policy analysis, known as Policy-Driven Process Mapping, for process discovery. Moreover, a framework is introduced in (Li et al., 2010) for policy-based process mining, which aims to automatically discover process models based on business policies. However, both of these approaches are distinct from the currently employed participatory and analytical techniques for process mapping, which are achieved through the utilization of business policies. They primarily focused on process discovery for analyzing process policies.

A metamodel was introduced by del-Río-Ortega et al. (2013) to comprehensively define process performance indicators. They also suggested strategies for linking components within business processes to Process Performance Indicators, accompanied by implementing the metamodel using description logic. (Strecker et al., 2012) and (Pinheiro de Lima et al., 2013) developed a performance measurement system focused on Process Performance Indicators.

A framework proposed by Cho et al. (2019) for clinician scheduling, based on simulation analysis and utilizing process mining techniques, plays a vital role in enhancing process performance within healthcare management. By optimizing clinician schedules effectively, the aim is to reduce waiting times for patient consultations and improve patient satisfaction. This direct relationship between the framework and process performance reflects the potential of the framework to enhance operational efficiency and effectiveness.

A method is proposed in (Delias et al., 2021) which focuses on enhancing organizational process improvement through an evidence-based approach. It emphasizes the significance of utilizing knowledge and implementing management tactics in this context. The study utilizes existing data on business process execution to create evidence-based plans for improving business processes. By comparing process executions across different business units, it assesses the adaptability and prevalence of process behaviors.

A data-driven approach is introduced in (Schuh et al., 2022) to detect process weaknesses and suggest improvements. The research introduces a central performance indicator based on event logs, which provides a method for prioritizing issues and enhancements. This approach streamlines the process of improving business processes.

However, it is important to note that the aforementioned studies are not directly applicable to assessing the impacts of business process redesign (Cho et al., 2017). This is because certain process performance indicators within the proposed methodologies focus on individual process instances, whereas assessments of Business Process Redesign (BPR) primarily employ holistic performance measurements, such as overall process performance.

The research gap identified in this paper relates to the current limitations in the field of process analysis. Current methods primarily focus on evaluating individual process instances using process mining techniques. While these approaches offer valuable insights into specific cases, they often lack a holistic perspective on overall process performance. The paper highlights the need for a novel approach that bridges this gap by integrating evidence-based policymaking and process mining. This integration allows for a more comprehensive assessment of process execution, including key performance metrics such as cycle time, lead time, and activity time, to provide a broader view of how processes are functioning as a whole. By combining these two methodologies, the research introduces an innovative approach to addressing this research gap and providing organizations with a more comprehensive understanding of their operational processes. This will lead to improved decision-making and performance optimization.

3. Methodology

In this section, we will explain the steps involved in the proposed method, as illustrated in Figure 1. The tools and techniques applied include Python and pm4py, which is a Python library that implements a variety of process mining algorithms.

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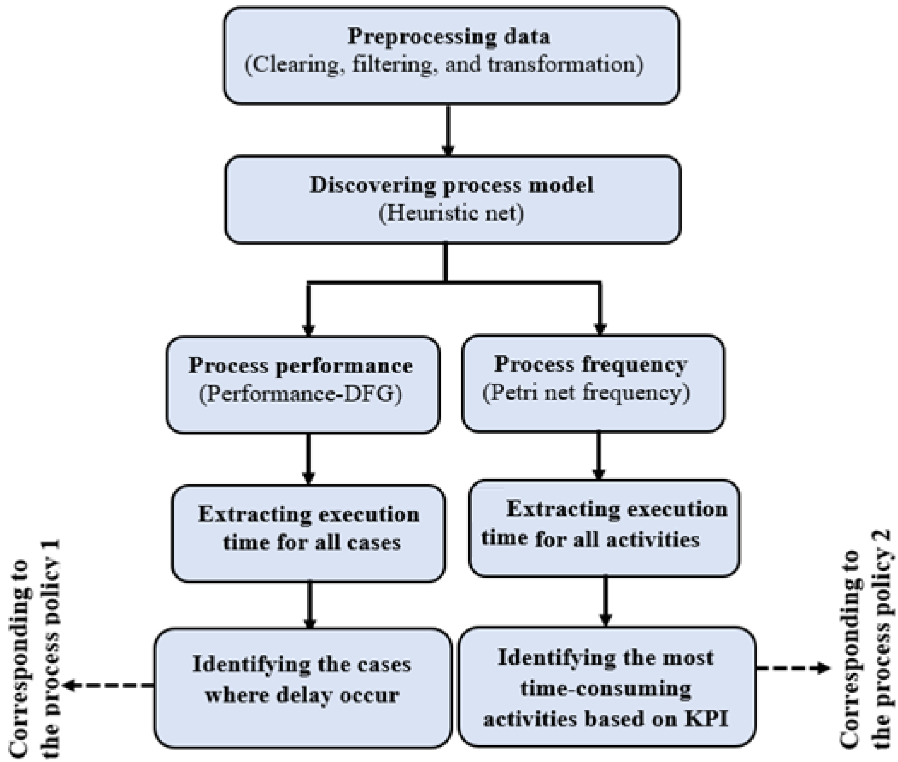

Figure 1. The proposed method

Regarding Figure 1, the event log related to the business process is initially cleared and filtered at the first step. Subsequently, the data is transformed into a data frame in preparation for the next step, which involves discovering the process model using the Heuristics net. In the next step, on the left-hand side of Figure 1, the process performance is modeled using a Directly-Follows graph (DFG). During this phase, a performance-DFG model of business processes and their flows is developed. However, it is necessary to calculate detailed information regarding execution time for all cases, including cycle time, lead time, and the associated ratio.

On the right-hand side of Figure 1, the process frequency model is documented using a Petri net. Similar to the performance-DFG, the Petri net can be enhanced with frequency data, just like the Directly-Follows graph. This involves employing a replay technique on the model and assigning frequencies to paths (PM4PY, 2023). The output of the three steps on the right side is the identification of the most time-consuming activities, by process policy 2. For instance, this policy ensures that the execution time of each activity is less than 10% of the total process execution time.

The proposed policies are implemented through a systematic process within the provided method. This verification process involves a systematic approach that includes data preprocessing, model discovery, and a comprehensive analysis of performance metrics. The final output enables the assessment of adherence to the designated policies and offers valuable insights into the procedure.

4. Implementation and Findings

In this study, the method is applied to a dataset to demonstrate its applicability. The dataset is sourced from www.data.4tu.nl and pertains to the loan application procedure within a financial institution in the Netherlands. This event dataset encompasses all submissions made through an online system from 2016 to 2017. The process involves several stages, including the submission of loan applications, validation of applications, decision-making on offer extensions, applicant responses, and confirmation of offer acceptance. Figure 2 presents the process model visualized in the form of a Heuristics Net. The Heuristics Miner algorithm operates on the Directly-Follows Graph, providing a way to handle noise and uncover common patterns. Process models, represented as Petri nets, have a clear interpretation: a process begins at the initial marking's place and ends at the final marking's place (PM4PY 2023).

According to Figure 2, the process comprises a total of 26 distinct steps, which can be categorized into three groups: activities related to the application (labeled as 'A_'), activities concerning offer creation (designated as 'O_'), and activities guiding the overall workflow (notated as 'W_'). In the process model, various colors are utilized to visually represent performance metrics linked to activities that usually carry a specific significance. For instance, the color pale blue is used to show the execution time of activities, while bright blue colors indicate longer durations. It's noteworthy that not all activities occur with the same frequency. Furthermore, the most frequently occurring tasks include "O_Created" and "O_Create offer," followed by "O_Sent" (both through mail and online channels), "W_Validate application," and "A_Validating." In contrast, the task that occurs least frequently is “W_Personal Loan collection.”

Figure 3 presents the performance-DFG model of the loan application process. Performance-DFG represents events/activities in a log as nodes, with directed edges linking nodes if a trace in the log shows the source event/activity followed by the target event/activity. These edges enable the calculation of performance metrics, such as the mean time between two events or activities (PM4PY 2023). Through the process frequency model, activities that consume more time in the business process are identified. Activity time, also known as processing time or execution time, refers to the duration required to complete a specific activity or task within a process.

The Performance-DFG serves as a crucial tool for calculating performance metrics, such as the mean time between two events or activities. This visualization enables the identification of activities that consume a significant amount of time in the business process. It is important to note that the execution time, including cycle time and lead time, is calculated for all scenarios within the loan application process. As shown in Table 1, the ratio is calculated for each case. A lower ratio value indicates that more time is wasted for that specific case. The inclusion of a few sample cases highlights the significance of this analysis.

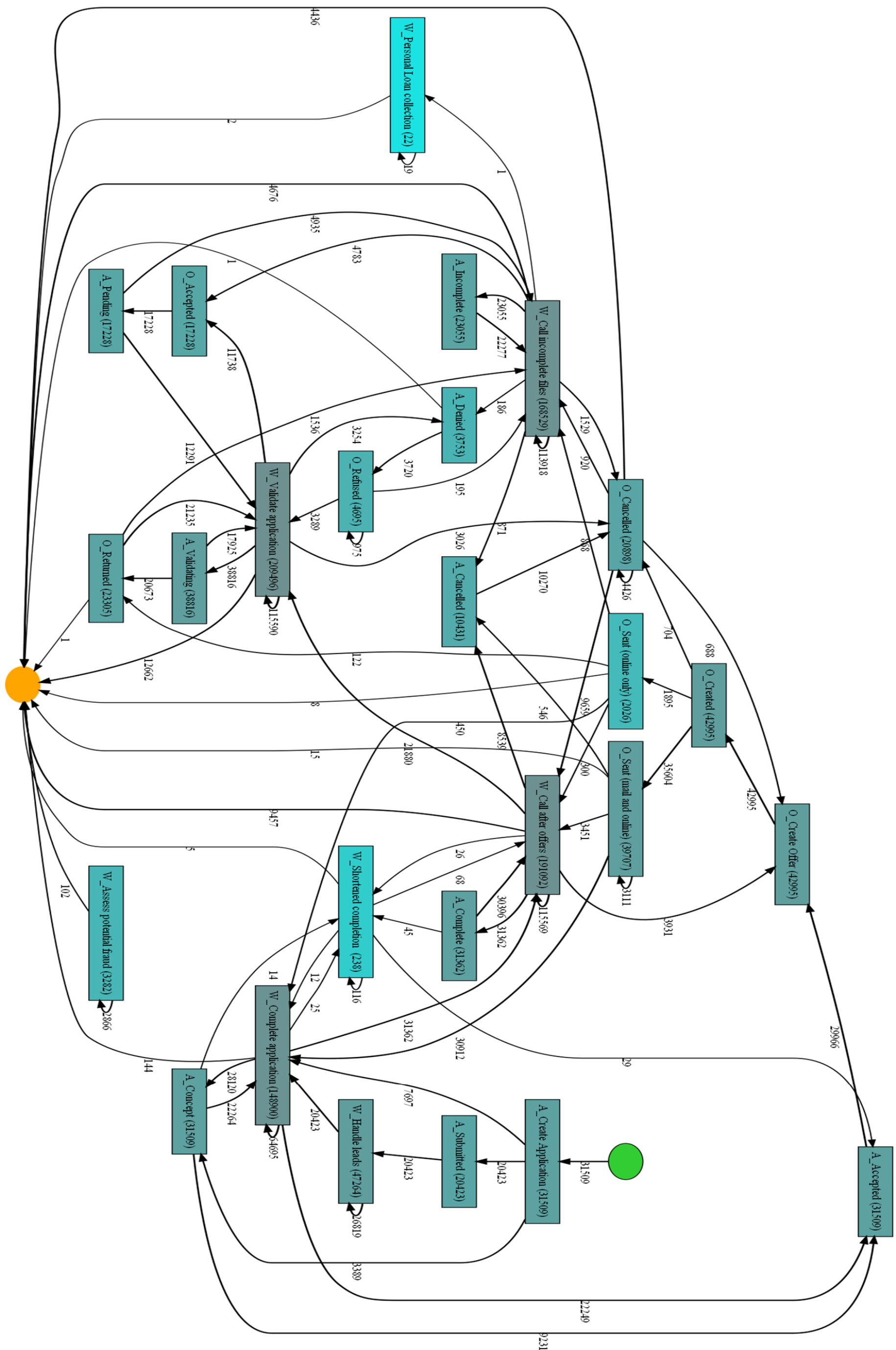

Figure 2. Process model (Heuristic net)

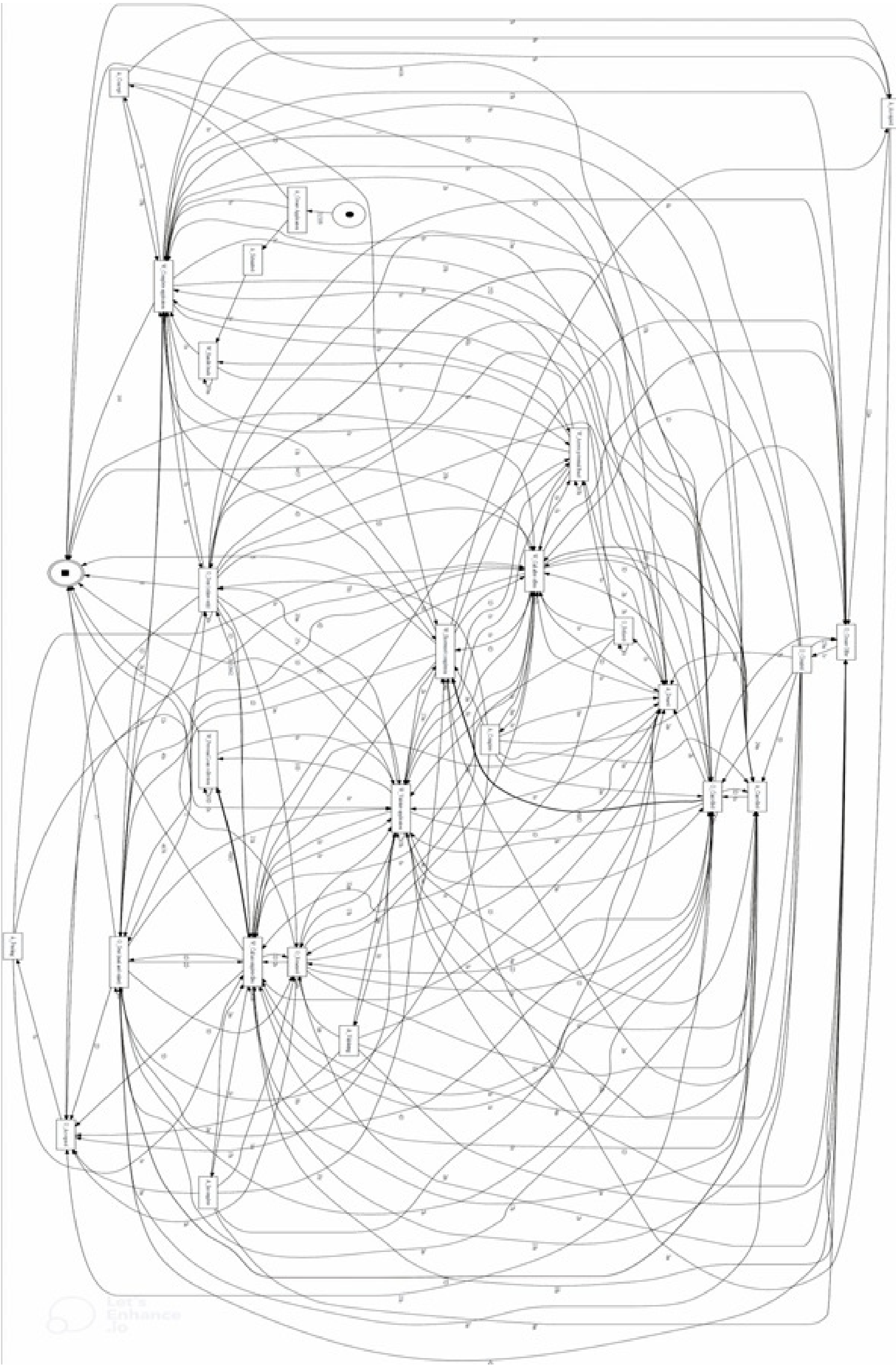

Figure 3. Performance-DFG

As mentioned earlier, following the visualization of the performance-DFG, the next step is to identify cases where delays occur, corresponding to process policy 1 (for example, ensuring that the ratio for each case should not be less than 0.2). Based on the performance-DFG depicted in Figure 3, the execution time, including cycle time and lead time, is calculated for all cases within the loan application process, as shown in Table 1. It's worth noting that due to the large number of cases, only some samples are provided here. The last column of the table displays the value of the ratio, which is obtained by dividing Cycle time by Lead time. A lower ratio value indicates more time wasted for each case. For example, the case with the ID "Application_1691306052" has a ratio less than 0.2, signifying that a significant amount of time is wasted in this case.

Table 1. Cases execution time

Case id	Cycle time	Lead time	ratio
Application_1691306052	13781.165	155618.225	0.088558
Application_1746793196	139282.736	683037.395	0.203917
Application_1878239836	33723.747	201326.587	0.167508
Application_1529124572	32028.36	628982.261	0.050921
Application_1120819670	35194.235	191956.481	0.183345
Application_180547487	42972.793	237409.677	0.181007
Application_1806387393	53702.807	202779.094	0.264834
Application_493034835	48578.772	234825.151	0.206872
Application_1474017032	50705.702	329464.469	0.153903
Application_1535675187	122198.446	357428.265	0.341882
Application_1405679737	1803826.214	2051586.52	0.879235
Application_446334558	438.475	900000	0.000487
Application_130460765	47363.266	384598.251	0.12315
Application_1588619628	30761.596	1440126.23	0.02136
Application_1624825294	676200.972	939705.244	0.719588
Application_1448214642	80127.776	351828.053	0.227747
Application_987262285	25247.154	225131.993	0.112144

Finally, in the last steps, after visualizing the process frequency model using a Petri net, the next step is to identify the most time-consuming activities, corresponding to process policy 2 (for example, ensuring that the execution time of each activity is less than 10% of all process execution time). The performance frequency model is depicted in Figure 4. This visualization helps identify the most frequently occurring activities, which are crucial for further analysis. Due to the relatively large number of activities in this process model, it appears somewhat complex and a part of the performance frequency model is presented here due to space constraints. The most frequently occurring activities are highlighted, and each of them is separately displayed (Figure 5 to Figure 8). These activities include “W_Complete application,” “W_Call after offers,” “W_Call incomplete files,” and “W_Validate application,” all of which consume more time compared to other activities in the process. These activities are displayed individually, offering a comprehensive understanding of their frequencies and performance metrics. The data provides insights into which activities are consuming more time compared to others and are therefore candidates for further optimization.

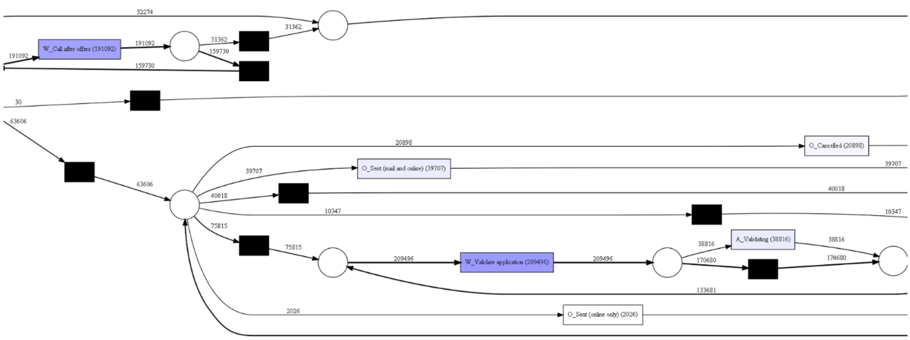

Figure 4. Part of the performance frequency model

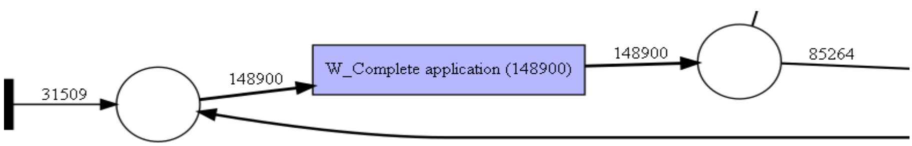

Figure 5. Performance frequency activity 1

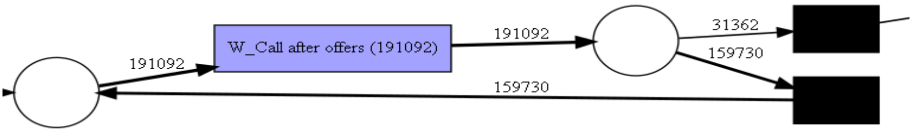

Figure 6. Performance frequency activity 2

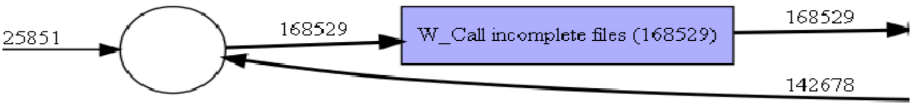

Figure 7. Performance frequency activity 3

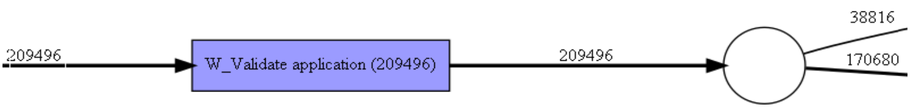

Figure 8. Performance frequency activity 4

The average duration (sojourn time) statistic offers insights into the amount of time dedicated to each activity, revealing the average time elapsed between the activity's initiation timestamp and its completion timestamp. Table 2 presents the amount of time spent executing each activity. Columns 1 to 3 respectively display the minimum (ST_min), maximum (ST_max), and average time (ST_mean) spent on each activity across all cases in the process. The last column (ST_sum) represents the total execution time of each activity across all cases in the process.

Table 2. Activities time

Activity	ST_min	ST_max	ST_mean	ST_sum
A_Accepted	201.062	24716658.7	1892125.92	59618995710
A_Cancelled	215.773	14607859.8	2582298.5	26935955635
A_Complete	215.773	24716658.7	1898040.35	59526341533
A_Concept	201.062	24716658.7	1892125.92	59618995710
A_Create Application	201.062	24716658.7	1892125.92	59618995710
A_Denied	201.062	22454262	1452076.16	5449641830
A_Incomplete	2942.291	24716658.7	1977709.7	45596097142
A_Pending	449.348	24716658.7	1566799.8	26992826874

Activity	ST_min	ST_max	ST_mean	ST_sum
A_Submitted	371.213	22454262	2013171.01	41114991582
A_Validating	449.348	24716658.7	1757840.23	68232326536
O_Accepted	449.348	24716658.7	1566799.8	26992826874
O_Cancelled	215.773	14607859.8	2495636.84	52153818701
O_Create Offer	201.062	24716658.7	2021885.87	86930982914
O_Created	201.062	24716658.7	2021885.87	86930982914
O_Refused	201.062	22454262	1553746.33	7294839022
O_Returned	449.348	24716658.7	1649096.31	38432189461
O_Sent (mail and online)	215.773	24716658.7	2016170.1	80056066105
O_Sent (online only)	449.348	11583640.3	2227970.9	4513869046
W_Assess potential fraud	169006.89	22454262	2488919.33	8168633225
W_Call after offers	215.773	24716658.7	1951664.73	3.72948E+11
W_Call incomplete files	2942.291	24716658.7	2158252.19	3.63728E+11
W_Complete application	201.062	24716658.7	1982221.38	2.95153E+11
W_Handle leads	371.213	22454262	2033971.8	96133643345
W_Personal Loan collection	22454262	24716658.7	23482624.1	516617730.4
W_Shortened completion	158420.42	12310865.7	2740705.73	652287963.4
W_Validate application	449.348	24716658.7	1773909.66	3.71627E+11

Regarding the aforementioned most time-consuming activities, certain Key Performance Indicators (KPIs) are defined, aligning with process policy 2 (ensuring that the execution time of each activity is less than 10% of all process execution time). These KPIs are defined as the execution times of each activity divided by the total execution time of all activities in the process.

KPI 1 = (Executive time W_Complete application) / (Executive time all activities) = 0.1259

KPI 2 = (Executive time W_Validate application) / (Executive time all activities) = 0.1585

KPI 3 = (Executive time W_Call after offers) / (Executive time all activities) = 0.159

KPI 4 = (Executive time W_Call incomplete files) / (Executive time all activities) = 0.155

Based on the above Key Performance Indicators (KPIs), the time spent on each activity, including "W_Complete application," "W_Call after offers," "W_Call incomplete files," and "W_Validate application," is more than 10% of the total process execution time. Therefore, the process manager must divide each of these activities into several parts or allocate additional organizational resources to each activity.

The proposed method offers a systematic approach to analyzing process execution time using process mining techniques. It involves data preprocessing, model discovery, and comprehensive performance metric analysis. This method offers insights into how well business processes align with defined policies and goals, thereby contributing to process efficiency and quality. The process of assessing execution time and identifying bottlenecks is a critical step in improving overall operational performance. In comparison to previous studies that primarily examined individual process instances and employed diverse performance measurement methods, the present study offers a more comprehensive approach. It integrates evidence-based policymaking with process mining, utilizing techniques such as Heuristics net, Directly-Follows graph (DFG), and Petri net to analyze execution time metrics, specifically Cycle time, Lead time, and Activity time. This approach leads to a more comprehensive understanding of overall process performance. The systematic assessment of execution time and the definition of Key Performance Indicators (KPIs) aligned with process policies provide valuable insights that can guide process optimization and resource allocation. Table 3 shows the comparison of this study with previous research.

Table 3. Comparison the proposed method with previous studies

Author (year)	Important Features of Previous Works	Important Features of This Study
Wang et al. (2009)	◇ Focus on assessing process performance with varied indicators. ◇ Examples of organization-wide policies (e.g., Business Continuity Plans, Records Management).	◇ Integration of evidence-based policymaking and process mining. ◇ Analysis of Cycle time, Lead time, and Activity time for process optimization.

Author (year)	Important Features of Previous Works	Important Features of This Study
Li et al. (2010), Popova and Sharpanskykh (2010)	◇ Proposal of methodologies for crafting individual process indicators. ◇ Use of a KPI ontology and an indicator modeling framework.	◇ Calculation of execution times for activities in the process. ◇ Definition KPIs for time-consuming activities.
Strecker et al. (2012), Pinheiro de Lima et al. (2013)	◇ Performance measurement system based on Process Performance Indicators. ◇ Linking components within business processes to Process Performance Indicators.	◇ Identification of cases with delays in the process. ◇ Calculation of Cycle time, Lead time, and the associated ratio for each case.
Cho et al. (2017)	◇ Emphasis on enhancing operational efficiency with Lean Six Sigma and BPR ◇ Focus on minimizing flow time and defects.	◇ Data-driven decisions for process optimization, resource allocation, and workflow enhancement.
Li et al. (2019)	◇ Discussion of performance metrics such as response times, waiting durations, and costs.	◇ Identification of time-consuming activities and KPIs for process optimization.

The practical implications of this research are significant for organizations aiming to optimize their business processes. By employing process mining techniques and focusing on execution time metrics such as cycle time, lead time, and activity time, companies can pinpoint inefficiencies and identify areas for improvement. The identification of time-consuming activities enables process managers to take targeted actions, such as process redesign, resource allocation, or workflow optimization. Additionally, aligning the definition of KPIs with process policies facilitates ongoing monitoring and ensures that processes adhere to predefined efficiency standards. Ultimately, the proposed approach empowers organizations to make data-driven decisions, enhance process quality, and improve overall performance. This improved understanding of process execution time can lead to better resource allocation, reduced delays, and more efficient workflows, all of which contribute to enhanced customer satisfaction and organizational competitiveness. By bridging the gap between evidence-based policymaking and process mining, this method offers a comprehensive perspective on process performance, benefiting organizations across diverse industries.

5. Conclusion

This study introduces a methodology that seamlessly integrates evidence-based policymaking with the powerful tools of process mining, enabling organizations to optimize their operational processes. The primary focus of our research centered on conducting an in-depth analysis of essential time-related metrics, such as cycle time, lead time, and activity time. Leveraging the capabilities of process mining, we conducted a comprehensive analysis of process inefficiencies and bottlenecks. This analysis provided empirical evidence that not only validates the existing policies but also offers valuable insights for their improvement. This methodological approach presents a structured framework for data-informed decision-making, promoting an environment of improved process excellence and workflow optimization. The implications of our approach extend far and wide, offering organizations an avenue to embrace a culture of evidence-based policy implementation. This, in turn, has the potential to enhance overall operational efficiency and elevate customer satisfaction. By bridging the realms of evidence-based policymaking and process mining, this method ushers in a new era of comprehensive insights into process performance, paving the way for continuous refinements. It is our aspiration that the outcomes of this research will inspire further investigations and practical applications in the field of evidence-driven process management, thus reshaping how organizations utilize data to enhance their performance.

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Mohsen Mohammadi

Mohsen Mohammadi Graduated from the National University of Malaysia (UKM) with a PhD in Information Technology (Industrial Computing) in 2014. He is currently an assistant professor at Esfarayen University of Technology, Iran.

His favorite research fields are process mining, Business processes analysis and modeling, and Information systems design.