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Enhancing Municipal Revenue Processes: A Case Study on Process Mining Approaches in Hamedan Province

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Abstract:

Process mining has gained significant attention in recent years as a method for analyzing and improving business processes through the examination of event data. Unlike traditional data mining, which focuses on isolated tasks, process mining provides a comprehensive view of entire processes, helping organizations understand how work is actually carried out. With the increasing availability of event data and advances in process discovery techniques, process mining has become an essential tool in Business Process Management (BPM) and Workflow Management (WFM) systems. This study evaluates four process mining algorithms: Alpha Miner, Alpha++ Miner, Genetic Miner, and Inductive Miner, in the context of enhancing the revenue processes of Hamadan's municipality. The goal is to improve efficiency, reduce delays, and optimize resource allocation in the municipality's revenue system. The results show that the Genetic Miner delivers the highest overall performance with an impressive score of 98%, followed by Inductive Miner at 96%, Alpha++ Miner at 94%, and Alpha Miner at 83%. The Genetic Miner's impact on the municipality's operations was particularly striking, leading to a 40% increase in revenue growth, a 33.3% reduction in revenue leakage, and a 50% improvement in payment processing time. These findings illustrate the power of process mining, particularly Genetic Miner, to reveal inefficiencies and enhance decision-making, ultimately contributing to better public service and more effective resource management. This research underscores the potential of process mining to transform municipal revenue processes, driving improvements in governance and operational efficiency.

Keywords: Process Mining, Event Log Analysis, Hamedan Municipality, Process Model Enhancement

1. Introduction

Process mining is an advanced analytical approach designed to uncover, monitor, and enhance real-world processes by examining event logs from information systems. In recent years, process mining methodologies have evolved significantly, benefitting from the exponential increase in available event data. This advancement has enabled organizations to leverage process mining for better process improvement and compliance management [1].

The process mining workflow starts with an event log, where each event denotes a specific action within a process and is linked to a particular case or process instance. The sequence of events within a case forms a complete "run" of the process. Event logs can also include supplementary details such as the resource performing the action, timestamps, and other data elements relevant to the event [2].

Process mining includes three main types of analysis. The first is process discovery, which automatically creates a process model directly from the event log without any prior information. Many organizations are impressed by how effectively these techniques can reveal actual processes from historical event data. The second type, conformance checking, involves comparing an existing process model with an event log to evaluate how well the model aligns with the recorded process. The third type, process enhancement, uses insights from the event log to refine or extend an existing process model [3].

Unlike traditional Business Process Management (BPM) methods that rely on manually crafted models, process mining is distinguished by its focus on the process itself, its ability to learn from historical data, and its reliance on empirical evidence rather than subjective judgments. By extracting insights from recorded behaviors in event logs, process mining provides a data-driven approach to BPM [4].

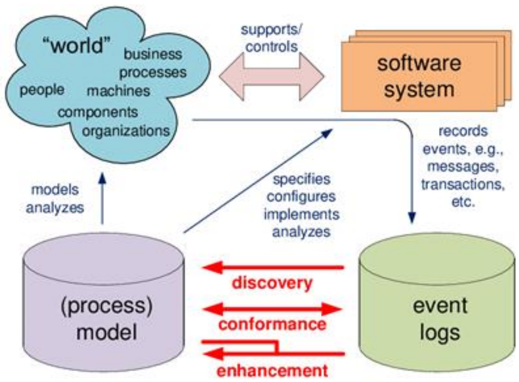

Fig. 1. The fundamental categories of process mining: (a) Process Discovery, (b) Conformance Checking, and (c) Process Enhancement (adapted from [5])

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Although process mining is related to data mining, it differs in its emphasis. While traditional data mining is centered around data analysis, process mining adopts a process-centric perspective. Various mainstream business process modeling techniques, such as Business Process Modeling Notation (BPMN), UML activity diagrams, Event-driven Process Chains (EPC), and Petri nets, are frequently used in process mining to model processes featuring concurrency, choices, iterations, and other critical characteristics. Unlike data mining, which primarily examines datasets, process mining focuses on event logs to gain a deeper understanding of and enhance underlying processes.

1.1 Event Logs

Digital event data is now common in all industries, economies, and households, and its growth is expected to continue. This expanding data landscape offers new opportunities for analyzing processes, moving away from traditional manual models to insights based on real event records. Central to process mining is the event log, which records the sequence of actions and serves as the foundation for analyzing and enhancing processes.

In this study, event logs were collected from the municipality of Hamadan province. These logs underwent a process of refinement, simplification, and transformation into structured tabular formats to support effective analysis and process improvements. Our primary goal is to optimize the revenue processes within the Hamadan municipality while evaluating the accuracy of different process mining miners. We aim to develop a comprehensive process model that illustrates the execution and resource allocation within these processes. To accomplish this, we apply four distinct process mining miners—Alpha Miner, Alpha++ Miner, Genetic Miner, and Inductive Miner—and compare their accuracy to determine the most effective approach for process optimization.

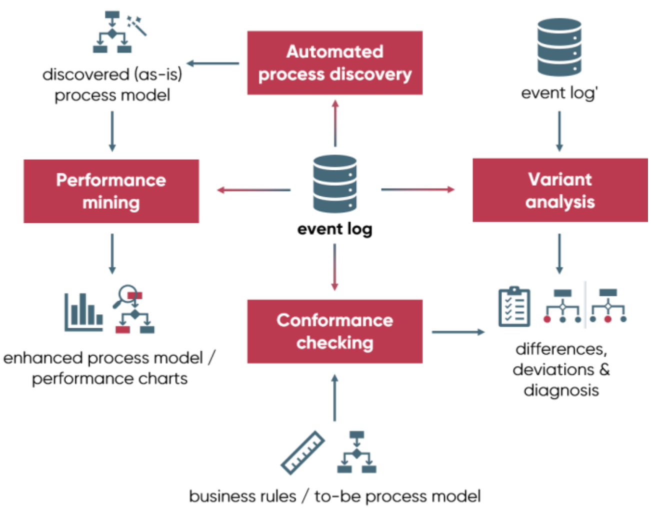

Fig. 2. Relationship between process mining and event logs (adapted from [6])

2. Related Works

In recent years, many studies have investigated how process mining techniques can be applied in different fields, showing that they are effective at identifying inefficiencies and improving business processes in various industries.

Paper [7] explores student behavior and interaction patterns during online quizzes within learning management systems (LMS). Employing a process-oriented methodology and process mining techniques, the study identifies distinct interaction sequences and offers insights into students' quiz strategies. This research has implications for both online education researchers and practitioners by enhancing the understanding of student engagement in LMS environments.

Paper [8] evaluates the application of process mining in Smart City contexts, addressing three critical research questions: 1) What are the prevalent issues in Smart Cities addressed by process mining? 2) What process mining methods are commonly used in Smart City applications? 3) What areas within Smart Cities have yet to see significant application of process mining? The study aims to identify challenges and opportunities in applying advanced process mining techniques to emerging Smart City issues.

Paper [9] investigates the role of process mining in self-regulated learning (SRL) by examining temporal and sequential dimensions of SRL processes. The research evaluates four process mining algorithms—Inductive Miner, Heuristics Miner, Fuzzy Miner, and pMineR—in the context of undergraduate education. The findings highlight that Fuzzy Miner and pMineR offer valuable insights into SRL processes, and their combined metrics enhance the understanding of temporal and sequential dynamics. The paper recommends that future SRL research should integrate various process mining algorithms and consider specialized tools for SRL analysis.

Paper [10] addresses the challenge of assessing in-hospital mortality risk for diabetic ICU patients, who face high risks during their hospital stay. The paper presents an innovative approach that combines process mining with deep learning techniques. By converting patients' medical history into event logs, the study constructs a process model to represent patients' historical hospital experiences. This model, integrated with demographic and medical data, improves mortality predictions compared to traditional severity scoring and standard machine learning methods. The paper validates these improvements using the Medical Information Mart for Intensive Care III dataset.

3. Methodology

In the following sections, the process begins with a discussion on the selection of event logs, followed by a detailed introduction to the mining techniques and methodologies employed in the study. Afterward, attention shifts to the evaluation phase, where the performance indicators and metrics used to measure the effectiveness and accuracy of the generated process models are thoroughly analyzed. This phase is crucial for our research, as it provides a clear understanding of how well each process model reflects the real-world processes and identifies opportunities for optimization and improvement. By comparing these performance metrics, the research will highlight which mining approach produces the most precise and efficient results. These insights will be instrumental in guiding the Hamadan municipality toward optimizing its revenue processes, ultimately leading to greater transparency and resource allocation.

3.1 Event Log Selection

For the purpose of enhancing the processes within the municipal revenue department, data was collected in 2023, focusing on key revenue-related activities. Event logs were generated based on these processes, which comprised 10 distinct steps, and a total of 29,240 instances were recorded during the execution of these processes. These logs were then summarized and structured into tabular formats for analysis. The event logs were subsequently imported into both "*ProM 5.2*" and "*ProM 6.12*" software using XML files for further processing.

Four different process mining miners were applied to these logs: Alpha Miner, Alpha++ Miner, Genetic Miner, and Inductive Miner. Each miner was used to discover and analyze the underlying process models, with the aim of comparing their performance in identifying bottlenecks, optimizing workflows, and providing insights into improving the overall efficiency of the revenue department.

3.2 Process Mining Miners

3.2.1 Alpha Miner (AM)

The Alpha Miner algorithm is one of the foundational methods in process discovery, commonly applied in process mining to generate a process model from event logs. It works by identifying frequent causal relationships between activities, starting with the first and last activities in the event log and then progressively exploring the log to uncover direct succession relations between these activities. This iterative approach continues until all direct causal dependencies have been mapped. The final process model is typically represented as a Petri net or process flowchart, visually depicting the causal links between activities. While widely used for its simplicity, the Alpha Miner has limitations, particularly in handling complex processes. In such cases, it may produce overly detailed models or fail to capture nuanced process behaviors accurately, which highlights the need for more advanced miners in certain scenarios [11].

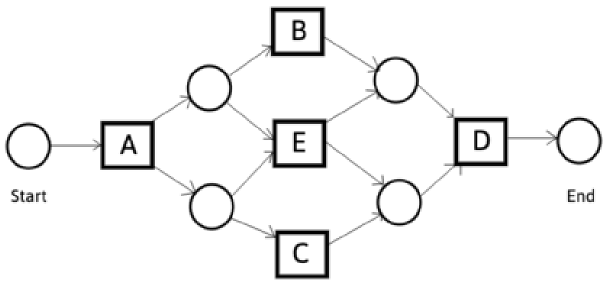

Fig. 3. Process model discovered using alpha miner (adapted from [12])

3.2.2 Alpha++ Miner (AM++)

The Alpha++ Miner is an advanced extension of the original Alpha Miner algorithm in process mining, designed to overcome some of its predecessor's limitations. Unlike Alpha Miner, which only focuses on direct causal relationships, Alpha++ Miner enhances process discovery by considering both explicit and implicit dependencies between activities. This broader perspective enables it to capture more intricate process behaviors and hidden dependencies that might not be immediately evident from the event logs.

In addition, Alpha++ Miner is equipped with mechanisms to handle noise and inconsistencies in the data. It applies filtering techniques to manage incomplete or missing data, ensuring that the resulting process models are more reliable. Another key enhancement is its use of heuristics and optimization strategies, which refine the process model by simplifying its structure without sacrificing accuracy. These improvements not only make the model more interpretable but also more robust in representing complex processes. Through these refinements, Alpha++ Miner provides a more precise and comprehensive approach to process discovery than the original Alpha Miner [13].

3.2.3 Genetic Miner (GM)

The Genetic Miner is a process discovery algorithm inspired by genetic algorithms, which are optimization techniques grounded in the concepts of natural selection and evolution. In process mining, the Genetic Miner utilizes these evolutionary principles to extract process models from event logs. The algorithm initiates with a random set of process models, each representing a possible solution. These models are evaluated based on a fitness score, which quantifies how accurately each model aligns with the event log data.

To evolve the population of models, the algorithm applies genetic operations like selection, crossover, and mutation. In the selection phase, models with higher fitness scores are more likely to be chosen for reproduction. The crossover step merges segments from two parent models to generate new offspring models, while mutation introduces minor random alterations, promoting genetic diversity within the population. This evolutionary cycle of selection, crossover, and mutation repeats over successive generations, with the goal of gradually improving model fitness. The process continues until a stopping criterion is met, such as reaching a predefined number of generations or achieving a satisfactory fitness level [14].

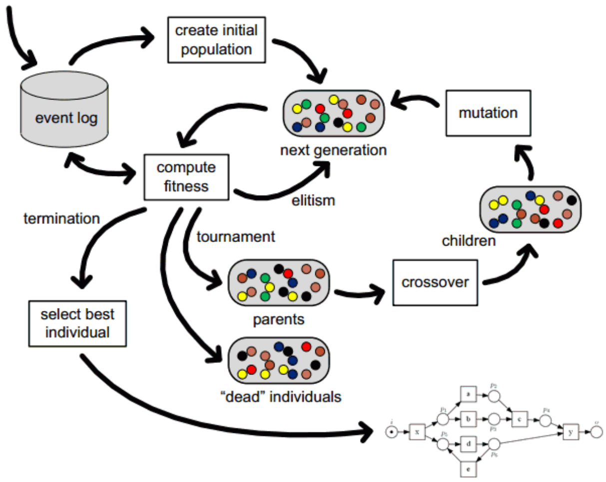

Fig. 4. Genetic miner algorithm overview (adapted from [15])

The final outcome is a process model that best represents the discovered process based on the event logs. This model can be visualized using notations such as Petri nets or process flow diagrams, providing a comprehensive representation of the process.

3.2.4 Inductive Miner (IM)

The Inductive Miner is a process discovery algorithm used in process mining, known for its ability to generate highly structured and sound process models from event logs. Unlike heuristic-based approaches, the Inductive Miner algorithm focuses on creating a hierarchical process model that guarantees soundness, meaning the discovered model can always complete its tasks without deadlocks or other anomalies.

The Inductive Miner works by recursively decomposing the event log into smaller fragments. It starts by identifying the most frequent behavioral patterns and splitting the event log into smaller subprocesses. These subprocesses are then analyzed individually, ensuring that the model captures structured behavior, such as sequences, choices, loops, and concurrent activities. One of the algorithm's strengths lies in its ability to precisely detect and model concurrency, a process characteristic where multiple activities can occur in parallel. It also handles loops effectively, offering a clear depiction of repetitive behavior in the process [16].

A key advantage of the Inductive Miner is its robustness when dealing with noise and incomplete data, making it particularly suitable for complex real-world processes. The algorithm is designed to simplify the process model while retaining accuracy, ensuring that the resulting model is easy to interpret and analyze. This model can be represented using notations such as Petri nets or process flow diagrams, giving a clear and structured view of the underlying process. The Inductive Miner’s ability to produce sound, structured models and handle complex behaviors makes it a powerful tool for discovering processes from noisy or large event logs.

3.3 Quality Metrics in Process Mining

In process mining, the evaluation of process models is crucial for ensuring that they accurately represent the real processes derived from event logs. To attain this, several key performance indicators—'fitness,' 'simplicity,' 'precision,' and 'generalization'—are employed. These metrics are essential in determining the quality, usability, and effectiveness of the discovered models [17].

3.3.1 Fitness

In process mining, fitness measures how well the discovered process model reflects the actual behavior captured in the event log. It evaluates the alignment between the process model's predicted behavior and the real events observed in the log. The calculation of fitness involves comparing the sequences and timing of activities in the model with those in the event log, assessing how closely the model can replicate the execution patterns of the real-world process. A high fitness score indicates that the model successfully captures the majority of the observed behavior, while a low score suggests that the model fails to represent critical aspects of the process. Fitness is determined using the following equation (1):

$$f = \frac{1}{2}\left(1 - \frac{\sum_{i=1}^{k} n_i m_i}{\sum_{i=1}^{k} n_i c_i}\right) + \frac{1}{2}\left(1 - \frac{\sum_{i=1}^{k} n_i r_i}{\sum_{i=1}^{k} n_i p_i}\right). \quad (1)$$

3.3.2 Simplicity

Simplicity measures how easily a process model can be understood and interpreted. It evaluates the clarity and straightforwardness of the model's representation. A model with high simplicity is less complex and more intuitive, making it easier for stakeholders such as process analysts, managers, and end-users to comprehend and use. Simplicity enhances the effectiveness of communication, decision-making, and process improvement efforts by providing a clear and manageable depiction of the process. A simpler model typically facilitates better understanding and maintenance, ensuring that stakeholders can engage with and act upon the model more effectively. Simplicity is assessed according to the following formula (2):

$$\partial s = \frac{|T| - (|T_{DT}| + |T_{IT}|)}{T} \quad (2)$$

3.3.3 Precision

Precision assesses the accuracy and correctness of a process model derived from event data. It measures how well the model reflects the true behavior of the process it represents. Precision is critical in process mining because the effectiveness of insights and decisions based on the model hinges on its accuracy. A model with high precision accurately captures the actual process, ensuring that the analysis and improvements are based on reliable data. This enhances the credibility of the process model and supports effective decision-making and process enhancement. Precision is calculated using the following equation (3):

$$\alpha_B = \frac{\sum_{i=1}^{k} n_i (|t_v| - x_i)}{(|t_v| - 1) \sum_{i=1}^{k} n_i} \quad (3)$$

3.3.4 Generalization

Generalization involves abstracting and simplifying a process model or event data to highlight higher-level patterns, trends, and commonalities. This process reduces the complexity and detail of the data to uncover more general insights about the process. In process mining, generalization is essential for identifying the underlying structure and key characteristics of the process. By focusing on common patterns and behaviors, generalization provides a clearer and more concise representation of the process, facilitating better understanding, decision-making, and targeted process improvements. Generalization is evaluated based on the following formula (4):

$$Q_g = 1 - \frac{\sum_{1}^{T} \left(\sqrt{\# \, exacution}\right)^{-1}}{T} \quad (4)$$

In summary, achieving an optimal balance among the four quality dimensions of fitness, simplicity, precision, and generalization is crucial for effective process mining. Each of these dimensions plays a vital role in ensuring that process models meet their intended goals and support organizational success.

Striking this balance requires careful consideration and adaptation to the specific needs and constraints of each process mining project. The ideal balance may vary depending on the project goals, requirements, and the context in which process mining is used. Therefore, it's important to approach process modeling carefully and to continually monitor and refine the models. This approach ensures that the models accurately reflect real-world processes while remaining clear, precise, and adaptable. Consequently, well-balanced process models become invaluable tools for analyzing and improving processes.

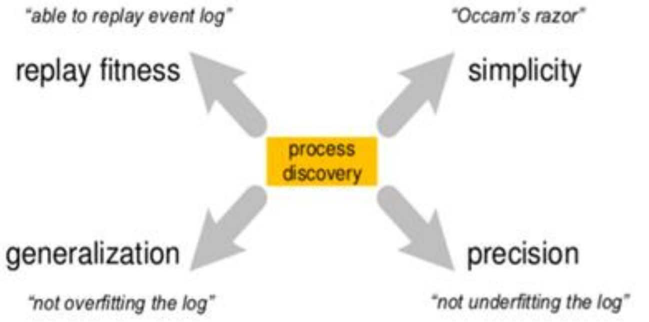

Fig. 5. Balancing key quality dimensions in process mining (adapted from [18])

4. Result and Discussion

This section presents a comprehensive analysis of various process mining models based on key quality dimensions: fitness, simplicity, precision, and generalization. These dimensions assess how well the models reflect the actual processes in the municipality of Hamedan Province and their practical impact, including improvements in revenue growth, revenue leakage, and payment processing time.

- **Fitness** measures how accurately each process model mirrors the real-world processes observed in the event logs. This metric helps determine how well the model captures the sequence and timing of activities as they occur in practice.
- **Simplicity** evaluates the clarity and manageability of the process models. A model's simplicity is crucial for ease of understanding and communication among stakeholders, which can significantly impact its practical utility.
- **Precision** assesses the correctness of the process model, focusing on how closely it aligns with the actual behaviors recorded in the event logs. High precision indicates that the model reliably reflects the underlying process without significant deviations.
- **Generalization** considers the model's ability to abstract and simplify complex data to reveal overarching patterns and trends. Effective generalization ensures that the model remains relevant and useful across various scenarios and conditions.
- **Revenue growth** shows how much the revenue has increased due to improvements in the process. It highlights how effectively the model optimizes revenue generation.
- **Revenue leakage** refers to the amount of lost or uncollected revenue. It demonstrates how the model helps identify inefficiencies and reduces these losses.
- **Payment processing time** is the time it takes to complete payments. A reduction in this time shows how the model streamlines the process and improves efficiency.

The models are compared based on these dimensions, and the impact of the best-performing model, as determined through this evaluation, will be discussed. This approach allows us to identify the most effective model for optimizing the revenue processes of the Hamedan municipality.

4.1 Evaluation of Quality Dimensions

4.1.1 Fitness

As depicted in Fig. 6, the Genetic Miner stands out with the highest fitness score, achieving an impressive value of 0.951. This fitness metric reflects the degree to which the Genetic Miner's process model accurately mirrors the actual revenue processes of the municipality. A score of 0.951 indicates a strong alignment with real-world operations, underscoring the model's ability to faithfully represent the revenue processes within Hamedan province municipality.

In comparison, the Alpha Miner yields a fitness score of 0.828, while the Alpha++ Miner achieves a score of 0.901. The Inductive Miner also performs well with a fitness score of 0.934. Despite these respectable results, the Genetic Miner's superior fitness score of 0.951 reinforces its dominance and suitability for enhancing the municipal revenue department's processes.

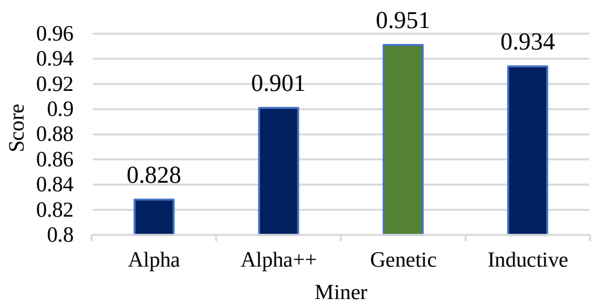

Fig. 6. Highest fitness score among miners

4.1.2 Simplicity

As shown in Fig. 7., all miners achieved a uniform maximum simplicity score of 1.0. This result indicates that regardless of the specific mining method used, each model maintained an optimal level of simplicity. This consistency reflects that all miners were equally effective in creating process models that are straightforward and easy to understand, ensuring that the complexity of the models did not hinder their interpretability.

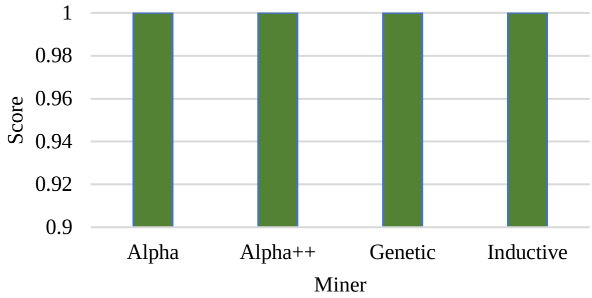

Fig. 7. Highest simplicity score among miners

4.1.3 Precision

As illustrated in Fig. 8., the Genetic Miner achieved an exceptional precision score of 1.0, indicating that its process model accurately reflects the expected outcomes and adheres perfectly to the revenue department processes of the municipality of Hamedan province. This perfect precision score highlights the Genetic Miner's superior accuracy in modeling the processes. For comparison, the precision scores of the other miners are as follows: Alpha Miner achieved a score of 0.625, Alpha++ Miner reached 0.928, and Inductive Miner attained a score of 0.972.

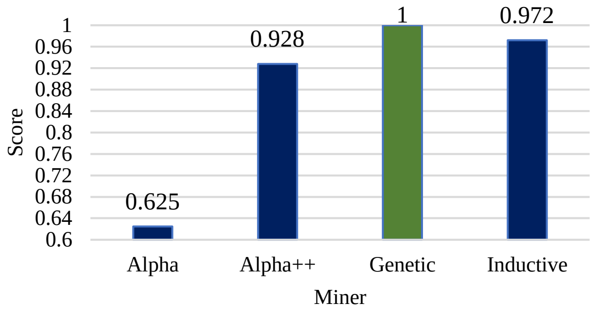

Fig. 8. Highest precision score among miners

4.1.4 Generalization

As illustrated in Fig. 9., the Genetic Miner achieved the highest generalization score of 0.978, demonstrating its exceptional ability to adapt and generalize the process model to a variety of scenarios.

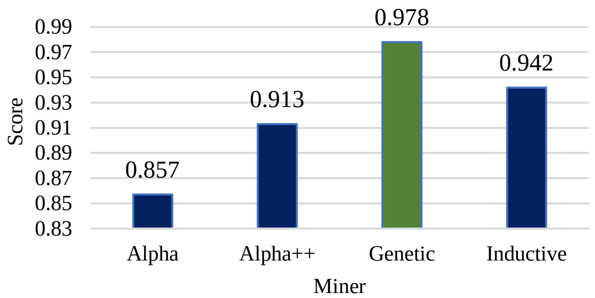

Fig. 9. Highest generalization score among miners

This impressive result underscores the Genetic Miner's strong performance in analyzing the revenue department processes within the municipality of Hamedan province. For comparison, the generalization scores of the other miners are as follows: Alpha Miner with 0.857, Alpha++ Miner with 0.913, and Inductive Miner with 0.942.

As illustrated in Fig. 10., the spider chart offers a clear visual comparison of the different mining techniques based on their performance in key metrics: fitness, simplicity, precision, and generalization. Each axis of the chart represents one of these dimensions, with the distance from the center indicating the level of achievement in that area. This visualization allows for an immediate assessment of how each mining method performs across these critical quality attributes.

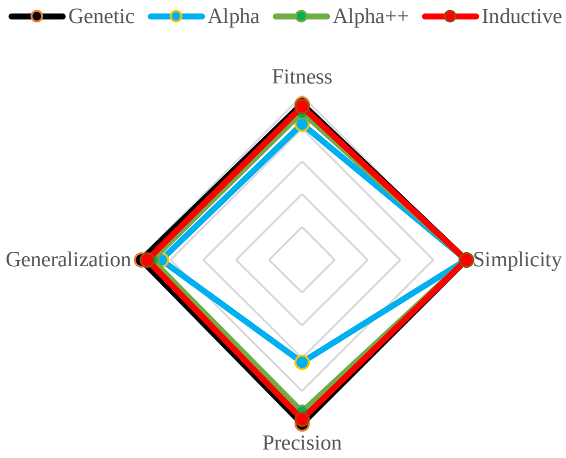

Fig. 10. Comparison of fitness, simplicity, precision, and generalization across all miners

4.2 Selecting the Optimal Model

As demonstrated in Fig. 11. and detailed in Table 1, the Genetic Miner was the most effective algorithm for analyzing the revenue department processes of Hamedan province municipality, achieving an impressive overall score of 98%. This score reflects the average across key performance metrics, including fitness, simplicity, precision, and generalization. In contrast, the Alpha Miner received the lowest overall score of 83%, indicating its relatively weaker performance. The Alpha++ Miner and Inductive Miner also performed well, with scores of 94% and 96%, respectively.
These results highlight the Genetic Miner's superior effectiveness in this specific context, while also suggesting that the Alpha Miner may require improvements or alternative approaches for more effective analysis of municipal revenue processes.

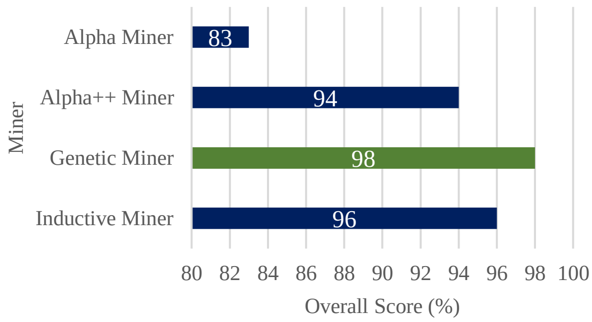

Fig. 11. Top-Performing process miner (overall score)

Table 1. Performance of process mining models

Miner	Fitness	Simplicity	Precision	Generalization	Overall
AM	0.828	1.0	0.625	0.857	83%
AM++	0.901	1.0	0.928	0.913	94%
GM	0.951	1.0	1.0	0.978	98%
IM	0.934	1.0	0.972	0.942	96%

4.3 Impact of Process Mining on Revenue Improvement

In this section, we evaluate the overall impact of the Genetic Miner model on the municipal revenue processes in Hamedan Province. The effectiveness of this model was assessed not only based on its quality dimensions such as fitness, simplicity, precision, and generalization, but also on its practical impact on improving the municipality's revenue generation and management. By examining key revenue-related metrics, including Revenue Growth, Revenue Leakage, and Payment Processing Time, before and after the implementation of the Genetic Miner, we aim to demonstrate how this model contributed to improving operational efficiency and financial transparency. Table 2 summarizes the improvements observed in these key revenue metrics following the implementation of the Genetic Miner.

Table 2. Performance improvements across key revenue metrics: Growth, Leakage, and Payment processing time

Metric	Before Process Mining	After Process Mining	Percentage Change
Revenue Growth	10%	14%	40% improvement
Revenue Leakage	6%	4%	33.3% improvement
Payment Processing Time	4 days	2 days	50% reduction

The implementation of Genetic Miner resulted in noticeable improvements in the municipality's revenue processes. Revenue growth increased from 10% to 14%, reflecting a 40% improvement. This increase suggests that the process mining model helped uncover opportunities for optimization and enhanced revenue generation. Revenue leakage decreased significantly, from 6% to 4%, marking a 33.3% reduction. This indicates that Genetic Miner effectively identified inefficiencies in the revenue processes, minimizing the loss of potential revenue. Additionally, payment processing time was reduced from 4 days to 2 days, a 50% improvement. This reduction enhances operational efficiency and ensures faster processing of payments, improving service delivery.

Overall, Genetic Miner proved to be highly effective in improving both the financial and operational aspects of the municipality's revenue management.

5. CONCLUSION AND FUTURE WORK

This study aimed to improve the revenue department processes in the municipality of Hamedan by creating a comprehensive process model that clarifies how resources are allocated and tasks are managed. To accomplish this, we utilized four distinct process mining miners: Alpha Miner, Alpha++ Miner, Genetic Miner, and Inductive Miner. We collected event logs from the municipality and converted them into an XML file for analysis using "*ProM 5.2*" and "*ProM 6.12*" software. The process models generated were assessed based on key performance metrics such as fitness, precision, simplicity, and generalization.

Our findings showed that Genetic Miner performed the best, with an impressive accuracy score of 98%, excelling in fitness, precision, and generalization. Alpha++ Miner and Inductive Miner also demonstrated strong performance with scores of 94% and 96%, respectively. Conversely, Alpha Miner had the lowest score of 83%, suggesting it may need further improvement or alternative approaches. All four miners maintained high levels of simplicity in their process models. Overall, the Genetic Miner stands out as the most promising tool for enhancing the revenue department processes within the municipality of Hamedan.

In terms of impact, the results highlighted that the application of Genetic Miner could drive substantial improvements in key revenue metrics, including a notable increase in revenue growth, a significant reduction in revenue leakage, and a faster payment processing time, all of which contribute to enhanced financial efficiency and operational effectiveness.

In future work, we plan to explore more process mining miners and advanced techniques. This study sets a strong foundation for improving revenue department processes.

Our focus will be on refining our models, enhancing performance, and gaining new insights to optimize revenue management and improve governance efficiency.

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