Creating a Data Generator and Implementing Algorithms in Process Analysis

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Abstract—Process mining is a new field of work that aims to meet the need of the business world to improve efficiency and productivity. This field focuses on analysing, discovering, managing, and improving business processes. Process mining uses event logs as a resource and works on this resource. Hence, the system is developed by analysing the event logs, including each step in the process model. Our study is made up of two significant stages: a data generator for processes and algorithms applied for discovering the created processes. In the first stage, the aim was to develop a simulator with the ability to generate data that could help process modelling and development. Within the framework of this study, a system was created that could work with various process models and extract meaningful information from these models. More productive and efficient processes can be developed as a result of this system. The simulator consists of three modules. The first module is the part where users create a process model. In this module, the user can create his own business process model in the system’s interface or select from other registered models. In the second module, team-based data are simulated through these process models. These generated data are used in the third module, called “analysis”, and meaningful information is extracted. In conclusion, the process can be improved considering the information about time, resource, and cost in the generated data. At the second stage, processes were discovered using alpha, heuristic, and genetic algorithms, which are process mining discovery algorithms and synthetic and real event logs. The discovered processes were demonstrated with Petri nets, and the algorithms’ performances were compared using the fitness function, accuracy rates, and running times. In our study, the heuristic algorithm is more successful because it improves the noise in the data and incomplete processes, which are the disadvantages of the alpha algorithm. However, the genetic algorithm yielded more successful results than the alpha and heuristic algorithms due to its genetic operators.

Index Terms—Alpha algorithm; Data generator; Genetic algorithm; Heuristic algorithm; Process mining; Petri nets.

I. INTRODUCTION

In our age, information processing systems play a crucial role in the business world. It is of great significance for businesses to make quick decisions and improve efficiency. At this stage, results such as the performance of the employees and the cost of the steps in the process are obtained by reviewing the business processes. By reviewing the steps in the processes in detail, information such as the completion time and cost of the steps is reached, the problematic parts of the process are detected, and the efficiency of this process can be enhanced [1], [2]. Process mining is a comparatively new field of research that includes process modelling and process analysis, on the one hand, and business intelligence and data mining, on the other. The most important purpose of process mining is to extract business processes from event logs recorded in today’s information systems and to discover, control, and improve them. Process discovery, model and log comparison, and deviation control, social network/organizational mining, automation of simulation models, model development, model repair, status estimation, and history-based recommendations are among the areas covered by process mining [3]. Today, the recording of event logs is one of the most significant parts of business processes. In almost every software used in corporate organizations, event logs are recorded, which helps them be analysed and observed. Analyses can be performed on these recorded event logs regarding the process.

Our study aimed to create a data generator that would perform process modelling, simulation, and analysis. By simulating processes that had not been used or had been thought to be used before, it was aimed at extracting meaningful information such as what kind of results the process would produce, how much time it could be completed in, and what kind of results the performance distributions between teams would produce in the case of dividing the process into teams in parallel. There are three main modules in the system developed in this study. The initial step of these modules is to define the process in the system. In the second module, the simulation module, log files complying with the previously designed process model are created. Finally, in the analysis module, meaningful information regarding the process, such as individual and team performance, is extracted from the generated event logs. It was intended to discover processes using synthetic event logs created using the data generator and real event logs available in today’s information systems. Several
process mining discovery algorithms, such as alpha, heuristic, and genetic algorithms, were used to discover the processes. The success rates of the algorithms were compared according to the fitness function, accuracy rates, and running times. Briefly, in this study, the aim was to develop a process mining system that could both generate process data and analyse and discover processes for synthetic or real process data. Scientific contribution of our study includes the production of synthetic data with different situations and scenarios for a process model, the visual examination of the flows of the processes, the implementation of widely used process mining algorithms, the development of a new software platform that can be used in the field of process mining.

The remainder of the article is organized as follows. Related and similar studies will be discussed in Section II. Process mining is presented in Section III. The proposed model is discussed in Section IV and its application with experimental study is detailed in Section V. The evaluation and conclusions are detailed in Section VI.

II. RELATED WORKS

In recent years, the number of studies on process mining has increased, and the importance of this subject is increasing with each passing day. A brief summary of previous similar studies on process mining is given below.

Sun, Liu, Qi, Du, Ren, and Liu [1] proposed to discover multiple-concurrency short-loop structures via Petri nets. This study consisted of the artificial model and the actual model. The activities are matched with a triangular two-degree loop or a quadrilateral two-degree loop. Then, two types of short-loop structures are identified from the incomplete logs. But this work has limitations in that it does not consider the impact of duplicate activities or invisible activities and needs to study more complex structures.

One of the applications of process mining in the healthcare field has been process mining analysis with event logs obtained from four different hospitals in Australia, and vital information about patients was reached. The results of the studies were tried to be given comparatively. However, one of the challenges of process mining is that it is quite difficult to analyse, find, and improve data in more than two multiple data sets. Since all information about patients is present together, comparative analysis of big data, visualization of data, and division of data bring about some difficulties. In this study, these shortcomings were tried to be eliminated, although partially [4]. In other study, a methodology for the application of process mining in healthcare entitled “Process Mining Project Methodology in Healthcare” was developed (PM2 HC) [5]. Moreover, it was developed over a series of steps involving bibliographical reviews on the methodologies of application of process mining in the general and on applications of process mining in health case studies. However, these works were not achieved, as categorical information about patients was not taken into account.

Yasmin, Bemthuis, Elhagaly, Wijnhoven, and Bukhsh [6] developed ProM to collect all process mining algorithms on a single platform. With this tool, it is possible to discover processes, measure processes’ fitness, and improve processes. ProM offers a platform that shows that many process mining algorithms such as the genetic, fuzzy, heuristic, and alpha algorithms function in connection with each other. It was tried analyse data records of 569 events and 299 cases obtained from the records of students at Taylan University [7]. This study aims to rearrange the extraction of information from sequential events. However, the desired success could not be fully achieved due to the noisy data and incomplete cases.

Koonce and Tsai [8] tried to create software for business management in production using a genetic algorithm. The purpose of this study is to specify the optimum business process by finding the shortest processing time from various operations that can be carried out against various activities. In the study, different operations were created for different processing times by setting various rules. However, the performance problem encountered by the genetic algorithm could not be fully addressed in this study. Weijters, van der Aalst, and Alves performed process discovery and analysis from 12,000 different event logs by employing a heuristic algorithm in process mining [9]. In the study, they worked on noisy data and processes that were not clearly expressed.

In another reviewed study, stroke patient care applications with process mining techniques were developed [10]. In this study, they used process mining to discover the treatment processes of stroke patients in different hospitals. They examined the events that the patients were associated with and conducted analyses. This study indicates that process mining techniques can be used successfully in clinical data from different hospitals and different patients. However, real-world healthcare problems are not practical or applicable, and necessary healthcare specificities are taken into account when developing new process mining techniques. Goedertier, De Weerdt, Martens, Vanthienen, and Baesens [11] discovered processes from the event logs of information systems in the telecom sector. Owing to the analyses of the event logs, it was concluded that processes could be created automatically and that meaningful data could be extracted.

Liu, Zhang, Li, and Jiao [12] integrated related processes using event graphics for operational decision support systems. They conducted analyses from the event logs generated for different scenarios. Their results demonstrate that event log analyses play a significant role in process management and development.

Dogan, Bayo-Monton, Fernandez-Llatas, and Oztaysi [13] aimed to investigate customer behaviors about gender by using their paths with process mining. They can determine the gender of customers if they go to the men’s or women’s bathroom on the behaviors of male and female customers. Furthermore, the study shows that the process mining technique is a viable way to analyse customer behavior using bluetooth-based technology. However, personalized guidance can be developed for customers. Customer-specific suggestions or future state prediction may be considered. And this study was performed on a single data set.

Nafasa, Waspada, Bahtiar, and Wibowo [14] developed the application of the alpha algorithm in the process mining application for online Learning Activities Based on Moodle.
event log data. The experimental conclusion proved that the implementation of the alpha algorithm can work correctly on the Moodle event log data. However, this study is needed for data analysis and pre-processing that is provided in Moodle event log data easily in integrated environment.

In our study, a new approach is presented to obtain information about activities and relations between them according to Petri nets obtained from event logs. Also, process mining discovery algorithms were used in addition to traditional algorithms used to measure the suitability of business processes. Since process mining is a new field in the world and there are few scientific studies in this field, a process mining system that performs process modelling, simulator, analysis, and discovery has been developed in this study to eliminate this deficiency.

The model we created has a great importance in the field of process mining in terms of having a unique data generator compared to previous studies. With the model we developed, unlike synthetic data used in the literature [15]–[17], it can perform a comprehensive analysis for the data sets and real data we have developed with its own data generator. Furthermore, our system analyses incomplete and noisy data sets apart from the completed data sets.

Augusto, Mendling, Vidgof, and Wurm [18] provide two major contributions to the measurement of process complexity and to the evaluation of process mining algorithms. First, they analysed existing measures for process complexity based on event logs. Second, they evaluated the identified set of process complexity measures, including our novel measures, using a benchmark collection of event logs and their corresponding automatically discovered process models [18].

In another article in [19], the authors focus on the study of automated process discovery using the Inductive visual Miner (iVM) and Directly Follows visual Miner (DFvM) algorithms to produce a valid process model for educational process mining to understand and predict the learning behavior of students. However, the performance of process mining algorithms in improving quality education and other benchmarking data sets obtained from alternate data should be explored [19].

Fauzi and Andreswari [20] used process mining techniques to extract streams from the event log. In the study, the discovery process was carried out to determine the flow carried out by the programmers in the software development team20. The authors only mentioned the software team discovery processes in their studies. In our study, many discovery processes such as health, education, and business processes were analysed. This system is aimed to be a reference for future studies in this field in all the world. In addition, the production of synthetic data with different situations and scenarios for an exemplary process model, the visual examination of processes’ flows, the implementation of commonly used process mining algorithms and the development of a software platform that can be used in the field of process mining constitute the original contribution of our study.

III. PROCESS MINING

Process mining is a new field of study that aims to meet the need of the business world to increase productivity and efficiency. This field carries out studies on the analysis, discovery, management, and improvement of work processes. Process mining uses event logs as a resource and studies on this resource. Thus, the system is developed by analysing event logs that comprise every step of the process model [21].

Process mining is a new scientific discipline that analyses and models processes, utilizes data mining methods, and has become popular in recent years. This discipline aims to determine processes using different algorithms and to calculate the performance of processes. One of the reasons for the popularity of process mining nowadays is finding useful information in big data. It also contributes to the development of processes in the business world [22]. The purpose of this field is to determine processes and to calculate their performance employing different algorithms. The widespread use of big data in information technologies is bringing some problems with it to the entities. Process mining enables effective and efficient use of data by reanalysing the processes, discovery, modelling, and improvement of processes by employing process mining techniques. Thus, the use of process mining techniques by large entities becomes mandatory in a competitive business environment.

The general structure of the process mining is shown in Fig. 1. Each process in the real world is kept in event logs as a sequence of events using software systems. Thereafter, information in such event logs is analysed by discovery, fitness check, and by modelling with improvement, which are stages of process mining. Thus, meaningful data are offered to people and systems.

![Fig. 1. General structure of process mining.](image)

In our study, although it contains a structure similar to the example process mining structure seen in Fig. 1, it provides the production of synthetic data with different situations and scenarios, the visual examination of the flows of the processes, the implementation of commonly used process mining algorithms, and the development of a software platform that can be used in the field of process mining.

An event is any recorded movement. An event can be started and completed, or it can be canceled after it has been started. The event log is the collection of events accepted as
input by a particular source in the process mining. Sequential states with a start and end point in a given time period represent an event log. An example order event log for process mining is created in Fig. 2. Detailed information about the order is given by showing it with a Petri net.

Here, order taking, bill payment, and delivery to the customer are carried out according to a certain time. The event log table for this business process example is shown in Table I.

![Fig. 2. Sample order event log [23].](image)

**TABLE I. EVENT LOG TABLE OF ORDER SAMPLE.**

| State ID | Event ID | Time       | Activity               | Person |
|----------|----------|------------|------------------------|--------|
| 1        | 1000     | 01.01.2013 | A (Product Order)      | Peter  |
| 1        | 1001     | 10.01.2013 | B (Products Receiving) | Micheal|
| 1        | 1002     | 13.01.2013 | C (Receiving Invoice)  | Frank  |
| 1        | 1003     | 20.01.2013 | D (Payment of Invoice) | Tanja  |
| 2        | 1004     | 02.01.2013 | A (Product Order)      | Peter  |
| 2        | 1005     | 03.02.2013 | B (Products Receiving) | Micheal|

**IV. OUR MODEL**

As seen in Fig. 3, our study consists of two main stages, namely, data generator and process mining discovery algorithms. In the first stage, there is a structure that can generate data with an automatic data generator. It consists of three submodules: process model creation, simulation, and analysis. In the second main stage, the performance of the processes in terms of accuracy, fitness, and time is evaluated by applying process mining discovery algorithms (alpha, heuristic, and genetic) for event logs, real data, and other synthetic data of the data produced by the data generator. Therefore, meaningful data are presented to individuals and systems.

![Fig. 3. The steps of our model.](image)

**A. Creation of the Data Generator**

In this study, a suitable data generator for real life was designed to develop process mining algorithms. This design consists of three main modules: process creation, data generator, and data analysis.

**B. Process Creation**

Any process model can be reviewed as an example while creating a process model. The credit card application process, the steps of which are shown in Fig. 4, was examined.

In the created system, processes with start and end points are entered, as stated in Fig. 5. The steps in the process entered in this study can be created as many times as desired and can form cycles within themselves in addition to branching. The user can give percentiles for the steps subject to branching, enabling the generated data to produce data close to the rates desired by the user. After determining the path of the process, the user sets the cost and time level for each step. Meanwhile, the positions of the person who performs the steps can be specified. By assigning the specified positions to the selected steps, it will be possible to analyse the people in that position in the data to be generated later.

There is also a section that allows the user to use the existing processes before moving to the data generation stage to make this step easier for the user and create different but similar processes and see the differences between them. When the user creates a process, this process is added to the existing process page in the system and is ready to generate data.
The simulation module is the section where event logs are created. While event logs are created, data are generated for the process model selected by the user. On the simulation screen, the user is asked to define some parameters. These parameters include the starting date of the process, the starting time of the workday, the ending time of the workday, and the area where the process will be applied during the day. The created system is flexible enough to allow the user to create a model as he desires, and Track Count and Team Count can be defined as desired. When the team count is entered, event logs related to the process are generated in parallel, assuming that each team starts the process on the same date and at the same time in the data generated with respect to these teams. Since the need for generating data in a different process completion count and team count in a certain process is inevitable for the user, he/she is requested to name each simulation he/she produces. Accordingly, the user was given the opportunity to decide on the optimum team count by performing different analyses for different team counts for the process he/she chose.

An interface was designed, as in Fig. 6, to examine the data generated after the simulation.

In the system we have developed, the user can observe which team continues from which steps on which track in
the generated data. There is information such as the start
time of the selected step, which employee performed it, and
duration and cost. Duration expresses the burden of the
operation performed in the selected step in terms of time,
while cost expresses the financial burden of the operation
in the system. By extracting the event logs of the data he/she
generated in XML format, the user can reach meaningful
information about the fitness, accuracy, and completion
times of the processes with process mining discovery
algorithms in the discovery module of the system.

D. Analysis

In the analysis module, the objective is to extract
meaningful information from the event logs created in the
simulation module.

On this screen, previous process simulations are listed,
and the user selects the process to be analysed. After the
selection of the model, the summary information is shown to
the user, as given in Fig. 7.

While the left table contains general information about
the process model, the right table displays information about
the selected team of the process model. The data from the
team selected in the summary analysis are compared to the
average data from the process, and a general performance
comparison can be made between the teams.

E. Team Comparison

As in Fig. 8 of the steps, graphs showing the time and
cost distributions of general, team-based, and selected tracks
are produced. Due to these graphics produced, the steps
with the highest cost and time in the process can be
determined and changes to be made in terms of improving
the process can be determined. However, for tracks between
teams, it is possible to identify the teams that finished in the
shortest time and the longest time, and to see which team is
working with which performance. It is possible to reach
information about which team completed the process in
which track and how long it took.

Thanks to the tool comparison structure, meaningful
analyses can be made from the data produced in accordance
with the multi-thread architecture. As a result of the
flexibility of the system, comparisons can be made by
generating data for the desired simulation at different times
and for different tool numbers.

F. Process Mining Discovery Algorithms

Every process in the real world is recorded in event logs
as sequential events through software systems. Afterward,
the information in these event logs is modeled and analysed
with discovery, fitness checking, and development, which
are process mining stages. Therefore, meaningful data are
presented to individuals and systems. Many different
algorithm approaches are used in process mining. These
algorithms are Alpha, Multi-Phase Miner algorithm,
Heuristic algorithm, Fuzzy Miner, and Genetic algorithm. In
this study, performance comparisons were made using alpha
and heuristic algorithms. As seen in Fig. 9, the most
important stage of process mining is the discovery of
processes from event logs and model creation. Various
process mining algorithms, especially alpha and heuristic
algorithms, can be used during process discovery.

Figure 10 shows the fitness checking stage of the
processes. At this stage, processes are monitored, and the
fitness of existing processes and processes obtained from
the event logs is checked. Thus, it is used to detect
differences between the event log and the model to
determine their positions in the process and to measure their
severity.
The purpose of the alpha algorithm is to form a workflow net (Petri net) from event logs. The steps of the alpha algorithm \((\alpha(W)) = (P_w, T_w, F_w)\) are given below [24], [25]. The \(P_w\) shown in this algorithm represents places of established (work flow steps) Petri net, \(T_w\) transitions, and \(F_w\) indicates combined status of all locations and transitions from input place to output place, i.e., established Petri net (work flow network). \(W\) refers to the log of a workflow on \(T_w\). \(T\) stands for transitions. Using \(T_w\) together refers to the transition of the workflow.

Algorithm 1. Alpha algorithm steps.

1. **Step 1:** \(T_w\) all transitions of event logs are established.
   \[ T_w = \{ t \in T | \exists_{\text{event}} t \in t \} \]
2. **Step 2:** \(T_i\) input places in source node are formed.
   \[ T_i = \{ t \in T | \exists_{\text{event}} t = \text{first}(\sigma) \} \]
3. **Step 3:** \(T_o\) output transitions of recipient are formed.
   \[ T_o = \{ t \in T | \exists_{\text{event}} t = \text{last}(\sigma) \} \]
4. **Step 4:** Discovered places in Petri nets are defined \((X_w \text{ and } Y_w)\).
   \[ X_w = \{(A,B) | A \subseteq T_w, B \subseteq T_w, \forall_{i \in i}, \forall_{a \in A} a \rightarrow W^b \subseteq \forall_{i \in i}, \forall_{a \in B} a \rightarrow W\} \]
5. **Step 5:** Discovered places in Petri nets are defined \((X_w \text{ and } Y_w)\).
   \[ Y_w = \{(A,B) \in Y_w | \forall_{A \in A}, \forall_{B \in B} (A \subseteq A' \land B \subseteq B') \} \]
6. **Step 6:** Places of each input and output nets are formed separately.
   \[ F_w = \{ p(A,B) | p \in Y_w \} \cup \{ t_w, o_w \} \]
7. **Step 7:** By integrating places obtained at Step 6 Petri net started to be formed.
   \[ F_w = \{ p(A,B) | p \in Y_w \land A \in A | \cup \{ (p(A,B))^b \} | (A, B) \in Y_w \land B \in B \cup \{ (t_w, o_w) \} | t \in T_w \} \]

As a consequence, the Petri net is obtained with the alpha algorithm.

In our previous study, a data generator simulation was performed [26]. In this simulation, many synthetic event logs were created.

In our study, a system was created that provides process discovery from event logs created with synthetic and real event logs, integrated with the data generator simulation carried out before. In this study, the Petri net created with the alpha algorithm for the credit application data set consisting of 7 activities, 227 statuses, and 856 event logs created by simulation is shown in Fig. 12.

**G. Alpha Algorithm**

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**H. Heuristic Algorithm**

The purpose of heuristic algorithm is to establish a Petri net that provides an optimum solution by using event logs [27]. The heuristic algorithm sequences transitions in the event log and removes less frequent transitions based on frequencies. The steps of the heuristic algorithm are as follows (see Algorithm 2).

Algorithm 2. Heuristic algorithm steps.

**Step 1:** All transitions from event logs are received. 
\[ T = \{t | \exists_{t \in \sigma} \}, \]

**Step 2:** Transitions calculated for a single loop length. 
\[ C_i = \{(a, a) \in T \times T | a \Rightarrow W^r \geq \sigma \}, \]

**Step 3:** Transitions calculated for length. 
\[ C_i = \{(a, b) \in T \times T | (a, b) \notin C_i A \Rightarrow 2 \ W^r \geq \sigma \}, \]

**Step 4:** Strongest output value is determined. 
\[ C_{o} = \{(a, b) \in T \times T | b \neq \text{End} \land a \neq b \land \forall_{a \neq t} [a \Rightarrow W^{t} \Rightarrow W^{r}] \}, \]

**Step 5:** Strongest input value is determined. 
\[ C_{o} = \{(a, b) \in T \times T | a \neq \text{Start} \land a \neq b \land \forall_{a \neq t} [a \Rightarrow W^{t} \Rightarrow W^{r}] \}, \]

**Step 6:** Weakest output connections of two loops length are determined. 
\[ C_{w} = \{(a, x) \in C_{o} | (a \Rightarrow W^{r}) < \sigma \land \exists_{y \in C} \land (a, b) \in C_{i} \land (b \Rightarrow W^{r}) \}, \]

\[ \Rightarrow (a \Rightarrow W^{r}) > \sigma \}, \]

**Step 7:** Weak output connections are excluded. 
\[ C_{o} = C_{o} - C_{w}, \]

**Step 8:** Weakest input connections of two loops length are determined. 
\[ C_{w} = \{(x, a) \in C_{o} | (x \Rightarrow W^{r}) \neq \sigma \land \exists_{y \in C} \land (y \Rightarrow W^{r}) \neq \sigma \}, \]

**Step 9:** Weak input connections are excluded. 
\[ C_{w} = C_{w} - C_{w}, \]

**Step 10:** Output transitions calculation is determined according to threshold value. 
\[ C_{w} = \{(a, b) \in T \times T | a \Rightarrow W^{r} \geq \sigma \lor \exists_{a \in C} \land ((a \Rightarrow W^{r}) \neq \sigma \lor W^{r} \neq \sigma) \}, \]

**Step 11:** Input transitions are determined according to threshold value. 
\[ C_{w} = \{(b, a) \in T \times T | (b \Rightarrow W^{r}) \geq \sigma \lor \exists_{b \in C} \land ((b \Rightarrow W^{r}) \neq \sigma \lor W^{r} \neq \sigma) \}, \]

In consequence, linked graph is formed (DG = C_i \cup C_o \cup C_w \cup C_w). 

In Fig. 13, the model created by the heuristic algorithm of the credit application process data that we used for the alpha algorithm above is shown. In this study, different models were obtained using alpha and heuristic algorithms and data from the credit application process.

![Graph of Heuristic Miner](image)

Fig. 13. Petri net created with the heuristic algorithm of the sample credit data set.

**I. Genetic Algorithm**

Genetic algorithm is one of the methods based on biological processes used to perform modelling for the solution of algorithm searching and optimization problems. Genetic algorithms are used to solve problems that are difficult or impossible to solve with traditional methods [28].

Genetic algorithm is being used commonly in different areas, primarily for optimization, as well as automated programming and information systems, mechanical learning, finance, tabulation problems, facility layout problems, traveling salesman problems, vehicle routing problems [29]. The steps of the genetic algorithm are shown

![Fig. 14.](image)

Algorithm 3. Genetic algorithm steps.

**Step 1:** Number of individuals determines mutation and crossover ratios.

**Step 2:** Random population is formed.

**Step 3:** Repeat Steps from Step 4 to Step 7 until new population is formed.

**Step 4:** Selection process is carried.

**Step 5:** Crossover applied.

**Step 6:** Mutation process applied.

**Step 7:** New baby individual is created.

**Step 8:** Best individuals solving the problem are generated.

The Petri net created with the genetic algorithm for the sample credit data set is shown in Fig. 15.
V. EXPERIMENTAL STUDY

Unlike the alpha algorithm, the heuristic algorithm calculates the frequency values between the activity groups in the event logs. In the alpha algorithm, each event log is taken once. In the heuristic algorithm, frequency values are obtained by using all the event logs. The frequency calculation is made by taking the sum of the activity groups that are related to each other.

To measure the performance of algorithms, several different criteria are used. Accuracy and time criteria, primarily fitness function developed in this study, are compared for process mining discovery algorithms.

The fitness function is calculated to identify the most suitable individual to a solution to the problem. The fitness function for alpha and heuristic is shown as F. Equation (1) expresses the proposed fitness function for the alpha algorithm

\[
F = \frac{1}{2} \left( \frac{s - y}{s} \right) + \frac{1}{2} \left( \frac{s - k}{s} \right)
\]

In (1), s is the total processes, y is the non-separable processes, and k is the remaining processes that can be separated. Equation (2) expresses the proposed fitness function for the heuristic algorithm

\[
F = \frac{3}{5} \left( \frac{s - (y + t)}{s} \right) + \frac{2}{5} \left( \frac{s - k}{s} \right)
\]

In (2), s is the total processes, y is the non-separable processes, t is the repeating processes, and k are the remaining processes that can be separated. The fitness function for the genetic algorithm is calculated in two ways, F_S and F_C. These calculations are calculated as in (3) and (4):

\[
F_S = 0.2x \frac{PEAS}{TAS} + 0.3x \frac{TTIS}{TIS} + 0.5x \frac{TUOTS}{TIS}
\]

\[
F_C = 0.4x \frac{PEAS}{TAS} + 0.6x \frac{TUOTS}{TIS}
\]

In (3) and (4), PEAS represents the number of activities parsed, TAS the number of all activities, TTIS the number of all completed tracks, TIS the number of all tracks, and TUOTS the number of all tracks suitable for completion.

Here, F_C is more advantageous compared to F_S. Because when there are uncompleted cases in F_S, the fitness function does not provide effective results. Moreover, when there is a parsing fault in F_S, the parsing ends.

Accuracy rate is found by the ratio of parsed processes to
the number of total processes. It is calculated in the same manner for all process algorithms. 

Time criteria means the average working period of algorithms.

A. Performance Analysis of Process Mining Discovery Algorithms for Simulation Data Sets

Table III lists the results of the process mining algorithms on various synthetic data sets generated using simulation. Missing Synthetic Data6 (Patient Follow-up Data) were created by deleting some activities in Synthetic Data5 (Patient Follow-up Data).

As the change between the fitness function of these two data is shown in Table III, the fitness function of the alpha algorithm decreased by 0.16 (0.78–0.62), while the fitness function of the heuristic algorithm decreased by 0.15 (0.83–0.68), and the fitness function of the genetic algorithm decreased by 0.04 (0.87–0.83). In the missing data, the change in the fitness function of the genetic algorithm decreased less than in the other algorithms.

B. Performance Analysis of Process Mining Discovery Algorithms for Synthetic Data Sets

Table IV presents the results of process mining algorithms in existing [30] various synthetic data sets.

Concerning the average fitness and accuracy values of the algorithms, the genetic algorithm yielded successful results compared to the heuristic and alpha algorithms. Moreover, it is observed that the heuristic algorithm yielded better results than the alpha algorithm.

C. Performance Analysis of Process Mining Discovery Algorithms for Real Data Sets

The results of the process mining algorithms on real data sets are presented in Table V [31], [32].

In Table V, some events were randomly deleted from the Missing Real Data3 (Patient Information) event log. Some events were randomly added to and deleted from the Missing and Noisy Real Data5 (Traffic) event log.

For these data sets, the performance of the alpha algorithm is lower than that of the heuristic and genetic algorithms. However, the genetic algorithm yielded better results than the heuristic algorithm.

D. Performance Evaluations of Process Mining Algorithms for the Same Data Set

In Table VI, the success results of the real data set related to a patient process obtained from a hospital are given.

We obtained data similar to this data set with our own data generator simulation. However, since we could not obtain a synthetic version of this data set, we only compared the performance of these two data sets with alpha, heuristic, and genetic process mining algorithms. Similar results were obtained as seen in Table VI.

| Simulation Data Sets   | Alpha | Heuristic | Genetic | Alpha | Heuristic | Genetic |
|------------------------|-------|-----------|---------|-------|-----------|---------|
| Data1 (Daily activity) | 1     | 1         | 1       | 100   | 100       | 100     |
| Data2 (Work application) | 0.97 | 1         | 0.99   | 95.5  | 97.5      | 96      |
| Data3 (Master application) | 0.92 | 0.94      | 0.97   | 93    | 95        | 97.5    |
| Data4 (Credit application) | 0.91 | 0.93      | 0.96   | 87.4  | 89.5      | 92.5    |
| Data5 (Patient Chart Data) | 0.78 | 0.83      | 0.87   | 79    | 84.5      | 86.7    |
| Missing Data6 (Patient Chart Data) | 0.62 | 0.68      | 0.83   | 60    | 65.3      | 72.5    |
| Avg                    | 0.86  | 0.89      | 0.93   | 85.8  | 88.6      | 90.8    |

| Synthetic Data Sets [26] | Alpha | Heuristic | Genetic | Alpha | Heuristic | Genetic |
|--------------------------|-------|-----------|---------|-------|-----------|---------|
| Synthetic Data1 (Exercise1) | 0.97 | 1         | 1       | 97.5  | 100       | 100     |
| Synthetic Data2 (Exercise2) | 0.92 | 0.98      | 0.95   | 95.5  | 97.5      | 95      |
| Synthetic Data3 (Exercise3) | 0.87 | 0.73      | 0.81   | 80    | 70.5      | 77.5    |
| Synthetic Data4 (Exercise4) | 0.72 | 0.81      | 0.84   | 70    | 85        | 86      |
| Synthetic Data5 (Exercise5) | 0.67 | 0.73      | 0.81   | 70    | 80.5      | 85.5    |
| Missing Synthetic Data6 (Exercise1) | 0.52 | 0.69      | 0.74   | 66.4  | 73.5      | 78      |
| Avg                      | 0.77  | 0.82      | 0.85   | 79.9  | 84.5      | 87      |
VI. CONCLUSIONS

In today’s information systems, information is recorded on events that take place in business processes. By reviewing these event logs, meaningful information about time, cost, and process can be extracted. Due to this information, it is possible to improve processes or measure the performance of the process.

At the first stage of this study, a web-based data generator was developed. In this data generator consisting of three main modules, process models can be created arbitrarily, data suitable for processes can be generated, and analysis and team comparisons can be made regarding the generated data. In the first module, a sample data model is created. In the simulation module, the second module, event logs are produced in compliance with the previously entered model. Meaningful information about the processes is extracted from the event logs produced in the analysis module.

In the second stage of this study, a system was created, enabling process discovery from existing event logs or event logs created with a data generator. After the data were taken in the MXML and XES formats and uploaded to the system, various process mining algorithms such as alpha, heuristic, and genetic algorithms were applied, and the results were compared according to fitness, accuracy, and time criteria.

When comparing the results of alpha and heuristic algorithms, the heuristic algorithm yielded more successful results than the alpha algorithm in terms of fitness and accuracy rates. The genetic algorithm yields better results than the heuristic algorithm regarding incomplete processes due to the application of genetic procedures (selection, crossover, and mutation).

When the results are compared in terms of the time criterion, the alpha algorithm ends in a shorter time than the heuristic and genetic algorithms for simple data. However, the genetic algorithm ends in shorter times than the alpha and heuristic algorithms for complex data.

In the future, the aim is to improve the system by integrating different algorithms into this study. Furthermore, it is recommended to develop studies to deal with process mining problems such as noisy data and incomplete processes, which are the disadvantages of our study.

CONFLICTS OF INTEREST

The authors declare that they have no conflicts of interest.

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