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REVIEW

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Financial technology decision support systems

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Abstract

The financial technology industry was the first and most successful to combine machine learning algorithms based on big data with artificial intelligence techniques. The use of decision support systems (DSSs) procedures will deliver financial products, service channels, service methodologies, and risk management in the quickest and most cost-efficient manners. The deep service value chain's high-end finance was significantly impacted by the inventive and quick development of smart artificial intelligence (AI) and machine learning (ML) techniques brought about by all of the decision-making processes. This study presents digital services, including DSS procedures utilized in financial service operations. The fundamentals of DSS approaches, as well as AI and ML, are then demonstrated, and an example application of a campaign management system for tax repayment rescheduling is provided.

Keywords: Fintech artificial intelligence, Fintech decision support systems, Fintech machine learning, Digital finance management, Financial service digitalization

Introduction

Financial companies, like other organizations, are financed by transaction costs. If there is no trust between the customer and the firm, market interactions on the production side and the customer side are defined as in risks, because of the principal-agent company dilemma and incomplete or lack of symmetric knowledge. To solve these problems that create risk, trust must be organized around costs imposed on institutions and consumers, such as contracting, search, and verification costs. Lending, for instance, is known as asymmetric information ex ante, as lenders have to know the risk profile of potential borrowers, and ex post, as they need to watch the repayment capacity of borrowers. A basic characteristic of payment markets is that they follow the track of payment obligations and prove the identity of account owners or the veracity of payment tokens. There are many parties included in the payment processing chain that must rely on the other links that do not show fraud or liability, and customers need trustworthy partners for lodging funds and safe processes for their delivery. Financial market investment and insurance have uncertainty around future outcomes, cross-selection, and moral hazard. Those generate investment products based on underwriting and execution services, which provide trust in the soundness of investments and processes that carry their ability to buy and sell. The existence of uncertainty about future artifacts, for instance, means a borrower can go bankrupt, which creates more frictions related to financial trust. In this perspective, financial service companies create many rules, processes, and criteria to provide safe and trustworthy financial services to combat uncertainty.

The introduction of technology to the financial sector is not a new application, but there are a number of boundaries that show the operating environment until recently. In the late twentieth century, the financial sector was already defined by a relatively high degree of computerization since most financial operations were dematerialized. Only payment services require physical cash or a check, and onboarding for new artifacts and services often requires in-person or document-based processes. There are many ways to reach and connect with customers routinely that require physical infrastructure, such as branches and automated teller machines. Customers who wish to transact with parties using other banks must use expensive and sometimes slow or challenging operations such as wire transfers. Even after the progress of digital payment systems and the dematerialization of securities, connectivity remained a barrier to entry. An organization must be licensed and part of a consortium of banks or brokerage houses to participate in a transaction network. Moreover, data processing and storage were expensive and required the services of bespoke mainframes and data centers. This constrains the volume of data that could be gathered, stored, analyzed, and exchanged to improve efficiency, price risk optimization, and configure products to customer needs. Most of the technological progress in finance is in two key areas that develop current technology-based finance [1]:

- Increased connectivity
- Low-cost computing and data storage

With the emergence of the Internet, mobile Internet, and the Internet of Things, the information rate doubled in growth, and the finance sector accumulated a big chunk of data in the transactions of business operations that included customer data, transaction data, and asset liability data. According to a research analysis, the banking business produced 820 gigabytes of data for every 1 million dollars in revenue. However, financial information is difficult to obtain, and only the most valuable data is used in that research.

Because of this perspective, the financial sector uses the deepest and most extensive application of artificial intelligence, decision support systems, or machine learning techniques. Its actors include not only technology organizations but also artificial intelligence technology services for financial organizations, as well as legacy financial organizations that apply technology, emerging financial formats, and financial regulatory authorities that still exist [2].

In the financial sector, AI renovates itself by developing procedures. AI helps the fiscal diligence to modernize and progress made in extending from credit decisions to quantifiable transactions and commercial risk administration. AI hits the break-even point of the financial industry. With the help of AI usage in the long term, great achievements will be comprehended over the coming time. The business is going to expect an additional $1 trillion by the 2030 year-end with outdated monetary organizations cutting 23% from their budget [3–5].

Background information Fintech DSS

AI is defined as machine systems with varying degrees of autonomy that can carry out a series of orders based on human goals, assumptions, suggestions, or judgments. More and more "big data" analytic and alternative information sources are being used by AI processes. According to this viewpoint, ML models that make use of such data are created to automatically learn from experience and information, improving prediction and performance without the need for human programming. The COVID-19 pandemic issue accelerated the rate of digitization across many industries, and remote working is now prevalent across many industries, particularly in the data services sector, with the exception of the manufacturing industry. According to predictions, the amount spent on AI globally will double between 2020 and 2024, rising from $50 billion to $110 billion [6]. The focus of artificial intelligence (AI), particularly in the finance industry, is on asset management, algorithmic trading, credit underwriting or blockchain financial services, fraud detection, credit risk calculations, and crowd funding, all of which are made possible by the availability of information and reasonable computing and storage costs. Financial AI applications typically enhance investor and consumer protection regulations and generate financial and non-financial hazards. Due to a lack of understanding of AI models and methodologies, the utility of AI fuels dangers that affect a financial institution's safety and attentiveness. An important issue when implementing AI models is how they interact with the current financial services and internal governance standards. Even when the technology-neutral paradigm is used in policy making, it presents a serious conundrum. Particular issues with consumer protection arise from AI. For instance, risks of unfair, biased, or discriminatory consumer results or data management and utility issues. These risks in the finance sector also amplify the weaknesses of the sophisticated techniques used, the adaptation of AI-based models, and the levels of their autonomy, as shown in Fig. 1 [6].

With the ease of commercially available advances in computer data storage, computing power, energy reliability, consumer analytic techniques, mobile communication, and new media, including social media, emerging financial services providers are beginning to incorporate AI technologies into their service offerings. 151 companies, including financial technology companies and established banks, participated in a recent study

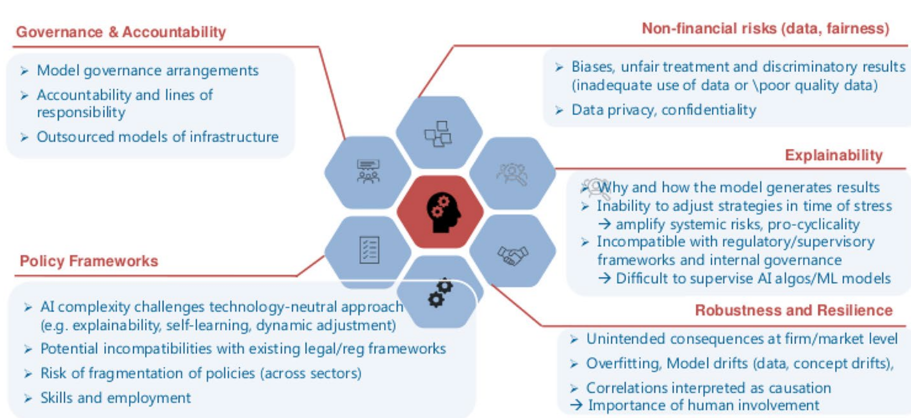

Fig. 1 Issues and risks related to the AI in Finance [6]

poll conducted by the World Economic Forum and the Cambridge Centre for Alternative Finance. Of them, 85% established some type of AI [7].

To give readers a quick overview, Fig. 2 summarizes how AI is affecting business models and activity in the financial sector [6] based on different digital financial applications:

- The analysis of alternative data points and effective real-time behavior is the use of AI in finance that is most frequently used:
- Enhancement of credit decisions
- Underline risks related to financial institutions and how to mitigate compliance obligations
- Identify financing problems of the business in emerging markets

The second significant application of AI in emerging market financial services is in the development of business models that automate and lower the cost of transaction processing for a broader range of customers. It involves firms and customers with lower incomes that gain access to financial products that are tailored to their unique needs through AI. For instance, AI software may automate customer administration and customer service functions in digital financial services, which lowers the cost of providing more customers with individualized support. According to Juniper Research, the use of chatbot apps by banks in the global economy would reduce operating costs by $7.3 billion in 2023. Another example is Bank BCP in Peru, which collaborates with International Business Machines (IBM) Watson to improve Arturito, a personalized chatbot that aids users in currency conversion, credit card payback, and access to round-the-clock customer service via Facebook. Another example is Banco Bradesco of Brazil, which collaborated with IBM Watson to create a chatbot that can connect to 62 different products and respond to 283,000 inquiries in a month with 95% accuracy.

Personalized banking is a further application of AI in the financial services industry. In recent years, "relationship banking" by financial institutions for major businesses and high-net-worth people has limited the expense of building tailored ties with clients. By leveraging AI and big data to automatically assess consumer behavior for straightforward savings and investment advice that is offered for free, financial

Fig. 2 Impact of the AI effects on business models and financial sector activities [6]

service providers check to utilize various services to remove the concentration of the large number of clients from the market. These robo-advices have the potential to increase financial inclusion if a large number of processes can be automated and the service prices for low-income clients are reduced. For instance, robo-advisors in developing nations like China, Brazil, and India where there is a pool of savings have the goal of avoiding the commission-based business model of current financial service brokers as well as the culture of financial advice acceptance from families and friends. These sets produce insufficient savings results. Additionally, the company's AI robo-assistant, Arthos, analyzes customer data to offer mutual fund suggestions that are relevant to each customer's risk profile and monitors financial decision-making concerns to generate a monthly rebalancing. The robot assistant as a chatbot in financial organization Arturito is depicted in Brazil in Fig. 3 [7].

Machine learning algorithms that cut expenses for businesses and solve operational issues to serve more customers are other sophisticated applications of AI in the financial services industry. Complex AI applications have a higher potential to remove the barriers to financial inclusion. For instance, weather risk transfer contracts are financial tools that shield farmers from climate difficulties by paying out for weather disasters that have already been identified in advance. In order to determine weather "event" problems, European Space Agency WorldCover project uses AI to assess weather satellites, weather stations, and agronomic data. Therefore, it relies on smart contracts that can generate automatic payouts using blockchain and AI. Farmers without bank accounts can activate their insurance coverage thanks to the automated payout expenses made possible by nonbank payment processors like M-Pesa (Mobile Pesa-money in Swahili language). In order to pinpoint the issues with insurance protection in emerging markets, it will be helpful to define and identify the limitations to the scalability of insurance solutions, such as in weather risk transfer contracts. Approximately 160 billion dollars, or 96% of the worldwide insurance protection risks, are traded on this market.

The application of AI in the financial services industry raises unique privacy and algorithmic bias issues. A vast array of dangers associated with credit reporting models were listed by the International Committee on Credit Reporting, including data errors, the use of data without the knowledge of customers, potential bias in algorithm design and

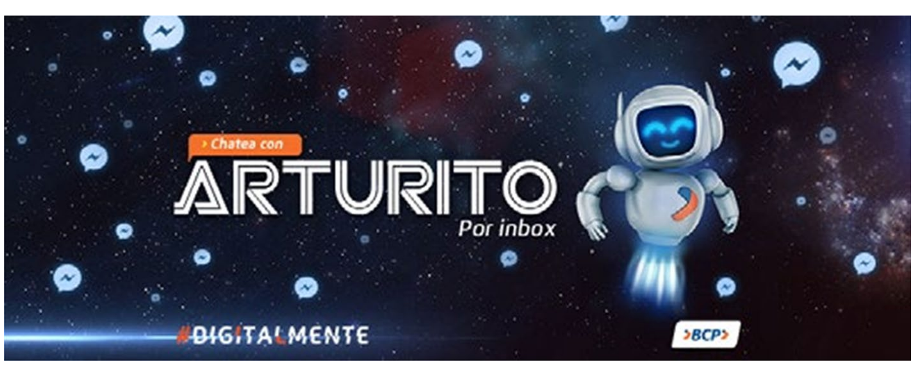

Fig. 3 Chat robo-assistant in Peru [7]

decision-making, and greater susceptibility to cyber risks. These issues are resolved by AI models that reverse data into the decision-making processes [7].

Every new cutting-edge technological goal in the market for AI-based financial services is to support decisions. Future investments, loans, financial products, and business operations all benefit from decision support in financial management and services. DSS is also carried by this AI in order to support it in context. For power utilities, companies, and organizations, DSS is an information system that focuses on computer activities to assist decision-making in planning, management, and operations. The theoretical research on decision-making for organizations conducted by the Carnegie Institute of Technology and the technological work on interactive computer systems conducted by the Massachusetts Institute of Technology in the 1960s served as the conceptual foundation for the development of DSS. Decision support began to take on significance in academia in the 1970s, and the first work that made this clear appeared in a conference and journal at that time. Computer science, simulation technology, software programming, cognitive science, and other scientific disciplines are all included in DSS. Structured, unstructured, and semi-structured obstacles must all be resolved for decision-making to take place. Techniques with explicit specifications and decision-making activities are referred to as structured issues. Contrarily, the steps for unstructured situations are predetermined, and the majority of the decision-making processes are monitored simultaneously. Decision-making is stated in a semi-structured instance, but optimal decision-making cannot be demonstrated. The aims of the DSSs differ for a wide range of levels in organizations and businesses. In businesses or organizations, there are three different organizational structures. Strategic planning is used to manage resource acquisition, utilization, and disposition and initially entails long-term policy planning. In the second scenario, management oversight ensures that the organization's goal is achieved by effectively gathering and utilizing the available resources. Operation control identifies the actual progress at the last stage. Regardless of the project or application type they are used in, DSSs must generally adhere to requirements [8]:

- Compatible to many decision processes and structures
- Interactive interface and friendly users
- Users can access and control
- Allow users to develop DSS freely
- Support modeling, data access and analysis
- To work in both standalone and web-based environment

A typical DSS system architecture relationship that must meet the aforementioned requirements is shown in Fig. 4 [8].

Usually, the foundation of DSS is the structural development of knowledge-based systems. In the literature, systems that are both user-friendly and independent of domain have also been developed. Typically, these are designs for expert systems. An Extension Decision Support System (XDSS) architecture was the DSS structure's original starting point. Domain, data dictionary, model, report generator, and graphical knowledge are the five components of the knowledge base. The architecture's components are all maintained by professionals. The problem that users have recognized and that the XDSS

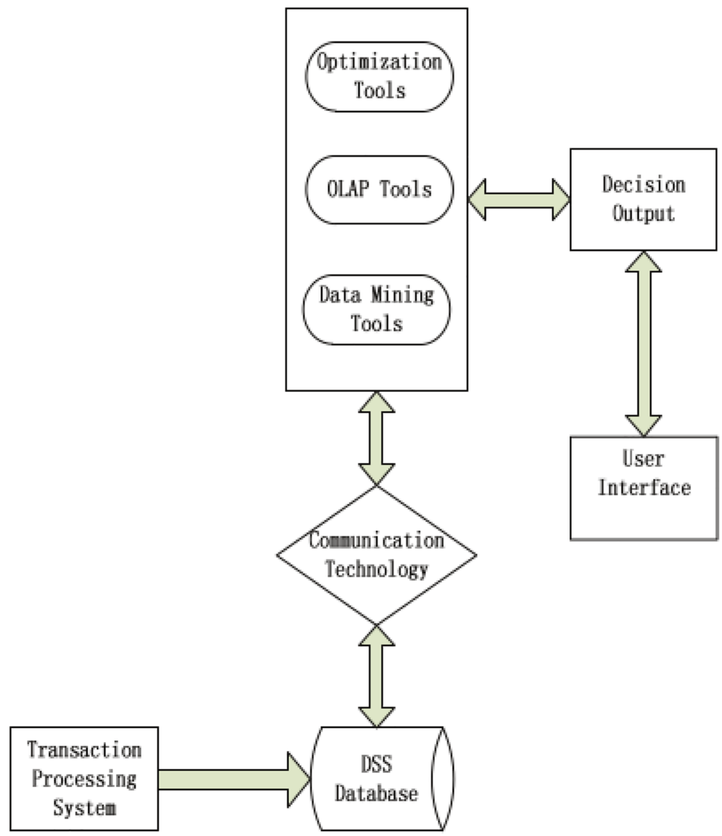

Fig. 4 Typical architecture of a DSS [8]

program has presented is understood by domain knowledge. The problem can then be divided into smaller problems so that the knowledge base units can be customized. The final stage is when all sub-problems integrated with the XDSS program are resolved. The XDSS architecture [8] is depicted in Fig. 5, how it connects to the database, model, and data via model.

The flexible logic base mode is another DSS design model. This model serves as an intentional database for a system that uses logic. It implies that the user can save a lot of rules. However, a different extension database (EDB) is used to store the real data. Models are applied to the DSS system in one of two ways—coded models or defined models—in order to lighten the effort. The similar method based on model-based architectures is employed by IBM Watson. Four generations make for the evolution of a DSS model management system. The generation of the DSS models is depicted in Fig. 6 [8].

Distributed information systems are currently widespread, as mentioned in the DSS framework. The reason as a principle is determined by the DSS's initial level of realization. The second level is where realization sets are chosen. At the highest level, justifications are assessed, and an estimation is produced as a result. Knowledge-based systems will determine the outcome in a more exact manner if the reasoning is reinforced with additional experience data based on the subject matter of experts or consultants. Risk management is the most efficient goal to manage customer requests, shifting financial status conditions in the market, and long-term trends in the

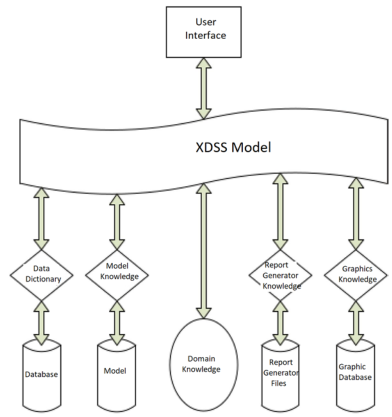

Fig. 5 XDSS architecture[8]

financial servicing environment of today. Knowledge assistance is important for the DSS approaches in this situation. As a paradigm, a common pattern for information mining over a distributed network is constructed. As shown in Fig. 7 [8], the collaborative DSS model is utilized here as a cutting-edge framework for DSS architecture.

Future trends in DSS architecture are based on cloud computing for database and service sharing. Services such as computation, data access and software applications are trend to share to the consumers. Three service models in cloud computing are software as a service (SaaS), platform as a service (PaaS), and infrastructure as a service (IaaS). In cloud computing for the selected service, a system for traffic control applied agent base system is used. n-tier architecture, namely platform, application, unified and fabric layers, is created in today's DSS structure. Clouds in customer

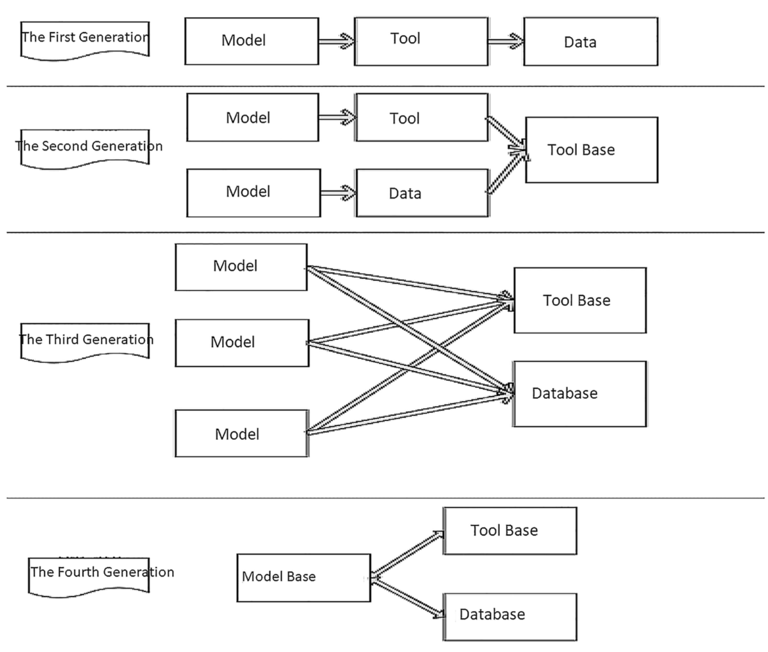

Fig. 6 Model architecture generations for DSS [8]

domain are concentrated on aim of the utility as in private cloud, public cloud, and internal cloud. The objective of DSS is to decrease the complexity in managing the technology in cloud systems. Implementation of DSS as an optimized way is to invest in communication techniques to reach to a better data mining.

In DSS system process, a big amount of internal and external data is necessary. In this respect, a robust data base is also significant in realizing a decision support system model training. Model is a effective process to describe and create decisions including simplification and expression practical world challenges. As the model is independent and data is specific to that model, then the organizational structure of the software application can be established. Financial service management is a decision-making process that has collection of data, models, methods, structural data and analysis of them to reach a decision. Quantified decision is only possible when large amounts of data with different information resources are connected and fuse these data via combined system functions so they can talk with each other with the help of the data management in the system. They can also exchange data of the financial management decision making.

DSS, AI and ML techniques

In decision-making models for DSS information systems, big data is analyzed with the help of pattern recognition methods as given in AI techniques, and some of the ML methods are also used to define the pattern and bias the model nodes in the prediction method of the process. In this respect, there are four types of AI or AI-based systems, such as reactive machines, limited memory machines, theories of mind, and self-aware AI. Figure 8 shows the types of AI given in the literature [9].

Machines are beneficial devices for looking at high-dimensional data and recognizing patterns. As this is realized, accurate and precise predictions can be made by the input

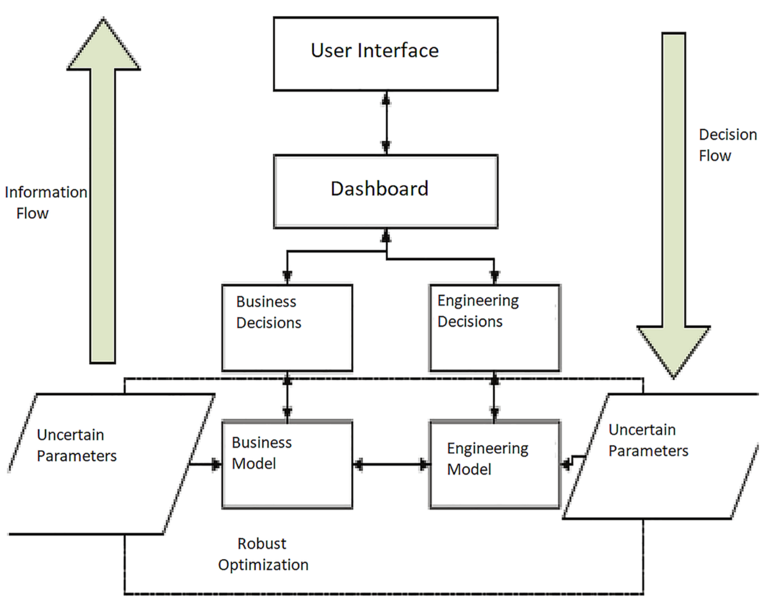

Fig. 7 Collaborative pattern DSS architecture [8]

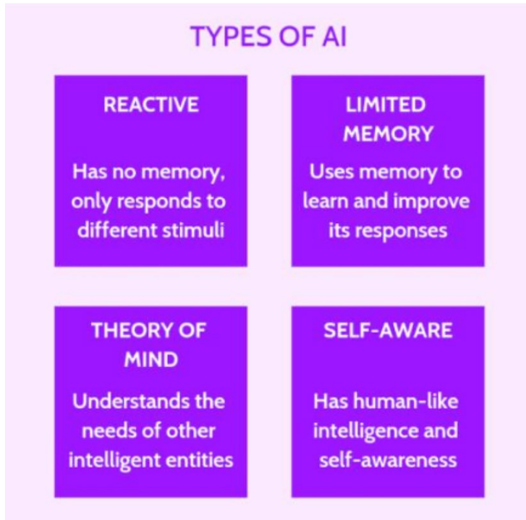

Fig. 8 Four types of AI [9]

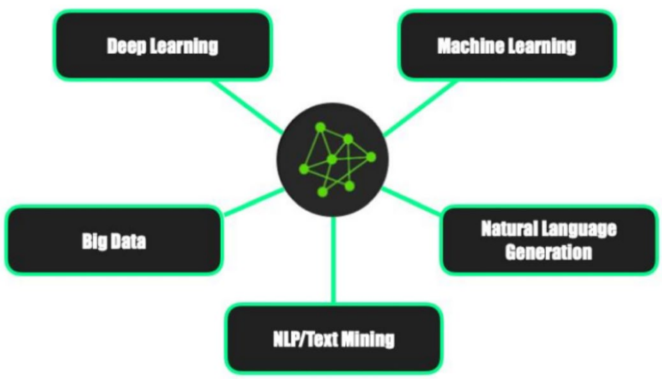

Fig. 9 AI subfields [9]

pattern model. There are multiple subfields of AI; it is not possible to cover all of them in this document. In the financial services field, most AI capabilities that are used are covered. In Fig. 9, subfields of AI are given [9].

Most humans interested in tech hear the sound of ML. ML is a technique of AI that has the capability of automatic learning and experience enhancement without being programmed. It is concentrated in the generation of computer software that can gather data and use it to learn for itself. Learning is a mechanism based on computational statistics and based on data, observations, experience, and instructions. This is determined by analyzing data patterns and reaching logical decisions related to the given instances that make the machines automatically learn and produce actions without human help. There are four types of ML: supervised ML, unsupervised ML, semi-supervised ML, and reinforcement ML. When ML techniques are more searched for, they can be found in deep learning (DL). DL is a segment of the wide family and is defined in artificial neural networks, especially convolutional neural networks. The DL algorithm is defined as the data being passed via nonlinear

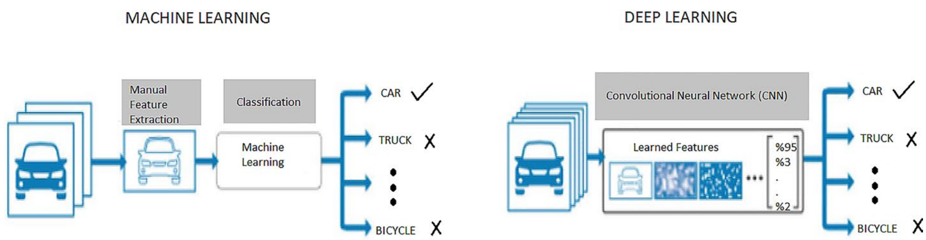

Fig. 10 Comparison of ML and DL [9]

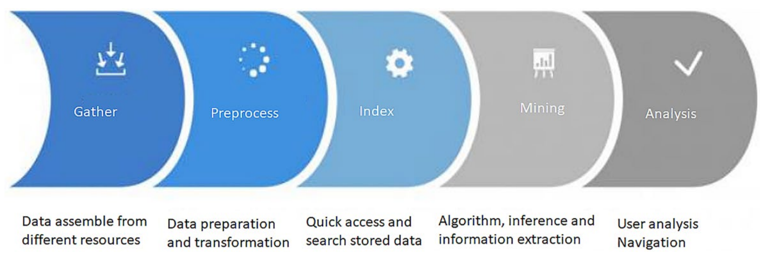

Fig. 11 Text mining technique [9]

series or nonlinear transformations before the output. Figure 10 shows the comparison of ML and DL at the same time with the applied techniques in their collection [9].

AI techniques collaborate with big data with respect to all the faces of data characteristics. These are data volume, data variety, data in motion, and data uncertainty. ML and DL techniques are all used by all facets of big data, but there are many challenges when the data is collected. Data can be untrustworthy or inappropriate. In this case, AI simply works with big data, which is structured before it is used in AI processes to make use of DSS information systems. In structuring data, text mining is most frequently used. Text mining is defined as text analytic, where it is used to analyze large chunks of text data provided by computer programs that can define topics, patterns, concepts, keywords, and other characteristics. Especially in fintech, such as robo-advisors or credit risk management systems, text mining is heavily used. Figure 11 shows how the text mining technique was processed [9].

An approach DSS in tax payment restructuring issues

In the financial services field, many DSS implementations of AI techniques are stated as examples to provide cost- and time-efficient operations for increasing financial customers. In this respect, a new application area for the financial services field is developing a campaign system based on multidimensional criteria-based DSS for tax payment restructuring prediction systems based on adaptive learning-based AI techniques. This system is devised as a solution where the affiliation of this study is governed client software project of a state financial organization department.

The financial organization stated that clients who make tax payments have problems with payment every year. In this case, tax payment restructuring regulations are published by the government to ease the payments of the tax owners. However, it is a big burden when the payment architecture of the current tax owner has to be restructured based on the condition of the client, the regulation rules of the tax payment restructure, past payment data, payment time in advance, and the classification of the tax owners as a group. Many of the personnel of the financial organization in the country have to calculate a restructure mechanism for the tax client and recommend the best prediction for the tax owner for their ease of payment. The objective is to return the tax as soon as possible as an income to the government, which is the main policy of the finance ministry. The problem is that since this is a human-calculated prediction, it is not known if it is the best maximum optimal prediction for the tax owner and financial organization's cash balance.

In this regard, the business operation analysis is made based on the demanded requirements, and criteria for the decisions are tried to be determined. The criteria for the input decision models for AI had to be specified. In this case, factor inputs for decision models are determined:

- Tax-owner groups
- Tax owners past tax payment characteristics
- Tax payment restructure regulation and control rules
- Restructured tax payment time period

For instance, if the tax owner groups are determined as customer micro-groups, advanced analytic and ML can make a classification for targeted segments. Figure 12 gives an user role classifications in the sale customer architecture that has the similar type of classifications tax payment of that perspective [10].

If the contact strategies via different channels are enough to help tax owners continue timely payment, financial organizations should also demand stronger measures, according to the tax owners capability to pay the tax. Tax owners with a high willingness but constrained capability to pay in the short term need to structure the tax payment via partial-payment plans or extensions. In these examples, where the taxpayer shows both low willingness and minimum capability to pay, financial organizations must concentrate on early settlement and cash balance. Advanced analytic, enabled by unstructured internal data sources from collections contact centers and external data sources such as old payment habits on other digital channels such as the Internet tax payment page, can enhance the precision of determination and willingness to pay.

In financial services, strong client engagement is the basis of maximizing client value, and leaders use advanced analytic to determine less engaged clients at risk of attrition and capable messages for timely nudges. As the client knows, a digital service is smart, so each tailored offer is delivered through the right channel at any time in the day. Rich internal explanation data for existing tax owners can give permission for financial organizations to create a finely calibrated strategy for each individual client, guided by resolved risks. AI-powered decision-making processes allow financial organizations to generate smart, highly personalized servicing experiences based on tax owner micro-segments. So that different channels can provide good service and a nice experience with interactions that are fast, simple, and efficient for tax repayments.

Customer type

	True low-risk	Absentminded	Dialer-based	True high-touch	Unable to cure
Targeted intervention	Use least experienced agents provided with set scripts	Ignore or use interactive voice message (segment will probably self-cure)	Match agents to customers; send live prompts to agents to modify scripts	Focus on customers able to pay and at high risk of not paying	Offer debt-restructuring settlements early for those truly underwater
Impact	Onscreen prompts guide agent–client conversation based on probability of breaking promises	10% of time saved, allowing for reassignment of agents to more difficult customers and specific campaigns	Matching and prompts can increase sense of connection and likelihood of paying	Added focus addresses higher probability of default rates in this segment	Significant increase in restructuring and settlements increases chance of collecting at least part of debt

Fig. 12 Customer type of classification example for tax owner micro-groups [10]

In financial organization facilities, this study is established with the organization's information management department a development environment for processing this tax payment restructuring campaign management DSS. Data architecture, data pipelines, application programming interfaces, and other significant units are available for building and deploying models through a standardized Capability Maturing Model Integration (CMMI)-based software development environment using an agile software scrum development process that is harmonized with enterprise strategy. It is established with a test lab environment with a semi-autonomous architecture, prototype development, and a factory for industrial-scale production of the solution. The aim is to generate value with a good AI technique to use in the DSS strategy. Figure 13 shows the software development of DSS in this project based on the project roles [10].

The final stage, from decision-making to messaging, is the ultimate domain for a digital campaign management system. Integrated with the software units across the full AI and analytic capability stack with the help of application program interface (APIs), data infrastructure, and engagement channels, the system can provide nearly instant processing of raw data to generate tailored messages via engaged communication channels. Figure 14 shows the final stage architecture for the digital architecture [10].

Method

In this study, the government organization does not share tax payment data, so simulated data is generated to assess the algorithms for DSS objectives. The method begins with seed-generated tax payment time serial data for 20 years for a single vehicle motor tax proprietor. The generated test data is then input into the ML algorithm to predict future payment data based on the test data. The machine learning (ML) algorithm utilized in this investigation is known as the "Prophet" algorithm. The Prophet algorithm makes three distinct scenario predictions. The initial scenario is a 20-year forecast, the second scenario is a 10-year forecast, and the final scenario is a 5-year forecast. The multi-decision criteria analysis (MDCA) method is then applied to the generated data

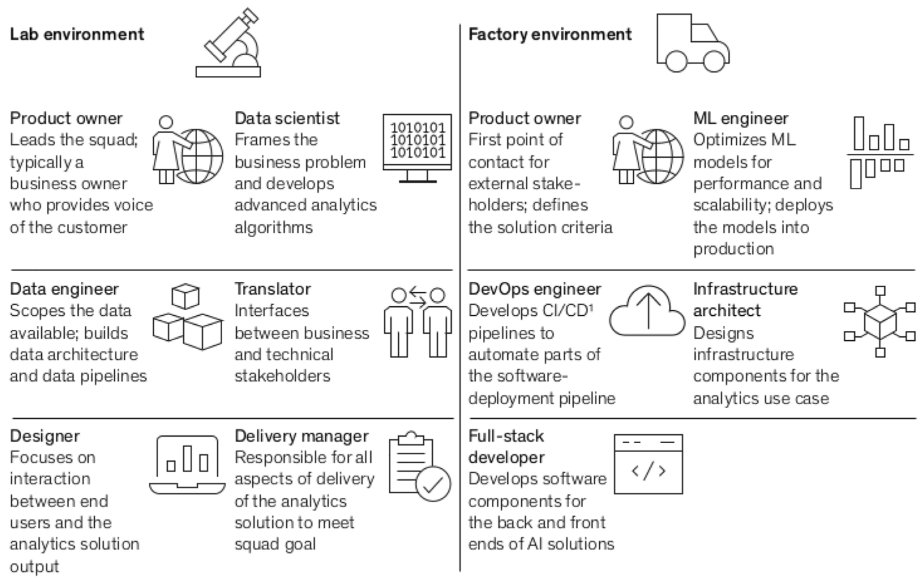

Fig. 13 Continuous development and continuous integration environment for the project [10]

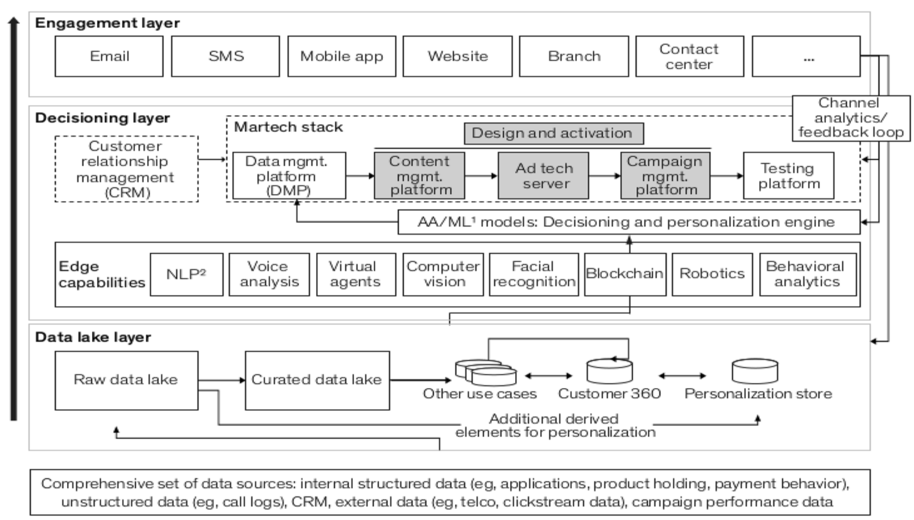

Fig. 14 Digital architecture for campaign management system [10]

to determine the best prediction based on the generated test data. As a decision analysis for the generated test data, the "Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS)" algorithm has been chosen on this occasion.

This research employs Python, a programming language based on the Anaconda 2022.10 framework. This research was conducted on a computer with an Intel i5 eighth-generation central processing unit (CPU), 20 gigabytes of random access memory, and the 64-bit Ubuntu 23.04 Lunar Lobster operating system. In Turkiye, motor vehicle tax (MTV) is paid twice a year using tax data generated by this task. Twenty years' worth of test data are generated for a particular tax owner. This data is generated using three distinct seed functions to produce payment logs for various dates. The government organization has a table of criteria and rules for payment amounts for various classifications of motor vehicles. A straightforward 1300 cc engine class is selected based on the table criteria, and 750 Turkish Lira are specified as the payment specification. Generation of tax payment initial seed functions generates Tax Value + Tax Value * 0.10 for 5, 10, and 20 years of payment series. 750 is used as the tax value in this function. In the second seed function, a random number generator with values between 0 and 750 is employed to generate a 5-, 10-, and 20-year payment series. A random number generator with values between tax value 900–1500 with 25 steps interval is used to generate a 5-, 10-, and 20-year payment series.

In the second step, the produced test values are logged into "csv" files to be used by the machine learning algorithm to generate new predictions. In the next phase of the ML algorithm, time series predictions based on 5 years, 10 years, and 20 years are generated. The generated serials for 5 years, 10 years, and 20 years also calculate the trends, multiplicative terms, lower and higher multiplicative terms, yearly additive terms, lower and higher additive terms, and y_hat prediction values.

In the final section of the method, matrices for the MDCA TOPSIS algorithm are defined for the criteria, alternatives, and generated test data variants. In execution, the MDCA TOPSIS algorithm employs weighted criteria for alternative decision ranks. On the basis of this fact, manual weights are specified and factorized for the alternative precedence levels. Then, the algorithm functions and makes the most accurate decisions based on the weighted criteria specified accordingly.

Prophet algorithm

Prophet is a trend topic algorithm based on a local Bayesian structural time series model. The Prophet algorithm is a prediction-based process coded in Python and R. Its speed is high and gives a complete automated prediction that is calibrated by the data analysis professionals. Forecasting is a widely known data science process that supports organizations with strategic planning, goal setting, and anomaly detection. In contrast to its importance, there are a couple of time series and analysis models with experience in time series modeling that are relatively rare. In this perspective, a practical approach a modular regression model with transformed parameters that could be calibrated by data analysis with domain knowledge about the time series. Prophet is a process for predicting time series data based on the additive model, where nonlinear trends are fit with a specified period, seasonality, and holidays.

It works with time series that have good seasonal effects and several seasons of historical data. Prophet is a good tool to recover missing data, shift trends, and typically handle outliers [11].

The Prophet algorithm was first introduced by Facebook as a simple and practical time series prediction model. The model can be fitted very quickly but automatically fills in the missing value without data preprocessing. Also, the model can calibrate periodicity flexibly, which is convenient for time series with outliers. The prediction model of the Prophet algorithm is based on four parts: trend items, cycle items, festival items, and error items. The composition of the terms is given below [12]:

$$y(t) = g(t) + s(t) + h(t) + e \tag{1}$$

$g(t)$ is the trend function used for fitting the non-periodic changes in time series; $s(t)$ is a periodic term function that fits the periodicity of a week or a year; $h(t)$ denotes the effect of special days such as holidays; and e is the error term that represents the error effect not considered.

$$g(t) = \frac{C}{1 + e^{(-k(t-m))}} \tag{2}$$

In (2), C is the saturation value, k is the growth rate, and m is the bias parameter.

$$s(t) = \sum_{n=1}^{N} \left[a_n \cos\left(\frac{2\pi nt}{P}\right) \right] + b_n \sin\left(\frac{2\pi nt}{P}\right) \tag{3}$$

In this formula, t represents period and P denotes the regular period length of time series.

$$\begin{aligned} &h(t) = Z(t)K_i, K_i \sim \text{Normal}(0, \sigma) \\ &Z(t) = [1(t \in D_1), \ldots, 1(t \in D_i), \ldots, 1(t \in D_L)] \end{aligned} \tag{4}$$

In Eq. (4), i represents holidays, D represents the collection of past and future holidays, and K represents the impact of each holiday on the forecast. The prediction of the Prophet model is a cycle process that integrates the analyst and automation processes. Combination increases the scope of application of the model and enhances its precision.

TOPSIS MCDA algorithm

The MCDA criteria decision process is an important decision-making device that involves both quantitative and qualitative factors. Nowadays, several MCDA techniques and processes are suggested to select the probable optimal options. TOPSIS is a MCDA method that was developed by Ching-Lai Hwang and Yoon in 1981, with further enhancements in 1987, and by Hwang, Lai, and Liu in 1993. TOPSIS is built on the concept of the chosen alternative, which must have the shortest geometric distance from the positive ideal solution and the longest geometric distance from the negative ideal solution. The TOPSIS method is an aggregation that compares the alternatives, normalizing scores for each criterion and calculating the distance between each alternative and the ideal alternative, which is defined as the best score in each criterion [13]. The weights of the criteria belong to the TOPSIS approach and can be calculated using the ordinal priority approach and the analytic hierarchy process. A decision of TOPSIS that the criteria are monotonically increasing and decreasing. Normalization is performed as the parameters or criteria are not in harmony in multi-criteria problems. The TOPSIS method is given as follows [14].

(1) Generate an evaluation matrix consisting of m alternatives and n criteria so that the alternatives and criteria intersect, given as $(x_{ij})_{m\times n}$.
(2) The matrix $(x_{ij})_{m\times n}$ is then normalized to form the matrix $R = (r_{ij})_{m\times n}$ using the normalization method

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{k=1}^{m} x_{kj}^2}}, \quad i = 1, 2, \ldots, m \quad j = 1, 2, \ldots, n$$

(3) Calculation of weighted normalized decision matrix

$$t_{ij} = r_{ij} \cdot w_j, \quad i = 1, 2, \ldots, m \quad j = 1, 2, \ldots, n$$

where $w_j = W_j / \sum_{k=1}^{n} W_{k,j}$ $j = 1, 2, ..., n$ so that $\sum_{i-1}^{n} W_i = 1$ and $\mathrm{W_j}$ is the original weight specified as the indicator w_j is the original weight given to the indicator w_j, $j = 1, 2, ..., n$

(4) Determine the worst alternative (A_{w}) and the best alternative (A_{b}):

$$A_{\mathrm{w}} = \{(\max(t_{ij}|i = 1, 2, ..., m)|j\epsilon J\_), (\min((t_{ij}|i = 1, 2, ..., m)|j\epsilon J_+)\} \equiv \{t_{wj}|j = 1, 2, ..., n\},$$

$$A_{\mathrm{b}} = \{(\min(t_{ij}|i = 1, 2, ..., m)|j\epsilon J\_), (\max((t_{ij}|i = 1, 2, ..., m)|j\epsilon J_+)\} \equiv \{t_{bj}|j = 1, 2, ..., n\},$$

where

$J_+ = \{j = 1, 2, ..., n|j\}$ associated with criteria that has the positive effect, and $J_- = \{j = 1, 2, ..., n|j\}$ associated with the criteria that has the negative effect.

(5) Compute the L^2 distance between the target alternative i and the worst condition A_{w}

$$d_{iw} = \sqrt{\sum_{j=1}^{n} (t_{ij} - t_{wj})^2}, \quad i = 1, 2, \ldots, m$$

and the distance between the alternative i and also best condition A_{b}

$$d_{ib} = \sqrt{\sum_{j=1}^{n} (t_{ij} - t_{bj})^2}, \quad i = 1, 2, \ldots, m$$

where d_{iw} and d_{ib} are L^2 norm distances from the target alternative i to the worst and best conditions, respectively.

Calculate the similarity to the worst condition:

$$S_{iw} = d_{iw}/(d_{iw} + d_{ib}), 0 \leq s_{iw} \leq 1, \quad i = 1, 2, \ldots, m.$$

$S_{iw} = 1$ if and only if the alternative solution includes the best condition; and
$S_{iw} = 0$ if and only if the alternative solution involves the worst condition
Rank the alternatives based on S_{iw} ($i = 1, 2, \ldots, m$).

Results and discussion

As mentioned in the method section, a ML method and a MDCA algorithm are used at the same time to calculate the best predicted motor vehicle tax payment series based on the generated test data alternatives. Generated test data for the motor vehicle tax payment pattern for a tax owner for 20, 10, and 5 years of time is used in the Prophet prediction algorithm to produce different yearly based forecasts. In the

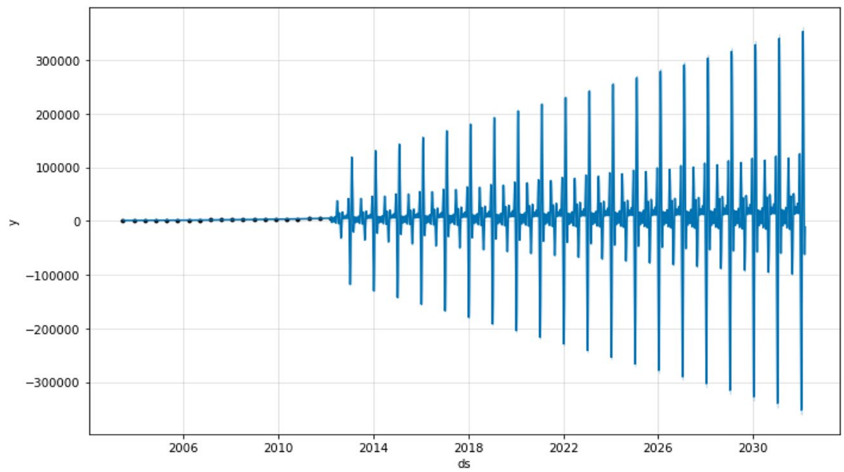

Fig. 15 Generated test data 1 time serial line forecast graph for 20 years

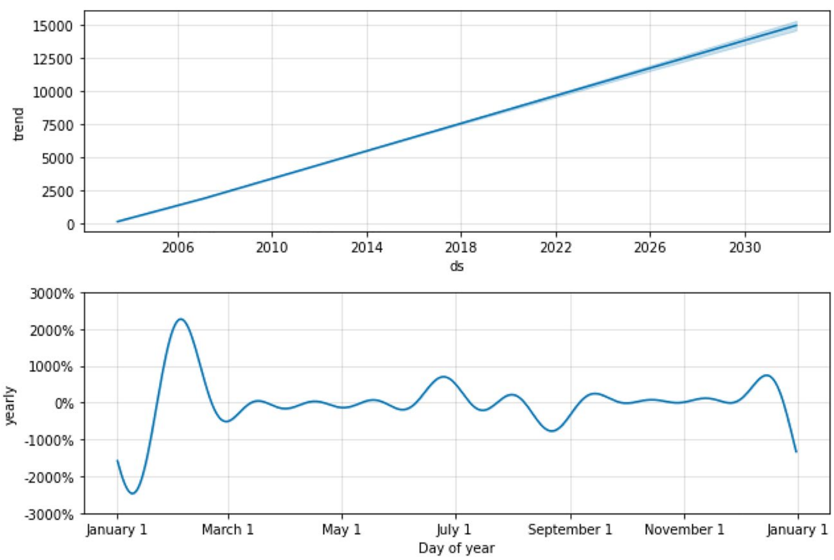

Fig. 16 Trend line graph and yearly terms graphs with Prophet algorithm for 20 years prediction

forecasts, trend lines, yearly terms, multiplicative terms, and predicted values are compared with the date values. Figure 15 displays the time series graph, Fig. 16 shows the trend line graph, and the yearly graph tracks the generated test data. The specified data creation function is described in the "Method" section.

Figure 17 shows the generated test data 1 time serial line forecast graph for 10 years, and Fig. 18 specifies trend line and yearly term graphs for 10 years prediction.

Figure 19 shows generated test data 1 time serial line forecast for 5 years, and Fig. 20 illustrates the trend line graph and yearly term graphs with 5 years prediction with test data 1.

The next generated serial tax payment data is generated with the second type of function, a seed random number generated between 0 and 750. The following graphs were

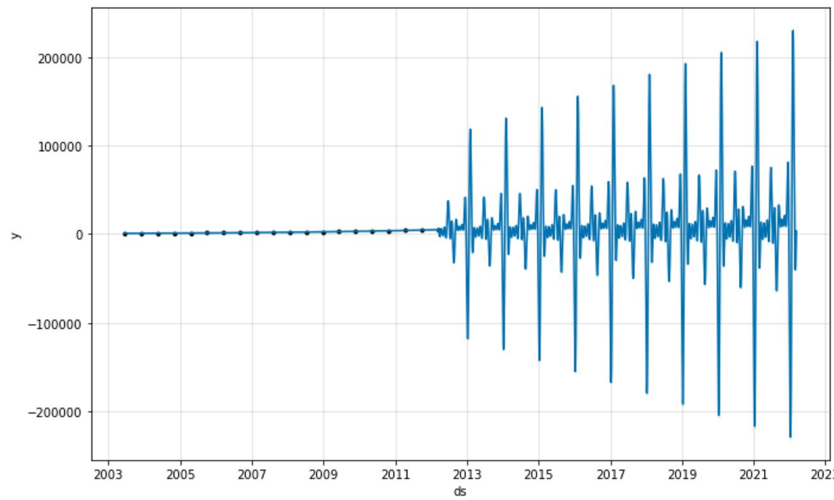

Fig. 17 Generated test data 1 time serial line forecast graph for 10 years

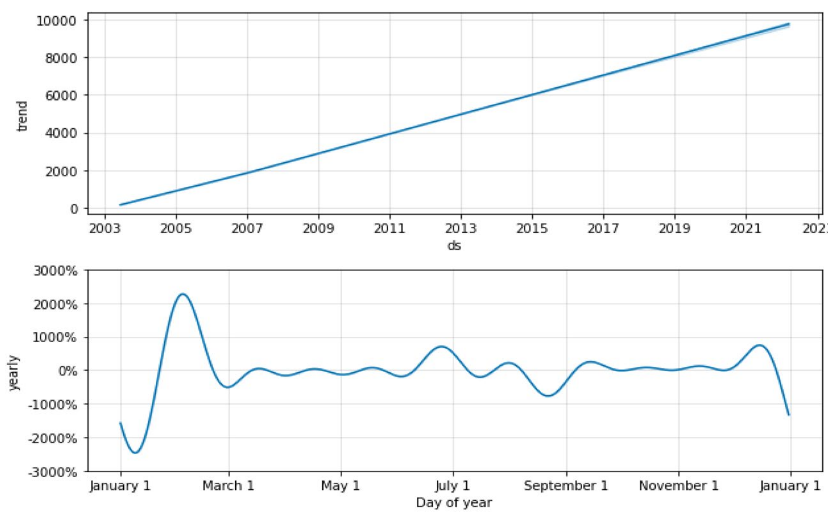

Fig. 18 Trend line graph and yearly terms graphs with Prophet algorithm for 10 years prediction

created for the generated test data: Fig. 21 shows a time serial graph and Fig. 22 shows a trend line graph and a yearly term graph for prediction with test data 2.

Figure 23 shows generated test data 2 time serial graph for 10 years, and Fig. 24 shows the trend line and yearly term graphs for 10 years with the test data 2.

Figure 25 denotes the generated time serial line with test data 2 for 5 years, and Fig. 26 shows the trend line and yearly term graphs with test data 2 for 5 years.

The next generated serial tax payment data is generated with the third type of function, a seed random number generated between 900 and 1500 range with 25 steps seed. The following graphs were created for the generated test data: Fig. 27 shows time serial graph, and Fig. 28 shows trend line graph and a yearly term graph.

In Fig. 29 shows time serial line forecast graph for 10 years and in Fig. 30 denotes the trend line and yearly term graphs for 10 years are given for test data 3.

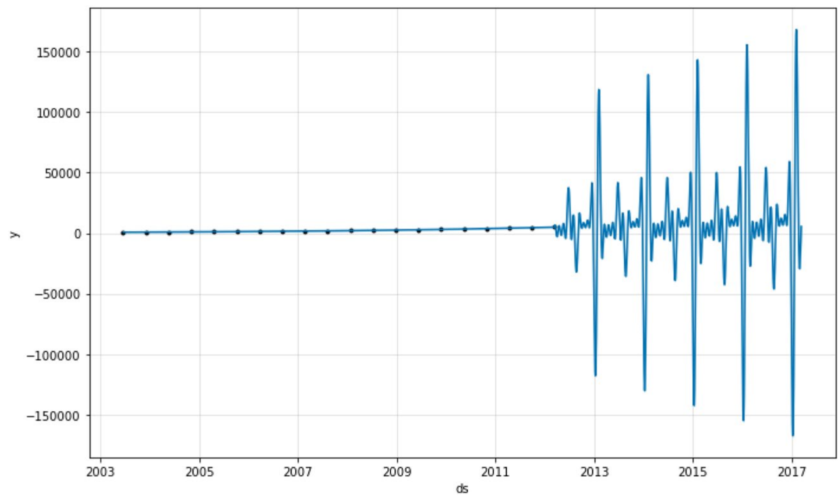

Fig. 19 Generated test data 1 time serial line forecast graph for 5 years

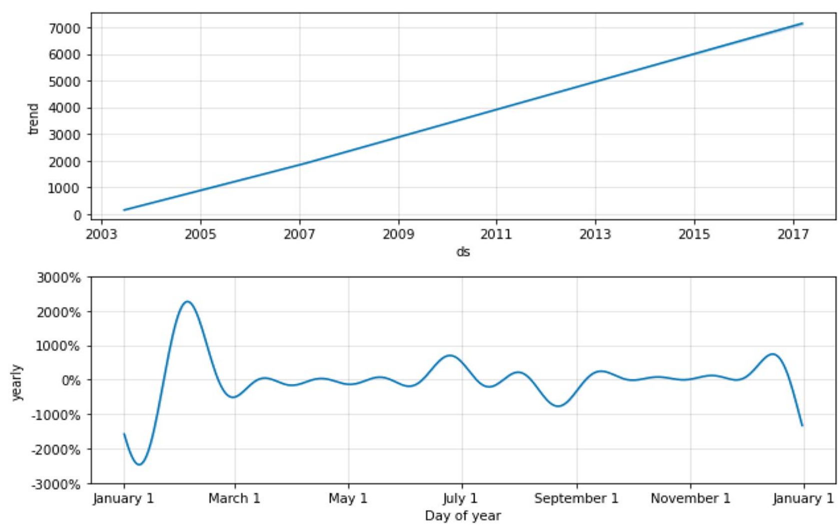

Fig. 20 Trend line graph and yearly terms graphs with Prophet algorithm for 5 years

In Fig. 31 time serial line forecast graph for 5 years and in Fig. 32 denotes the trend line and yearly term graphs for 5 years are given for test data 3.

Afterward, generated forecast tax payment serial data for 20, 10, and 5 years is given to the MDCA TOPSIS algorithm to decide which alternatively generated test data is the best for tax payment serial for the motor vehicle tax payment for a 1300 cc engine. The following table shows the generated analysis of tables as a result of the TOPSIS algorithm. In this algorithm, the weights of the criteria are selected as the trends, multiplicative terms, yearly terms, and additive terms are given to the algorithm. Manual weight is selected as a coefficient in the computations based on the presence of the criteria in the calculations. Table 1 and 2 and Fig. 33 bar charts are generated for the MDCA TOPSIS decision of 5, 10, and 20 years for simulated data with tax value $= 750 + 750 * 0.10$ seed function:

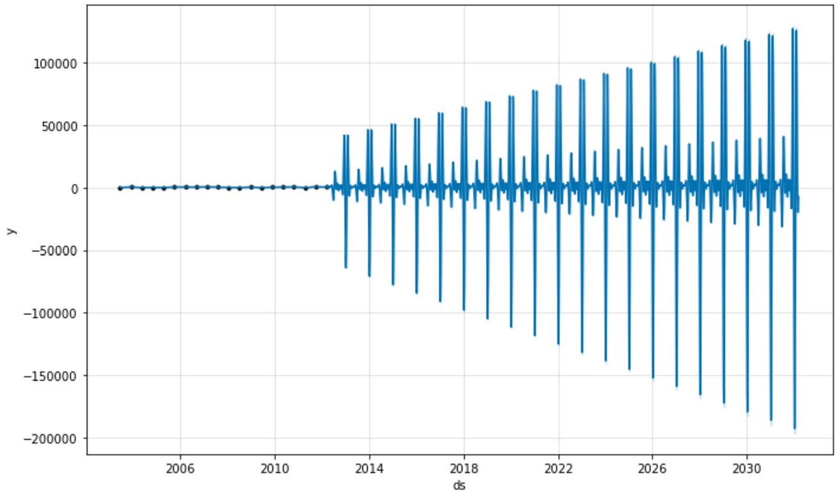

Fig. 21 Generated test data 2 time serial line forecast graph

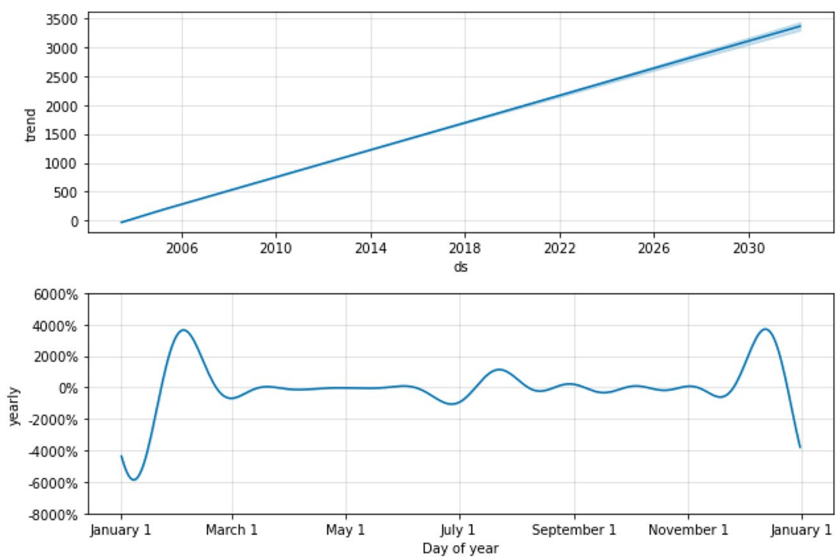

Fig. 22 Trend line graph and yearly terms graphs, with Prophet algorithm for 20 years

Tables 3 and 4 and Fig. 34 bar chart are generated for MDCA TOPSIS decision 5, 10, and 20 years for TaxValue = 0–750 range seed function.

Tables 5 and 6 and Fig. 35 bar chart are generated for MDCA TOPSIS decision of 5, 10, and 20 years for tax value 900–1500 range with 25 steps seed function.

Conclusion

From all the results given above, it can be seen that the MDCA TOPSIS-based decision criteria show the tax payment serial forecasts with three different seed functions simulated test data for 20 years are the first choice serials to pay the tax. That means for a tax

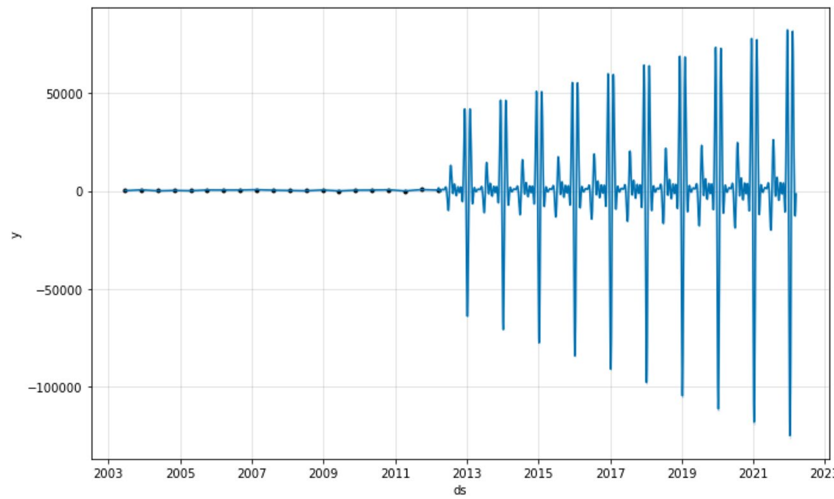

Fig. 23 Generated test data 2 time serial line forecast graph

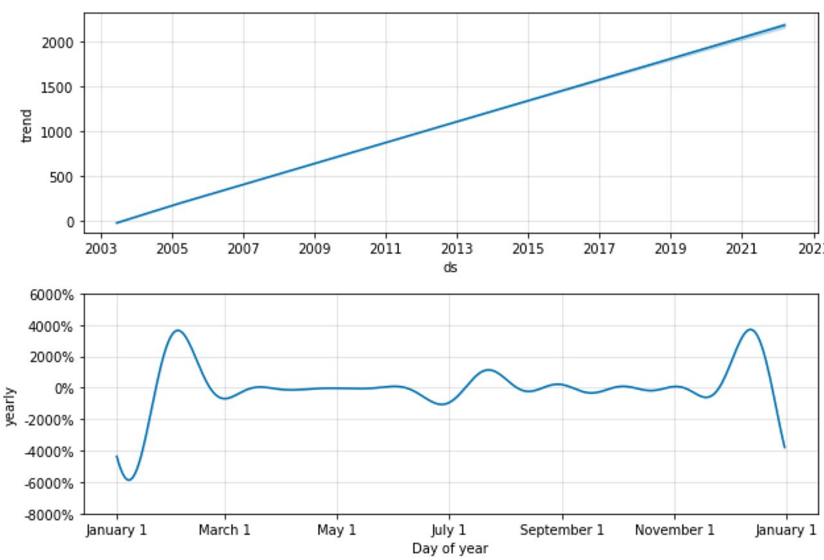

Fig. 24 Trend line graph and yearly terms graphs, with Prophet algorithm for 10 years

owner of a motor vehicle tax payment a person can decide to pay in 20 years so tax payer can ensure the incursion of the money and feel safe if the tax portions are distributed in a long time run. Both the ML type of algorithm and the MDCA algorithm show harmony and integration as an example of the recommended DSS system in this study.

Based on the aforementioned facts, DSS and AI techniques for big data analysis provide cost savings, risk mitigation, and increased customization. This will enable economic expansion through improved demand integration and increased investment. The three prospects for financial services that are most widely acknowledged are "Risk Management, Customer/Client Targeting and Customer/Client Engagement." This study

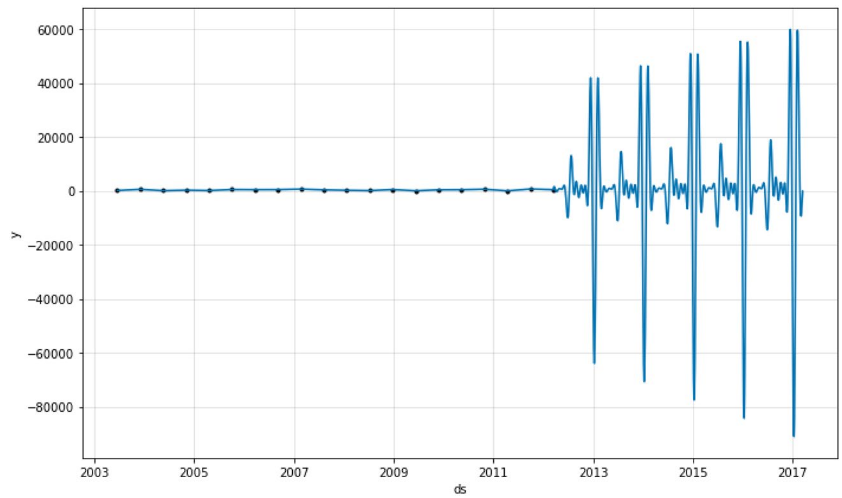

Fig. 25 Generated test data 2 time serial line forecast graph

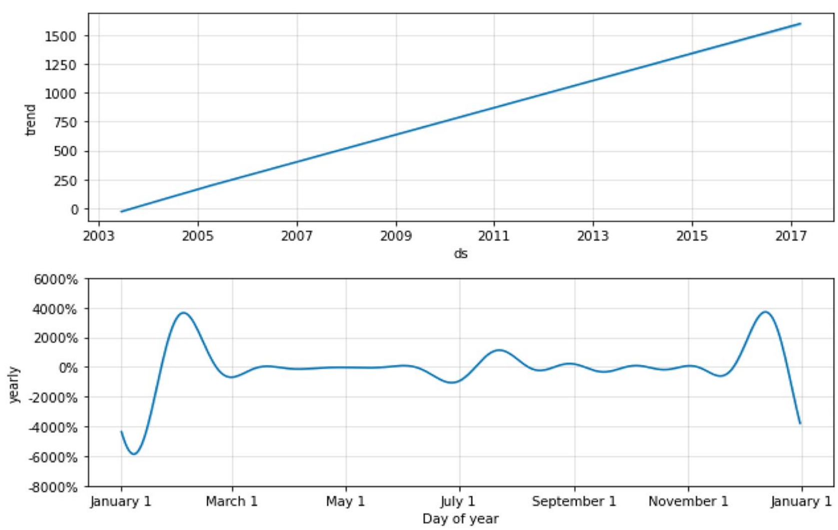

Fig. 26 Trend line graph and yearly terms graphs with Prophet algorithm for 5 years

demonstrates how customer interaction and risk management in financial operations would boost operational efficiency without a person in the loop failing with the aid of DSS based on AI techniques.

DSS with AI has developed and expanded globally in recent years, and there is a high degree of faith that robots can reliably handle financial processes. Most choices will likely be made by machines in the near future without errors or fraud. With the additional information clusters of the customers or clients all behaviors in transportation, daily life skills, health, and relatives behavior patterns, financial decisions of tax repayment restructure predictions, credit decisions, investment decisions, fund transfers decisions, fraud detection in customer payment patterns, and robo-advisory

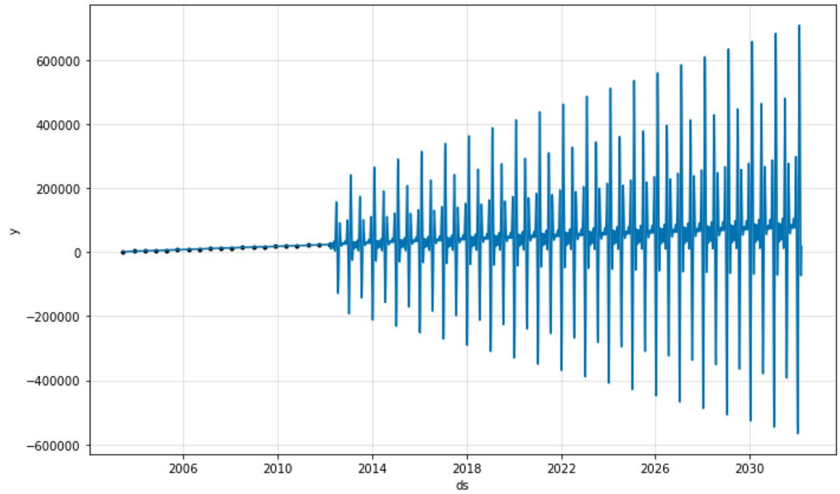

Fig. 27 Generated test data 3 time serial line forecast graph

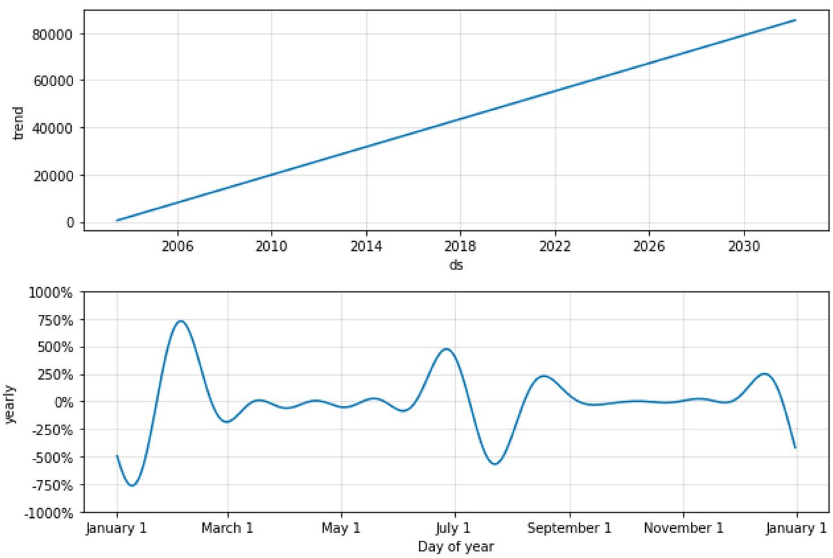

Fig. 28 Trend line graph and yearly terms graphs with Prophet algorithm for 20 years

decisions will be much more precise. Future DSS: A machine will make judgments, complete tasks, manage time, carry out tasks, produce work instructions, safeguard financial resources, make wise financial decisions, lower risks, complete tasks quickly, and carry out error-free operations.

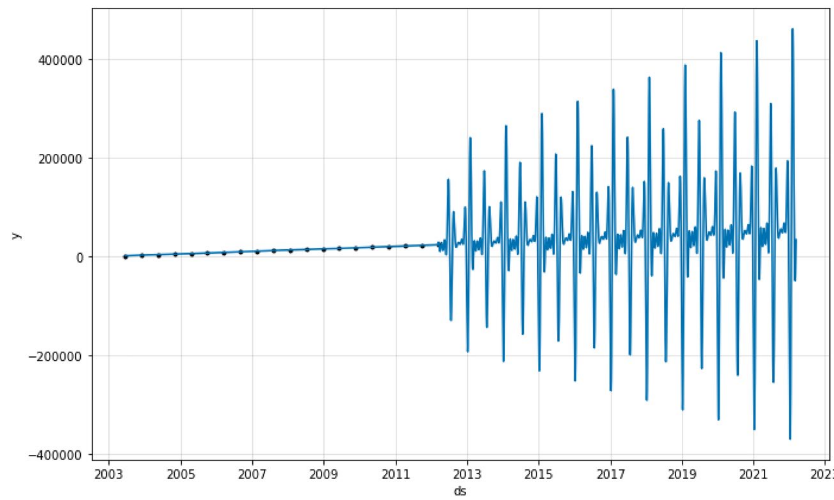

Fig. 29 Generated test data 3 time serial line forecast graph

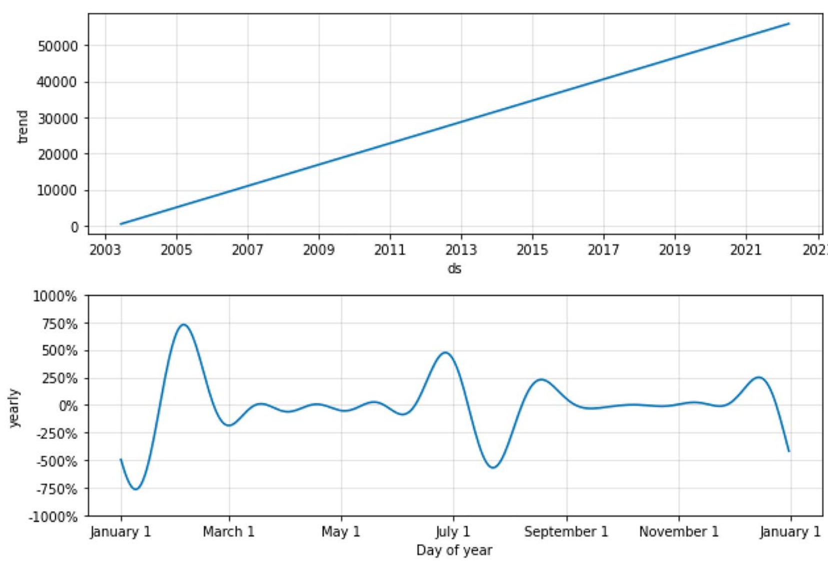

Fig. 30 Trend line graph and yearly terms graphs with Prophet algorithm for 10 years

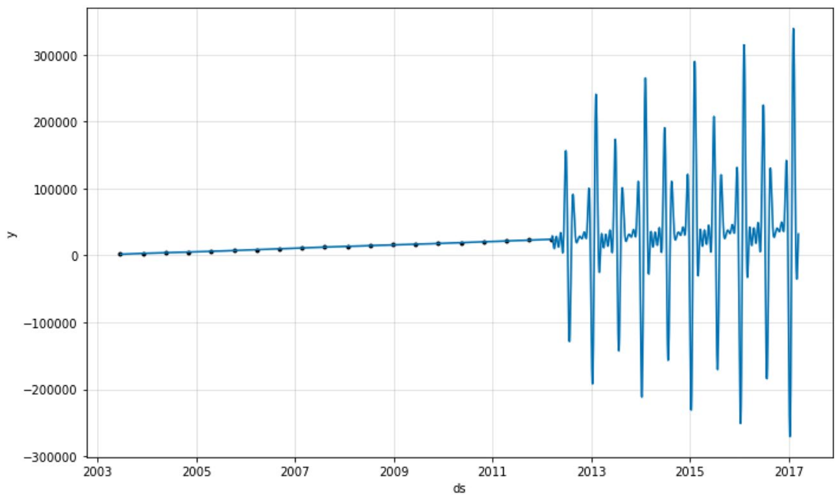

Fig. 31 Generated test data 3 time serial line forecast graph for 5 years

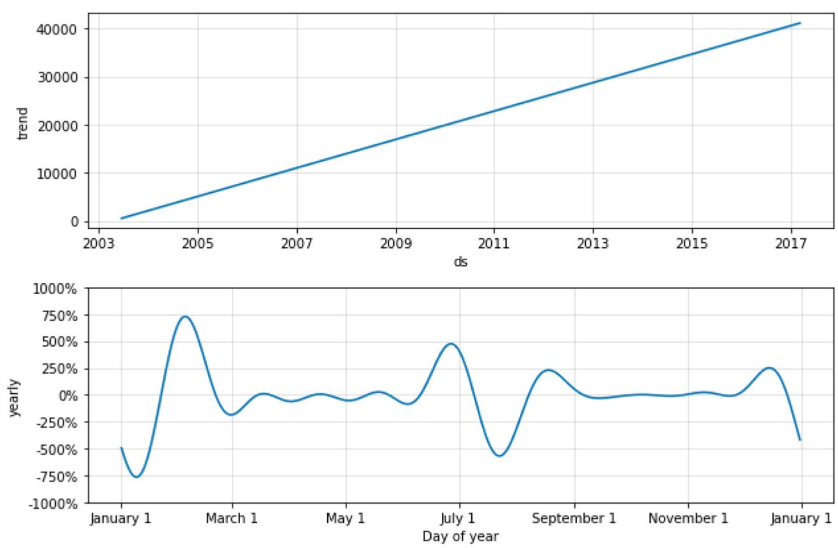

Fig. 32 Trend line graph and c) Yearly terms graphs with Prophet algorithm for 5 years

Table 1 Normalized criteria data for MDCA TOPSIS for 5, 10, and 20 years for tax value $750 + 750 * 0.10$ seed function

Alternatives	Trend	multiplicative_terms	yearly	y_hat
Generated test data 1	0.433828	0.843936	0.843936	0.434196
Generated test data 2	0.532044	0.444858	0.444858	0.532118
Generated test data 3	0.727133	0.299788	0.299788	0.726859

Table 2 Normalized criteria data for MDCA TOPSIS for 5, 10, and 20 years for tax value 750 + 750 * 0.10 seed function

Alternatives	Performance score	Rank
Generated test data 1	0.399788	2
Generated test data 2	0.389626	3
Generated test data 3	0.600212	1

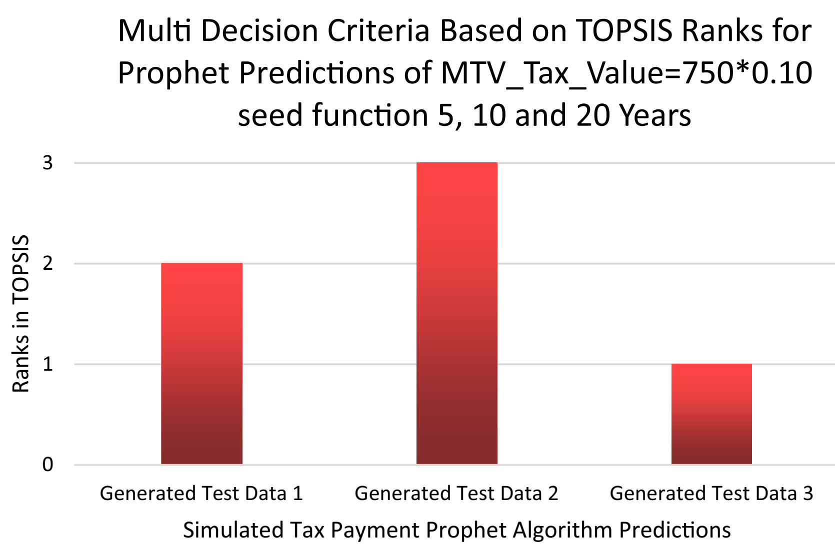

Fig. 33 Rank bar chart for 5, 10, and 20 years forecast for generated test data with tax value 750 + 750 * 0.10 seed function

Table 3 Normalized criteria data for MDCA TOPSIS for 10 years

Alternatives	Trend	multiplicative_terms	Yearly	y_hat
Generated test data 1	0.432791	0.813385	0.813385	0.433322
Generated test data 2	0.531663	0.46815	0.46815	0.531894
Generated test data 3	0.72803	0.345312	0.345312	0.727544

Table 4 Normalized criteria data for MDCA TOPSIS for 5, 10, and 20 years for TaxValue = 0–750 range seed function

Alternatives	Performance score	Rank
Generated test data 1	0.399386	2
Generated test data 2	0.389471	3
Generated test data 3	0.600614	1

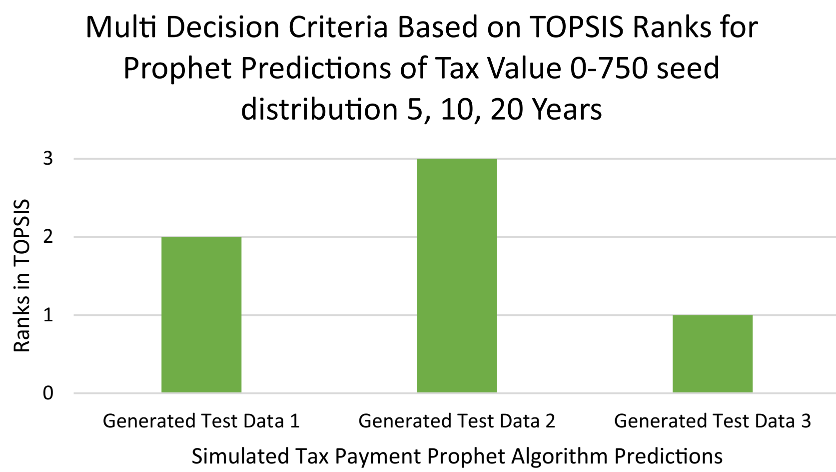

Fig. 34 Rank bar chart for 5, 10, and 20 years forecast for generated test data with Tax Value = 0–750 range seed function

Table 5 Normalized criteria data for MDCA TOPSIS for 5, 10, and 20 years for tax value 900–1500 range with 25 steps seed function

Alternatives	Trend	multiplicative_terms	Yearly	y_hat
Generated test data 1	0.435874	0.830232	0.830232	0.435956
Generated test data 2	0.532813	0.458187	0.458187	0.53284
Generated test data 3	0.725344	0.317458	0.317458	0.725275

Table 6 Normalized criteria data for MDCA TOPSIS for 5, 10 and 20 years for tax value 900–1500 range with 25 steps seed function

Alternatives	Performance score	Rank
Generated test data 1	0.400413	2
Generated test data 2	0.390481	3
Generated test data 3	0.599587	1

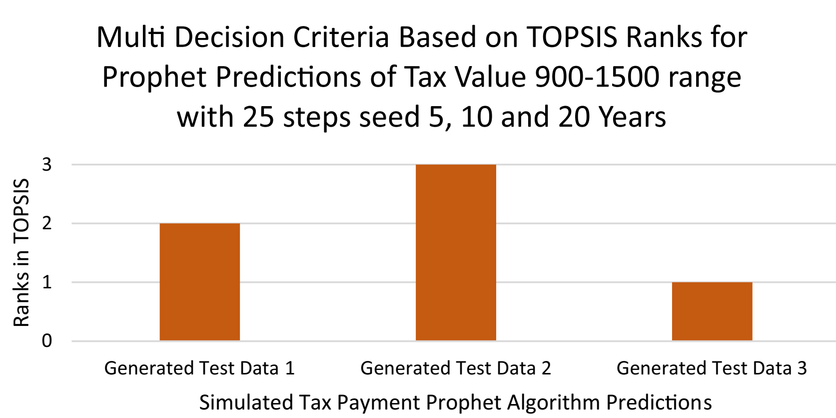

Fig. 35 Rank bar chart for 5, 10, and 20 years forecast for generated test data with tax value 900–1500 range with 25 steps seed function

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Author contributions
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Availability of data and materials
All of the data given in this study stated in the document.

Declarations

Ethics approval and consent to participate
During the study work, there is no potential financial or non-financial conflict of interest. Also with the study no informed consent of human participants and/or animals are no used in the study and complied to the widely accepted ethical codes of world accepted research and literature.

Consent for publication
Author consents to participate in the research and states that the research is not directly benefit for author and participation in research is all voluntary work.

Competing interests
There is no competing of interest related to this study.

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