Scientific Journal of the Military University of Land Forces
ISSN: 2544-7122 (print), 2545-0719 (online)
2021, Volume 53, Number 3(201), Pages 507-518
DOI: 10.5604/01.3001.0015.3404

Original article

AI for augmenting human judgement in Business Processes Management

Łukasz Osuszek*, Stanisław Stanek

Faculty of Management,
General Tadeusz Kościuszko Military University of Land Forces, Wrocław, Poland,
e-mail: Lukasz.osuszek@danone.com; stanislaw.stanek@awl.edu.pl

INFORMATION

Article history:

Submited: 14 November 2019

Accepted: 31 January 2020

Published: 15 September 2021

* Corresponding author

ABSTRACT

The paper outlines the recent trends in the evolution of Business Process Management (BPM) – especially the application of AI for decision support. AI has great potential to augment human judgement. Indeed, Machine Learning might be considered as a supplementary and complimentary solution to enhance and support human productivity throughout all aspects of personal and professional life.

The idea of merging technologies for organizational learning and workflow management was first put forward by Wargitsch. Herein, completed business cases stored in an organizational memory are used to configure new workflows, while the selection of an appropriate historical case is supported by a case-based reasoning component. This informational environment has been recognized in the world as being effective and has become quite common because of the significant increase in the use of artificial intelligence tools.

This article discusses also how automated planning techniques (one of the oldest areas in AI) can be used to enable a new level of automation and processing support.

The authors of the article decided to analyse this topic and discuss the scientific state of the art and the application of AI in BPM systems for decision-making support. It should be noted that readily available software exists for the needs of the development of such systems in the field of artificial intelligence. The paper also includes a unique case study with production system of Decision Support, using controlled machine learning algorithms to predictive analytical models.

KEYWORDS

artificial intelligence, machine learning, decision support, business process management, adaptive case management, knowledge management

Introduction

Artificial Intelligence (AI) refers to a wide variety of algorithms and methodologies that enable software to improve its performance over time as it obtains more data. In computer science, AI research is defined as the study of "intelligent agents": any device that perceives its environment and takes actions that maximize its chance of success at some goal [1]. Colloquially, the term "artificial intelligence" is applied when machines mimic the "cognitive" functions that humans associate with other human minds, such as "learning" and "problem solving" [2].

AI has huge potential to augment human judgement. Even now, AI (especially Machine Learning) can be used as a supplementary and complimentary solution to enhance and support human productivity throughout all aspects of personal and professional life. Because of the pace of modern life, BPM systems must increase their level of automation to ensure the responsiveness and flexibility necessary for proactive management. Some AI researchers have focused their efforts on testing dynamic domains that include active control over computing units and physical devices. In this context, automated planning, which is one of the oldest areas in AI, is conceived as an approach based on a model for the synthesis of autonomous behaviours in an automated manner from the model.

Process Management and AI

The idea of merging technologies for organizational learning and workflow management was first presented by Wargitsch [3]. In his system, completed business cases stored in an organizational memory are used to configure new workflows. The selection of an appropriate historical case is supported by a case-based reasoning component.

Because business processes are necessarily at the heart of all work, through AI, use cases and business cases will be intimately enmeshed with business process infrastructures. The business purpose of AI is to support decisioning, probably at scale, as repetitive decisioning is encoded in organizational business processes. AI and BPM therefore go hand-in-hand. This enables an inductive approach to workflow execution and adaptation by processing traces of manually enacted workflows.

In the scientific literature about BPM and AI, the most common problem is the selection of activities in the workflow process through two different approaches [4], one based on learning and the other based on modelling.

In a learning-based approach, further process steps are based on lessons learned. Learning methods, if properly learned in the field of representative data sets, have the greatest promise and potential because they are able to discover and possibly interpret meaningful formulas for a given task to help make more effective decisions. For example, teaching techniques have recently been applied to BPM [5] for predicting future states or properties of current business process enforcement. However, the learned solution is usually a "black box", meaning there is no clear understanding of how and why a given answer was chosen. As a result, the ability to explain why the AI algorithm has made such a decision can become a complex task.

Conversely, in the modelling approach, the controller responsible for the choice of action is derived automatically from a model that expresses the dynamics of the domain of interest, actions and conditions of the goal [6]. The key point is that all models are designed as generic, that is, they are not related to specific domains or problems.

Many research activities include the use of such planning techniques in the context of BPM, covering different stages of the process lifecycle. In the design phase, existing literature focuses on using planning to automatically generate business process models that are able to achieve certain goals, starting with a full or incomplete process domain description. Some research work also exists that use planning to cope with problems for the Run-Time phase, for example, to accommodate running processes to cope with unusual situations. Finally, in the diagnosis phase, literature reports some work that use planning to reconciliation. Process activities can, hence, be represented as planning actions together with their preconditions and effects stating what contextual data may constrain the process execution or may be affected after an activity completion [7]. This type of informational environment has become common in the world, and there has been a significant increase in the use of artificial intelligence tools. Indeed, today, software for the needs of the development of such systems in the field of artificial intelligence readily exist.

A. Vujovic [8] states that investment and implementation of artificial intelligence show significant results, particularly in attempts to gain higher profit. Artificial intelligence is the area of science and engineering that deals with the development of systems that mimic human intelligence, with the tendency to replace him in some activities based on knowledge. The use of AI can address the problems of human absence, cost of services, disinclination of people to provide knowledge and similar. However, from the standpoint of the necessities of knowledge, and for the purposes of quality management systems, there are evident gaps in current understanding of how to best use AI techniques [9] and how to apply Machine Learning (ML).

What ML should be doing is simply augmenting human interaction especially where it cannot be person-to-person. Even today, ML can improve human decision-making, e.g. cause and effect analysis of bottlenecks and limitations, especially in terms of availability of production lines – as described in a case study.

AI support for BPM decision-making

Through a detailed analysis of literature sources and software, We found an evident gap in applying artificial intelligence tools for improving business process performances based on van der Aalst [10] systems, and especially in case reasoning.

Not surprisingly, many BPM vendors focus on AI as a means to reduce the complexity of tuning and optimizing the very processes the systems manage. While the idea of using analytics to monitor process execution is nothing new, AI can now take that a step further through the use of machine learning to provide guidance on optimization.

By the integration of the machine learning component into a Business Process Management System, a new inductive approach to the creation of a workflow application is enabled.

It seems of utter importance to define artificial intelligence in the context of BPM. AI seems to have the potential to be applied to different aspects in BPM – and in different ways. The impact of AI on “process flow charting”, for example, seems very interesting. Within the process innards, predictive analytics, driven by lineal or multiple regressions of statistical relevant process data sets can lead to pattern recognition, which then can support an AI as part of BPMS.

Further analysis of the state of the art and latest market overview points that idea of AI and decision support in process management has several interesting possibilities:

1. Machine Learning Will Optimize Processes: Analytics have taken over everything, including process management. In the past, operators had access to data, but were not provided actionable guidance. The emergence of AI takes those analytics a step further by providing actionable insights.
2. Unstructured Data Becomes Organized: BPM traditionally excels at moving structured processes towards an automated manner. Unstructured processes on the other hand, are a different story since patterns are not so readily available. AI technologies including natural language processing (NLP) close the gap by providing sentiment analysis and the possibility to convert unstructured data to something more organized.
3. New Interfaces, New Opportunities: The arrival of new technologies presents new interfaces and user experiences, including voice commands and chat. According to Koplowitz [11], numerous vendors have integrated these types of features into their BPM systems to offer easier instruction handling and processing of automated tasks.
4. Decision recommendation: In most automated business processes, humans have to make decisions, like "Approve/Reject the loan", "Authorize/Decline a purchase request", and so on. Given the BPM Suite has the history of previous decisions and the result of those decisions, it could recommend the best decision based on the learning from previous process instances.

However, AI is not a welcomed concept by everybody. Pega Company recently did a global survey about AI to find out what consumers really think about AI. In doing so, they surveyed 6000 consumers in 6 different countries. As a result, it turned out that 1 out of 4 people think AI will take over the world, and more of those people think that AI will come after their jobs. As we learned in the 80's and with expert systems – the AI of the time – AI will not do so – notably because it is very difficult to completely model any given domain.

AI is useful if you can actually codify some model (possibly ignoring the tacit). But it must be underlined that such models are only applicable for narrow distributions of outcomes – but will be useless for the outliers or "black swans" [See: 12] found in the larger fat-tailed worlds where most business lives. Today's AI is still difficult (i.e. expensive) to do for non-trivial things.

However, given that BPM is very much about microeconomics-driven process repetition patterns, i.e. characterized by narrow distributions, AI is especially suitable as a complement to BPM technology. The narrow scope of business automation where BPM thrives also defines a narrow scope of data and behaviour where AI is more technically feasible. The alternative idea is that big data, AI and ML can be at the heart of discovering something new.

Modern interface approaches

Many companies claim to use AI with a human touch to service customers better. Such approach uses ML for defining business ontologies that help to clearly define the terminology of a knowledge domain. It is similar to explaining to a child what a word means, but once user input can be matched to a domain knowledge model, ambiguity in design and Use Case Interactions are reduced and text or speech becomes a well-working input to an application. In the current state of the art, ML can learn to recognize input correctly in a given context of a capability map and interface the user to the right transactions, guided by user-defined boundary rules and regulative constraints. Like in the human brain, this comes about due to a mix of inherited and trained capabilities.

AI has the ability to take human cost and latency out of processes, as well as to provide new interfaces that customers enjoy. With faster and more user-friendly operations, customers are happier, stay loyal and do not look for alternatives.

Initiation of and interaction with processes has been implemented by voice recognition. Voice recognition could replace the need for a traditional BPM UI. However, the described scenario ignores the biochemical aspect – that human memory and decision-making is driven by hormones and neuro-transmitters that cannot be emulated in software. It will still lack the human drives, and as such, compassion and empathy, while strangely that is what most people consider to be necessary for 'better' decisions.

Emotional weighting is the basis of decision-making in all forms of intelligence that we know. It is the key for the complexity of our interaction through language.

Humans do not use logic to make decisions, rather they use emotions [13]. Using logic requires correct data and perfect control – which are both unattainable. Therefore, humans developed the ability to come to decisions under uncertainty [14] using a wide variety of decision biases [15]. These are not, however, fallacies, but are very practical, simplified decision mechanisms.

In the near future, Cognitive Systems will become important as they are able to use Natural Language to process the communication between machine and human, so processes can use this system to automate this communication, and these systems can take decisions when they understand what the customer are asking for, and decide what action has to be made to solve the question.

Finding valuable patterns in business data

The idea is that by connecting AI to existing BPM tools, and delivering the data generated by digitized processes to AI systems, companies could do even more work to cut human latency (and thus costs) out of processes, while also delivering a better end product to customers.

AI technologies are often able to find important facts, patterns, relations and/or other types of new knowledge that would not have been found using standard analysis techniques such as regression analysis. The new knowledge gained can then be used to aid decision-makers in determining organizational actions.

The best business cases for AI involve huge risk or cost reductions, but the very nature of these business cases means that business likely already has a non-AI solution in place (via older technology and management processes). So, now the AI business case is not from zero, but for replacement.

AI/ML main value, hence lies in providing "better suggestions", not "better decision-making". This is because it can be:

- Self-adapting: Adjusting and fine-tuning processes automatically as data patterns reveal opportunities to make small changes.
- Self-repairing: Identifying trends in data that highlight inefficiencies within process roadmaps and make changes to fix them.

Broad AI adoption will only happen when it can be bought off-the-shelf. Because otherwise it is too expensive for most organizations (technically and concerning skill levels). If the customer can buy a tunable image recognition system to deploy for some small but nagging problem, he will do it. He will not hire a data scientist for edge cases. He will let, however, the vendor hire the data scientist, and when the customer hires the "tunable image recognition system", he probably will not think of it as AI.

AI might transform both the process for creating solutions and the structure of the solutions themselves. It has long been stressed that a proper BPM or ACM solution must be structured to be easily changed as business requirements change, but it was expected that people will make those changes. A solution that is structured for AI to change is likely quite different and it might be considered as a future.

This idea of connecting AI to already existing BPM tools and delivering the data generated by digitized processes to AI systems, allows companies to do even more work to cut human errors out of processes, while also delivering a better finished product to customers.

By analysing large amounts of medical data, the healthcare organization's AI is helping clinicians give faster and more accurate treatment to their patients and has the ability to learn to make better decisions going forward. For patients, the AI-driven healthcare system alleviates some of the burdens on a system struggling to keep up with ever-growing demand. By implementing these technologies, the organization can make better health decisions, diagnose disease and other health risks earlier, avoid expensive procedures, and help their patients live longer – which are all actionable insights driven from data patterns and big data analytics.

Big Data, decisions and hypothesis building mechanisms

Another applicable AI technology is data mining, a process consisting of two distinct categories – verification-driven and discovery-driven. In verification-driven data mining, a prior hypothesis is formed about the nature of relationships among data. The result of the mining process is then used to reach a conclusion regarding the validity of this hypothesis. Discovery-driven data mining starts without any preconceived notion regarding the nature of relationships among data. It is the task of the data mining system to find significant patterns in the data.

Discovery-driven data mining is divided into two sub-categories:

- supervised learning (classification),
- unsupervised learning (clustering).

Supervised learning is equivalent to learning with a teacher and involves building a model for the specific purpose of optimally predicting some target field in the historical database (the value of which can be used to gauge whether the right or wrong prediction was made).

In contrast, unsupervised learning does not have any well-defined goal or target to predict (and, thus, no particular supervision over what is a right or wrong answer). Techniques such as clustering, and detection of association rules fall into the category of unsupervised learning.

Decision theory offers few models that are related to human reasoning. There are some recent exceptions; non-classical decision models do not rely on expected utility.

However, as proven by experiments in the area of Decision Support Systems – it is not necessary to have a sophisticated hypothesis as long as the system is interactive and that the evaluation is left to the decision-maker.

Case Studies and real examples of A.I. in Business Decisions Management

The example below shows a modern scenario of A.I. application to one of the business processes from the manufacturing area. The industry of food production is experiencing right now the 4th industrial revolution. This is the time when data and effective algorithms (A.I.) could make a difference and improve production efficiency and competitiveness. The use case scenario described in the article renders the actual context with business and operational challenges, targets and problems.

Business decision support system with machine learning enhancements

Business context and assumptions:

- orders come from many suppliers, cooperation is based on framework agreements,
- orders are placed with 24 completion dates,
- delays in the execution of orders result in high contractual penalties,
- production takes place on many production lines, in a multi-shift system, not every order can be implemented on any line,
- a change of the manufactured assortment requires retooling and reconfiguration of the line, the planned changeover time (depending on the order) varies from 2 to 4 hours,
- line efficiency (OEE) varies from 40 to 70% and depends on the age of the equipment (failure rate), while efficiency losses depend directly on the organization of the order fulfilment process and quality depends on the operator's experience,
- unscheduled downtimes are also significantly influenced by the maintenance organization in the case of accumulation of failures, the problem is to prioritize service orders.

Problems and challenges:

- Lack of information about symptoms of hazards on the production line in the timely execution of the order. Information on problems with the implementation of the production plan at the change should be available in advance so that corrective actions can be initiated (change of production line, launch of additional line, giving higher priority in removing failure, etc.).
- Lack of information about the priority of orders executed on production lines. As a result, in the case of problems with the implementation of one order, when it is necessary to run an additional line, it is possible to suspend the execution of another order, which may also result in contractual penalties. There is no current information on the costs of making production decisions on the scale of all production (all orders processed).
- Lack of priorities in the execution of orders also causes problems with prioritizing the maintenance service in making service orders.
- Lack of experienced staff among operators and maintenance services (caused by minimum employee turnover). Depending on the operator on the line, starting the production after retooling can last 50% longer than the prescribed normative time. In addition, the number of deficiencies is largely dependent on the operator's experience. Similar problems occur with service orders. Employees have very different levels of experience and of having the necessary powers to handle failures.

Many of the software suppliers are trying to build a modern solution for uses cases like the one described. Most advanced solutions are based on data gathering and using mathematical models and A.I. to better support business via strategical decisions.

Adaptive decision support system with predictive algorithms

This example shows how A.I. model could be helpful and gives useful insights for business and operations based on production monitoring – for early warning about hazards. Once again, the process illustrates a real use case from the manufacturing area.

For each order, the production volume is planned in 30 or 60-minute intervals at the change. The planned production volume is determined taking into account the performance standards of the lines and operational operating time of the machines (i.e. the duration of the change after taking into account planned shutdowns). The data from the implementation are obtained in several ways: on lines, where it is possible to automatically record the production – data acquisition takes place in real time. However, where, due to technological reasons, there is no possibility to measure production on an ongoing basis, performance is calculated on the basis of any breaks at work recorded by the operators. On the basis of the performance, the forecast of production volume at the end of the change is estimated. If the performance is lower than expected due to, for example, unplanned downtime and/or performance reduction, based on the forecast, the missing quantity at the end of the change is estimated and a decision is made to start additional production on another line.

For example, an unplanned 120-minute line stoppage in the 3rd and 4th shift hours causes production of at least 800 units lower than planned (unless another unplanned downtime occurs). With 12-hour changes, information about serious threats to the plan implementation, after 3 hours of change, forces the decision to launch additional production on a different line. The most important question in the case under consideration is: which lines should be stopped and adapted to carry out additional production from line 1? Assuming that the additional line will have the same performance as line 1, the required, additional production will take only 2 hours of work time, and the changeover time can be much larger than the production itself (in the extreme case – 4 hours). The order from line 1 will be executed at the expense of the loss of performance on the additional line and probably problems with the execution of the previous order on this line. Making the best decision in the considered conditions requires knowing the priorities for all orders and the costs of delays, including long-term costs of lost profits due to the deterioration of the bargaining position in relations with clients.

Monitoring of technical condition of production lines – predictive maintenance

No less important in the process of making decisions about starting supplementary production is knowledge about the technical condition of the line (failure of machines and devices) and cooperation of production with maintenance. In the analysed example, the line failure occurred after the third hour of work and lasted 120 minutes. It is therefore legitimate to ask a few basic questions. First of all, was the two-hour failure removal justified? What was the reaction time of the maintenance response to the service request in relation to the time of solving the problem? Second, could the failures be predictable and did the maintenance work do everything to avoid this failure?

The first question is related to the organization of maintenance in the enterprise. Monitoring the response time (taking orders) and solving the problem of the lack of availability of the website is often a critical factor in minimizing unplanned line stops. On the one hand, an efficient communication channel between production (operator) and maintenance is required (information on the monitors on the production hall and smartphone service technicians); on the other hand, finding quick solutions to the accessibility problem by the leader (coordinator) is also possible.

Predictive models with ML:

- Forecast of the planned production execution at the change (based on line performance and on-going breaks at work).
- Order execution forecast for a production cycle involving more than one change and engaging more than one production line (additionally, the forecast takes into account the changeover times).
- Failure forecast of lines and components (machines and devices included in the production line). The forecast is estimated in two ways, the first one is based on failure statistics (survival models), the second is built upon the basis of observations of key machine and device parameters, and expert knowledge of supervised machine learning algorithms (where the goals to be achieved are known).

Analytical models (indicative):

- Causal analysis of production deviations from the planned OEE values per change, commission, week, month and annual.
- Cause and effect analysis of bottlenecks and limitations, especially in terms of availability of production lines (based on failure rates, technical condition of devices, expert systems and controlled machine learning algorithms).
- Cause and effect analysis of the failure rate of machines and devices, also in terms of service costs of the line.

Summary

AI systems can be very simple, like business rules that replicate a simple human decision – or extremely complex – like executing real-time customer “conversations” in a call-center, while still providing a natural experience to the customer. Advances in data processing speeds, lower costs, big data volume, and the integration of data science into technology has made practical AI a reality for many organizations and has brought it within reach of many more. Modern customer interaction systems now frequently include actual “learning” – the ability of the system to consistently improve performance through interpretation of historical patterns, actions taken and an understanding of what is considered a successful outcome.

At the moment, we are already witnessing the transformation of BPM due to recent advances in research on AI (#8). In this context, we can see how automated planning can offer a mature paradigm for introducing autonomous behaviour in BPM in order to streamline decision-making processes and speed up workflow. An unquestionable advantage of planning systems is the use of search algorithms powered by intelligent heuristics, which allow effective scaling to large problems.

Many BPM/ DMS vendors applied a form of machine learning to continuously improve Next-Best-Action recommendations, by capturing a feedback loop so that the results of previous recommendations can inform future recommendations. Another example of machine learning includes text analytics and sentiment analysis. This is where sentiment analysis engines determine whether a tweet (or any other text) was "positive", "negative", or "neutral". Rather than programming the system to understand the sentiment of a block of text through a complex set of business rules, the system is "taught" by being fed a large number of text blocks and the sentiment associated with each. The system then discovers and builds connections between words and patterns in the text and the sentiment, allowing it to discover the sentiment of new blocks of text.

Artificial Intelligence and Business Process Management together offers a better understanding of business processes as they are happening, plus a view to the future, with better, smoother operations from start to finish.

The consultancy McKinsey & Company estimates that AI (#AI next digital frontier, 2016, McKinsey Global institute) can automate as much as 45 percent or more of any particular job, allowing workers to focus on higher level mission-critical activities that cannot be as easily accomplished with technology. All of this leads to conclusion that AI will be for sure part of the next generation of BPM and DSS systems.

Acknowledgement

No acknowledgement and potential founding was reported by the authors.

Conflict of interests

All authors declared no conflict of interests.

Author contributions

All authors contributed to the interpretation of results and writing of the paper. All authors read and approved the final manuscript.

Ethical statement

The research complies with all national and international ethical requirements.

ORCID

Łukasz Osuszek https://orcid.org/0000-0002-3695-7512

Stanisław Stanek https://orcid.org/0000-0001-9939-4350

References

1. Russell SJ, Norvig P. *Artificial intelligence. A modern approach*. 2nd Ed. Upper Saddle River, NJ: Prentice Hall; 2003.
2. Schank RC. *Where's the AI*. AI Magazine. 1991;12(4):38-49.
3. Wargitsch C, Wewers T, Theisinger F. *WorkBrain: Merging Organizational Memory and Workflow Management Systems*. In: *In Workshop of Knowledge-Based Systems for Knowledge Management in Enterprises at the 21st annual German Conference on AI (KI-97)*. Kaiserslautern, Germany; 1997.
4. Geffner H, Bonet B. *A concise introduction to models and methods for automated planning*. San Rafael, Calif.: Morgan & Claypool; 2013.
5. Maggi FM, Dumas C, Ghidini M. *Predictive monitoring of business processes*. In: Jarke M, Mylopoulos J, Quix C, Rolland C (eds.). *Advanced information systems engineering. 26th international conference, CAiSE 2014, Thessaloniki, Greece, June 16-20, 2014. Proceedings*. Cham: Springer; 2014.
6. Marella A. *What Automated Planning Can Do for Business Process Management*. Business Process Management Workshops. 2017. DOI: 10.1007/978-3-319-74030-0_1.

7. Ferreira HM, Ferreira DR. *An integrated life cycle for workflow management based on learning and planning*. International Journal of Cooperative Information Systems. 2006;15(4):485-505. DOI: 10.1142/S0218843006001463.
8. Vujovic A. *Improvement of business processes performances based on management systems by using artificial intelligence*. PhD thesis. University of Montenegro; 2008.
9. Metaxiotis KS, Askounis D, Psarras J. *Expert systems in production planning and scheduling: A state-of-the-art survey*. Journal of Intelligent Manufacturing. 2002;13(4):253-60.
10. van der Aalst WM, Weske M, Grünbauer D. *Case handling: a new paradigm for business process support*. Data & knowledge engineering. 2005;53(2):129-62.
11. Koplowitz R. *The Forrester Wave™: Digital Process Automation Software, Q3 2017*, [online]. Forrester. 5 July 2017. Available at: https://www.forrester.com/report/The+Forrester+Wave+Digital+Process+Automation+Software+Q3+2017/-/E-RES136905 [Accessed: 21 October 2019].
12. Taleb NN. *The Black Swan: The Impact of the Highly Improbable*. New York: Random House; 2007.
13. Damasio AR, Tranel D. *Nouns and verbs are retrieved with differently distributed neural systems*. Proceedings of the National Academy of Sciences of the United States of America. 1993;90(11):4957-60. DOI: 10.1073/pnas.90.11.4957.
14. Gigerenzer G. *How to Make Cognitive Illusions Disappear: Beyond "Heuristics and Biases"*. European Review of Social Psychology. 1991;2(1):83-115.
15. Kahneman D, Tversky A (eds.). *Choices, Values and Frames*. New York: Cambridge University Press; 2000.

Biographical note

Łukasz Osuszek – MSc., 18 years in IT and New Technologies industry. Author of many technical and scientific articles, patents and books. Strong technical background (held positions of lead developer, system architect and director of implementation department). He gained experience by providing quality solutions to Document Management Systems and Business Process Management. An important element of these projects was to analyze the business requirements, system architecture design, optimization of processes and applications. Experienced in consultative sales of enterprise IT solutions. Business oriented sales leader focused on driving new technologies and software.

Stanisław Stanek – Dr. hab. Eng., Professor at MULF, started his academic career after 10 years of research work at the Institute of Management of Polish Academy of Sciences and in the industry. His research interest covers decision support and artificial intelligence. In 1990, he started working as an academic at University of Economics in Katowice, where he defended his postdoctoral dissertation on Methodology of Decision Support System Design, managed the Department of Computer Science and was a member of the University Senate and Editorial Committee of the University Publisher. Since 2011, he has been working at Gen. Tadeusz Kościuszko Military University of Land Forces, where as Associate Professor, he continues research work on making decisions under risk conditions. Author or co-author of over 250 scientific publications.

Sztuczna inteligencja dla wzbogacenia procesu decyzyjnego w zarządzaniu procesami biznesowymi

STRESZCZENIE

W artykule przedstawiono najnowsze trendy w ewolucji zarządzania procesami biznesowymi – zwłaszcza zastosowanie sztucznej inteligencji do wspomagania decyzji. Sztuczna inteligencja ma ogromny potencjał, by wzmocnić ludzki osąd. Uczenie maszynowe może być uważane za dodatkowe i uzupełniające rozwiązanie zwiększające i wspierające produktywność ludzi we wszystkich aspektach życia osobistego i zawodowego.

Idea łączenia technologii uczenia się organizacji i zarządzania przepływem pracy została przedstawiona przez Wargitscha. Ukończone sprawy biznesowe przechowywane w pamięci organizacyjnej służą do konfigurowania nowych przepływów pracy. Wybór odpowiedniego przypadku historycznego jest poparty komponentem wnioskowania opartym na przypadkach. To środowisko informacyjne zostało uznane na świecie ze względu na znaczny wzrost wykorzystania narzędzi sztucznej inteligencji. Istnieje duża liczba kwalifikujących się do użycia i łatwo dostępnych algorytmów na potrzeby rozwoju systemów sztucznej inteligencji wspierającej procesy biznesowe.

W tym artykule omówiono także, w jaki sposób można zastosować techniki automatycznego planowania (jeden z najstarszych obszarów AI), aby umożliwić nowy poziom automatyzacji i wsparcia przetwarzania.

Wdrożenie sztucznej inteligencji wykazuje znaczące wyniki, szczególnie w celu uzyskania wyższego zysku. Autorzy artykułu postanowili przeanalizować ten temat i omówić stan wiedzy naukowej oraz zastosowanie sztucznej inteligencji w systemach BPM do wspomagania decyzji. Artykuł zawiera także unikalne studium przypadku z systemem produkcji wspomagania decyzji, wykorzystujące algorytmy kontrolowanego uczenia maszynowego do predykcyjnych modeli analitycznych.

SŁOWA KLUCZOWE sztuczna inteligencja, nauczanie maszynowe, wsparcie decyzyjne, zarządzanie procesami biznesowymi, adaptacyjne zarządzanie sprawami, zarządzanie wiedzą

How to cite this paper

Osuszek Ł, Stanek S. *AI for augmenting human judgement in Business Processes Management*. Scientific Journal of the Military University of Land Forces. 2021;53;3(201):507-18.

DOI: http://dx.doi.org/10.5604/01.3001.0015.3404