SILESIAN UNIVERSITY OF TECHNOLOGY PUBLISHING HOUSE

SCIENTIFIC PAPERS OF SILESIAN UNIVERSITY OF TECHNOLOGY 2024
ORGANIZATION AND MANAGEMENT SERIES NO. 208

QUANTUM ARTIFICIAL INTELLIGENCE IN MANAGEMENT OF SELECTED BUSINESS PROCESSES

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Purpose: The aim of the article is to present potential applications of Quantum Artificial Intelligence (QAI) in enhancing Business Process Management (BPM), with a particular focus on predictive analytics.
Design/methodology/approach: The primary research methods include a critical analysis of the literature. Deep neural network testing was also conducted to identify efficient predictors and detectors for BPM systems. In addition, intensive computational experiments were carried out to analyze the quality of solutions defined by the proposed quantum-inspired algorithms.
Findings: The results of theoretical research and numerical experiments confirmed that QAI technology, developed within cutting-edge machine learning models and natural language processing (NLP), has a significant impact on enhancing BPM. In the context of predictive analytics in BPM systems, quantum predictive models trained on neural networks play a key role in increasing forecast accuracy. Furthermore, leveraging the power of NLP for task automation enables to extract insights and optimize processes, ultimately achieving business objectives more efficiently.
Practical implications: The obtained results form the basis for recommendations on how QAI models, developed within machine learning and NLP, can enhance not only current business processes but, most importantly, predictive analysis.
Social implications: By implementing QAI effectively and consistently, organizations can improve decision-making based on precise data analysis rather than relying on intuition or the experience of decision-makers.
Originality/value: The authenticity of the research results stems from clear ideas for the effective use of quantum technologies developed in the fields of machine learning and NLP to enhance BPM, particularly in the area of predictive analytics.
Keywords: process optimization, quantum predictive analytics, intelligent decision support.
Category of the paper: research paper.

1. Introduction

Business Process Management (BPM) should optimize various crucial business processes to enhance efficiency, agility, and performance. BPM involves analyzing and modeling business processes to achieve strategic business objectives. Besides, designing and implementing critical tasks provide additional solutions to meet important deadlines. Furthermore, it is also important to monitor and continuously improve processes in order to achieve the appropriate goals faster. Integrating artificial intelligence (AI) into BPM enables organizations to streamline operations, improve decision-making and enhance customer experiences (Lotko, 2022). Moreover, it enables achieving greater agility and competitiveness in a dynamic business environment (Bartlett, Kabir, Han, 2023).

Recently, quantum computing has been developing very intensively, resulting in the creation of quantum artificial intelligence (QAI), which refers to applying quantum computing principles to augment the capabilities and performance of artificial intelligence systems. QAI uses the unique properties of quantum mechanics to solve computational problems more efficiently than classical methods. Therefore, it has a great potential to enhance several aerials of business process management (Beheshti, Yang, Sheng et al., 2023), in particular, improving business analytics (Wolniak, 2024).

The groundbreaking nature and revolutionary potential of quantum technologies in the context of business process management are beyond doubt, while the scarcity of empirical research in this field highlights the urgency and importance of addressing such topics (Lotko, 2005a). Therefore, the subject of Quantum AI in managing selected business processes, explored in this article, holds not only significant theoretical value but also immense practical potential (Lotko, 2005b). Its interdisciplinary nature, innovativeness, and relevance to modern enterprises and the global economy make it one of the key research areas of the 21st century. Quantum AI integrates advanced computing, quantum mathematics, management, and organizational theories, positioning research on Quantum AI as interdisciplinary and transcending the boundaries of a single discipline, contributing to the advancement of both technical and social sciences.

Moreover, the development of QAI technologies aligns with global trends in the digitalization of the economy and the search for innovative tools to support sustainable development. Quantum AI, as a technology of the future, addresses challenges such as the need to process massive datasets (big data), the growing complexity of management systems, and the necessity for real-time decision-making (Gajdzik, Wolniak, Grebski, 2024).

Quantum AI not only accelerates processes but also facilitates more accurate decision-making in dynamic environments. Quantum algorithms, such as quantum optimization and quantum machine learning, enable the resolution of problems that are beyond the capabilities of classical computational methods. This is particularly crucial in areas like supply chain optimization, market forecasting, and real-time personalization of products and services Applications based on Quantum AI technology not only enhance efficiency but also help businesses respond more effectively to market changes, which is critical in a rapidly evolving business environment. In this context, Quantum AI can have specific applications in managing processes such as predicting consumer behavior, optimizing dynamic pricing strategies, and managing financial risk in real-time (Hassan et al., 2024).

Quantum AI technologies hold strategic importance for the economy and the competitiveness of enterprises. The implementation of quantum technology in management can provide a significant competitive advantage. In the face of global technological competition, Quantum AI in business process management is becoming a critical tool for enhancing efficiency and innovation within companies (Wolniak, 2023).

Quantum technologies can be developed in machine learning and natural language processing (NLP) to improve and automate repetitive tasks within business processes. By implementing this strategy effectively and consistently, organizations can strengthen their competitive position, drive growth, and thrive in dynamic and competitive markets. Moreover, QAI can analyze historical data to predict future outcomes and trends that can help forecast demand, identify potential bottlenecks or failures in processes, and optimize resource allocation. The great potential of QAI concerns applications in business process analysis that involve identifying and under-standing the current state of business processes within an organization. It includes gathering data, mapping out workflows, and identifying areas for improvement by QAI (Beerepoot et al., 2023).

For example, quantum computing can also help optimize smart city systems by enabling faster processing of large amounts of data, improving the efficiency of various city services, such as transportation and energy management (Gajdzik, Wolniak, Grebski et al., 2024). Moreover, quantum sensing technologies can be used to improve the accuracy of measurements and monitoring in smart cities, such as detecting changes in air quality, water levels, or traffic flow (Balicka, 2023b; Balicka, 2020). Moreover, while quantum tools are still in their early stages of development, their potential for improving the functionality and efficiency of smart city infrastructure is substantial (Wolniak, Stecuła, 2024; Bocciarelli, D'Ambrogio, Panetti, 2023).

This paper presents solutions for how quantum artificial intelligence models can improve some fields of BPM. Related work is submitted in Section II. Then, the quantum solutions are characterized in Section III. Next, Section IV presents some studies under predictive analytics by quantum processors. Predictive analytics in BPM can help organizations anticipate process failures, optimize resource allocation, and improve decision-making. Natural Language Processing (NLP) in BPM systems is described in Section V. Finally, the important conclusions and future work are dis-cussed in Section VI.

2. Related Work

BPM is concerned with analyzing, designing, and managing work processes within and across organizations, which often involves information technology. Beerepoot et al. discussed the biggest business process management problems that must be solved. The first crucial problem relates to digital innovation, particularly the BPM-driven value creation from data. The data deluge and associated technological proliferations have considerably changed the landscape of how businesses are run (Beerepoot et al., 2023). Digital business transformation plays a crucial role in achieving sustainable development and supporting intelligent production processes (Gajdzik, Wolniak, Grebski et al., 2024). The efficient processing of an increasing volume of data, including leveraging the potential of QAI, plays a crucial role, particularly in the development of predictive analytics. Quantum technologies combined with predictive analytics have the potential to revolutionize business process management, particularly in the areas of optimization, monitoring, and event prediction (Wolniak, 2023b). To fully harness their potential, organizations should begin exploring practical applications of these technologies, for example, through proof-of-concept models, to gain a competitive edge in the emerging digital era. Artificial intelligence supported by quantum technologies can be applied across various areas of business process management (Lei et al., 2016).

Another problem is an expansive BPM. Despite large investments in BPM, organizations are still left with process fragments by seeing ‘process trees’ rather than the entire ‘BPM forest’. This was evident during the COVID-19 pandemic, with organizations struggling with many ad-hoc and often uncoordinated process changes. BPM approaches that put individual processes at the center of their attention are unlikely to be able to address ‘big processes’, i.e., processes that stretch far beyond the boundaries of an enterprise, are closely intertwined with other processes, and are impacted by various management disciplines (Lei et al., 2016).

Moreover, the problem of automated process redesign is still important. Despite all automation efforts, process redesign has remained a manual, cognitively demanding task, making it time-consuming, labor-intensive, and error-prone. Constructing digital twins supports business processes duo to various factors. This particular problem arises in the context of planned changes. It may include reordering two or more tasks, adding a task, adding a resource, changing the decision logic of a branching point, or automating a task. These changes may positively or negatively impact performance measures, e.g., cycle time, activity processing time, or resource utilization (Lei et al., 2016).

Bartlett, Kabir, and Han presented a review on Business Process Management system design subject to the role of virtualization and work design (Bartlett, Kabir, Han, 2023). This study explored the integration of BPM, virtualization, and work design to enhance organizational performance and productivity. Virtualization and work design in BPM systems may enhance flexibility, scalability, and agility. Organizations can effectively respond to dynamic business needs and market conditions by leveraging virtual resources, thus eliminating the constraints of physical proximity. An analysis revealed promising avenues for future research, emphasizing the role of usability in BPM system design and its impact on task accomplishment. A holistic approach to BPM system design has emerged as crucial, encompassing process modeling, automation, workflow management, integration, analytics, reporting, governance, and continuous improvement (Bartlett, Kabir, Han, 2023).

Chang, Chen, Xu, and Xiong compared various BPM tools (Chang et al., 2023). The benefits of integrating BPM tools into businesses are presented, too. Three BPM tools, namely Bizagi BPM Suite, ProcessMaker and Flokzu are analyzed on a real business process. Among the tools evaluated, Bizagi and Flokzu have a more intuitive user interface, and Process Maker is the least user-friendly tool. Bizagi is recommended for large and middle-sized organizations and Flokzu for smaller organizations (Chang et al., 2023).

AI-augmented BPM systems are an emerging class of process-aware information systems empowered by trustworthy AI technology because they enhance the execution of business processes to make these processes more adaptable, proactive, explainable, and context-sensitive. A vision of this system is presented in (Dumas et al., 2023). Besides, the lifecycle of processes, core characteristics, and a set of challenges to realize systems are studied, too.

Dunzer, Tang, Höchstädter, Zilker, and Matzner described design principles for using BPM systems to achieve operational excellence to reduce costs and improve the quality of their business processes (Dunzer et al., 2023). This study follows an action design research approach to design these systems with a medium-sized company. There are concurrently evaluated tracking performance indicators aligned with the company's objective. Moreover, seven design principles are discussed to improve business processes continuously. These design principles comprise user management, process modeling, automation, logging, monitoring, integration, and case handling (Dunzer et al., 2023).

We can see that artificial intelligence can be utilized in Business Process Management in several ways to improve efficiency, accuracy, and decision-making (Balicka, 2023a). AI technologies like robotic process automation (RPA) can automate repetitive and rule-based tasks within business processes. AI-powered bots can perform tasks such as data entry, document processing, form filling, and basic decision-making. Smart algorithms can analyze historical process data to identify inefficiencies, bottlenecks, and opportunities for optimization. Machine learning techniques can predict process outcomes, forecast resource requirements, and optimize process parameters to improve overall performance.

BPM data fusion involves several stages: acquisition, preprocessing, feature extraction, data fusion, and decision-making. Each stage involves specific algorithms and techniques to handle and integrate the various data types into a unified framework. We can say that data fusion is a critical aspect of system development, as it allows city organizations to leverage the vast amounts of data generated by various systems and devices to make informed decisions, improve efficiency, and enhance the quality of life for residents (Akan, 2023).

Besides, quantum artificial intelligence can support important systems like monitoring complex infrastructure, the guidance of autonomous vehicles, smart buildings, and medical diagnosis. Techniques for quantum-inspired multi-sensor data fusion use algorithms and rules of machine learning, statistical estimation, and pattern recognition (Balicki, 2023; Taherdoost, Madanchian, 2024).

Big Data changes the approach to BPM by integrating data from many sources to produce comprehensive and specific unified data (Balicki J., Balicka H., Dryja, 2021; Ayed, Halima, Alimi, 2015). Therefore, the quality of Big Data in organizations depends on services provided by some public platforms (Durán, Pozas, Rocha, 2024; Saif et al., 2023). Deep learning algorithms can be effectively used (Ji et al., 2013). Artificial neural networks are used not only to improve processes but also to model them (Lotko, 2018). However, deep artificial neural networks are usually developed for classification, clustering, and prediction, and we recommend improving their metrics by using quantum mechanisms (O'Leary, 2013; Zhou et al., 2010).

BPM uses recommendation systems, too. Ravi, Subramaniyaswamy, Varadharajan, Gao, and Indragandhi proposed a hybrid quantum-induced swarm intelligence clustering for the urban trip recommendation in a smart city (Ravi et al., 2018). This novel user clustering approach is based on Quantum-behaved Particle Swarm Optimization for the collaborative filtering-based recommender system. The recommendation approach has been evaluated on real-world, large-scale datasets of Yelp and TripAdvisor for hit rate, precision, recall, f-measure, and accuracy. The evaluation results prove the usefulness of the generated recommendations and depict the users' satisfaction with the proposed recommendation approach (Marz, Warren, 2014; Ravi et al., 2018).

Blockchain is a very useful technique that can securely organize diverse organizational processes. Chen, Gan, Hu, and Chen studied the construction of a post-quantum blockchain for organizations (Chen et al., 2020). It finds wide applications, especially in distributed environments, where entities such as wireless sensors must be certain of the server's authenticity. As contemporary blockchain techniques that address concerns have not been designed, a blockchain is proposed in the post-quantum setting. It seeks to discover how it can resist attacks from quantum computing (Chen et al., 2020).

3. Quantum solutions

Quantum AI and quantum machine learning can be used to analyze historical process data and identify patterns, trends, and correlations that can help predict future process behavior. Predictive analytics can be applied to forecast demand, identify customer preferences, anticipate maintenance needs, and optimize resource allocation within business processes. AI-powered decision support systems can assist human decision-makers by providing real-time insights, recommendations, and predictions based on process data analysis. These systems can help optimize decision-making in areas such as resource allocation, risk management, pricing, and strategic planning.

Natural Language Processing (NLP) systems enable computers to understand, interpret, and generate human language, which can be valuable in BPM for tasks such as text analysis, sentiment analysis, and information extraction from unstructured data sources such as emails, customer feedback, and social media. Beheshti, Yang, and Sheng, et al. proposed transforming business process management with generative artificial intelligence, using Generative Pre-trained Transformers (GPT) (Beheshti, Yang, Sheng et al., 2023).

Generative Pre-trained Transformer is a state-of-the-art machine learning model capable of generating human-like text through natural language processing (NLP) (Beheshti, Yang, Sheng et al., 2023). GPT is trained on massive amounts of text data and uses deep learning techniques to learn patterns and relationships within the data, enabling it to generate coherent and contextually appropriate text. We can use the GPT technology to generate new BPM models. ProcessGPT has the great potential to enhance decision-making in data-centric and knowledge-intensive processes in organizations. The model can be integrated with NLP and machine learning techniques to provide insights and recommendations for process improvement. Furthermore, the model can automate repetitive tasks and improve process efficiency, enabling knowledge workers to communicate analysis findings and supporting evidence and make decisions. It offers a powerful tool for process augmentation, automation, and improvement. It demonstrated how ProcessGPT can be a powerful tool for augmenting data engineers in maintaining data ecosystem processes within large bank organizations. A scenario highlights the potential of this approach to improve efficiency, reduce costs, and enhance the quality of business operations through the automation of data-centric and knowledge-intensive processes. These results underscore the promise of ProcessGPT as a transformative technology for organizations looking to improve their process workflows (Beheshti, Yang, Sheng et al., 2023). Introducing quantum technology to ProcessGPT may increase the efficiency of that approach.

QAI can be used to continuously monitor business processes in real time and detect anomalies, deviations, and potential issues. Algorithms can trigger alerts, notifications, and automated responses when predefined thresholds or conditions are met, allowing organizations to address problems and maintain process quality proactively. QAI-powered systems can analyze customer data to personalize and customize the customer experience throughout the BPM lifecycle. This can include personalized product recommendations, targeted marketing campaigns, dynamic pricing strategies, and tailored customer support interactions (Li, Chosler, 2007; Li et al., 2018).

QAI technologies can enable dynamic and adaptive business processes that can automatically adjust and reconfigure themselves in response to changing conditions, requirements, and objectives. This flexibility allows organizations to quickly respond to market dynamics, regulatory changes, and customer preferences while maintaining process efficiency and effectiveness (Lei et al., 2016).

By leveraging AI technologies in BPM, organizations can streamline operations, improve decision-making, enhance customer satisfaction, and gain a competitive edge in today's rapidly evolving business landscape. Deep neural networks and the Internet of Things are based on technological trends that can reshape the BPM systems. These technological trends increasingly influence each other because IoT can transmit less data to make better decisions. These technologies will allow decision-makers to access, process, and deliver data more efficiently, providing enhanced and personalized experiences. Advances in deep learning are critical to turn information into knowledge and to embed autonomy and intelligence into organizations. At the current moment of the city monitoring, thousands of sensors create the complex image of the organization that can change dynamically. The size of these images are constrained by the computational cost of deep learning (Zhou et al., 2010).

Figure 1 shows training progress of an neural network after feature selection for the German Traffic Sign Detection Benchmark Dataset. The network identifies the traffic sign from images on German roads (Schmidhuber, 2014).

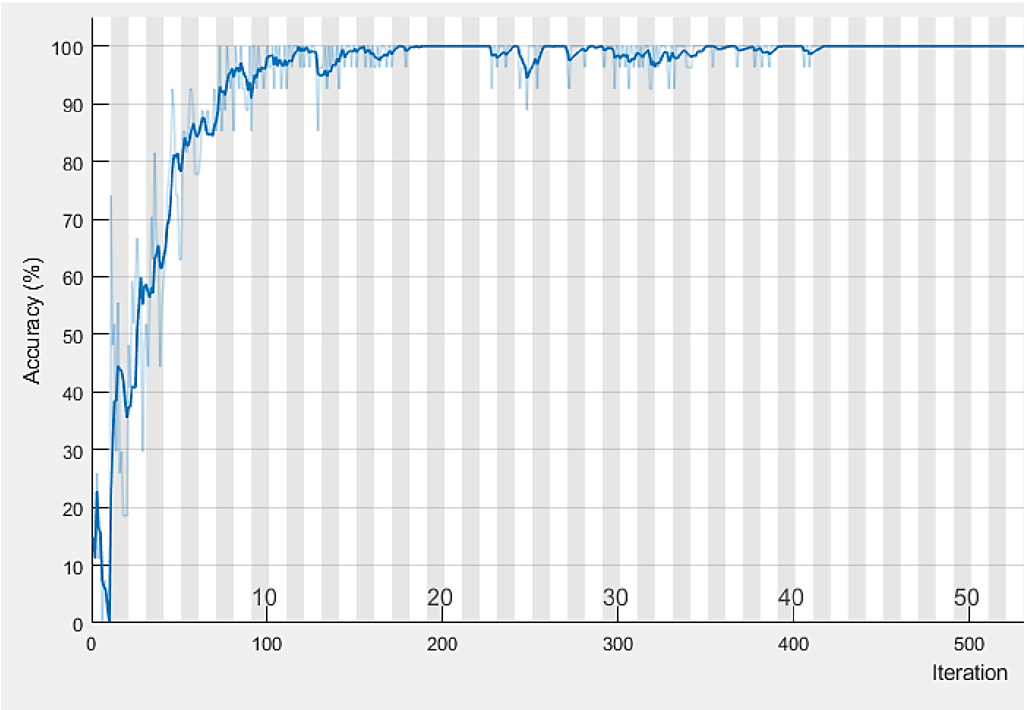

Figure 1. The accuracy improvement by the neural network training for the German Traffic Sign Detection Benchmark Dataset.

Source: Own study.

In an organization, the Internet of Things connects an output layer of distributed sensors with edge devices and a core layer of cloud servers (Figure 2). IoT alters the trusted interaction between citizens, services, and applications with the sensors embedded into the real-world environment. Social networks, advanced artificial intelligence, and cloud platforms change the standards of producing, consuming, and interacting with content, services, and objects. They are the new approach for our societies related to communication, exchange, business, and knowledge management. Advances in language technologies decrease language barriers. Besides, deep learning can be personalized and tailored to each citizen's needs, competencies, and abilities (Krizhevsky, Sutskever, Hinton, 2012).

Figure 2 shows a diagram of data fusion with the Internet of Things in an organization. Education and information of citizens are important to understand and use collective intelligence to make efficient decisions. Data fusion provides accurate information from sensors via IoT to the edge layer devices and the BPM cloud servers. By combination of data fusion with the IoT, we can create new innovative models of BPMs.

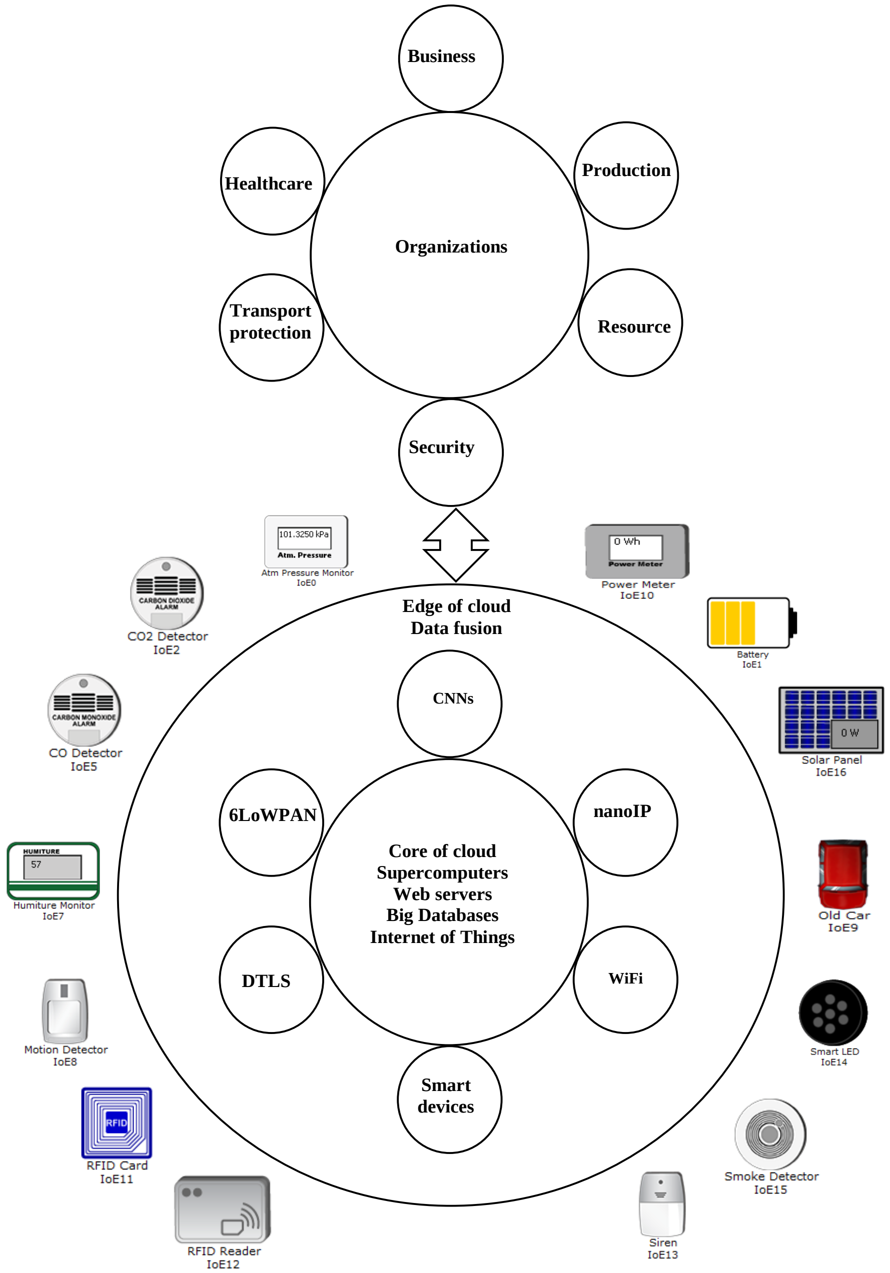

Figure 2. Internet of Things for supporting BPM system.

Source: Own study.

4. Quantum Predictive Analytics

Predictive analytics in BPM systems uses data from the organization's environment to predict future events or outcomes. It involves extracting patterns, trends, and relationships from past data to forecast likely future scenarios. Data is collected from various sources and can include historical records, transactional data, customer interactions, sensor data, social media data, and more. Data needs to be cleaned, processed, and prepared for analysis. This involves removing duplicates, handling missing values, normalizing data, and transforming variables.

Feature selection involves identifying the most relevant features that have predictive power and removing irrelevant or redundant ones. The predictive model is trained using historical data, where the input features and corresponding target values are used to train the model. During training, the model adjusts its parameters to minimize the difference between the predicted and actual values. The model can be used to make predictions on new, unseen data. The model takes the input features from new data instances and generates predictions for the target variable (Tian et al., 2023).

Predictive models are deployed into production systems where they can generate real-time predictions. Models are regularly monitored to ensure their accuracy and reliability. They can be retrained or updated with new data to maintain their effectiveness (Zhao, 2017).

Predictive analytics has numerous applications across BPM. It can be used for various tasks such as customer churn prediction, sales forecasting, risk assessment, fraud detection, demand forecasting, predictive maintenance, and personalized recommendations. BPM systems require powerful technologies based on the AI paradigm (Gadatsch, 2023). The open issue is the balancing of deep artificial neural network workload among edge and cloud servers (Węglarz, Błażewicz, Kovalyov, 2006). Figure 3a) shows minimization both the CPU workload of the bottleneck computer (denoted as $\hat{Z}_{max}$) and the communication workload of the bottleneck server ($\tilde{Z}_{max}$) for BPM predictive analytics (Balicki, 2022).

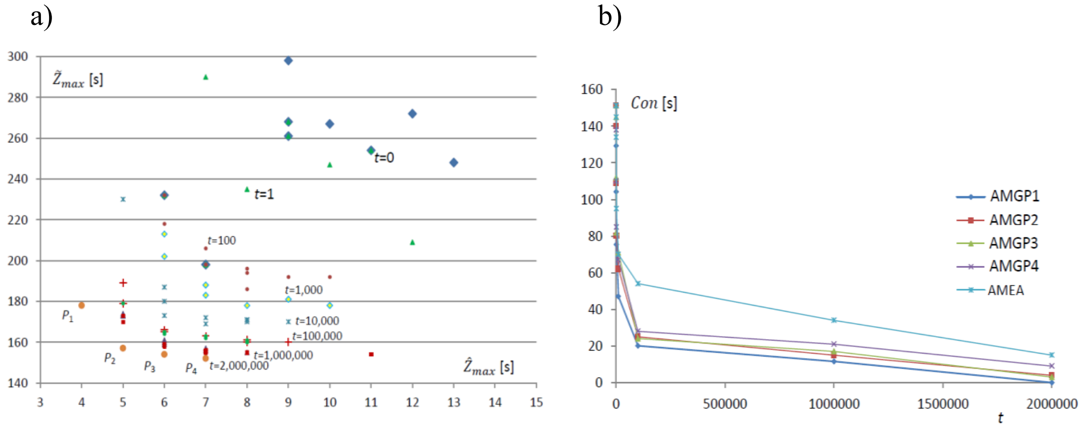

Figure 3. Evolution and convergence: a) Migration of evaluations towards the Pareto front; b) Outcomes convergences for some multi-objective algorithms.

Source: Own study.

5. Natural Language Processing in BPM systems

NLP technologies in BPM systems can unlock new capabilities, improve operational efficiency, enhance customer engagement, and drive innovation across the entire process lifecycle. NLP enables organizations to harness the power of natural language to automate tasks, extract insights, and optimize processes, ultimately enabling them to achieve their business objectives more effectively and competitively.

NLP-powered sentiment analysis can be used to analyze customer feedback, social media mentions, and online reviews to gauge customer sentiment, identify emerging trends, and detect potential issues or opportunities within business processes. By integrating sentiment analysis into BPM systems, organizations can monitor customer perceptions, prioritize actions, and continuously improve customer experience.

NLP techniques such as information retrieval, question answering, and knowledge graph analysis can facilitate knowledge management and discovery within BPM. Organizations can enhance knowledge sharing, collaboration, and decision support across business processes by automatically indexing, categorizing, and summarizing knowledge assets such as documents, wikis, and knowledge bases.

To extend features of NLP, we introduce quantum improvements. A qubit can exist in more than one state (a superposition), and can be represented by the Bloch sphere. We use Bra-ket (or Dirac) notation. The inner (or dot) product of two states can be denoted as a bracket $\langle\alpha \mid \beta\rangle$. The qubit can be modeled as a two-layer quantum bit from the Hilbert space H2 with the base B=$\{|0\rangle,|1\rangle\}$. The qubit may be in the "1" binary state, in the "0" state, or in any superposition of them (Arute et al., 2019). The state x_m of the *m*th qubit in the *register* can be written, as follows (Arute et al., 2019):

$$\boldsymbol{Q_m = \alpha_m|0\rangle \oplus \beta_m|1\rangle}, \tag{1}$$

where:

αm and βm – the complex numbers that specify the amplitudes of the states 0 and 1, respectively;

$\oplus$ – a superposition operation;

m – the index of the qubit, $m = \overline{1, M}$.

The value $|\alpha_m|^2$ is the probability that we observe the state "0". Similarly, $|\beta_m|^2$ is the probability that state "1" is measured. The qubit is characterized by the pair (α_m, β_m) with the constraint, as below (Balicki, 2023):

$$\boldsymbol{|\alpha_m|^2 + |\beta_m|^2 = 1} \tag{2}$$

Dirac notation is often used to select a basis. The basis for a qubit (two dimensions) is $|0\rangle = (1{,}0)$ and $|1\rangle$= (0,1). An alternative common basis consists of the eigenvectors of the *Pauli-x* operator: $|+\rangle = \frac{1}{\sqrt{2}}(1{,}1)$ and $|-\rangle = \frac{1}{\sqrt{2}}(1,-1)$. The most commonly used representation of a quantum register is the matrix, as follows:

$$\boldsymbol{Q} = \begin{bmatrix} |\boldsymbol{\alpha_1}| & \dots & |\boldsymbol{\alpha_m}| & \dots & |\boldsymbol{\alpha_M}| \\ |\boldsymbol{\beta_1}| & \dots & |\boldsymbol{\beta_m}| & \dots & |\boldsymbol{\beta_M}| \end{bmatrix} \tag{3}$$

However, the state $Q_m = \alpha_m|0\rangle \oplus \beta_m|1\rangle$ of the *m*th qubit can be represented as the point on the 3D Bloch sphere (Figure 4), as follows (Balicki, 2022):

$$\left|\boldsymbol{Q_m}\right\rangle = \ \mathbf{cos}\frac{\boldsymbol{\theta_m}}{\mathbf{2}}\left|\mathbf{0}\right\rangle + \boldsymbol{e^{i\phi_m}}\,\mathbf{sin}\frac{\boldsymbol{\theta_m}}{\mathbf{2}}\ \left|\mathbf{1}\right\rangle, \boldsymbol{m} = \overline{\mathbf{1}, \boldsymbol{M}} \tag{4}$$

where: $0 \ \le \ \theta_m \le \pi$ and $0 \le \ \phi_m \le 2\pi$.

Two angles θ_m and ϕ_m determines the localization of *m*th qubit on the Bloch sphere. The North Pole represents the state |0⟩, the South Pole represents the state |1⟩, and the points on the equator represent all states in which 0 and 1 are the same. Thus, in this version of the quantum-inspired genetic algorithm, *M* Bloch spheres represent the gene states. In addition to the representation of (3), we can, therefore distinguish the following other models of the register:

$$\boldsymbol{Q^{sign}} = \begin{bmatrix} |\boldsymbol{\alpha_1}| & \dots & |\boldsymbol{\alpha_m}| & \dots & |\boldsymbol{\alpha_M}| \\ \boldsymbol{sign}(\boldsymbol{r_1}) & \dots & \boldsymbol{sign}(\boldsymbol{r_m}) & \dots & \boldsymbol{sign}(\boldsymbol{r_M}) \end{bmatrix} \tag{5}$$

where: r_m – the random number from the interval [-1; 1].

$$\boldsymbol{Q^{vector}} = [|\boldsymbol{\alpha_1}|, \dots, |\boldsymbol{\alpha_m}|, \dots, |\boldsymbol{\alpha_M}|] \tag{6}$$

$$\boldsymbol{Q^{angle}} = \begin{bmatrix} \boldsymbol{\theta_1} & \dots & \boldsymbol{\theta_m} & \dots & \boldsymbol{\theta_M} \\ \boldsymbol{\phi_1} & \dots & \boldsymbol{\phi_m} & \dots & \boldsymbol{\phi_M} \end{bmatrix} \tag{7}$$

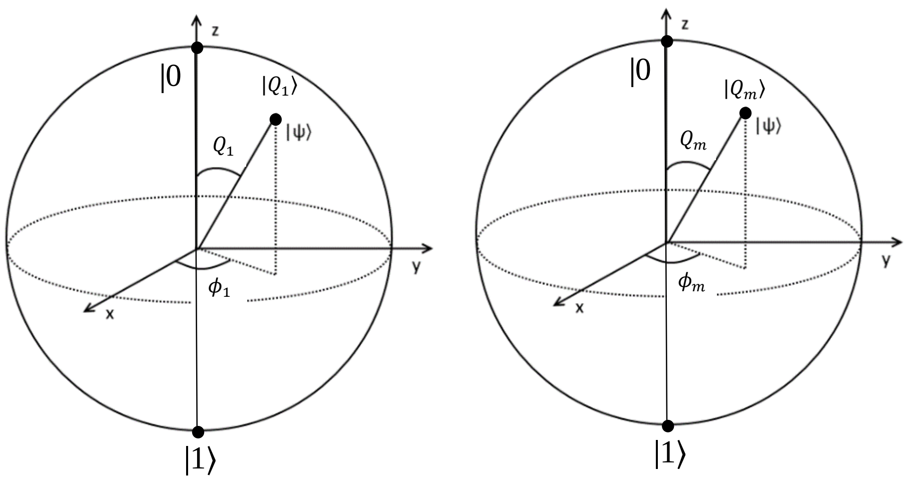

Figure 4. The Bloch spheres of the quantum register with M qubits.

Source: Own study.

There are two important criteria for deep learning. The first one is accuracy, and the second criterion is the F1 score. We evaluate their values due to each epoch. Afterward, we evaluate the fitness of each binary chromosome by using the ranking procedure with non-domination sorting. We determine non-dominated solutions from the current population and copy them to the archive after verification.

A rotation gate *Ry* is a single-qubit rotation through the positive or negative angle *θm* [radians] around the *y*-axis, as follows (Balicki, 2023):

$$\boldsymbol{Ry(\theta_m)} = \begin{bmatrix} \boldsymbol{cos}\left(\frac{\theta_m}{2}\right) & -\boldsymbol{sin}\left(\frac{\theta_m}{2}\right) \\ \boldsymbol{sin}\left(\frac{\theta_m}{2}\right) & \boldsymbol{cos}\left(\frac{\theta_m}{2}\right) \end{bmatrix} \tag{8}$$

Besides, we can define a rotation gate *Rx* around the *y*-axis, as follows:

$$\boldsymbol{Rx(\theta_m)} = \begin{bmatrix} \boldsymbol{cos}\left(\frac{\theta_m}{2}\right) & -\boldsymbol{i}\ \boldsymbol{sin}\left(\frac{\theta_m}{2}\right) \\ -\boldsymbol{i}\ \boldsymbol{sin}\left(\frac{\theta_m}{2}\right) & \boldsymbol{cos}\left(\frac{\theta_m}{2}\right) \end{bmatrix} \tag{9}$$

To complete these operators, we introduce a rotation gate *Rz* around the *z*-axis, as follows:

$$\boldsymbol{Rz(\theta_m)} = \begin{bmatrix} \boldsymbol{e}^{-\frac{\theta_m}{2}} & \boldsymbol{0} \\ \boldsymbol{0} & \boldsymbol{e}^{\frac{\theta_m}{2}} \end{bmatrix} \tag{10}$$

Figure 5 shows the modification of the quantum register by Hadamard gates and rotation gates *Rx*, *Ry*, and *Rz* by quantum processor Starmon-5 (Balicki, 2023).

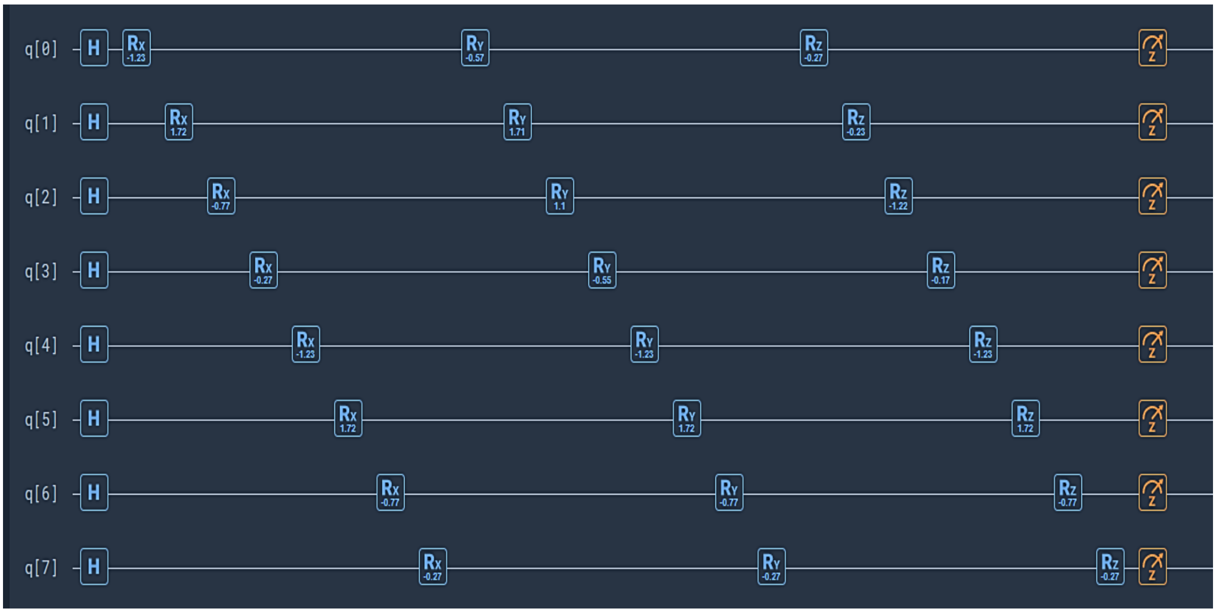

Figure 5. A diagram of a modification of the quantum register.

Source: Own study.

Figure 6 shows a histogram after updating the quantum register using the rotation gates *Rx, Ry, Rz*.

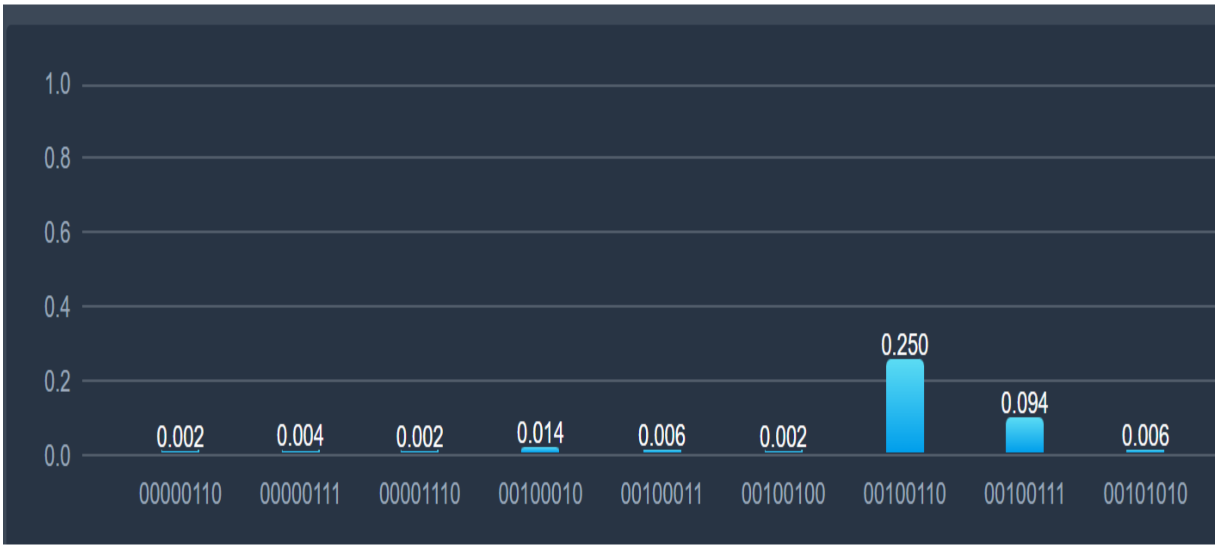

Figure 6. Histogram after updating the quantum register.

Source: Own study.

Because of quantum interference, the probability distribution of the binary chromosomes is a stippled intensity pattern provided by light interference in laser scatter. Consequently, some binary chromosomes are much more likely to occur than others. Digital algorithms for calculating this probability distribution are exponentially more difficult as the number of qubits (width) and number of gate cycles (depth) rise (Balicki, 2023).

6. Concluding Remarks and Future Work

Data fusion based on Convolutional Neural Networks and Long Short-Term Memory Neural Networks can strongly support BPM systems, where the time series of Big Data streams can be reduced to send an edge and core cloud via the Internet of Things. Some intelligent agents in edge computing can significantly support the efficiency of the proposed approach.

The major contributions of this paper are:

- An introduction to the concept that quantum deep transfer learning implemented by the pre-trained Convolutional Neural Networks can filter features of the city image by fusion from sensors to the edge computing layer via the IoT.
- A development of LSTMs for supporting edge computing in the smart city cloud.
- A presentation of some results from the laboratory city cloud simulations.

Our future work will focus on testing other deep neural networks to find efficient predictors and detectors for BPM systems. Besides, quantum-inspired algorithms can also be considered to support big data processing (Beheshti et al., 2023).

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