jet INTL JOURNAL OF ELECTRONICS AND TELECOMMUNICATIONS, 2025, VOL. 71, NO. 1, PP. 225–234
Manuscript received December 20, 2024; revised March, 2025. doi:10.24425/ijet.2025.153566

Influence of IQT on research in ICT, part 2

Piotr Suszyński, Jan Dubiński, Adam Ignaciuk, Pedro Jimenez-Soler, Emil W. Pituła, Piotr Wójtowicz, and Ryszard S. Romaniuk

***Abstract*—The advanced Quantum Information Technologies subject for Ph.D. students in Electronics Engineering and ICT consists of three parts. A few review lectures concentrate on topics which may be of interest for the students due to their fields of research done individually in their theses. The lectures indicate the diversity of the QIT field, resting on physics and applied mathematics, but possessing wide application range in quantum computing, communications and metrology. The individual IQT seminars prepared by Ph.D. students are as closely related to their real theses as possible. Important part of the seminar is a discussion among the students. The task was to enrich, possibly with a quantum layer, the current research efforts in ICT. And to imagine, what value such a quantum enrichment adds to the research. The result is sometimes astonishing, especially in such cases when quantum layer may be functionally deeply embedded. The final part was to write a short paragraph to a common paper related to individual quantum layer addition to the own research. The paper presents some results of such experiment and is a continuation of previous papers of the same style.**

***Keywords*—ICT, QIT, biomedical engineering, electronics and communications engineering, sensors, quantum machine learning, quantum Internet, quantum computing, cybersecurity, quantum networks, quantum sensors**

I. Introduction

ADVANCED lecture for a group of diverse Ph.D. students is a demanding task. They are strongly concentrated on their individual research efforts. Timing of their Ph.D. study is demanding and they try to omit things which do not help them to go forward with the research. The subject on the Quantum Information Technology is designed in this way as not to slow down their work but to help and perhaps shed a new light on their research from a completely different yet very modern and promising perspective, the quantum one. The quantum perspective, especially when used against your serious personal research effort, is really very useful in the most of cases. Quantum integrated circuits are natural extensions of photonic integrated circuits. Quantum methods are used in simulations of large high energy experiments. Quantum simulators and annealers are used for research on molecular dynamics in material engineering and technology. IQT is used in a number of security solutions. A lot of photonic crystal technologies may be extended into quantum level. Quantum sensors include also a new generation of ionizing radiation devices and systems. Quantum dot dynamics is used in cancer diagnostics and therapy. IQT is used in automobiles and in aeronautics. Artificial Neural Network are extended successfully to quantum version. Power engineering start to adapt some quantum methods. IQT promise for faster and more precise genome sequencing and data analysis. Smart quantum antennas may enter into operation in G6 technology. Quantum batteries combine new materials and start to use quantum supercapacitors. IQT will be indispensable in banking and other security solutions.

Authors are with Warsaw University of Technology, Poland (corresponding author e-mail: piotr.suszynski.dokt@pw.edu.pl). Chapters written by: II - P.Suszyński, III - J.Dubiński, IV - A.Ignaciuk, V - P.Jimenez-Soler, VI - E.Pituła, VII - P.Wójtowicz.

II. Neural Networks training with quantum speedup to power bioinformatics

A. Genome sequencing

The cost to sequence a human genome fell multiple orders of magnitude over the last decades [1] and this fueled the explosive growth of data volumes from genome sequencing available for various analyses. Data is available not only for DNA sequences but also mRNA, proteins, DNA methylation and other data types, for example obtained by filtering sequence parts bound to marker molecules, which in turn can give information about DNA 3D structure [2] - a key to understanding gene expression. One of the ways in which we might use this data is for trying to understand genomic grounds for various diseases. Genomic variant classification, as well as other problems in genome sequencing data analysis, are perfect fields for Machine Learning methods application and this is currently happening at tremendous pace. The architecture that eventually „ate" the vast majority of the ML field are neural networks. We'll now try to answer the question how quantum computing could improve this excellent tool.

B. Quantum computing and Machine Learning

Quantum methods for Machine Learning are still in their infancy. We have rigorous time complexity analysis and proofs of quantum speedup only for a subset of quantum algorithms. The fact that the Grover speedup, which is just quadratic, is the best achievable one for oracle lookups [3] serves as a reminder to tread carefully. We don't have a proof that would tell us how the BQP (bounded-error quantum polynomial) complexity class is related to the NP class, all we know for sure as of know is that $P \subseteq BQP \subseteq PSPACE$.

Quantum Neural Networks [4] [5] are the architectures that were proposed to realize the neural networks on a quantum computer. The key to classical NN capacity are the nonlinearities that are applied as part of each neuron computation, as their activation functions. Without them the whole multilayer network would be equivalent to a set of linear equations. Quantum circuits are composed of unitary transformations, so they are linear. Fortunately the measurement operation is nonlinear and we can carefully apply it to introduce the nonlinearities needed for the computation. However, there are several problems with QNN, one of them is the Barren plateaus problem [6], which arises from the vanishing of the loss function gradient in the exponential Hilbert space. Another one is the mentioned lack of proofs for a possible quantum speedup for some of proposed methods. The problem is not just in building a fault tolerant quantum computer with a lot of qubits, it's also the immaturity of quantum algorithms.

C. Neural Ordinary Differential Equations

We'll now explore other possible routes of obtaining a speedup in neural networks training and to do that we'll review one of well known papers in the ML field. The Neural ODE paper [7], which proposes an architecture generalizing the ResNet architecture. ResNets introduced the so called residual connections, which are just skip connections - they were one of the enablers of very deep learning, fighting the vanishing gradient problem[1]. It turns out that such residual connection can be viewed as a realization of the Euler method for numerically computing an ordinary differential equation. Neural ODE architecture replaces the multiple layers of ResNet network with a black-box ODE solver and then applies a clever trick to be able to propagate the loss function gradient without „opening" the black box solver. It was shown that such NN can work just as well as normal neural networks.

D. Quantum methods for solving ODEs

What does the Neural ODE concept has in common to the topic of quantum speedup of neural networks training? The answer is that there are known quantum methods for solving ODEs and it was shown that such methods may give an exponential speedup over classical methods. In 2014 [8] it was shown how to solve linear ODEs, basing on the HHL algorithm [9] for numerically solving systems of linear equations and in 2020 and 2021 it was shown how to solve nonlinear ODE with exponential speedup on a quantum computer [10] [11].

E. Quantum Neural ODE

My main contribution is to propose to use a quantum solver for ordinary differential equations in the Neural ODE architecture, and through this potentially obtain an exponential speedup in training neural networks. To the best of my knowledge this article is the first one to propose such idea.

There are however several problems with this idea:

[1]which is also a problem in classical neural networks although growing with the number of layers, as opposed to Barren plateaus in QNN which gets worse with every additional qubit

First issue: The quantum speedup of the HHL algorithm is not a speedup from $O(exp(N))$ to $O(poly(N))$ but rather from $O(poly(N))$ to $O(log(N))$. This is problematic because while we can solve the differential equation exponentially faster the operation of reading the result, of size N, into classical bits must necessarily take $O(N)$ time, thus nullifying the whole speedup. This is mentioned in the HHL paper and also quantum ODE papers and a solution to this problem given is to compute some reduction of the result on the quantum computer or treat these algorithms as a subroutine of a larger quantum algorithm. The result must be processed further on the quantum computer.

Second issue: The authors of the [11] paper proved the exponential speedup for the case when the nonlinearity of the ODE is quadratic and also is further limited - they parametrized it by parameter R and provided a proof valid for $R < 1$. In the experiments they managed to obtain exponential speedup for larger values of R, as high as 44, but they did not consider non-quadratic equations. In the paper by the second group [10] a more general case of a nonlinear ODE is considered but still the paper introduces a condition limiting the nonlinearity of the equation.

This is a serious problem, the nonlinearities used in NN today almost always involve either exponential terms or non-smooth, abrupt changes, as is the case with ReLU, and it is not entirely clear if a viable NN could be constructed without them. Paper [10] specifically mentions that:

> *„The approximations leading to the quantum solution, equation (17) of the nonlinear equation (1), must necessarily break down if the nonlinearity leads to large exponential growth [...] Indeed, if they did not break down, one could use the method to amplify exponentially small differences in the initial wave function, which would allow the solution of NP-complete problems on a quantum computer!"*

It is worth mentioning that in 1988 it was proven that training a 3 neuron, 2 layer neural network is NP-complete [12], although this was done only for a specific case of an activation function. On the other hand following decades showed that it is not necessary to reach a global minimum in order to end up with a useful neural network and also that increasing the dimensionality of the network likely brings the local minima closer to the global minimum [13].

F. Identified solutions

I considered following possible routes to explore regarding the listed problems:

First issue:

- Since $P \subseteq BQP$ and we can implement all classical logical gates using the quantum Toffoli gates we should be able to effectively implement the classical neural network along with the backpropagation algorithm on a quantum computer (this would not be the same as QNN, which try to utilize the quantumness of qubits). If we do that then it might be possible to keep the exponential speedup of the ODE computation.

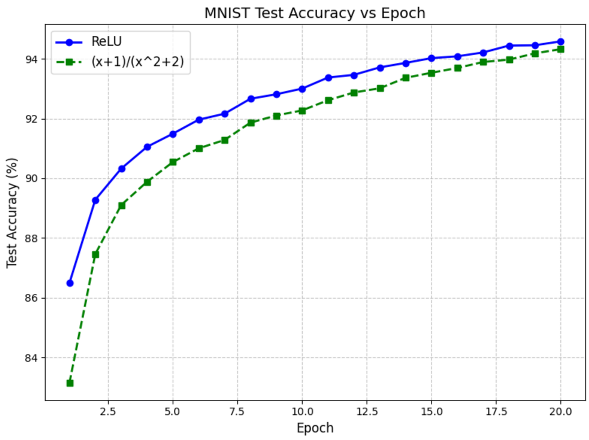

Fig. 1. MNIST ReLU vs $\frac{x+1}{x^2+2}$

- Maybe we could apply some clever reduction of the ODE solution on the quantum computer, measure it and further proceed on a classical computer - more work would be needed to determine if this is a viable route.

Second issue: I performed experiments using $\frac{x+1}{x^2+2}$ as an activation function[2] and this network was able to learn the XOR function, which famously require at least two layer neural network with non linear activation function, as well as obtain comparable results on the MNIST digit classification (see figure 1). On the other hand $\frac{x+1}{x^2+2}$ is still not a quadratic polynomial. More analysis would be needed to determine if nonlinear differential equations containing functions of this form would benefit from exponential speedup.

G. Summary

1) Advancements in ML through the use of quantum algorithms should benefit the analysis of data obtained from genome sequencing
2) It is not currently known whether quantum computers could deliver exponential speedup for NP-complete problems
3) Using quantum computers as ODE solvers might be a possible route to train certain types of neural networks, although this requires further research

III. QIT in Fast Machine Learning Simulations

At the European Organization for Nuclear Research (CERN), scientists investigate the fundamental properties of matter using the Large Hadron Collider (LHC). This advanced particle accelerator enables High Energy Physics (HEP) experiments by recreating the extreme conditions that existed shortly after the Big Bang through particle collisions. The immense energy densities generated during these collisions allow for the emergence of rare physical phenomena, including the production of exotic particles and unusual states of matter.

Analyzing the results of these collisions requires detailed simulations that model the responses of individual detectors within the LHC. These simulations are crucial for both advancing scientific research and optimizing detector calibration. The current standard approach relies on Monte Carlo simulations that statistically model physical interactions between colliding particles. Newly generated particles are propagated through the detectors in a step-by-step manner using specialized transport frameworks such as GEANT [14].

Despite their effectiveness, Monte Carlo-based simulations face significant limitations. They are computationally intensive, challenging to parallelize, and exhibit linear scalability relative to the number of simulated events. Additionally, they require highly specific implementations of interaction models tailored for these transport packages.

A. Fast Machine Learning Simulations for High Energy Physics

To overcome the limitations of Monte Carlo-based simulations, a promising alternative based on machine learning has been proposed recently [15]–[18], where traditional simulation frameworks are replaced by generative models. CERN's vast data resources provide a unique environment for advancing generative machine learning techniques aimed at producing high-fidelity synthetic data that closely mirror the statistical properties of real data. This approach bypasses the need for computationally expensive step-by-step particle propagation inherent in Monte Carlo methods by directly generating simulation outcomes based on input conditional data.

Existing efforts in this field leverage various state-of-the-art approaches to generative modeling, including autoencoders [19], Generative Adversarial Networks [20] (GANs), diffusion models [21], and normalizing flows [22]. Each approach has demonstrated distinct advantages in simulation accuracy, scalability, and efficiency.

Autoencoders [19] offer a powerful approach for compressing and reconstructing complex data distributions. They excel in learning efficient, low-dimensional representations of high-dimensional data, which makes them particularly suitable to apply in the fast simulation context [23]–[25]. However, autoencoders struggle with generating diverse or high-quality samples due to limitations imposed on the latent space in the training process. To mitigate this, one approach is to avoid imposing arbitrary regularizations on the latent space, allowing the autoencoder to learn representations driven solely by the data's inherent structure [26]. Another strategy is to introduce a physically motivated regularization based on theoretical models, ensuring that the learned representations align with known scientific principles [27].

GANs [20] are well-known for generating high-quality, realistic data samples through adversarial training. Their ability to learn complex data distributions makes them particularly suitable for tasks in HEP simulations [16], [28], [29]. However, GANs can suffer from mode collapse, where certain data modes are underrepresented. To address this limitation, research efforts have focused on introducing regularization techniques that encourage the exploration of diverse data modes while maintaining fidelity [30]. Additional strategies such as incorporating auxiliary tasks and refining loss functions have been shown to further improved the generation process [31].

[2] the function was rescaled and shifted to have $[0, 1]$ codomain

Diffusion models [21] generate data through iterative denoising processes, which ensures high sample quality but often comes at the cost of extended inference times. Despite that inherent limitation, diffusion models have also gained traction in the HEP simulations domain [32], [33]. In this context, a critical area of research involves accelerating the inference process to enhance computational efficiency. Efforts have focused on optimizing the sampling methods, enabling greater speed-ups compared to traditional Monte Carlo-based approaches [34], [35].

Recently, flow-based models [22] have also proven to constitute an effective approach for HEP simulations [36]–[38]. Such models provide exact likelihood estimation, enabling highly accurate density modelling and data generation. However, their primary limitation is the relatively high computational cost of training and inference on large-scale datasets.

In summary, fast machine learning-based simulations constitute a viable alternative to traditional Monte Carlo methods in HEP. Existing research in that field leverages a variety of state-of-the-art generative models to generate high-fidelity synthetic data. Results in multiple HEP applications demonstrate the advantages of this approach, offering a considerable reduction of inference time and required computational resources.

B. Quantum Generative Models for High Energy Physics Simulation

Recently, Quantum Neural Networks (QNNs) have garnered significant attention for their capacity to represent and manipulate information with efficiency impossible to achieve for classical neural networks. This capability is particularly essential to CERN's computational challenges, where the sheer volume and complexity of data necessitate more efficient processing techniques. Crucially in this context, QNN-based alternatives have already been proposed for autoencoders [39], GANs [40], diffusion models [41] and normalizing flows [42].

In this vein, quantum generative models are slowly emerging as a transformative approach in HEP simulations [43]–[51]. These methods could deliver exponential speed-ups in simulation processes, addressing CERN's most significant computational bottlenecks and potentially replacing the classical machine learning methods in the future.

Among the various quantum generative models, Quantum Generative Adversarial Networks (QGANs) have shown remarkable promise. Rehm et al. [44] demonstrated a full quantum GAN model capable of generating simplified eight-pixel calorimeter shower images, marking a step toward more complex simulations. This model generates individual images with pixel energy values, contrasting with previous models that produced averaged probability distributions. The study also compared the full quantum GAN with hybrid quantum-classical models, highlighting the potential advantages of fully quantum approaches in terms of accuracy and efficiency.

In this field, Bravo-Prieto et al. [46] introduced style-based QGAN designed for generating high-energy particle collision data. This approach combines advanced quantum circuit designs with style-based GAN architectures. The proposed quantum generator model does not follow the traditional approach where the prior noise distribution is provided to the quantum generator through its initial layer. Instead, the prior noise is embedded into every single-qubit and entangling gate within the network.

In the realm of autoencoders, another advancement involves Quantum Variational Autoencoders (QVAE). Hoque et al. introduced CaloQVAE [43], a hybrid quantum-classical generative model designed to simulate high-energy particle interactions within calorimeters. This model combines quantum annealing with classical machine learning techniques to efficiently generate realistic simulation data.

For Quantum Diffusion Models (QDM), Cacioppo et al. [47] explored the concept of applying such methods to simulate high-energy physics processes, namely parton showers, which are challenging to model using classical models. Their approach leverages parameterized quantum circuits (PQCs) to iteratively construct quantum states, encoding complex particle interaction patterns. By embedding quantum diffusion steps within PQCs, they effectively bridge classical generative models and quantum state learning.

Overall, the discussed applications of quantum generative models in the HEP simulation domain highlight the promising potential of this technology. The growing research in this field underscores the transformative impact of Quantum Information Technologies within this particular context.

C. Challenges in Quantum Generative Models

Despite these promising advances, quantum generative models face several challenges. One of the most pressing issues is the limited availability of high-quality quantum hardware, which constrains the scale of simulations that can be performed [52]. Moreover, current quantum computing devices suffer from decoherence, leading to reduced model fidelity and reliability [53]. Additionally, designing quantum circuits for complex generative tasks remains a highly specialized problem requiring domain-specific knowledge [54], which slows down the advancements in this field. Another challenge is the integration of quantum models with classical systems, where hybrid architectures introduce additional complexity [54]. Furthermore, efficient training of quantum models involves optimizing non-convex loss functions across a high-dimensional parameter space, posing significant computational hurdles [55], in particular for more challenging generative problems at a realistic scale.

IV. Quantum Technologies in Dosimetry

A. Optically Stimulated Luminescence Dosimetry

Optically stimulated luminescence (OSL) is a widely used technique for measuring the accumulated radiation dose in natural and synthetic materials, with applications in medicine [56], dosimetry [57], and many others. OSL is a process in which material that was exposed to ionizing radiation, after being subjected to certain optical stimulation, begins to emit light, the intensity of which is proportional to the absorbed dose of radiation. Despite its widespread applications and remarkable advances, the practical deployment of OSL technology remains constrained by the size and complexity of existing instrumentation. To overcome these limitations, there is growing interest in the miniaturization of this technology, with particular focus on leveraging quantum detectors.

B. Quantum dots in dosimetry

Quantum dots (QD's) are nanoscale to microscale semiconductor particles. QD's exhibit quantum confinement, and because of that can be precisely tuned in manner of their optical and electrical properties [58]. One of the features of quantum dots is that with smaller size, they tend to emit light at shorter wavelengths of visible light (they are blue-shifted) and larger quantum dots emit at longer wavelengths (red-shifted). One of many materials that are used for creating such complex devices as QD's is carbon, which allows for their usage in the fields of chemical sensing, biosensing, bioimaging, nanomedicine, photocatalysis and electrocatalysis [59]. Among all those applications, it is not surprise, that it is possible to find an usage for QD's in ionizing radiation sensing. In one of the works [60] authors have investigated the influence of gamma radiation of intensity 0.034 Gy per minute from cadmium-60 on three different quantum dots. Those dots were of sizes 2.5, 3.3 and 6.3 nm, with central wavelength emitted on 480, 530 and 640 nm respectively. Quantum dots were produced from CdSe/ZnS material, obtained from company Sigma-Aldritch. It was shown, that with increasing concentration of QD's their resistance to the irradiation increases. Moreover, quantum dots with greater size are more resilient to the radiation than the smaller ones - the green dots are damaged more than red ones after being irradiated with the same dose. Another technique regarding measurement of radiation is by colloidal quantum dots (cQD's) - quantum dots synthesized and suspended in a liquid solution, forming a stable colloid. For one of the performed researches [61] authors used QD's consisting of core made of CdSe and shell of CdS/ZnS. The QD's were spherical, with size raging from 3 to 4 nm and emission peak in 610 nm. In this case, QD's were used only as a material, which was susceptible to radiation, with two different setups for measurement - first composed of additional plastic fiber, that guided light emitted from the cQD's into the CCD camera. In the second setup, cQD's were prepared in the form of liquid dispersions contained in glass recipients. In both cases, the elements containing cQDs were irradiated by Clinac iX linear accelerator with MV irradiation, and the CCD camera for signal collecting was placed away from the beam. The collected data showed, that signal obtained from cQD's was linear up to 400 kGy of irradiation, with mean R-test greater than 0.9999. With this research, it was deemed possible for setups with QDs to be used as a scintillating dosimeters – wide range of linearity of signal which is modeled by Gaussian curve. Although authors have met with some obstacles, in the form of Cherenkov component, that was created in the plastic fiber at 6 MV of radiation. This one however, can be removed during post-irradiation data analysis.

C. Conclusions

In conclusion, there exist promising potential for QDs as innovative dosimetry devices for ionizing radiation. Properties of QDs, including their size-dependent optical and electronic characteristics, and ability to generate measurable luminescent or electrical responses to radiation exposure, underscore their suitability for this application. Extensive experimental evidence demonstrates that QD-based systems can achieve accurate radiation detection making them a valuable tool for a wide range of fields requiring constant monitoring of the absorbed dose, for the health and safety of personnel. Although the technology comes with many advancements, it is important to note that many different challenges are yet to be met in order to integrate QD's - based systems in everyday use technology.

V. QIT IN DIGITAL TWINS

In today's fast-evolving field of digital simulation and predictive modeling, the concept of a digital twin is breaking new ground as a transformative technology that finds use across many sectors. At its heart, a digital twin serves as a virtual mirror of a physical system or process, capturing its real-world counterpart with remarkable fidelity inside a digital structure [62], [63]. This technology facilitates real-time monitoring, simulation, and control, which are essential in areas such as manufacturing, healthcare, and especially in precision agriculture through the deployment of Unmanned Aerial Vehicles (UAVs) [63], [64], [65]. The introduction of quantum computing adds a new layer to digital twins, known as Quantum Digital Twins (QDTs), integrating quantum algorithms to improve the processing and analytical abilities of these virtual models [66], [67], [68]. For UAVs employed in precision agriculture, QDTs hold the promise of substantially enhancing flight paths and navigation systems, crucial for activities like crop monitoring, spraying, and data collection. This chapter explores the fusion of quantum computing with digital twin technology, emphasizing its impact on UAV dynamics modeling, particularly in improving operational efficiency and predictive accuracy in complex and dynamic settings.

A. Quantum Computing Fundamentals

Quantum computing fundamentally differs from classical computing because it utilizes principles of quantum mechanics to process information [62], [68]. The primary unit of information is known as the quantum bit, or qubit, contrary to traditional binary bits, a qubit can exist in several states simultaneously due to a quantum characteristic known as superposition. This unique ability allows quantum computers to process numerous possibilities at once, significantly boosting their capacity for certain types of computational tasks. Another vital aspect of quantum computing is entanglement, a phenomenon where pairs or groups of qubits become so interconnected that the condition of one qubit can instantly affect the condition of others, no matter the physical distance separating them [69].This property is harnessed in quantum computing to link qubits in a way that enhances information processing capabilities. Moreover, quantum interference allows quantum computers to amplify correct paths or solutions while cancelling out paths that lead to incorrect answers. These capabilities make quantum computing particularly suited to solving optimization and simulation problems much more efficiently than classical computers. In the context of UAVs, the application of quantum computing could revolutionize how data from various sensors and real-time inputs are processed. Quantum algorithms can dramatically reduce the time required to compute optimal flight paths, navigate complex weather patterns, or avoid obstacles, thereby enhancing the UAV's autonomy and responsiveness.

B. Digital Twins in the Context of Quantum Computing

Digital twins, which are contemporary virtual representations of physical systems, have transformed predictive analytics, system monitoring, and optimization in numerous industries [64], [70]. At their essence, digital twins combine real-time data from sensors and various data sources with cutting-edge simulation technologies to construct dynamic, current models of physical objects or processes. These models facilitate accurate predictions and simulations, essential for enhancing operational efficiency and advancing product development [62]. Digital twins have revolutionized complex systems, ranging from small components like engines to large-scale infrastructures such as factories or entire cities. It also provide the ability to monitor and simulate production lines in real time, making possible to respond to disruptions or inefficiencies. For instance, in aerospace, digital twins of aircraft engines play a crucial role in predicting wear and tear, enabling better maintenance scheduling and reducing downtime effectively [71]. However, the complexity and computational demands of these simulations increase exponentially with the scale and intricacy of the systems involved. Traditional computing systems, while capable, often face limitations in processing power and speed, particularly with large-scale or highly detailed simulations [72].

C. Integrating Quantum Technology with Digital Twins

Quantum computing offers a transformative potential in handling the computational challenges faced by traditional digital twins. Quantum technologies utilize principles such as superposition and entanglement to perform calculations at speeds unattainable by classical computers, particularly for tasks involving optimization, simulation, and machine learning. In the realm of digital twins, the integration of quantum computing—forming what are referred to as Quantum Digital Twins (QDTs)—promises to enhance the capability of digital twins significantly. Quantum-enhanced digital twins can perform more complex simulations faster, manage larger datasets, and provide more accurate predictions in real-time [68]. For instance, in UAV dynamics modelling, a QDT could simulate numerous potential flight scenarios in a fraction of the time required by traditional methods. This capability is crucial for precision agriculture, where UAVs must adapt to constantly changing environmental conditions. Quantum computing could enable these UAVs to dynamically optimize flight paths and operational strategies, enhancing efficiency and effectiveness.

D. Practical Implementations

The integration of Quantum Digital Twins (QDTs) for UAV dynamics exemplifies the capability of quantum algorithms

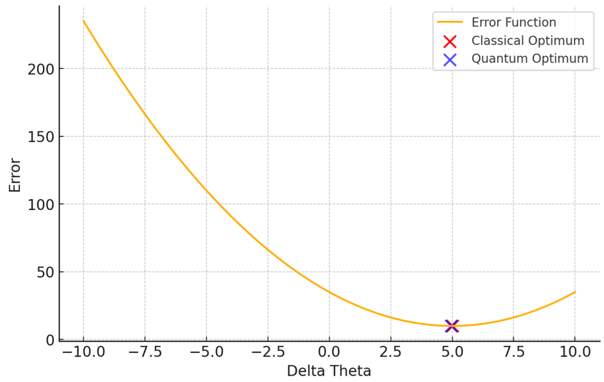

Fig. 2. Comparison of Classical and Quantum Optimization

in refining complex tasks within the digital twin framework. These examples illustrate the application of quantum computing to intricate challenges in UAV operations, such as minimizing error in flight path predictions and solving ordinary differential equations (ODEs) that model UAV dynamics.

1) Minimizing Error in Flight Path Predictions: The first case study employs the Quadratic Unconstrained Binary Optimization (QUBO) framework to enhance UAV control parameters, aiming to minimize prediction errors in flight paths [73]. The Quantum Approximate Optimization Algorithm (QAOA), implemented using Qiskit, optimizes settings that align with operational constraints to reduce prediction errors [74]. The QUBO problem formulation optimizes variables representing changes in speed, angle, and attack angle, with each assigned a specific weight reflecting its impact on the overall flight path error. The mathematical formulation for this optimization is:

$$E = \sum_{i=1}^{3} w_i x_i, \tag{1}$$

where x_i represents the control parameters (changes in speed, angle, and attack angle) and w_i are the weights assigned to each parameter. Solving this QUBO problem allows for the determination of the optimal adjustments to the UAV's control parameters, thereby enhancing the accuracy and reliability of the UAV's navigation systems. As an example on figure 2, it can be seen a simulation performed in QisKit, to demonstrate the applicability to optimize the angle of pitch based on elevator deflection.

2) Solving Ordinary Differential Equations Using Quantum Computing: The second case addresses the challenge of solving ODEs that describe UAV dynamics using a quantum computing approach. The dynamics are encoded into a Hamiltonian, represented by:

$$H = (X \otimes I) + (Y \otimes Y) + (Z \otimes Z), \tag{2}$$

where X, Y, and Z are the Pauli matrices, which are fundamental components in defining quantum operations. A quantum circuit is constructed to simulate this Hamiltonian, enabling the modelling of UAV behaviour under various flight conditions [69]. The circuit begins with an initial state representing the UAV's current state and evolves according to the specified Hamiltonian through quantum simulation techniques. This evolution facilitates the observation of potential flight behaviours and supports real-time adjustments to control strategies, essential for improving UAV operational efficiency and safety.

E. Conclusion

Quantum digital twins represent a transformative development in the digital and physical modelling of UAVs, offering enhanced capabilities for handling the complexities of real-time data and decision-making processes. As quantum hardware and algorithms continue to evolve, the potential for QDTs to significantly improve the efficiency and performance of UAVs in precision agriculture and beyond is immense. The practical implementations explored in this chapter underscore the transformative potential of quantum computing in revolutionizing traditional digital twin technologies for UAV dynamics. By enabling faster and more accurate simulations and solutions to complex optimization problems, quantum computing significantly enhances the capabilities of digital twins. As quantum hardware and algorithms continue to advance, the scope for Quantum Digital Twins (QDTs) to improve complex systems like UAVs in precision agriculture and beyond will expand, leading to greater operational efficiencies and more sophisticated applications. Future research should focus on developing robust quantum algorithms tailored for digital twin applications, improving quantum error correction techniques to enhance system reliability, and expanding quantum computing infrastructure to support larger-scale implementations, setting the stage for widespread adoption and technological evolution in this promising field.

VI. Quantum-enhanced optical biosensing

Quantum-enhanced optical biosensing represents a highly interdisciplinary field that integrates the principles of optics, optoelectronics, nanotechnology, nanomaterials and biotechnology to enable the study of biological systems at the nanoscale. This field focuses on the development, advancement and application of optical sensing platforms meant for investigation of biological entities — such as molecules, cells or tissues — with high sensitivity and in real time. The addition of quantum technologies offers the potential to overcome limitations of traditional sensing tools by leveraging various quantum effects to obtain more in-depth information. The need for novel, highly sensitive, and sustainable biodetection methods has become increasingly critical in light of global health challenges such as persistent environmental pollutants, the emergence of drug-resistant pathogens, and pandemics like the recent COVID-19 outbreak. Modern optical sensors typically rely on physical phenomena such as interference, refraction, photon scattering, and resonance to enhance sensitivity and specificity when analysing external media [75]. However, biological information in such media can be confined to small volumes, exists in low concentrations or even occur as interactions between single molecules. For optical systems to detect changes at sub-wavelength scales, labelled detection is often required. Labelled detection is a way of introducing signal transducers to the observed system that can be optically identified. At this point the integration of quantum technologies can significantly advance the capabilities of biodetection. By employing quantum tools such as quantum dots (QDs), nitrogen-vacancy centres in nanodiamonds (NV-NDs), and Förster Resonance Energy Transfer (FRET) is possible for quantum-enhanced optical biosensing systems to address key limitations of conventional techniques.

A. Quantum Dots

QDs are nanoscale semiconductor particles whose unique size-dependent fluorescence occurs from quantum confinement effects. Recent advancements have focused on the development of heavy-metal free QDs such as carbon quantum dots (CQDs). CQDs that exhibit reduced cytotoxicity compared to traditional QDs, which results in high biocompatibility. For instance, recent studies demonstrated the application of CQDs in rapid disease detection [76], as well as in miRNA-222 biosensing, where with the use of CQDs, the biosensor achieved a detection limit of 1.9 fM - an order of magnitude lower than that of conventional colorimetric approaches [77].

B. NDs

NV centres in nanodiamonds represent another promising quantum tool for biosensing. NV centres are atomic-scale defects in the diamond lattice that exhibit stable fluorescence emission. Changes to the charge state of these centres—from neutral to negatively charged—affect their spin state, which in turn affect fluorescence emission. This phenomenon allows NDs to act as highly sensitive quantum sensors, where their great magneto-optical properties and biocompatibility make them ideal for biosensing. A recent study demonstrated the NV-ND-based biosensor that has been developed for the ultra-rapid and selective detection and quantification of viral RNA of SARS-CoV-2 [78].

C. FRET

FRET is another powerful quantum-enhanced biosensing technique. It involves non-radiative energy transfer between an excited donor molecule and an acceptor molecule. Both of witch are positioned within 10 nm distance. Energy tranfer mechanism, resulting in radiative emission, enables the detection of previously unmeasurable molecular interactions in real time by using optical detection platforms. Recently, a novel two-step FRET biosensor was introduced for ratiometric detection of S. aureus bacteria in food samples, achieving an ultra-low detection limit of 1 CFU/mL. This two-step approach utilised two dyes to eliminate concerns of false-positive results that are common in single-donor FRET systems.

VII. Example of quantum technologies in space segment

The space segment is usually a great opportunity and has many possibilities for research in any field. This time, quantum technology comes in front. Nowadays, quantum technology is used in many research cases and in many areas. There is still much to explore and learn. Some of the most popular, regarding space, are quantum communication, quantum sensing, and quantum computers. The development of these cases is still ongoing despite many challenges, such as cosmic radiation, size, energy and resource requirements, and costs.

A. *Quantum Key Distribution [79] [80]*

Constant growth in technology requires more efficient and more secure ways of communication. By efficiency, people can see the time to deliver the transmission to the destination or the bandwidth needed to take a message. As the research is expanding all over the Earth, the idea is to go beyond and include space objects in the transmissions. Quantum communications are also used in the space segment and now have positive perspectives. Quantum Key Distribution is a communication method that assures the security of transmissions. It uses the principles of quantum mechanics to transmit cryptographic keys securely. The communication is similar to the classical encrypted way, so there is a sender, receiver, encryptor, decryptor, message, and the key required to decode the message. The key is distributed in public channels but with the involvement of quantum technology. By quantum domain, the key is distributed from source to destination. This ensures the speed and security of the key's transmission. Security is provided by a simple quantum principle – whoever eavesdrops on the quantum channel changes its internal states. In this way, any attempt to look at the transmission would not provide information from the original message. Many agencies are now at the end of their research to launch the first prototypes in the near future.

B. *Quantum sensing [81] [82] [83]*

A constant need for knowledge about the Earth is required to provide health and compatibility with natural life. From space, people can have an inside view of the globe and constantly examine it. In space research regarding Earth, many sensors could be used. These sensors use quantum phenomena such as superposition and entanglement to achieve extremely high precision in measuring physical quantities. They can be divided into types:

- Quantum magnetometers – measurement of the magnetic field of the Earth and space
- Quantum accelerometers – measurement of accelerations, which is important in GPS-free navigation
- Quantum gravimeters – mapping Earth's gravitational field

These sensors have many possible applications:

- Monitoring climate change (tracking changes in the masses of glaciers and ocean waters, studying sea levels)
- Geodesy and mapping (creating precise gravity maps, locating natural resources)
- Studying gravitational waves (quantum sensors on satellites can increase the sensitivity of gravitational waves from deep space)
- Navigation (precise navigation systems without the need for GPS communication)

The last case is quite interesting since the aviation sector recently suffered from GPS jamming and spoofing [84]. Typical usage of these sensors onboard airplanes could be reliving in such cases.

C. *Quantum computers*

The constant growth of collected data from any kind of receiver requires huge computing potential to process this information. The space segment is nothing different. On satellites, quantum computers would enable fast data processing, for example, processing data from space telescopes or optimizing satellite trajectories. Quantum computers would also accelerate simulations conducted in space.

D. *Conclusion on the quantum space segment*

Many use cases of quantum technology in the space segment were discussed. The use of QKD technology on satellites would provide a better level of data security. Quantum sensors will enable precise studies of climate, geology, and gravitational waves, allowing for a better understanding of Earth. Quantum computing has the potential to revolutionize the analysis of scientific data and the optimization of space missions.

VIII. Discussion, Conclusions

Quantum Computing has the potential to deeply affect multiple domains. In this paper the authors, who are PhD students in diverse fields, tried to take a fresh look at the possible applications of Quantum Technologies in their research areas. This resulted in multiple views on the subject as well as some ideas which may lead to further research work.

References

[1] "Wetterstrand ka. dna sequencing costs: Data from the nhgri genome sequencing program (gsp)," www.genome.gov/sequencingcostsdata, accessed: 2024-12-01.

[2] E. Lieberman-Aiden, N. L. van Berkum, L. Williams, M. Imakaev, T. Ragoczy, A. Telling, I. Amit, B. R. Lajoie, P. J. Sabo, M. O. Dorschner, R. Sandstrom, B. Bernstein, M. A. Bender, M. Groudine, A. Gnirke, J. Stamatoyannopoulos, L. A. Mirny, E. S. Lander, and J. Dekker, "Comprehensive mapping of long-range interactions reveals folding principles of the human genome," *Science*, vol. 326, no. 5950, pp. 289–293, 2009. [Online]. Available: https://www.science.org/doi/abs/10.1126/science.1181369

[3] C. H. Bennett, E. Bernstein, G. Brassard, and U. Vazirani, "Strengths and weaknesses of quantum computing," *SIAM Journal on Computing*, vol. 26, no. 5, pp. 1510–1523, 1997. [Online]. Available: https://doi.org/10.1137/S0097539796300933

[4] A. J. da Silva, T. B. Ludermir, and W. R. de Oliveira, "Quantum perceptron over a field and neural network architecture selection in a quantum computer," *Neural Networks*, vol. 76, pp. 55–64, 2016. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0893608016000034

[5] M. Schuld, I. Sinayskiy, and F. Petruccione, "The quest for a quantum neural network," *Quantum Information Processing*, vol. 13, no. 11, pp. 2567–2586, Nov 2014. [Online]. Available: https://doi.org/10.1007/s11128-014-0809-8

[6] J. R. McClean, S. Boixo, V. N. Smelyanskiy, R. Babbush, and H. Neven, "Barren plateaus in quantum neural network training landscapes," *Nature Communications*, vol. 9, no. 1, p. 4812, 2018. [Online]. Available: https://doi.org/10.1038/s41467-018-07090-4

[7] R. T. Q. Chen, Y. Rubanova, J. Bettencourt, and D. Duvenaud, "Neural ordinary differential equations," in *Proceedings of the 32nd International Conference on Neural Information Processing Systems*, ser. NIPS'18. Red Hook, NY, USA: Curran Associates Inc., 2018, p. 6572–6583.

[8] D. W. Berry, "High-order quantum algorithm for solving linear differential equations," *Journal of Physics A: Mathematical and Theoretical*, vol. 47, no. 10, p. 105301, feb 2014. [Online]. Available: https://dx.doi.org/10.1088/1751-8113/47/10/105301
[9] A. W. Harrow, A. Hassidim, and S. Lloyd, "Quantum algorithm for linear systems of equations," *Phys. Rev. Lett.*, vol. 103, p. 150502, Oct 2009. [Online]. Available: https://link.aps.org/doi/10.1103/PhysRevLett.103.150502
[10] S. Lloyd, G. D. Palma, C. Gokler, B. Kiani, Z.-W. Liu, M. Marvian, F. Tennie, and T. Palmer, "Quantum algorithm for nonlinear differential equations," 2020. [Online]. Available: https://arxiv.org/abs/2011.06571
[11] J.-P. Liu, H. Øie Kolden, H. K. Krovi, N. F. Loureiro, K. Trivisa, and A. M. Childs, "Efficient quantum algorithm for dissipative nonlinear differential equations," *Proceedings of the National Academy of Sciences*, vol. 118, no. 35, p. e2026805118, 2021. [Online]. Available: https://www.pnas.org/doi/abs/10.1073/pnas.2026805118
[12] A. L. Blum and R. L. Rivest, "Training a 3-node neural network is np-complete," *Neural Networks*, vol. 5, no. 1, pp. 117–127, 1992. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0893608005800103
[13] B. D. Haeffele and R. Vidal, "Global optimality in neural network training," in *2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2017, pp. 4390–4398.
[14] S. Agostinelli, J. Allison, K. Amako, J. Apostolakis, H. Araujo, P. Arce, M. Asai, D. Axen, S. Banerjee, G. Barrand *et al.*, "Geant4—a simulation toolkit," *Nuclear instruments and methods in physics research section A: Accelerators, Spectrometers, Detectors and Associated Equipment*, vol. 506, no. 3, pp. 250–303, 2003.
[15] J. Dubiński, K. Deja, S. Wenzel, P. Rokita, and T. Trzciński, "Machine learning methods for simulating particle response in the zero degree calorimeter at the alice experiment, cern," in *AIP Conference Proceedings*, vol. 3061, no. 1. AIP Publishing, 2024.
[16] M. Paganini, L. de Oliveira, and B. Nachman, "Accelerating science with generative adversarial networks: An application to 3d particle showers in multilayer calorimeters," *Physical Review Letters*, vol. 120, no. 4, Jan. 2018. [Online]. Available: http://dx.doi.org/10.1103/PhysRevLett.120.042003
[17] K. Deja, T. Trzciński, and Ł. Graczykowski, "Generative models for fast cluster simulations in the tpc for the alice experiment," in *Information Technology, Systems Research, and Computational Physics*. Springer, 2019, pp. 267–280.
[18] A. Radovic, M. Williams, D. Rousseau, M. Kagan, D. Bonacorsi, A. Himmel, A. Aurisano, K. Terao, and T. Wongjirad, "Machine learning in high energy physics community white paper," *Journal of Physics G: Nuclear and Particle Physics*, vol. 46, no. 6, p. 063001, 2019.
[19] D. P. Kingma and M. Welling, "Auto-encoding variational bayes," *arXiv preprint arXiv:1312.6114*, 2013.
[20] I. Goodfellow, J. Pouget-Abadie, M. Mirza, B. Xu, D. Warde-Farley, S. Ozair, A. Courville, and Y. Bengio, "Generative adversarial nets," in *Advances in Neural Information Processing Systems*, 2014, pp. 2672–2680.
[21] J. Sohl-Dickstein, E. A. Weiss, N. Maheswaranathan, and S. Ganguli, "Deep unsupervised learning using nonequilibrium thermodynamics," in *Proceedings of the 32nd International Conference on Machine Learning*, 2015, pp. 2256–2265.
[22] D. J. Rezende and S. Mohamed, "Variational inference with normalizing flows," in *Proceedings of the 32nd International Conference on Machine Learning*, 2015, pp. 1530–1538.
[23] E. Buhmann, S. Diefenbacher, E. Eren, F. Gaede, G. Kasieczka, A. Korol, and K. Krüger, "Getting high: High fidelity simulation of high granularity calorimeters with high speed," *Computing and Software for Big Science*, vol. 5, no. 1, p. 13, 2021. [Online]. Available: https://doi.org/10.1007/s41781-021-00056-0
[24] S. Diefenbacher, E. Eren, F. Gaede, G. Kasieczka, A. Korol, K. Krüger, P. McKeown, and L. Rustige, "New angles on fast calorimeter shower simulation," 2023. [Online]. Available: https://arxiv.org/abs/2303.18150
[25] K. Rogoziński, J. Dubiński, P. Rokita, and K. Deja, "Particle physics dl-simulation with control over generated data properties," *arXiv preprint arXiv:2405.14049*, 2024. [Online]. Available: https://arxiv.org/abs/2405.14049
[26] K. Deja, J. Dubiński, P. Nowak, S. Wenzel, and T. Trzciński, "End-to-end sinkhorn autoencoder with noise generator," *arXiv preprint arXiv:2006.06704*, 2020. [Online]. Available: https://arxiv.org/abs/2006.06704
[27] J. N. Howard, S. Mandt, D. Whiteson, and Y. Yang, "Learning to simulate high energy particle collisions from unlabeled data," *Scientific Reports*, vol. 12, no. 1, May 2022. [Online]. Available: http://dx.doi.org/10.1038/s41598-022-10966-7
[28] CMS Collaboration, "Gan-based simulation of cms detector response," CERN, Preprint, 2019.
[29] G. R. Khattak, S. Vallecorsa, F. Carminati *et al.*, "Fast simulation of a high granularity calorimeter by generative adversarial networks," *European Physical Journal C*, vol. 82, p. 386, 2022.
[30] J. Dubiński, K. Deja, S. Wenzel, P. Rokita, and T. Trzciński, "Selectively increasing the diversity of gan-generated samples," in *International Conference on Neural Information Processing*. Springer, 2020, pp. 260–270.
[31] P. Bedkowski, J. Dubiński, K. Deja, and P. Rokita, "Deep generative models for proton zero degree calorimeter simulations in alice, cern," *arXiv preprint arXiv:2406.03263*, 2024. [Online]. Available: https://arxiv.org/abs/2406.03263
[32] O. Amram and K. Pedro, "Denoising diffusion models with geometry adaptation for high fidelity calorimeter simulation," *Phys. Rev. D*, vol. 108, no. 7, p. 072014, 2023.
[33] P. Devlin, J.-W. Qiu, F. Ringer, and N. Sato, "Diffusion model approach to simulating electron-proton scattering events," *Phys. Rev. D*, vol. 110, p. 016030, Jul 2024. [Online]. Available: https://link.aps.org/doi/10.1103/PhysRevD.110.016030
[34] M. Kita, J. Dubiński, P. Rokita, and K. Deja, "Generative diffusion models for fast simulations of particle collisions at cern," *arXiv preprint arXiv:2406.03233*, 2024. [Online]. Available: https://arxiv.org/abs/2406.03233
[35] C. Jiang, S. Qian, and H. Qu, "Choose your diffusion: Efficient and flexible ways to accelerate the diffusion model in fast high energy physics simulation," *arXiv preprint arXiv:2401.13162*, 2024.
[36] M. Wojnar, "Applying generative neural networks for fast simulations of the alice (cern) experiment," *arXiv preprint arXiv:2407.16704*, 2024.
[37] S. Schnake, D. Krücker, and K. Borras, "Calopointflow ii generating calorimeter showers as point clouds," *arXiv preprint arXiv:2403.15782*, 2024.
[38] E. Buhmann, C. Ewen, D. A. Faroughy, T. Golling, G. Kasieczka, M. Leigh, G. Quétant, J. A. Raine, D. Sengupta, and D. Shih, "Epic-ly fast particle cloud generation with flow-matching and diffusion," *arXiv preprint arXiv:2310.00049*, 2023.
[39] J. Wu, H. Fu, M. Zhu, H. Zhang, W. Xie, and X.-Y. Li, "Quantum circuit autoencoder," *Physical Review A*, vol. 109, no. 3, Mar. 2024. [Online]. Available: http://dx.doi.org/10.1103/PhysRevA.109.032623
[40] C. Zoufal, A. Lucchi, and S. Woerner, "Quantum generative adversarial networks for learning and loading random distributions," *npj Quantum Information*, vol. 5, p. 103, 2019. [Online]. Available: https://doi.org/10.1038/s41534-019-0223-2
[41] A. Cacioppo, L. Colantonio, S. Bordoni, and S. Giagu, "Quantum diffusion models," 2023. [Online]. Available: https://arxiv.org/abs/2311.15444
[42] S. Lawrence, A. Shelby, and Y. Yamauchi, "Quantum states from normalizing flows," 2024. [Online]. Available: https://arxiv.org/abs/2406.02451
[43] S. Hoque, H. Jia, A. Abhishek, M. Fadaie, J. Q. Toledo-Marín, T. Vale, R. G. Melko, M. Swiatlowski, and W. T. Fedorko, "Caloqvae: Simulating high-energy particle-calorimeter interactions using hybrid quantum-classical generative models," *arXiv preprint*, 2023. [Online]. Available: https://arxiv.org/abs/2305.07284
[44] F. Rehm, S. Vallecorsa, M. Grossi, K. Borras, and D. Krücker, "A full quantum generative adversarial network model for high energy physics simulations," *arXiv preprint*, 2023. [Online]. Available: https://arxiv.org/abs/2305.07284
[45] S. Y. Chang, S. Herbert, S. Vallecorsa, and E. Combarro, "Quantum generative adversarial networks in a high energy physics context," *CERN Document Server*, 2023. [Online]. Available: https://cds.cern.ch/record/2751529
[46] C. Bravo-Prieto, J. Baglio, M. Cè, A. Francis, D. M. Grabowska, and S. Carrazza, "Style-based quantum generative adversarial networks for monte carlo events," *arXiv preprint*, 2023. [Online]. Available: https://arxiv.org/abs/2110.06933
[47] A. Cacioppo, L. Colantonio, S. Bordoni, and S. Giagu, "Quantum diffusion models for quantum data learning in high-energy physics," *Quantum Information*, 2024, presented at QTML 2024. [Online]. Available: https://arxiv.org/abs/2311.15444
[48] A. Alonso, S. Carrazza, and S. Lammel, "Quantum machine learning in the atlas experiment at cern," *Proceedings of Science*, vol. ICHEP2020, p. 505, 2020.

[49] L. Nagano, A. Miessen, T. Onodera, I. Tavernelli, F. Tacchino, and K. Terashi, "Quantum data learning for quantum simulations in high-energy physics," *Physical Review Research*, vol. 5, no. 4, p. 043250, 2023.

[50] S. Y. Chang, S. Herbert, S. Vallecorsa, E. F. Combarro, and R. Duncan, "Dual-parameterized quantum circuit gan model in high energy physics," *arXiv preprint arXiv:2103.15470*, 2021.

[51] O. Kiss, M. Grossi, E. Kajomovitz, and S. Vallecorsa, "Conditional born machine for monte carlo event generation," *Physical Review A*, vol. 106, no. 2, p. 022612, 2022.

[52] M. D. Insights, "Potential and challenges of quantum computing hardware technologies," 2021. [Online]. Available: https://www.mckinsey.com/capabilities/mckinsey-digital/our-insights/tech-forward/potential-and-challenges-of-quantum-computing-hardware-technologies

[53] Q. C. R. Group, "Decoherence in noisy intermediate-scale quantum devices," *arXiv preprint*, 2022. [Online]. Available: https://arxiv.org/abs/2201.08047

[54] R. C. on Hybrid Systems, "Challenges in integrating hybrid quantum-classical systems," *arXiv preprint*, 2022. [Online]. Available: https://arxiv.org/abs/2203.05567

[55] Q. M. L. R. Group, "Training quantum models on high-dimensional data," *arXiv preprint*, 2022. [Online]. Available: https://arxiv.org/abs/2204.07789

[56] G. S. S. e. a. Sahil, Natanasabapathi, "Study of dosimetric properties of lib3o5:ag using the osl/ta-osl method for medical radiation application," *J. Electron. Mater.*, 2024. [Online]. Available: https://doi.org/10.1007/s11664-024-11544-5

[57] J. I. K. J. L. Pradhan, A. S.; Lee, "Recent developments of optically stimulated luminescence materials and techniques for radiation dosimetry and clinical applications." *Journal of Medical Physics*, vol. 33(3), pp. 85–99, 2008. [Online]. Available: 10.4103/0971-6203.42748

[58] L. Kouwenhoven and C. Marcus, "Quantum dots," *Physics World*, vol. 11, p. 35, 1998. [Online]. Available: 10.1088/2058-7058/11/6/26

[59] W. S. Shi Ying Lim and Z. Gao, "Carbon quantum dots and their applications," *Chem. Soc. Rev*, vol. 44, pp. 362–381, 2014. [Online]. Available: 10.1039/C4CS00269E

[60] L. D. E. . S. D. R. Hobson, P. R., "Effect of gamma radiation on potential ionising radiation detectors and dosimeters based on quantum dots," *IEEE Nuclear Science Symposium Conference Record*, 2011.

[61] D. L. C. N. A. Marie-Ève Delage, Marie-Ève Lecavalier and L. Beaulieu, "Dosimetric properties of colloidal quantum dot-based systems for scintillation dosimetry," *Phys. Med. Biol*, vol. 64, pp. 362–381, 2019.

[62] M. Amir, C. Bauckhage, A. Chircu, C. Czarnecki, C. Knopf, N. Piatkowski, and E. Sultanow, "What can we expect from quantum (digital) twins?" [Online]. Available: https://aisel.aisnet.org/wi2022/workshops/workshops/15

[63] Q. Qi, F. Tao, T. Hu, N. Anwer, A. Liu, Y. Wei, L. Wang, and A. Y. C. Nee, "Enabling technologies and tools for digital twin," vol. 58, pp. 3–21. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S027861251930086X

[64] Y. Yang, W. Meng, and S. Zhu, "A digital twin simulation platform for multi-rotor UAV," in *2020 7th International Conference on Information, Cybernetics, and Computational Social Systems (ICCSS)*, pp. 591–596, ISSN: 2639-4235. [Online]. Available: https://ieeexplore.ieee.org/abstract/document/9336872

[65] Quality evaluation of digital twins generated based on UAV photogrammetry and TLS: Bridge case study. [Online]. Available: https://www.mdpi.com/2072-4292/13/17/3499

[66] Z. Lv, C. Cheng, and H. Song, "Digital twins based on quantum networking," vol. 36, no. 5, pp. 88–93, conference Name: IEEE Network. [Online]. Available: https://ieeexplore.ieee.org/abstract/document/9963997

[67] Digital twin—the simulation aspect. [Online]. Available: https://www.researchgate.net/publication/303900830_Digital_Twin-The_Simulation_Aspect

[68] M. Schuld, I. Sinayskiy, and F. Petruccione, "An introduction to quantum machine learning," vol. 56, no. 2, pp. 172–185, publisher: Taylor & Francis _eprint: https://doi.org/10.1080/00107514.2014.964942. [Online]. Available: https://doi.org/10.1080/00107514.2014.964942

[69] A. Barthe, M. Grossi, J. Tura, and V. Dunjko, "Continuous variables quantum algorithm for solving ordinary differential equations," in *2023 IEEE International Conference on Quantum Computing and Engineering (QCE)*, vol. 02, pp. 48–53. [Online]. Available: https://ieeexplore.ieee.org/document/10313758/?arnumber=10313758

[70] Z. Qu, Y. Li, B. Liu, D. Gupta, and P. Tiwari, "DTQFL: A digital twin-assisted quantum federated learning algorithm for intelligent diagnosis in 5g mobile network," pp. 1–10, conference Name: IEEE Journal of Biomedical and Health Informatics. [Online]. Available: https://ieeexplore.ieee.org/abstract/document/10210652

[71] U. Kumari and P. Malhotra, "Use of digital twin in predicting the life of aircraft main bearing," in *Simulation Techniques of Digital Twin in Real-Time Applications*. John Wiley & Sons, Ltd, pp. 261–288. [Online]. Available: https://onlinelibrary.wiley.com/doi/abs/10.1002/9781394257003.ch12

[72] Digital twin framework for aircraft lifecycle management based on data-driven models. [Online]. Available: https://www.mdpi.com/2227-7390/12/19/2979

[73] E. Boros, P. L. Hammer, R. Sun, and G. Tavares, "A max-flow approach to improved lower bounds for quadratic unconstrained binary optimization (QUBO)," vol. 5, no. 2, pp. 501–529. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1572528607000400

[74] M. Maronese, L. Moro, L. Rocutto, and E. Prati, "Quantum compiling," in *Quantum Computing Environments*, S. S. Iyengar, M. Mastriani, and K. L. Kumar, Eds. Springer International Publishing, pp. 39–74. [Online]. Available: https://doi.org/10.1007/978-3-030-89746-8_2

[75] X. Li, N. Chen, X. Zhou, P. Gong, S. Wang, Y. Zhang, and Y. Zhao, "A review of specialty fiber biosensors based on interferometer configuration," *Journal of Biophotonics*, vol. 14, no. 6, p. e202100068, 2021. [Online]. Available: https://onlinelibrary.wiley.com/doi/abs/10.1002/jbio.202100068

[76] V. Pilla, S. R. de Lima, A. A. Andrade, A. C. Silva, and N. O. Dantas, "Fluorescence quantum efficiency of cdse/cds magic-sized quantum dots functionalized with carboxyl or hydroxyl groups," *Chemical Physics Letters*, vol. 580, pp. 130–134, 2013. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0009261413008671

[77] Y. Zhong, L.-X. Huang, M.-T. Lin, Z.-Y. Zhang, A.-L. Liu, and Y. Lei, "A y-shape-structured electrochemiluminescence biosensor based on carbon quantum dots and locked nucleic acid probe for microrna determination with single-base resolution," *Biosensors and Bioelectronics*, vol. 238, p. 115583, 2023. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0956566323005250

[78] C. Li, R. Soleyman, M. Kohandel, and P. Cappellaro, "Sars-cov-2 quantum sensor based on nitrogen-vacancy centers in diamond," *Nano Letters*, vol. 22, no. 1, pp. 43–49, Jan 2022. [Online]. Available: https://doi.org/10.1021/acs.nanolett.1c02868

[79] J. e. a. Yin, "Satellite-based entanglement distribution over 1200 kilometers," *Science*, 2017. [Online]. Available: https://doi.org/10.1126/science.aan3211

[80] S.-K. e. a. Liao, "Satellite-relayed intercontinental quantum network," *Physical Review Letters*, 2018. [Online]. Available: https://doi.org/10.1103/PhysRevLett.120.030501

[81] Quantum technology: Sensing and imaging. [Online]. Available: https://researchcentre.army.gov.au/library/land-power-forum/quantum-technology-sensing-and-imaging

[82] F. R. Cardoso, D. Z. Rossatto, G. P. L. M. Fernandes, G. Higgins, and C. J. Villas-Boas, "Superposition of two-mode squeezed states for quantum information processing and quantum sensing," *Physical Review A*, 2021. [Online]. Available: https://doi.org/10.1103/PhysRevA.103.062405

[83] B. Kantsepolsky, I. Aviv, R. Weitzfeld, and E. Bordo, "Exploring quantum sensing potential for systems applications," *IEEE Access*, vol. 11, pp. 31 569–31 582, 2023.

[84] J. Steiner and P. Lukeš, "Wide-area gps interference over europe from an unknown source," in *2022 New Trends in Civil Aviation (NTCA)*, 2022, pp. 51–55.