bitkom

Future Computing

Overview of Technological Landscape
(Executive Version)

Inhalt

Introduction

Nowadays progress in society, science, and technology is closely linked to the advances in IT and computing technologies. From healthcare to finance, transportation to manufacturing, agriculture to chemical industry: computing technologies affect almost every aspect of the modern economy. With the increasing complexity of problems, we seek to solve, as well as environmental impact of these technologies, there is a growing need for accessible, scalable, and more powerful computing that is also energy efficient.

For over 60 years, progress in computing power was driven by Moore's Law, which states that the number of transistors on a microprocessor chip doubles every two years. Today, though, we are approaching the physically defined limitations of this law and it is becoming increasingly difficult to double computing power every two years. As a result, experts are discussing various computational concepts, architectures and platforms that could – in the mid and long term – further expand the boundaries of modern computing.

In this paper we provide an overview of some of the most prominent technological approaches that promise to expand the current computing landscape by offering advantages in terms of computing power scaling, energy efficiency and applicability to a new range of problems. This includes new computing concepts such as quantum or neuromorphic computing as well as new computing platforms such as optical or chemical computing.

It is important to note that all future computing concepts utilize at least one new approach on these levels of abstraction:

- New basic concepts of computation e. g. based on quantum effects, based on principles of information processing inspired in the brain, based on non-deterministic emergent effects or on the dynamics of chemical reactions. Each of these directions also requires new computer hardware architectures.
- New platforms or information carriers: Some of these approaches require entirely new classes of devices e. g. molecule sensors in chemical computing, but most approaches can improve existing devices in a novel way (e. g. analog CMOS for neuromorphic computing or photonics for optical and quantum computing).

Although each approach has its unique strengths and challenges, it is anticipated that the potential benefits will result from combining various technologies in an efficient manner. This paper will explore technological approaches across different levels of abstraction. However, providing a comprehensive description of every conceivable computing approach is beyond the scope of this paper.

Our goal is to offer guidance to anyone who seeks to gain a better understanding of the currently emerging computing landscape and to help evaluate these approaches based on potential benefits for businesses in the future.

How to read this document

In this paper, we categorize each future computing approach according to the framework presented below.

- **Short description:** An overview of the respective computing approach and functionality, including an estimation of the current technology readiness level (TRL).
- **Benefits:** Potential benefits of the technology as compared to classical digital computing available today.
- **Limitations:** Inherent theoretical or physical limitations of the approach, e. g. in terms of problems classes the technology can address.
- **Applications and Use-Cases:** Applications denote potential usage domains. A Use-Case is ademonstrated proof-of-concept or an implemented solution (when available).
- **Physical Area of Use:** We differentiate between three main deployment and consumption options of the technology: cloud-based, on-premises, or edge computing.
- **Development Challenges: Existing** technological challenges which needs to be overcome for a practical and industrial use of the technology

At the end of the paper, we provide a curated list of resources for further reading on each specific approach.

As this paper represents a condensed executive version of our more elaborate «Future Computing» report, the reader is referred to the full-length version for a more in-depth analysis, including a comprehensive list of attributes and more detailed descriptions.

List of used abbreviations

- ASIC - Application-specific integrated circuit
- AI - Artificial Intelligence
- CMOS – Complementary metal-oxide-semiconductor
- CPU – Central processing unit
- DNA – Deoxyribonucleic acid
- DNN – Deep neural network
- EU – European Union
- FPGA – Field-programmable gate array
- GPU – Graphic processing unit
- IC – Integrated Circuit
- IMC – In-memory computing
- IMP – In-memory processing
- MB – Megabyte. 1 MB = 1,024 kilobytes (kB) = 1, 048,576 bytes
- ML – Machine learning
- nm – Nanometer. 1 nm = 10^{-9} m
- PIC – Photonic integrated circuit
- PIM – Processing in memory
- QC – Quantum Computing
- QUBO – Quadratic unconstrained binary optimization
- RAM – Random Access Memory
- RNA – Ribonucleic acid
- RSA – Rivest–Shamir–Adleman, a public-key cryptosystem
- TRL – Technology readiness level
- VMM – vector matrix multiplication

Technology readiness levels

The Technology Readiness Level (TRL) scale was introduced into the EU funded projects arena in 2014 as part of the Horizon 2020 framework program[1]. This document uses the same scale with the following definitions:

- **TRL 1** – basic principles observed
- **TRL 2** – technology concept formulated
- **TRL 3** – experimental proof of concept
- **TRL 4** – technology validated in lab
- **TRL 5** – technology validated in relevant environment (industrially relevant environment in the case of key enabling technologies)
- **TRL 6** – technology demonstrated in relevant environment (industrially relevant environment in the case of key enabling technologies)
- **TRL 7** – system prototype demonstration in operational environment
- **TRL 8** – system complete and qualified
- **TRL 9** – actual system proven in operational environment (competitive manufacturing in the case of key enabling technologies or in space)

[1] TRL Scale in Horizon Europe and ERC - explained - Enspire Science Ltd.

Technology		TRL	Benefits	Limitations	Applications	Area of Use	Challenges
Quantum Computing (QC)		0 – 6[2]	▪ Solving bigger, more complex problems ▪ Handling more data ▪ High energy efficiency	▪ Limited stability ▪ Not a universal computer ▪ No universal advantage	▪ Optimization ▪ Forecasting, scenario modelling ▪ Chemical simulation	▪ Cloud ▪ On-premises ▪ Edge	▪ Hardware scaling ▪ Identifying business-relevant problems ▪ Integration with classical computing ▪ Quantum storage
Neuromorphic Computing		2 – 7[3]	▪ High energy efficiency ▪ High processing speed ▪ Robustness	▪ Not efficiently representing numbers ▪ Based on incomplete approximations of the brain	▪ Medicine ▪ Computer vision ▪ Autonomous robots and self-driving cars	▪ Edge ▪ Cloud	▪ Distributing memory among multiple processors on a chip ▪ Scalable messaging and interconnect architectures ▪ New algorithms, software and design tools
Optical Computing	**Analog**	7	▪ Extremely parallelizable ▪ Ultra-low power consumption and low latency ▪ Mature fabrication nodes	▪ Power loss during electronic-optical conversions	▪ Deep learning ▪ Data encryption	▪ Cloud ▪ Edge	▪ Large area footprint ▪ Scaling
	Digital	4		▪ Intrinsically low light-light interaction hinders operation	▪ General use	▪ Cloud ▪ On-premises	▪ Alternative architectures needed ▪ Chip integration and material development ▪ Optical memory
Digital Annealing		9	(As compared to QC) ▪ Full connectivity among bits ▪ High precision in problem formulation ▪ Large problem sizes solvable ▪ No special environment needed	▪ Restricted to combinatorial optimization problems ▪ Close to optimal solution, no guarantee for the global optimum	▪ Traffic flow optimization ▪ Drug design ▪ Portfolio optimization ▪ Production planning	▪ Cloud ▪ On-premises	▪ Not every combinatorial optimization problem is suited ▪ Additional resources to formulate problems with higher order polynomials
DNA Computing		3 – 4	▪ Extremely parallelizable ▪ High energy efficiency ▪ High storage density (for DNA storage)	▪ Low signal propagation speed (hours) ▪ Weak scaling ▪ Propensity for discrete problems	▪ Combinatorial problems, search, scheduling, clustering ▪ Cryptography and intrusion detection	▪ Cloud	▪ Large-scale parallelization to compensate for slow signal propagation ▪ Lowering the operation costs ▪ Mapping business problems

[2] TRL depends on the physical realization of qubits (highest is for superconducting qubits)

[3] Differs for neuromorphic chips used for inference (TRL 6 – 7) and training (TRL 2 – 4)

1 Quantum Computing

Dr. Jannis Ehrlich (Fraunhofer IWM),
Dr. Oliver Oberst (IBM), Dr. Christoph
F. Strnadl (Software AG)

1.1 Short Description

Quantum computing (QC) is computing based on direct manipulations of quantum systems by discretely transforming their respective quantum states[4]. Instead of bits with just the two states »0« or »1«, present in classical computers, quantum computers use qubits which can have any state in between.

A quantum computer is a statistical computer which returns the results of a (quantum) algorithm according to a certain probability distribution corresponding to the quantum state measured. Thus, the same instructions must be run many times to obtain a reasonable statistic for the »correct« (intended) result.

Like classical computing, QC comprises hardware, software, and quantum algorithms.

As of today, many different physical realizations of quantum computers utilizing various hardware platforms, including e. g. ion traps, superconducting circuits, neutral atom arrays, various solid-state approaches, optical quantum computing etc. The question of the most economic quantum computing »hardware« has yet to be answered. Technology Readiness Level strongly depends on the qubit realization technology, varying between 0 to 6 (7 being the demonstration of »quantum advantage«).

1.2 Benefits

Quantum computing offers the promise of identifying and executing suitable (quantum) algorithms with significantly better scaling in problem size than classical computers. This allows computations on much more data and the solution to problems that are out of reach for classical computers.

Furthermore, some quantum algorithms may provide a significant (polynomial or, in cases, even exponential) speed-up over conventional algorithms (i. e., dramatically reduced execution times). This feature of QC will widen the problem space towards more complex and longer-lasting algorithms including more data, larger systems, finer resolution, and better accuracy. Besides, being »green« by physical principles quantum computing offers the potential for significant energy savings compared to classical computing.

1.3 Limitations

- **Quantum computing does not extend the limits of computability**: It cannot compute what classical computers cannot – albeit much slower – compute.

[4] adapted after N.D. Mermin 2007, *Quantum Computer Science*.

- **Limited stability:** Quantum computers easily interact with their environment in uncontrollable ways, which can alter or destroy the quantum state and the information stored in it.
- **Not a universal computer**: While quantum computers can outperform classical computers in certain types of computations, classical computers may still be better suited for many tasks.
- **No universal quantum advantage exists**: While quantum computers have the potential to provide significant speedups for certain types of problems, this advantage does not apply to all conceivable algorithms or problems.

1.4 Applications

- **Optimization**: financial analysis, portfolio optimization, traffic routing, logistics, resource management[5]
- **Forecasting and scenario modelling**: risk, weather, traffic patterns, scenarios such as the impact of natural disasters or spread of a virus in a population[6]
- **Simulation:** atomistic simulations of materials and dynamics of chemical reactions (materials science, drug discovery)
- **Further special algorithms**: quantum machine learning[7], quantum AI, quantum multi-agent systems, quantum chemistry, high energy physics
- **Cryptography**: factoring large numbers for breaking RSA encryption

1.5 Physical Area of Use

- **Cloud:** Most organizations will use services offered by third-party providers accessed over the public Internet.
- **On-premises:** Option for organizations with dedicated capabilities, specialized requirements and sufficient financial resources (research centers, universities, military and defense, public administration, banks).
- **Edge** (Mobile) approaches are developed allowing for smaller quantum computing systems to be administered with reasonable effort.

1.6 Development Challenges

- **Hardware scaling**: Even though typical quantum algorithms only need a small number of logical qubits; current QC technologies require a factor of thousand more physical qubits to form a single logical one.
- **Lack of business-relevant quantum computing algorithms:** The prime challenge is to identify quantum algorithms that solve real business problems more efficiently than classical ones.

[5] Example: Industry Quantum Computing Applications QUTAC Application Group
[6] Example: Forecasting financial crashes with quantum computing. R. Orus, S. Mugel, E. Lizaso
[7] Example: Supervised learning with quantum enhanced feature spaces, Havlíček, V., Córcoles, A.D., Temme, K. et al.

- **Efficient integration and communication of quantum and classical computing** is crucial, as most quantum algorithms only speed up specific steps in a larger classical algorithm.
- **Quantum computers cannot really »store« information:** Qubits' physical properties limit their ability to store data beyond the computation process, which restricts the size and complexity of problems solvable with quantum computers.

2 Neuromorphic Computing

Dr. Johannes Leugering (Fraunhofer IIS), Bert Klöppel (T-Systems), Ferdinand Pscheidl (Fraunhofer EMFT), Villads Pors Schjelde (Infineon Technologies AG), Dr. Mira Wolf-Bauwens (IBM)

2.1 Short Description

Neuromorphic Computing is a multidisciplinary field that aims to build sensors, processors, and algorithms based on principles observed in neurobiology. It involves designing systems that mimic the morphology of biological neural systems, featuring many simple processing elements that run concurrently and communicate via point-to-point connections instead of shared memory. The field aims to bring power efficiency and low latency to machine learning tasks like image classification and voice detection by adopting some of the characteristics of the human brain, implemented using analog, mixed-signal or asynchronous digital circuits. While the neuromorphic computing field is still dominated by academic research, several start-ups and research divisions of larger companies have demonstrated prototypes and first products in recent years.

2.2 Benefits

- Higher energy efficiency to a factor between 4 and 16 compared to semiconductor technology[8]
- Execution speed
- Robustness against noise, local failures, and device variability
- Enhancing efficiency and enabling growth of network size for DNN applications.

2.3 Limitations

- For neuromorphic computing with spiking neural networks spike-rates are an inefficient way of representing numbers. This makes a direct conversion of deep neural networks inefficient. More efficient approaches are an active area of research but currently both software support and competitive network architectures are still missing. Therefore, neuromorphic chips are currently not competitive for many tasks that are done well by conventional computers[9].
- Neuromorphic computing is motivated by our current, incomplete understanding of the brain, which may not capture critical aspects of cognition such as the role of neurotransmitters and hormones, different neuron morphologies and cell types, and specific neural circuits. If cognition relies on these phenomena, current

[8] Rao, A., Plank, P., Wild, A. et al. A Long Short-Term Memory for AI Applications in Spike-based Neuromorphic Hardware. Nat Mach Intell 4, 467–479 (2022).
[9] Are neuromorphic systems the future of high-performance computing? – Physics World

neuromorphic computing approaches might result in too incomplete approximations to be of practical use.

2.4 Applications

- **Medicine**: Neuromorphic computing's compatibility with organic materials and ability to receive or respond to environmental data has potential applications in improving drug delivery systems and enhancing prosthetics.
- **Computer vision**[10]: Neuromorphic computing can be applied to event-based vision sensors that generate images similarly to the human eye. These sensors respond to changes in light intensity extremely quickly. This fast response time does no longer lead motion blur or delayed response, making them ideal for uses in robot vision and virtual and augmented reality technology.
- **Autonomous robots and self-driving cars**[11]**:** Due to their low energy consumption and short reaction times, neuromorphic chips are well-suited for on-board processing in self-driving cars, drones, or satellites, i. e. where decisions need to be made autonomously and cloud-connectivity and power-budget are limited. In addition, neuromorphic chips offer potentially higher reliability in high noise environments. These benefits could make autonomous robots and driverless cars more economical, safer and more suitable for varying environments.

2.5 Physical Area of Use

- **Edge:** Neuromorphic chips are particularly well-suited for use on the edge, as they can process data more efficiently and quickly with limited cloud-connectivity.
- **Cloud** solutions are used for tasks that require more computational power and data processing capabilities.

2.6 Development Challenges

- **Being able to distribute large amounts of memory among many processors on a single chip:** Neuromorphic chips rely on the parallelization of a very large number of processes. Therefore, the required data needs to be placed in memory close to these processors, which requires new architectures and memory technologies.
- **Developing competitive neural network architectures for neuromorphic devices:** Neuromorphic computing will have to compete with neural networks deployed on conventional hardware. This can only be achieved by finding new algorithms and neural network topologies optimized for neuromorphic devices.
- **Developing scalable messaging and interconnect architectures**: The parallelization of neuromorphic devices also requires a previously unseen amount of communication between these processors. Since communication can be highly irregular and sparse, completely new interconnect architectures and design tools are needed.
- **New algorithms, software and design tools** must be developed to incorporate and leverage the specifics of neuromorphic circuits. Current hardware is developed to

[10] PureSentry contamination detection | Cambridge Consultants
[11] Edge-AI & Neuromorphic – Efficient Processing of Time Series Data for Control & Prediction

optimize performance for current neural network algorithms, which are in turn optimized to run well on current hardware. Breaking this cycle requires a large effort of hard- and software co-development.

3 Optical Computing

Dr. Michael Kissner (Akhetonics)

3.1 Short Description

Optical Computing promises to remedy some of the problems that plague electronics such as power consumption and data bottlenecks. There are two common approaches: The digital domain, which aims to replace the standard electronic processor and the analog domain, focusing on artificial intelligence (AI) acceleration. There is also an optical approach in QC which is out of focus of this section.

- **Digital:**
  By using all-optical transistors as building blocks, any computer architecture can be converted to an all-optical processor. This would make computing extremely energy efficient and a lot faster. Currently, there are sufficient all-optical transistor concepts for which the research phase is completed. These can be used for optical digital computing. With switching speeds approaching the Petahertz domain, they promise a speed-up compared to current electronic transistors found in modern CPUs. Optical digital computing enables the use of current software on a new and improved platform. It is the only all-optical approach in optical computing, meaning no electronics for data manipulation are needed. The TRL is currently around 4.
- **Analog**
  Optical analog computing is used to directly model mathematical functions in the optical domain. Using linear optical devices, it is possible to do vector-matrix multiplications (VMM) which can be implemented in AI systems. The working principle exploits the wave properties of light: By constructively interfering two light beams one can »add« them and by attenuating (or dimming) one can »multiply« the first result by a constant. Using these two linear operations in sequence allows for the famed vector-matrix multiplication. The TRL is currently around 7, with the first companies releasing their products.

3.2 Benefits:

- **Extremely parallelizable:** Photons do not interact strongly with other photons or even some materials. This allows a high degree of parallelization, since it is possible to have multiple light beams with different wavelengths doing parallel computation without crosstalk.
- **Ultra-low power consumption and low latency:** Using almost perfectly transparent materials allows for extremely efficient waveguides that act almost like a superconductor.
- **130/250 nanometer (nm) fabrication nodes:** No leading-edge manufacturing processes are required.

3.3 Limitations

- **Digital**
  Low light-light interaction: To create an all-optical transistor, two light beams must interact with each other. This can only be done using highly specialized materials, long interaction lengths or very intense light beams.
- **Analog**
  Electronic processing bottleneck: Not many operations that can be performed using a completely linear PIC. All modern neural networks also require a non-linear activation function. Converting between optical and electronic domains repeatedly leads to power and speed losses.

3.4 Applications

- **Digital**
  General Purpose: Use-cases include anything that a regular CPU, GPU or ASIC can currently do.
- **Analog**
  Application Specific: Linear Mathematical Operations and Fourier Transforms are the current main use-cases.
  - **Deep learning**: VMM is the main computation component in deep learning, so AI accelerators mostly use the analog approach.
  - **Data encryption**: Fourier Transforms enable secure data processing, which has thus far been held back by the speed of computation.

3.5 Physical Area of Use

- **Digital**: cloud and on-premises
- **Analog:** cloud and edge

3.6 Development Challenges

- **Very large footprint** of the IC due to low transistor densities, leading to larger processors at the moment.
- **Digital**
  - **Need for alternative architecture approaches:** von Neumann architecture is not well suited for the optical domain. Alternatives are being explored such as the Harvard architecture, the pushdown automata or the finite-state machine.
  - **Chip integration** of non-linear photonics and the associated material development to allow for scaling of the circuits.
  - **Optical memory** is still not as abundantly available as in electronics.
- **Analog**
  - **Scaling** without sacrificing latency and power and reducing the input/output bottleneck introduced by electronics.

4 Digital Annealing

Dr. Stefan Walter (Fujitsu)

4.1 Short Description

Digital Annealing systems are quantum-inspired special purpose hardware devices, designed to solve large combinatorial optimization problems very fast. The problems need to be formulated as an Ising model or equivalently as a Quadratic Unconstrained Binary Optimization (QUBO). Digital Annealing systems search for the lowest energy value of the energy function. In many cases the basis of the search algorithm is a Simulating Annealing approach which is enhanced using hardware techniques such as GPUs, FPGAs or ASICs, and/or quantum-inspired algorithms. The hardware approaches specifically tailored to solve Ising type problems make Digital Annealing systems a powerful and competitive computing technology. Digital Annealing is a mature technology, proven by actual systems in operational environments. Therefore TRL 9 can be assigned. Depending on the realization, their power consumption is comparable to the CPUs and GPUs.

4.2 Benefits

The key advantages of Digital Annealing compared to quantum approaches are:

- **Full connectivity among bits** allows for solving more complex and more realistic problem scenarios without an additional overhead of embedding the problem, i. e. all bits can be used to encode the problem.
- **High gradation** allows for high precision in the formulation of the combinatorial optimization problem.
- **Large problem sizes solvable:** Existing annealers can handle between 100 000 bits up to 10 million bits using a combination of hardware and software technologies.
- **No special environment needed:** Digital Annealer can be implemented in standard 19-inch rack enclosures used in data centers. No cryogenic or vacuum environment is needed.

4.3 Limitations

- **Special purpose:** Digital Annealing systems are restricted to solving combinatorial optimization problems only.
- **Only close to optimal solution**: Digital Annealing systems are based on simulated annealing. There is no guarantee for the global optimum of the optimization problem. A close to optimal solution obtained in a very short time is, however, often sufficient.

4.4 Applications and Use-Cases

- **Combinatorial optimization problems:** The aim is to find a minimum energy solution for a given energy function. Combinatorial optimization problems are very complex optimization problems often with a huge number of variables and therefore the search space is usually too large to search exhaustively by brute force methods.
- **Problem examples** include the travelling salesman problem, graph partitioning, graph coloring, and Boolean satisfiability problems. These types of problems represent a significant number of challenges in many industries e. g.:
  - **Mobility**: e. g. traffic flow optimization[12], scheduling
  - **Life science**: e. g. drug design
  - **Finance**: e. g. portfolio optimization, arbitrage optimization
  - **Manufacturing**: e. g. production planning [13], transport planning, assignment problems, warehouse optimization

4.5 Physical Area of Use

- **Cloud**: with APIs providing suitable interfaces for access from the public internet.
- **On-premises**: in case of special requirements to the solution (such as security issues or latency and real time demands)

4.6 Development Challenges

- **Not every combinatorial optimization problem is suited:** Every linear optimization problem can be cast into QUBO form and can then be solved using a Digital Annealing system. Sometimes, however, this approach won't provide the potential speed-up or an increased solution quality. Therefore, it is essential to identify business problems benefiting from using a Digital Annealing system.
- **Additional resources (i. e. bits) required for problems using higher order polynomials to be cast into QUBO form.**

[12] MOZART: Traffic management through traffic signal control by Quantum-Inspired (fujitsu.com)

[13] Fujitsu, Toyota Systems leverage Fujitsu's Quantum-Inspired Digital Annealer to streamline automobile production sequence : Fujitsu Global

5 DNA Computing

Dr. Christoph F. Strnadl (Software AG)

5.1 Short Description

DNA computing (in the wider sense) is a subset of molecular or chemical computing involving DNA, RNA, or highly related molecules. It comprises **DNA storage** which uses the structure of shorter strands of DNA /RNA to store information and **DNA computing in the narrower sense** where typical chemical mechanisms (e. g. complementarity of the two strands of RNA/DNA) and machinery (e. g. enzymes) are used to deliberately manipulate information stored in DNA/RNA strands. Today, several different realizations of DNA computing exist capitalizing on distinct chemical characteristics of the DNA/RNA molecules and the substrates they operate in.
Currently, DNA computing in general is at TRL 3-4 while dedicated implementations of DNA storage may already have reached TRL 5.

5.2 Benefits

- DNA computing parallelizes excellently (10^{18} DNA strands per one liter of water) at an extraordinary energy efficiency - about one billion times more energy efficient than current day electronic devices. To the extent that computation (i. e. the underlying chemical reactions) occurs inside living cells, biological error-correction mechanisms are available (in theory).
- DNA storage: Besides its incredible storage density (seven orders of magnitude (10^7) more than tape storage and three orders more than flash memory), DNA storage excels with a (evolutionary) proven track record as information bearer at longevity, durability (up to 1 million years), and energy efficiency (eight orders of magnitude (10^8) better than that of flash memory).

5.3 Limitations

- **DNA computing** intrinsically suffers from low signal propagation speed (hours), weak scaling and a propensity for discrete problems.
- **DNA storage's** most important limitation is the very high access latency in the order of minutes or hours brought about by the physico-chemical laws of nature itself.

5.4 Application Areas

- **DNA computing** may be applied to classical problems like combinatorial problems (e. g. Travelling Salesperson Problem), search, scheduling or clustering. Algorithms have been also formulated in cryptography and intrusion detection. In connection with living cells (organism) DNA computing may be used in nanomedicine (bio-sensing, intelligent diagnostics of molecular-level conditions). When coupled to suitable materials, it may be used for DNA barcoding, product tagging, or even for controlling »smart« materials.

- **DNA storage** may provide the ultimate long-term highly energy efficient and fully biodegradable information storage and archiving solution.

5.5 Physical Area of Use

- **Cloud**: Due to the (current) complexity of operating DNA computers including DNA storage[14], this will most likely result in a cloud computing (SaaS) model.

5.6 Development Challenges

- **Large-scale parallelization**: Due to the intrinsically low signal propagation speed of chemical reactions DNA computing must be parallelized to an unprecedented extent in order to yield acceptable computational throughput technical realization.,
- **Lowering the costs:** The current cost base for manipulating DNA strands in a lab needs to be reduced by a factor of 1 million (e. g. through automatization or better error-correction) to make it feasible.
- **Mapping of business problems:** Limited computational complexity of the underlying (discrete) information structure renders the mapping of business problems onto a DNA computing machinery and algorithms quite difficult.
- **Improving DNA storage:** Storage will have to scale beyond the currently available size (in the order of 100 MB[15]), to reduce latency and increase write speeds from today's ca. 500 bit/s.

[14] Today, this means running a state-of-the-art genetic laboratory
[15] 1 MB = 1 Megabyte = 1,024 Kilobytes (kB) = 1,048,576 Bytes

6 Further computing approaches

Dr. Roman Bansen (Agentur für Innovation in der Cybersicherheit), Dr. Christoph F. Strnadl (Software AG)

- **Smartdust**
  Smartdust usually refers to a system of many tiny microelectromechanical devices such as sensors or robots. They are operated wirelessly on a computer network and are distributed over an area to perform tasks, usually sensing, and communicate via radiofrequency[16] . There are, however, theoretical concepts for these tiny devices to contain a simple processor. Intelligent control could use mesh networking of these devices in different ways from those of traditional computer networks.
- **Brain-Computer interface**
  Brain-machine interfaces or brain-computer interfaces refer to the direct communication between the brain's electrical activity and an external computer. While usually used for augmenting or repairing human cognitive or sensory-motor functions and technically not a computing approach, it might radically change our way to operate and interact with computers in the future[17] [18] [19].
- **Spintronics**
  The term spintronics, or spin transport electronics, generally describes any kind of application or solid-state device which does not only use the fundamental electric charge of electrons but also their intrinsic spin. This adds a further degree of freedom to be utilized. Technically, this includes a whole range of already commercialized devices like the read heads of magnetic hard drives or magneto-resistive RAM and even certain approaches in quantum computing the focus with respect to future computing lies on the development of spin-based transistors, which could have several potential advantages over classical transistors.
- **Bio-neuronal networks**
  In contrast to the artificial neural networks in neuromorphic computing, this approach uses biologically real nerve cells (neurons) as an interface to silicon-based electronics. Currently, the Australian startup Cortical Labs is looking to commercialize this »dishbrain« technology. Similar approaches are being pursued by researchers at the University of Texas in Austin[20].
- **Approximate computing**
  The umbrella term »approximate computing« includes several different computation techniques that – in contrast to a classical computer – return possibly inaccurate results. They could be used for any kind of application where an

[16] Iyer, V., Gaensbauer, H., Daniel, T.L. et al. Wind dispersal of battery-free wireless devices. Nature 603, 427–433 (2022).
[17] Science & Tech Spotlight: Brain-Computer Interfaces | U.S. GAO
[18] 3 Brain-Computer Interface Technology Trends (patsnap.com)
[19] Frontiers | Progress in Brain Computer Interface: Challenges and Opportunities (frontiersin.org)
[20] Kireev, D., Liu, S., Jin, H. et al. Metaplastic and energy-efficient biocompatible graphene artificial synaptic transistors for enhanced accuracy neuromorphic computing. Nat Commun 13, 4386 (2022).

approximate result is sufficient for its purpose. In many non-critical scenarios, approximation within certain boundaries could provide significant gains in performance and energy, while still achieving acceptable result accuracy. Approaches and strategies for approximate computing include, amongst others, the use of approximate arithmetic circuits, approximate storage and memory or software-level approximation[21, 22].

- **Associative machine**
  An associative machine is a freely programmable machine composed of associative memories. In contrast to a classical Von Neumann processor, an associative machine is not built around an arithmetic logic unit but consists of associative units. Usually, associative matrices are used as associative memories. This way, the associative machine acquires properties of fault tolerance, which makes it particularly interesting for pattern recognition, completion and extraction. Associative machines require completely different programming paradigms, called associative programming, where a program line is associated with its successor and data can be queried in a fault-tolerant manner[23, 24].
- **In-memory computing (IMC) / In-memory processing (IMP) / Processing in memory (PIM)**
  In today's widespread Von Neumann computing architecture, the memory interface is a major hurdle for overall processing speed, slowing down many calculations. The IMC architecture eliminates the detour via the processor's main memory: Processing and storage of data takes place on the same chip. As stored data is accessed much more quickly when it is placed in RAM or flash memory, in-memory processing allows data to be analyzed much faster. Moreover, complex algorithms can potentially be processed with significantly lower power consumption. In-memory computing is sometimes also classified as a neuromorphic computing approach. The way it functions, and the combination of fast computing power and low energy consumption make IMC particularly interesting for AI applications[25].
- **Field Programmable Gate Array (FPGA)**
  An FPGA is an integrated circuit consisting of (i) input/output blocks and (ii) user-configurable logic blocks, which are linked together via (iii) programmable interconnections. Therefore, engineers can configure FPGAs according to desired requirements *after* they have been manufactured and deployed (hence, *field* programmable, contrary to ASICs – application specific ICs).[26] Despite their size, cost and power disadvantages compared to ASICs, they are used for hardware acceleration (e. g. encryption, video format conversions, AI/ML algorithms) or to enhance security in heterogeneous and/or changing environments where the deployment of classical ICs (CPUs, GPUs) or ASICs no longer is cost-effective.

[21] W. Liu, F. Lombardi and M. Schulte, "Approximate Computing: From Circuits to Applications [Scanning the Issue]," in Proceedings of the IEEE, vol. 108, no. 12, pp. 2103-2107, Dec. 2020
[22] Approximate Computing | SpringerLink
[23] assoziativmaschine.de
[24] Assoziativcomputer: Hildesheimer Grüße an die NSA - Digital - FAZ
[25] S. Ghose, A. Boroumand, J. S. Kim, J. Gómez-Luna and O. Mutlu, "Processing-in-memory: A workload-driven perspective," in *IBM Journal of Research and Development*, vol. 63, no. 6, pp. 3:1-3:19, 1 Nov.-Dec. 2019
[26] Michael Mattioli. 2022. FPGAs in Client Compute Hardware: Despite certain challenges, FPGAs provide security and performance benefits over ASICs.

7 Further Reading

Quantum Computing

- WEF insight Report »State of Quantum Computing: Building a Quantum Economy«
- Leitfaden »Quantentechnologien in Unternehmen«
- Quantum Computing White Paper (Software AG)
- Industry Quantum Computing Applications, QUTAC Application Group

Neuromorphic Computing

- The Femtojoule Promise of Analog AI - IEEE Spectrum
- J. Leugering, »Neuromorphe Hardware – Hardware für neuronale Netze«, DESIGN & ELEKTRONIK, 7/2020

Optical Computing

- Pierre Ambs, »Optical Computing: A 60-Year Adventure«, Advances in Optical Technologies, vol. 2010, Article ID 372652, 15 pages, 2010.
- Miller, D. Are optical transistors the logical next step?. *Nature Photon* **4**, 3–5 (2010)

Digital Annealing

- Mohseni, N., McMahon, P.L. & Byrnes, T. Ising machines as hardware solvers of combinatorial optimization problems. *Nat Rev Phys* **4**, 363–379 (2022).
- Kochenberger, G., Hao, JK., Glover, F. *et al.* The unconstrained binary quadratic programming problem: a survey. *J Comb Optim* **28**, 58–81 (2014).

DNA Computing

- Katz E (2020): DNA Computing: Origination, Motivation, and Goals – Illustrated Introduction
- Meiser, Linda C., et al. »Synthetic DNA applications in information technology.« Nature Communications 13.1 (2022): 1-13.

Bitkom represents more than 2000 companies of the digital economy. Their annual turnover for IT and telecommunications services alone is 190 billion Euro, including exports of 50 billion Euro. Bitkom members employ more than 2 million people in Germany. These members number more than 1,000 small and medium-sized enterprises, over 500 start-ups and virtually all global players. They offer software, IT services, telecommunications or Internet services, manufacture devices and components, are active in the area of digital media or form part of the digital economy in some other way. 80% of the companies have their head office in Germany, while 8% each come from Europe and the USA, and 4% from other regions. Bitkom promotes and drives the digital transformation of the German economy, and champions broad involvement of society in digital developments. The objective is to make Germany one of the world's leading digital business locations.

Publisher
Bitkom e.V.
Albrechtstr. 10 | 10117 Berlin

Contact Person
Dr. Natalia Stolyarchuk | Head of Future Computing & Microelectronics
T 030 27576-187 | n.stolyarchuk@bitkom.org

Responsible Bitkom Working Group
AK High Performance Computing and Quantum Computing

Authors and Contributors:
Dr. Roman Bansen (Agentur für Innovation in der Cybersicherheit), Dr. Jannis Ehrlich (Fraunhofer IWM), Dr. Michael Kissner (Akhetonics), Bert Klöppel (T-Systems), Dr. Johannes Leugering (Fraunhofer IIS), Dr. Oliver Oberst (IBM), Ferdinand Pscheidl, Villads Pors Schjelde (Infineon Technologies AG), Dr. Christoph F. Strnadl (Software AG), Dr. Stefan Walter (Fujitsu), Dr. Mira Wolf-Bauwens (IBM).

Titelbild
© Scanrail – stock.adobe.com