Artificial Intelligence as a Catalyst for Fusion Energy

By **Alex F. Savin**, **Harry Westhead**[1], **Philip Horton**[1], and **Richard A. Johnson**[1]

SUMMARY

- AI models, such as digital twins and surrogate models, offer significant potential to speed up and improve the design and optimisation of fusion reactors, but must be applied in targeted areas where sufficient high-quality data exists to ensure trustworthy results.
- The scarcity of experimental data in fusion presents challenges for AI implementation; thus, a problem-specific approach is recommended, focusing on well-benchmarked aspects like transport phenomena and adaptive reactor control.
- A symbiotic relationship between the AI and fusion sectors could accelerate innovation in both fields—fusion provides sustainable energy for AI's growing demands, while AI delivers the advanced modelling and control needed to realise commercial fusion energy.

1 Mewburn Ellis LLP, Aurora Building, Counterslip, Bristol, BS1 6BX

1. INTRODUCTION

Nuclear fusion – often heralded as always being "30 years away" [1] – is now, finally closer than ever with groundbreaking scientific milestones being passed on a regular basis [2, 3]. In addition to scientific breakthroughs, the commercial fusion sector is expanding with impressive momentum, with the sector attracting over $2.6 billion USD in 2024/2025, taking total investment in private sector fusion companies to over $9.7 billion USD [4]. Beyond the 'core' fusion companies, the supply chain is also developing at pace with companies in Europe, Asia, North America and Australia all contributing to building a supply chain from a near-standing start [5].

Over and above merely attracting investment, many of these fusion companies are also reporting remarkable progress on their route towards the commercialisation of fusion [6-13], with the overwhelming majority of fusion companies self-reporting a target of delivering power to the grid between 2030 and 2035 [4].

However, while progress to date is impressive, it is equally clear that there are significant scientific and engineering challenges to overcome in the quest to commercialise fusion. While the trajectory for many of the plethora of fusion approaches is undoubtedly positive, it remains the case, as can be seen from Figure 1, that only the National Ignition Facility at the Lawrence Livermore Laboratory has reported experimental success of attaining ignition [3, 14, 15]. Even then, ignition is only a first hurdle to overcome. Strictly speaking 'ignition' (also referred to as scientific breakeven), only compares the amount of energy put into the fuel with the amount of energy obtained from the fusion reaction. In order to be commercially viable, fusion needs to go one step further and obtain more energy from the fusion reactions than is put into the entire reactor system overall. This level of yield is, as of yet, unattained.

Addressing these challenges will require the development and implementation of a whole suite of new technologies, ranging from high-temperature superconductor (HTS) magnets [16], laser amplifiers [17] and diodes [18], and improvements in fuel cycle systems [19]. These new technologies, coupled with the inherent stochasticity of high-temperature, high-pressure plasma physics [20] makes it incredibly challenging to model the performance of fusion reactors and, consequently, improve and iterate the designs of these reactors.

In the nuclear fission, or 'nuclear' sector, it is already appreciated [21, 22] that AI will be a valuable tool for achieving systems integration in nuclear reactors. The same is true for fusion. However, where conventional nuclear reactors are well-understood systems that can provide an abundance of training data for the development of optimisation algorithms [23], and surrogate models [24], this is not the case for nuclear's cousin fusion.

This article therefore outlines a measured and limited approach to implementing AI models in a manner that incrementally improves the understanding of fusion reactor physics and engineering to ensure that the outputs of AI models can be trusted to improve reactor design. By producing reliable outputs, we assert that the burgeoning fusion supply chain will benefit from an instilled confidence in the projections put forward by the fusion sector. This confidence is vital for facilitating the development and growth of a global commercial fusion sector

After specifically considering the potential for the use of digital twins [25] to enhance fusion reactor design, we briefly discuss the potential symbiosis between the AI industry and the fusion sector, as well as the nuclear industry more widely, to highlight the mutual benefit for both industries if they each support the successes of the other.

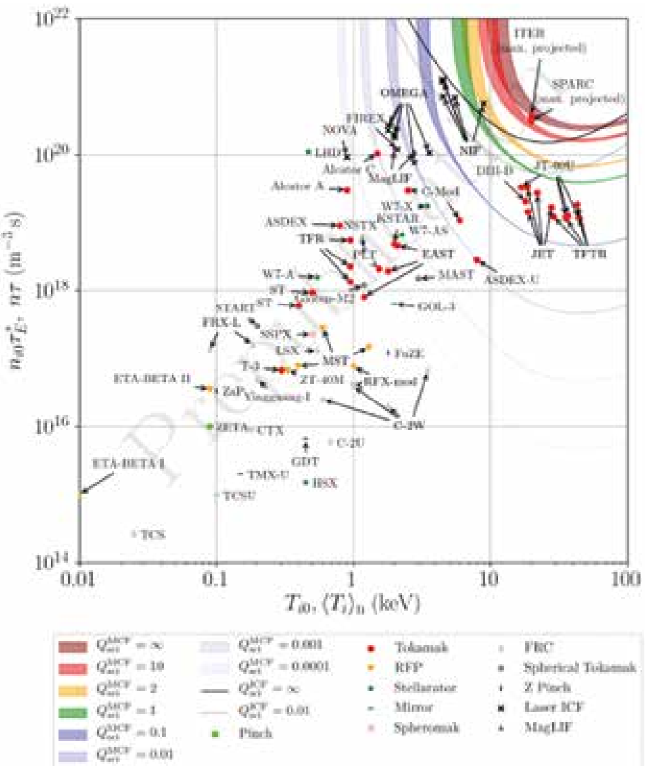

FIGURE 1: Obtained from Wurzel & Hsu [15]. A graph depicting the experimentally inferred Lawson parameters of fusion experiments. To date only NIF has successfully demonstrated ignition conditions (top right corner).

2. DIGITAL TWINS FOR FUSION

Historical approaches to computationally model physical systems has involved running codes to solve the governing physical equations (e.g., Maxwell's equations of electromagnetism, Newton's laws of motion, laws of conservation, equations governing fluid mechanics, and the like) to predict, numerically, the performance of physical systems. This is, in part, because many of the equations governing physical phenomena are only solvable numerically. For example, the stochastic elements arising from turbulence in fluid dynamics make it impossible to find an exact solution to the Navier-Stokes equations in such circumstances. As these systems become evermore complex, the costs, in terms of processing power and time, associated with these numerical approaches also escalates. There is, therefore, a continuing need to adopt more efficient approaches to computational analysis and prediction.

Digital twins, and surrogate models more widely, are examples of these more efficient computational tools, and have already been deployed across a range of industries with great success [26]. For example, models have been proposed to integrate surrogate modelling capabilities into the control systems of nuclear plants to improve the automation of analysis and control [21]. Instead of methodically and painstakingly solving governing physical equations to precisely model the performance of a system, digital twins are trained, using real obtained experimental data, to emulate real systems to predict a likely outcome for a given set of input parameters. That is, the models are trained to infer, based on a compilation of historic experimental results, the most likely physical outcome for a system operating with a given set of parameters. As digital twins are trained to infer their emulated predictions using a data-based approach, they are not constrained by the costs associated with a thorough and detailed calculation of the governing physical equations.

However, the successful deployment of such models requires high-quality training to build trust between the models and their end-users. In the vast majority of cases, this data is available as actual real measurements of the performance of an entire system being digitally twinned (e.g., there is a plethora of data about the performance of nuclear reactors).

In the case of fusion, there is – as yet – only one facility achieving ignition (although as noted above, even ignition is not sufficient for commercialisation) [3, 14, 15], and so real data indicative of whole-reactor performance for fusion reactors capable of achieving ignition or higher yields is much more limited. As such, there is significantly less whole-reactor data available for training surrogate models and digital twins. As the old adage goes, "Garbage In, Garbage Out" [27], so how can AI models which, inherently, require training on high-quality data be used to support R&D in the fusion space?

The solution, we posit, is to deploy digital twins in a specific and limited manner, targeted towards modelling specific aspects of a fusion reactor to answer well-defined and well-understood problems. This approach is, in fact, already in the early stages of adoption at the HL-3 tokamak in China, where a digital twin system is being developed and deployed to model just the temperature distribution within the vacuum chamber of HL-3 [28].

Over and above modelling temperature distributions, we suggest that fusion reactor design could also benefit from the targeted application of digital twins to the modelling of transport phenomena in fusion plasmas. Heat transport [29-31] and particle transport [32, 33] within fusion plasmas are already known to be critically important processes requiring precise control to optimise the performance of fusion reactors.

While the physics governing fluid transport is well-understood, solving the governing equations in the presence of turbulence generally requires a probabilistic approach. In particular transport phenomena in fusion plasmas are subject to the stochastic impacts of turbulence [34], and an abundant range of system-specific plasma instabilities [35, 36]. This makes it difficult, if not impossible to analytically determine the impact of transport effects without the use of large-scale models such as Vlasov-Fokker-Planck codes which have been developed and iterated upon for decades [37, 38]. These models can take several hours, even days, to numerically calculate the distribution functions for a given plasma, and, as such, consume significant computing resources.

However, transport phenomena are readily measurable using experimental techniques [39-44]. This makes digital twinning an ideal candidate for reducing the processing costs associated with optimising solutions to transport problems. As digital twins are simplified models that are data-driven, as opposed to physics-based, a digital twin is capable of solving problems much faster than a physics-based model [45]. This is readily extensible to fusion reactors. Provided the application of the digital twin is limited to modelling phenomena for which sufficient amounts of high-quality data is available, such as transport, digital twins offer an exciting route for improving the efficiency of reactor design and optimisation.

We propose that surrogate models such as digital twins could and should be applied in a piecewise fashion to the overarching problem of reactor design, with each model being trained to optimise the parameters for a specific and targeted problem for reactor design for which experimental data is available in both high quantity and high quality. For example, inertial confinement fusion approaches, as schematically illustrated in Figure 2 could implement a series of surrogate models to optimise: (i) laser beam profiles, (ii) target geometries, (iii) transport phenomena, (iv) target-loading configurations, and/or (v) diagnostic set-ups. Meanwhile, magnetic confinement fusion approaches could implement a series of surrogate models to optimise: (i) HTS magnet arrangements, (ii) magnetic field patterns and strengths, (iii) fuel injection procedures, (iv) shielding material performance, (v) plasma transport phenomena, and/or (vi) diagnostic set-ups, as is depicted similarly in Figure 3. As the reader will no doubt appreciate, these lists are not exhaustive but rather exemplary of the broad potential applicability of surrogate models to fusion reactor design and optimisation. What is important is that models are applied in a deliberately targeted fashion, with a piecewise layering of models – each of which can be independently validated with real experimental data, to build trust in the overall optimisation procedures. Moreover, above and beyond the application of surrogate models to reactor design, it may also be feasible and even desirable to apply these piecewise models to sensitivity analysis [46] to build an understanding of which parameters are most impactful on reactor performance.

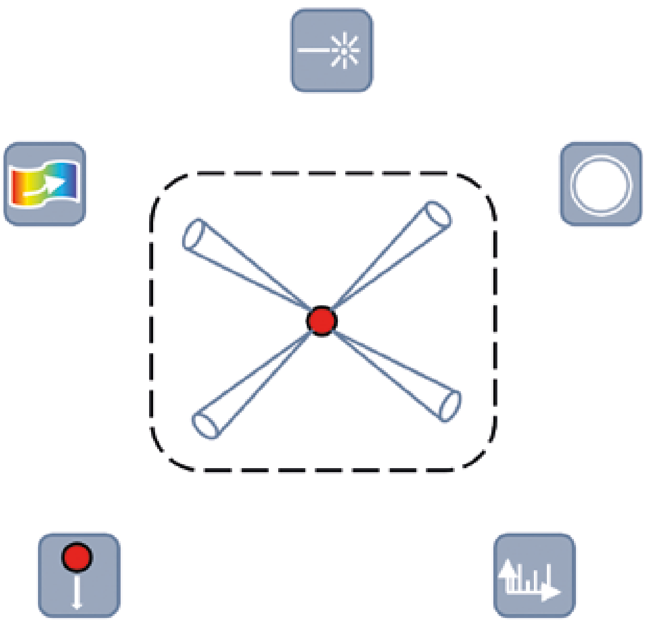

FIGURE 2: Schematic illustrating the potential applicability of discrete surrogate models/digital twins (peripheral objects) to the development of an inertial fusion energy reactor. Digital twins could be suitably and separately applied to one or more of (clockwise from top): (i) laser beam profiles, (ii) target geometries, (iii) diagnostic set-ups and measurements phenomena, (iv) target-loading configurations, and/or (v) transport phenomena.

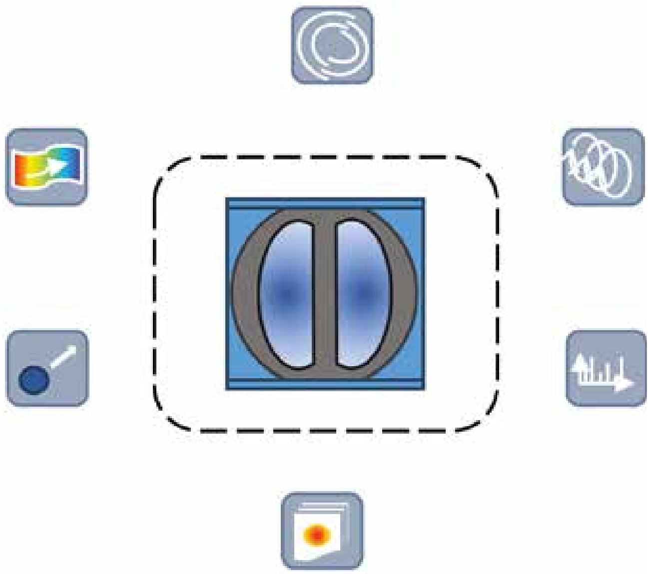

FIGURE 3: Schematic illustrating the potential applicability of discrete surrogate models/digital twins (peripheral objects) to the development of a magnetic fusion energy reactor. Digital twins could be suitably and separately applied to one or more of (clockwise from top): (i) HTS magnet arrangements, (ii) magnetic field patterns and strengths, (iii) diagnostic set-ups and measurements, (iv) shielding material performance, (v) fuel injection procedures, and/or (vi) transport phenomena.

3. FURTHER OPPORTUNITIES FOR THE APPLICATION OF AI

Beyond surrogate models, AI has the potential to shape other elements of reactor design and control in the fusion sector. AI-controllers for adaptively controlling actuators based on prediction from deep reinforcement (DRL) models have already been demonstrated on the DIII-D National Fusion Facility [47]. There, researchers demonstrated that their DRL models are able to adaptively respond to detected fluctuations within a few tens of milliseconds, thereby limiting the development of parasitic instabilities that could disrupt the confinement of the plasma. Such rapid, adaptive, control of operational parameters is far superior to anything achievable by manual control by a human operator.

Meanwhile, in inertial fusion research, generative AI is being used to optimize target design [48], a critical problem that must be solved to successfully commercialise laser-driven fusion. More broadly, the use of AI has been flagged by the Clean Air Task Force as being a critically important tool for building a fusion materials database to assist with materials selection [49].

Fusion would also stand to take inspiration from its more experienced cousin, the traditional nuclear industry. From robotics software [50] to wider systems control [21], from data analysis [51] to reporting that complies with regulatory requirements [52], the nuclear industry has already begun to see the successful adoption of AI to improve systems and processes across the organisational workflow. Fusion should take heed of this experience and adapt it to their needs.

4. MUTUAL BENEFIT

It's not just fusion that stands to benefit from AI, AI also stands to benefit from the nuclear and fusion revolutions.

When the development of a commercial fusion reactor is successful, Big Data will be offered the prospect of harnessing an inexhaustible source of clean energy. With the ever-booming growth of AI, there is already a huge demand for sustainable energy source to power AI-data centres [53]. Indeed, it is commonly and publicly highlighted by leaders in the AI industry that an energy breakthrough is necessary to support the growth of AI [54].

Large data centres will be vital to support the widespread use of AI and cloud-based computing applications. According to the International Energy Agency, overall capital investment by Amazon, Google, and Microsoft in new data centres contributed to 0.5% of US GDP in 2023 [55]. The power demand for data centres in the US alone is projected to increase to up to 12% of the total US electricity consumption by 2030 [56]. With many countries announcing pledges to achieve net zero emissions within the next few decades, there is a desire to meet these demands without the use of fossil fuels. Enter both fission and fusion.

Beyond being an energy supply, the high-performance computing requirements associated with achieving fusion also provide a bedrock for building a skilled AI workforce to deliver the next-generation developments in AI and high-performance computing more generally [57]. No doubt, it is this combination of benefits that has driven, and will likely continue to drive, the biggest tech companies in the world to invest significantly in the success of fusion companies, as recently evidenced by Google's recent power purchase agreement with US fusion company Commonwealth Fusion Systems [58], and OpenAI CEO Altman's multi-million investment in Helion Energy [59].

It is clear the AI industry seeks to benefit from the advancement of nuclear fusion, and that nuclear fusion stands to flourish by exploiting the capabilities of new and developing AI algorithms. Recognition of the synergies between these two industries is extending beyond the private sector, as governments also begin to see the potential symbiotic benefits. For example, the UK government announced earlier this year that it will deliver the first AI Growth Zone at the headquarters of the UK Atomic Energy Authority [60]. This public sector initiative aims not only to invest in AI infrastructure in the UK but also to advance fusion energy research, a clear demonstration of the strategic convergence of AI and fusion.

With a clear trajectory across academia, the public sector, and the private sector of a growing closeness between the fusion and AI sectors, it is clear that the futures and interests of both industries are set to become ever more closely aligned.

5. CONCLUSIONS OR CONCLUDING REMARKS

Many of the physics and engineering challenges impeding the successful commercialisation of fusion energy stand to benefit from the judicious application of AI models to make the optimisation of reactor design and control more accurate, reliable and efficient. However, as discussed above, it is important to note that a model is only as good as the data used to train it and, given the relative scarcity of fusion reactor data when compared with more established physical systems (such as conventional nuclear systems), any approaches to implementing AI solutions in the fusion sector require careful adaptation so that each model deployed is applied only to situations against which the model's veracity can be fully tested and benchmarked. This leads to the conclusion that models such as surrogate models and digital twins can still be implemented to assist fusion R&D, but must be deployed in a piecewise fashion to iteratively construct an overall reactor model, instead of adopting the more conventional approach of training a digital twin to treat an entire reactor system holistically.

Through the careful and targeted application of AI to fusion engineering, the progress of commercialisation could be significantly accelerated, thereby bringing the ambition of a commercial fusion reactor closer to fruition. Conversely, as a potentially significant source of carbon-free energy and a breeding ground for an engaged high-skill workforce, it is in the interest of Big Tech companies to support the development of fusion so that this emerging industry can contribute to the continued development of the new AI data centre paradigm.

MEWBURN ELLIS LLP

Mewburn Ellis LLP is a European Intellectual Property (IP) firm that works with organisations of all sizes, helping them to navigate their business journey. The firm brings together over 350 staff including over 50 partners and 110 qualified patent and trademark attorneys spread across offices in London, Bristol, Manchester, Cambridge, and Munich.

The firm supports organisations of all sizes through every stage of the IP lifecycle and advise about patent, trademark and registered designs, as well as any IP-related disputes and legal and commercial requirements.

REFERENCES

[1] J. Sheffield. Panel discussion on prospects of fusion power. https://www.osti.gov/biblio/5705749, 1986.
[2] B. Foster. French fusion reactor stuns world by sustaining nuclear reaction for 22 minutes in breakthrough energy milestone. https://glassalmanac.com/french-fusion-reactor-stuns-world-by-sustaining-nuclear-reaction-for-22-minutes-in-breakthrough-energy-milestone/, 2025.
[3] The Indirect Drive ICF Collaboration. Achievement of Target Gain Larger than Unity in an Inertial Fusion Experiment. Phys. Rev. Lett. 132, 065102, 2024.
[4] Fusion Industry Association. The global fusion industry in 2025, Fusion Companies Survey by the Fusion Industry Association, 2025.
[5] Fusion Industry Association. The Fusion Industry Supply Chain 2025, 2025.
[6] Commonwealth Fusion Systems. Commonwealth Fusion Systems Magneet Success Propels Fusion Energy Toward the Grid. https://cfs.energy/news-and-media/commonwealth-fusion-systems-magnet-success-propels-fusion-energy-toward-the-grid, 2024.
[7] Energynews. TAE Technologies halves cost of fusion reactors with experimental breakthrough. https://energynews.pro/en/tae-technologies-halves-cost-of-fusion-reactors-with-experimental-breakthrough/#google_vignette, 2025.
[8] M.-S. Liu, H.-S. Xie, Y.-M. Wang, J.-Q. Dong, K.-M. Feng, X. Gu, X.-L. Huang, X.-C. Jiang, Y.-Y. Li, Z. Li, B. Liu, W.-J. Liu, D. Luo, Y.-K. M. Peng, Y.-J. Shi, S.-D. Song, X.-M. Song, T.-T. Sun, M.-Z. Tan, X.-Y. Wang, Y.-M. Yang, G. Yin, and H.-Y. Zhao. ENN's roadmap for proton-boron fusion based on spherical torus. Phys. Plasmas. 31, 6, 2024.
[9] Nuclear Engineering International. General Fusion achieves plasma breakthrough. https://www.neimagazine.com/news/general-fusion-achieves-plasma-breakthrough/, 2024.
[10] Helion Energy. Helion Energy Breaks Ground on Site of Its Next-Generation Fusion Facility in Everett, Washington. https://www.helionenergy.com/articles/helion-energy-breaks-ground-on-site-of-its-next-generation-fusion-facility-in-everett-washington/, 2021.
[11] E. Maartensson, and S. McNamara. Early design workflow and progress of Tokamak Energy's high-field spherical tokamak fusion pilot plant for the US DOE Milestone-Based Fusion Development Program. 66th Annual Meeting of the APS Division of Plasma Physics, 2024.
[12] World Nuclear News. Zap starts up demo fusion power plant system. https://www.world-nuclear-news.org/articles/zap-starts-up-demo-fusion-power-plant-system, 2024.
[13] Optics.org. Xcimer Energy completes first private-sector electron-beam excimer laser. https://optics.org/news/16/6/22, 2025.
[14] S. E. Wurzel, and S. C. Hsu. Progress toward fusion energy breakeven and gain as measured against the Lawson criterion. Phys. Plasmas. 29, 6, 2022.
[15] S. E. Wurzel, and S. C. Hsu. Continuing progress toward fusion energy breakeven and gain as measured against the Lawson criterion. arXiv:2505.03834, https://doi.org/10.48550/arXiv.2505.03834, 2025.
[16] Y. Zhai, D. van der Laan, P. Connolly, and C. Kessel. Conceptual design of HTS magnets for fusion nuclear science facility. Fusion Engineering and design, 16, 112611, 2021.
[17] J. D. Sadler, L. O. Silva, R. A. Fonseca, K. Glize, M. F. Kasim, A. Savin, R. Aboushelbaya, M. W. Mayr, B. Spiers, R. H. W. Wang, R. Bingham. R. M. G. M. Trines, and P. A. Norreys. Advantages to a diverging Raman amplifier. Communications Physics, 1, 19, 2018.
[18] C. Hafner, C. Holly, H.-D. Hoffman, L. Gruber, M. Crowley, L. Woods, R. Walker, P. Thiagarajan, S. McDougall, K. Boucke, K. Hurley, G. Lui, J. Jandeleit, A. Zeitschel, R. Hulsewede, and R. J. Deri. Status and Perspectives of High-Power Pump Diodes for Inertial Fusion Energy Lasers. A white paper prepared for the IFE Science & Technology Community Strategic Planning Workshop 2022, 2022.
[19] UK Atomic Energy Authority, and Department for Energy Security and Net Zero. UKAEA and Eni partner to develop tritium fuel cycle facility. https://www.gov.uk/government/news/ukaea-and-eni-partner-to-develop-tritium-fuel-cycle-facility, 2025.
[20] B. D. Wirth, K. Nordlund, D. G. Whyte, and D. Xu. Fusion materials modelling: Challenge and opportunities. High-Performance Computing for Materials Design to Advance Energy Science, 36, 216-222, 2011.
[21] C. C. Pain, A. Tehrani, D. Luxat, S. Naderi, B. Chen, C. E. Heaney, and P. N. Smith. Using AI to Model Systems in Nuclear Science and Engineering. Nuclear Future, pp. 50-57 November/December 2024, 2024.
[22] EPSRC. Tomorrow's Engineering Research Challenges. https://www.ukri.org/wp-content/uploads/2022/07/EPSRC-090822-TERCReport.pdf, 2022.
[23] A. K. Ziver, C. C. Pain, J. N. Carter, C. R. E. de Oliveira, A. J. H. Goddard, and R. S. Overton. Genetic algorithms and artificial neural networks for loading pattern optimisation of advanced gas-cooled reactors. Annals of Nuclear Energy, 31(4):431-457, 2004.
[24] C. C. Pain, A. Therani, C. E. Heaney, B. Chen, K. Nwegbu, T. Phillips, A. Jones, S. Dargaville, A. G. Buchan, P. Smith, M. Bankhead, and D. Cacuci. Computational Modelling in Nuclear Science and Engineering: The Role of Artificial Intelligence. Nuclear Future, September/October 2023, 2023.
[25] S. Haag, and R. Anderl. Digital twin – Proof of concept. Manufacturing Letters, 15, B, pp. 64-66, 2018.
[26] C. Semeraro, M. Lezoche, H. Panetto, and M. Dassisti. Digital twin paradigm: A systematic literature review. Computers in Industry, 130, 103469, 2021.
[27] R. Stenson. Is This the First Time Anyone Printed 'Garbage In, Garbage Out?' Atlas Obscura, https://www.atlasobscura.com/articles/is-this-the-first-time-anyone-printed-garbage-in-garbage-out, 2016.
[28] Nuclear Engineering International. China's fusion reactor debuts digital twin. https://www.neimagazine.com/news/chinas-fusion-reactor-debuts-digital-twin/?cf-view, 2024.
[29] C. Wang, S. Kobayashi, K. Nagasaki, D. Qiu, M. Luo, P. Zhang, K. Y. Watanabe, R. Seki, A. Miyashita, Y. Kondo, S. Inagaki, F. Kin, T. Minami, S. Kado, S. Ohshima, S. Konoshima, T. Mizuuchi, and H. Okada. Improvement of core heat transport in NBI plasmas of heliotron J using high-intensity gas puffing. Plasma Phys. Control. Fusion 66, 022001, 2024.
[30] S. Moradi, J. Anderson, M. Romanelli, H.-T. Kim, JET contributors, X. Litaudon, A. Abduallv, M. Abhangi, P. Abreu, M. Afzal, K. M. Aggarwal, T. Ahlgren, J. H. Ahn, K. Aho-Mantila et al. Global scaling of the heat transport in fusion plasmas. Phys. Rev. Research, , 013027, 2020.

REFERENCES (CONT)

[31] A. Chrisment, P. Loiseau, J.-L. Feugeas, P.-E. Masson-Laborde, J. Mathiaud, V. Tikhonchuk, and Ph. Nicolaï. Analysis of a kinetic model for electron heat transport in inertial confinement fusion plasmas. Phys. Plasmas, 29, 062301, 2022.
[32] C. Angioni, E. Fable, M. Greenwald, M. Maslov, A. G. Peeters, H. Takenaga, and H. Weisen. Particle transport in tokamak plasmas, theory and experiment. Plasma Phys. Control. Fusion, 51, 124017, 2009.
[33] S. X. Hu, K. A. Nichols, N. R. Shaffer, B. Arnold, A. J. White, L. A. Collins, V. V. Karasiev, Z. Zhang, V. N. Goncharov, R. C. shah, D. I. Mihaylov, S. Jiang, and Y. Ping. A review on charged-particle transport modelling for laser direct-drive fusion. Phys. Plasmas, 31, 040501, 2024.
[34] X. Garbet. Turbulence in fusion plasmas: key issues and impact on transport modelling. Plasma Phys. Control. Fusion, 43, A251, 2001.
[35] S.E. Shaparov, B. Alper, H. L. Berk, D. N. Borba, B. N. Breizman, C. D. challis, I. G. J. Classen, E.M. Edlund, J. Eriksson, A. Fasoli, E. D. Fredrickson, G. Y. Fu, M. Garcia-Munoz, T. Gassner, K. Ghantous, V. Goloborodko, N. N. Gorelenkov, M. P. Gryzanevich, S. Hacquin, W. W. Heidbrink, C. Hellesen, V. G. Kiptily, G. J. Kramer, P. Lauber, M. K. Lilley, M. Lisak, F. Nabais, R. Nazikian, R. Nyqvist, M. Osakabe, C. Perez von Thun, S. D. Pinches, M. Podesta, M. Porkolab, K. Shinohara, K. Schoepf, Y. Todo, K. Toi, M. A. Van Zeeland, I. Voitsekhovich, R. B. White, V. Yavorskij, and ITPA EP TG and JET-EFDA Contributors. Energetic particle instabilities in fusion plasmas. Nucl. Fusion, 53, 104022, 2013.
[36] D. S. Montgomery. Two decades of progress in understanding and control of laser plasma instabilities in indirect drive inertial fusion. Phys. Plasmas, 23, 055601, 2016.
[37] A. R. Bell, R. G. Evans, and D. J. Nicholas. Elecron Energy Transport in Steep Temperature Gradients in Laser-Produced Plasmas. Phys Rev. Lett., 46, 243, 1981.
[38] A. R. Bell, and M. Sherlock. The fastVFP code for solution of the Vlasov-Fokker-Planck equation. Plasma Phys. Control. Fusion, 66, 035014, 2024.
[39] N. P. Dover, O. Tresca, N. Cook, O. C. Ettlinger, R. J. Kingham, C. Maharjan, M. N. Polyanskiy, P. Shkolnikov, I. Pogorelsky, and Z. Najmudin. Optical Imaging of Laser-Driven Fast Electron Weibel-like Filamentation in Overcritical Density Plasma. Phys. Rev. Lett., 134, 025102, 2025.
[40] N.R. Walkden, F. Militello, J. Harrison, T. Farley, S. Silburn, and J. Young. Measurement and modelling of intermittent transport phenomena in the MAST scrape-off layer. EUROFUSION WP15Er-PR(16) 14716, https://scipub.euro-fusion.org/wp-content/uploads/WP15ERCP16_14716_submitted.pdf, accessed 23-07-2025.
[41] V. S. Udintsev. Measurements of temperature and density in magnetic confinement fusion devices. Nuclear Instruments and Methods in Physics Research Section A: Accelerators, Spectrometers, Detectors and Associated Equipment, 623, 2, 2010,
[42] X. Zhao, X. H> Yuan, Y. G. Dong, K. Glize, Y. H. Zhang, J. Zheng, C. Q. Xing, H. C. Gu, C. L. Zhang, Y. Dai, K. fang, Z. Zhang, R. Yan, F. Y. Wu, and J. Zhang. Measurements of laser-plasma instabilities in double-cone ignition experiments relevant to the direct-drive conditions at Shenguang-II Upgrade laser facility. Nucl. Fusion, 64, 086069, 2024.
[43] R. V. Perez, W. U. Boegline, D. S. Darrow, M. Cecconello, I. Klimek, S. Y. Allan, R. J. Akers, D. L. Keeling, K. G. McClements, R. Scannell, M. Turnyanskiy, A. Angulo, P. Avila, O. Leon, C. Lopez, O. m. Jones, N. J. Conway, and C. A. Michael. Investigating fusion plasma instabilities in the Mega Amp Spherical Tokamak using mega electron volt proton emissions. Rev. Sci. Instrum. 85, 11D701, 2014.
[44] F. Wasser, Ş. Zähter, M. Rivers, S. Atzeni, F. P. Condamine, G. Cristoforetti, G. Fauvel, N. Fischer, L. A. Gizzi, D. Hoffman, P. Koester, T. Laštovička, J. F. Myatt, R. L. Singh, M. Sokol. W. Theobald, S. Weber, T. Ditmire, T. Forner, and M. Roth. Investigation of laser plasma instabilities driven by 527 nm laser pulses relevant for direct drive inertial confinement fusion. Phys. Plasmas, 31, 022107, 2024
[45] L. Wright, and S. Davidson. How to tell the difference between a model and a digital twin. Advanced Modeling and Simulation in Engineering Sciences, 7, 13, 2020.
[46] A. Saltelli, S. Tarantola, F. Campolongo, and M. Ratto. Sensitivity Analysis in Practice: A Guide to Assessing Scientific Methods, John Wiley & Sons Ltd., 2002.
[47] J. Seo, S.K. Kim, A. Jalalvand, R. Conlin, A. Rothstein, J. Abbate, K. Erickson, J. Wai, R. Shousha, and E. Kolemen. Avoiding fusion plasma tearing instability with deep reinforcement learning. Nature, 626, 746-751, 2024.
[48] M. B. Tayeb, V. Tikhonchuk, and J.-L. Fueageas. ICF target optimization using generative AI. Phys. Plasmas, 31, 103903, 2024.
[49] Clean Air Task Force. A Survey of Artificial Intelligence and High Performance Computing Applications to Fusion Commercialization. https://www.catf.us/resource/a-survey-of-artificial-intelligence-and-high-performance-computing-applications-to-fusion-commercialization/, 2024.
[50] M. L. Wald. Artificial Intelligence Goes Nuclear. The Breakthrough Institute. https://thebreakthrough.org/journal/no-20-spring-2024/artificial-intelligence-goes-nuclear, 2024.
[51] W. Picot. Enhancing Nuclear Power Production with Artificial Intelligence. IAEA Bulletin, 64-3, 2023.
[52] ForoNuclear. The use of Artificial Intelligence in the nuclear sector. https://www.foronuclear.org/en/updates/in-depth/the-use-of-artificial-intelligence-in-the-nuclear-sector/#:~:text=In%20practice%2C%20AI%20systems%20can,reliability%20of%20the%20nuclear%20infrastructure, 2024.
[53] A. Savin. 'Small' Nuclear – the solution for Big Data? https://www.mewburn.com/news-insights/small-nuclear-the-solution-for-big-data, 2024.
[54] Reuters. OpenAI CEO Altman says at Davos future AI depends on energy breakthrough. https://www.reuters.com/technology/openai-ceo-altman-says-davos-future-ai-depends-energy-breakthrough-2024-01-16/, 2024.
[55] T. Spence, and S. Singh. What the data centre and AI boom could mean for the energy sector. International Atomic Energy Authority. https://www.iea.org/commentaries/what-the-data-centre-and-ai-boom-could-mean-for-the-energy-sector, 2024.
[56] M. Yanez-Barnuevo. Data Center Energy Needs Could Upend Power Grids and Threaten the Climate. Environmental and Energy Study Institute, https://www.eesi.org/articles/view/data-center-energy-needs-are-upending-power-grids-and-threatening-the-climate#:~:text=More%20forceful%20forecasts%20from%20the,of%20total%20U.S.%20electricity%20consumption., 2025.
[57] UK Atomic Energy Authority. International Computing. https://ccfe.ukaea.uk/programmes/fusion-futures/international-computing/, accessed 23-07-2025.

REFERENCES (CONT)

[58] Digitalisation World. Fusion-powered data centres: Google purchases 200MW of fusion power from US$2 billion startup. https://digitalisationworld.com/news/70232/fusion-powered-data-centres-google-purchases-200mw-of-fusion-power-from-us-2-billion-startup, 2025.

[59] Helion Energy. Announcing Helion's latest fundraise of $500 million. https://www.helionenergy.com/articles/announcing-500-million-fundraise/, 2024.

[60] Department for Science, Innovation and Technology, and F. Clark MP. Investors and local authorities gear up as AI Growth Zone delivery gathers speed. https://www.gov.uk/government/news/investors-and-local-authorities-gear-up-as-ai-growth-zone-delivery-gathers-speed, 2025.

RICHARD A. JOHNSON

Chairperson, Partner, Patent Attorney

Richard develops and manages IP portfolios for clients in the UK and abroad, contributing to and assisting in the formulation and execution of IP strategies. Richard also handles patent prosecution at the European Patent Office and the UK Intellectual Property Office for a wide range of clients including on advanced nuclear technologies. His clients are primarily based in the UK, US, and China, spread across a range of diverse technical sectors including precision health, technical fabrics, telecommunications, affective computing and nuclear fusion and fission technologies. As chairperson at the firm, Richard is responsible for all Partnership business as well as being a member of the firm's Management Board. He holds an MPhys in physics from the University of Oxford.

ALEX F. SAVIN

Patent Attorney

Alex works across all stages of the patent life cycle from invention capture and drafting, through prosecution, to opposition proceedings at the EPO. He is experienced in helping start-up companies and SMEs build and manage their patent portfolios and has particular expertise in the nuclear sector, including fusion and power generation, and in the field of optics & photonics. He has an MPhys degree in Physics and a DPhil in Atomic & Laser Physics, both from the University of Oxford. His research focussed on designing and implementing high-power laser experiments exploring inertial confinement approaches to nuclear fusion at major international laboratories dedicated to laser-driven fusion in the US, UK and Europe including the Lawrence Livermore National Laboratory, and the Central Laser Facility.

HARRY WESTHEAD

Associate, Patent Attorney

Harry is a patent attorney in the firm's engineering and ICT team. His specialisms include power generation, nuclear reactor safety systems, image processing, radar systems, optical systems, cryptography, and medical devices including wearables, laryngoscopes, and surgical endoscopes. He works with a variety of different clients including UK-based start-ups, universities, and SMEs as well as multinational companies and international attorneys in Japan and USA. He holds an MPhys degree with a professional placement at a nuclear power plant from the University of Bath.

PHILIP HORTON

Patent Technical Assistant

Philip is a trainee patent attorney working in the engineering practice group. He has an MEng in Chemical Engineering from the University of Cambridge. He worked as a process engineer at a MOF-focused startup, where he led the scale up of their manufacturing process and worked on the development of MOF-based adsorptive systems including hydrogen storage, carbon capture, and air purification.