The SMARTHEP European Training Network

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Abstract. **S**ynergies between **MA**chine learning, **R**eal-**T**ime analysis and **H**ybrid architectures for efficient **E**vent **P**rocessing and decision making (SMARTHEP) is a European Training Network with the aim of training a new generation of Early Stage Researchers to advance real-time decision-making, effectively leading to data-collection and analysis becoming synonymous.
SMARTHEP will bring together scientists from the four major LHC collaborations which have been driving the development of real-time analysis (RTA) and key specialists from computer science and industry. By solving concrete problems as a community, SMARTHEP will bring forward a more widespread use of RTA techniques, enabling future HEP discoveries and generating impact in industry. The students will contribute to European growth, leveraging their hands-on experience machine learning and accelerators towards concrete commercial deliverables in fields that can most profit from RTA, such as transport, manufacturing, and finance.
This contribution presents the training and outreach plan for the network, as well as some of its early results, and is intended as an opportunity for further collaboration and feedback from the CHEP community.

1 Introduction

The **S**ynergies between **MA**chine learning, **R**eal-**T**ime analysis and **H**ybrid architectures for efficient **E**vent **P**rocessing and decision making (SMARTHEP) European Training Network is a European Union Horizon-funded training network, with a focus on the real-time analysis techniques deployed in high energy physics (HEP) research and in industry. The network centres around 12 doctoral students across Europe employed as Early Stage Researchers (ESRs) within the Marie Skłodowska-Curie Actions (MSCA) framework. The network commenced in September 2021 and will conclude in September 2025, with each ESR position spanning the 3 years from September 2022 to September 2025.

This proceedings sets out the principles, approach and work of the SMARTHEP network, as presented on 9$^{\text{th}}$ May 2023 at CHEP2023.

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2 SMARTHEP as a European Training Network

SMARTHEP is organised as a European Training Network, funded through the 2020 EU Horizon funding call. The primary aim of the network is to train 12 ESRs, whilst building synergies between HEP and industry. The network takes a novel approach to building such synergies, structuring each ESR position (a 3 year period of doctoral study) around secondments in both HEP and industry. To achieve this, the network is formed of a series of partnerships between universities, research institutes and organisations in industry, as listed in Table 1.

Category	Partners
Universities	Lund University Sorbonne University (LPNHE & LIP) Technische Universität Dortmund University of Bologna University of Geneva University of Heidelberg University of Helsinki University of Manchester Universidade Santiago de Compostela (IGFAE) Vrije Universiteit Amsterdam
Research institutes	CERN CNRS NIKHEF
Industry partners	IBM France Lightbox Point 6 University of Manchester Institute for Data Science and AI Verizon Connect Ximantis

Table 1. The 18 organisations which form the SMARTHEP network, listed by organisation type.

The network is structured as 7 Work Packages (WPs), as laid out in Figure 1. WP1 and WP2 define the organisation of the network; WP3 and WP4 introduce the techniques and tools of real-time analysis to the network; WP5 and WP6 use said techniques and tools to produce results for HEP and industry; WP7 makes these results available and promotes their wider use and adoption.

2.1 Partnerships with universities and research institutes

Within the network The network has a particular focus on physics at the Large Hadron Collider (LHC). Each ESR is thus affiliated to one of the four major experiments based at the LHC: ALICE, ATLAS, CMS and LHCb. The network duration coincides with Run 3 of the LHC, 2022-2025. As such, ESR projects and outcomes have a focus on delivering required work for said experiments.

2.2 Partnerships with industry

A unique feature of the network is the extensive cooperation between HEP and industry across all ESR positions. RTA approaches have seen significant adoption in industry in recent years, with many organisations turning to RTA as a means to handle “big data”.

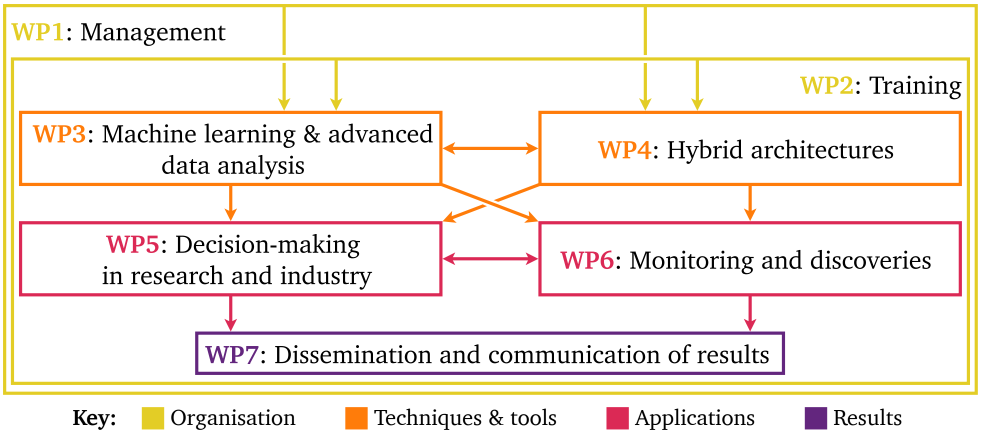

Figure 1. The structure of WPs within the SMARTHEP network. WP1, "Management", covers the overarching management of the network by the Project Manager, Project Coordinator, and Executive Board. WP2, "Training", sets out training and career development for network participants, provided by partners of the network, discussed further in Section 5.3. WP3, "Machine learning & advanced data analysis", develops machine learning techniques for use in RTA contexts, as discussed in Section 3.1. WP4, "Hybrid architectures", focuses upon the deployment of non-CPU architectures for acceleration of data processing, discussed in Section 3.2. WP5, "Decision-making in research and industry", uses the work of WP3 and WP4 to develop RTA-based decision-making technologies. WP6, "Monitoring and discoveries", also applies WP3 and WP4 to RTA approaches in data analysis. WP7, "Dissemination and communication of results", publication and propagation of results from work completed by particpants.

3 Real-time analysis

The challenge of rapidly processing large quantities of data is common to both HEP and industry, and remains a significant hurdle to progress in both areas. [1] Recent advances in computing have enabled the possibility of processing data in real-time, i.e. as data is collected (also commonly referred to as "online" processing). [2] Real-time analysis (RTA) is thus an umbrella term for such approaches, encompassing a number of state-of-the-art data processing techniques. By processing data online, resources (computing power, storage space, energy, etc.) can be saved and new insights can be obtained from the data recorded, as shown in Figure 2.

RTA techniques have seen widespread adoption across HEP, in particular amongst trigger and data acquisition (TDAQ) systems. Since it is not possible to record the detector output and carry out event reconstruction at the LHC collision rate of 40MHz, a trigger must be devised to select only those events which are relevant to the physics goals of a given experiment. Such a trigger conventionally consists of a hardware trigger acting directly on parts of the detector output, and a staged software trigger, applying gradually more fine-tuned selections with increasing amounts of reconstructed event detail.

In industry, the limitations of the scale of "big data" looms over many applications of computing. However,

Successful implementation of RTA approaches rests upon the . In particular, in the areas of machine learning and hybrid architectures, which are summarised in Sections 3.1 & 3.2.

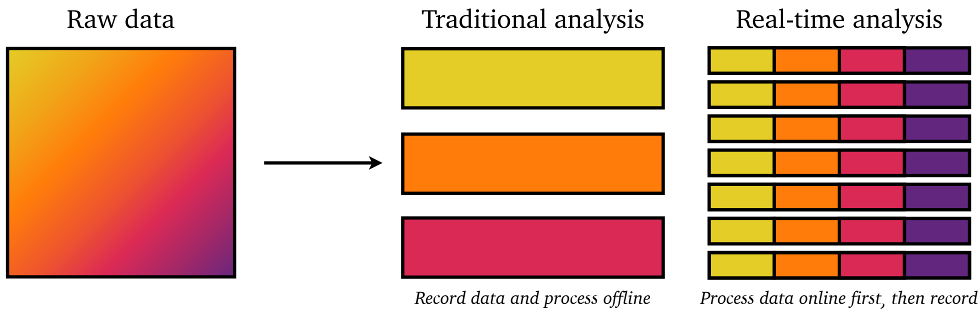

Figure 2. The traditional and real-time analysis approaches to processing raw data. Traditional approaches rely on recording all data and processing this offilne. Real-time analysis reverses this, processing data as it is produced and recording only the relevant processed information, enabling larger volumes of processed data to be stored.

3.1 Machine learning

Machine learning (ML), a catch-all for a number of techniques and technologies wherein algorithms are trained to analyse data, enables rapid decision making and pattern recognition across a broad range of use cases. [3] Whilst general consumer access to ML models is a relatively recent phenomenon, ML already has an extensive history, with the foundations being laid in the 1950s and 1960s. [4, 5] In HEP, this history begins in the 1990s with the use of classifiers in offline physics analysis, and has since developed to a variety of classification on pattern recognition/anomaly detection techniques for both online and offline use. [6, 7]

Leading with the firs of these tools, ML classifiers are algorithms classed with classification. Many such algorithms exist, with Boosted Decision Trees (BDTs) and Neural Networks (NNs) amongst those employed across the field. The use of BDTs in signal selection for offline physics analysis has become standard practice, e.g. in suppresion of combinatorial background in the LHCb experiment measurement of the $B_s^0 - \bar{B}_s^0$ oscillation frequency. [8] However, classifiers are also used to aid event reconstruction, e.g. in the CMS boosted event shape tagger, a NN trained to discriminate between possible t, $W^{\pm}$, Z^0 and H candidates within an event. [9] In industry, ML classifiers are used frequently in content deliver

Machine learning techniques can also be applied to pattern recognition and anomaly detection—tasks which cannot be realistically carried out on the scales of data presently being analysed. In industry, this is applied intuitively to fraud detection, wherein subtle details in data such as the transactions of a customer. In HEP [10]

3.2 Hybrid architectures

Typical computational resources consist of Central Processing Units (CPUs), processors which are designed for general purpose computation (i.e. varied tasks with significant variety in computing/memory resources), with large on-board memory and often multiple processing cores. Alternative architectures, such as those shown in Figure 3, can be applied in conjunction or in place of CPU architectures to accelerate processing where tasks are not well-suited are to CPU architectures alones.

Field-programmable gate arrays (FPGAs) are integrated circuits which can be programmed by the user for specific tasks. [11] An FPGA consists of many simple logic circuits with a small amount of on-board memory, formed into logic blocks, each of which are

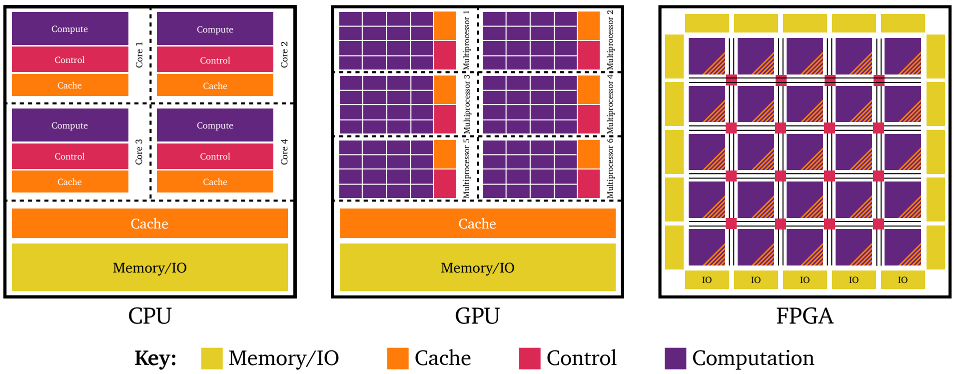

Figure 3. Comparison of CPU, GPU and FPGA architectures. A CPU is typically formed of several cores, each containing computational, control and cache resources, and a centralized cache, memory and input/output (IO) interface. GPUs are formed similarly, with centralized cache, memory and IO, and many multiprocessors; however, each multiprocessor contains a greater proportion of computational resources, which are themselves partitioned to perform tasks in parallel. FPGAs are structured in a radically different way, with memory and IO connected to many interlinked control blocks, each primarily formed of simpler logic gate arrangements and often accompanied by a small cache.

connected via switch matrices. [12] FPGAs are thus well-suited to bespoke, computationally light but highly parallelisable tasks, such as low-level trigger decisions, wherein simple selections must be made rapidly. [13] In industry, FPGAs have seen adoption . However; a lack of on-board memory limits the deployment of FPGAs to more intensive tasks.

Graphical Processing Units (GPUs) can also be employed to . [14] Historically, the use of GPUs has been

4 Early stage researchers

The 12 ESRs form the core of the network, with the training and partnerships providing a scaffold for the completion of their respective outcomes. These ESRs work with HEP and industry partners throughout the 3 years of their doctoral study.

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Shortly after the commencement of the ESR positions, each ESR supervisor completed a Personal Career Development Plan with their ESR. This document details the

4.1 Structure of ESR positions

Each ESR is enrolled as a doctoral student at a partner university for 3 years. This university is typically also the primary institution of the ESR, though the industry-centred ESR positions 2 and 10 (discussed in Section 2) are carried out with industry partners near to the university of enrollment. Where partner universities require a longer period of study or typically provide extensions to a 3 year study programme, commitments to further enrollment are provided by each partner university where necessary. At the end of the period of doctoral study, each ESR will receive a doctorate in particle physics from their university of enrollment.

ESRs

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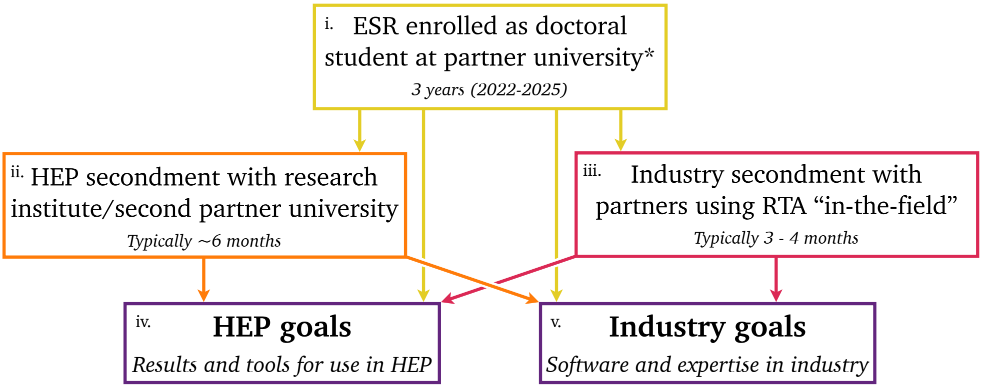

Figure 4. Diagram of the structure of a SMARTHEP ESR position. Each ESR is enrolled (i.). During the course of their enrolment, they will undertake secondments with network partners in HEP (ii.) and industry (iii.). Through the combination of their primary and secondment work, each ESR will achieve several goals in HEP (iv.) and industry (v.), as discussed in further detail in Section 5.1.

Each ESR will undertake a secondment in HEP during their studies, either at another partner university or a partner research institute. This is generally organised to last for 6 months, though this varies from project to project.

In addition to their time working in HEP, each ESR will also spend time working in industry, typically as a secondment of 3-4 months (though this is again flexible to the specific programme of each ESR position).

4.2 Examples of ESR positions

The 12 ESR positions of the network are summarised in Table 2.

Early-stage researcher	Primary affiliation	Secondments	
		HEP	Industry
ESR1: Patin Inkaew	University of Helsinki	CERN	Verizon Connect
ESR2: Laura Boggia	IBM France (enrolled at University Sorbonne)	CNRS	IBM France
ESR3: Leon Bozianu	University of Geneva	IGFAE	Lightbox
ESR4: Sofia Cella	University of Geneva	CNRS	Lightbox
ESR5: Fotis Giasemis	Sorbonne University	CERN	Ximantis
ESR6: Daniel Magdalinski	VU Amsterdam/NIKHEF	TU Dortmund	Point 8
ESR7: Jamie Gooding	TU Dortmund	CERN	Ximantis
ESR8: Micol Olocco	TU Dortmund	CERN	Point 8
ESR9: Carlos Cocha	University of Heidelberg	TU Dortmund/IGFAE	Verizon Connect
ESR10: Joachim Hansen	Lund University	CERN	Ximantis
ESR11: Henrique Piñeiro Monteagudo	Verizon Connect (enrolled at University of Bologna)	Sorbonne University/ University of Manchester	Verizon Connect
ESR12: Pratik Jawahar	University of Manchester	CERN	UoM IDSAI

Table 2. Please write your table caption here

To paint a clearer picture of how the positions take shape, a few examples are taken from Table 2. Jamie Gooding (ESR7) is based at Technische Universität Dortmund, working on real-time event selection at the LHCb Experiment, with a HEP secondment of $\approx$ 6 months at

CERN to support this work and a 3-4 month industry secondment with Ximantis, working on real-time traffic monitoring. Laura Boggia (ESR2)

5 Network outcomes

As an obligation to the European Union, intended network outcomes were laid out as a set of deliverables. These deliverables act to a guide the progression of the network and its participants. Key outcomes of the network are discussed in the following sections.

5.1 Goals of HEP and industry

The core outcomes of the network are a set of goals, which are completed on behalf of the network partners by the network participants. These goals vary, with the majority associated to a specific ESR position, for example, the goal of "calibration of ALICE TPC for heavy-ion physics" associated to ESR10, Joachim Hansen.

5.2 RTA whitepapers

As a deliverable of the network, the participants will write a series of whitepapers reviewing the current RTA state-of-the-art. The four whitepaper topics are listed in the following subsections and an overview is given for each. At time of writing, these whitepapers are expected to be submmited for publication by the end of 2023.

5.2.1 ML for RTA

The first network whitepaper provides a review of current ML applications to HEP in RTA contexts and corresponding best practices. Examples of such applications range from data-taking, e.g. in particle identification at the ALICE experiment, to offline analysis, e.g. anomaly detection for diject resonance searches at the ATLAS experiment. [15, 16]

5.2.2 Hybrid architectures at the LHC

The use of hybrid architectures by LHC experiments is reviewed in the second SMARTHEP whitepaper. Acceleration of tasks such as selection and reconstruction by hybrid archetictures was developed significantly during Run 2 of the LHC (2015-2018). Run 3 deployments of hybird architectures capitalise on this progress, e.g. in the use of FPGAs in the ALICE Central Trigger System and the use of GPUs in the ATLAS High Level Trigger farm. [17, 18]

5.2.3 Trigger and data acquisition systems of the LHC

In the third whitepaper, the TDAQ systems of LHC experiments are reviewed, with a focus upon best practices for both TDAQ hardware and software. As such, this whitepaper reviews topics ranging from upgrades to the ATLAS TDAQ system, to the Allen framework of the LHCb experiment enabling software trigger operation at a 30 MHz readout rate. [19, 20]

5.2.4 RTA techniques at LHC experiments

The final whitepaper focuses on the use of RTA techniques at LHC experiments, in particular in the context of RTA-enabled searches and anomaly detection. For example, in dark photons searches carried out by the CMS and LHCb experiments, which require access to signals previously excluded by prior non-RTA frameworks. [21, 22] To avoid overlap with the whitepaper discussed in Section 5.2.3, this whitepaper does not cover the use of RTA approaches in trigger systems. An exception is made for cases wherein the trigger system forms an inherent part of a process, e.g. RTA-enabled searches where trigger systems provide offline-quality data for direct analysis use.

5.3 Training of ESRs

Funding is allocated within the network for participants to attend relevant training activities. In the case of ESRs, training and career devlopment is discussed in writing their respective PCDP, providing a clear overview of their intended and requested training activities. Examples of such activities include attendance of specialist industrial training sessions and academic schools. Training is also provided within the network, between participants, for example in the First SMARTHEP School on Collider Physics and Machine Learning discussed in Section 6.2.

5.4 Software and digital assets

The work of the ESRs will generate a number of digital assets (e.g. software packages, data processing tools), with many being applicable beyond narrow academic/industrial applications.

The network is committed to producing making any produced digital assets **F**indable, **A**ccessible, **I**nteroperable, and **R**eusable (FAIR). [23] Under these guiding principles

Additionally, our assets and results should be open and accessible to the wider community. To implement these commitments, a project on GitHub has been created to host such assets, https://github.com/SMARTHEP. Other assets and resources will be made available on the network website, https://smarthep.org.

6 Network events

Network events form a backbone of the SMARTHEP network, giving participants unique opportunities to meet, exchange ideas and develop. Whilst the events of the network are focused on an ESR audience, SMARTHEP has made many events available to additional interested early career scientists working/studying at SMARTHEP institutes.

6.1 SMARTHEP Kick-off Meeting

To mark the commencement of the ESR positions, a kick-off meeting was held at the University of Manchester from 21st to 25th November 2022. This meeting formally introduced ESRs to the network, discussing the objectives and organisation of the network, in addition to introducing the topics-of-work of each ESR. The meeting also served as an opportunity for participants from all sides of SMARTHEP to meet in person, network and discuss ideas. To facilitate this, a visit to the Jodrell Bank Centre for Astrophysics was held. A review paper-writing course was organised by academic writing consultancy group Scriptoria, to train ESRs ahead of the writing of the 4 whitepapers discussed in Section 5.2.

6.2 First SMARTHEP School on Collider Physics and Machine Learning

The First SMARTHEP School on Collider Physics and Machine Learning was hosted by Université de Genève between 10^{st} to 13^{th} November 2022. The school delved into many aspects directly relevant to the network, through a varied programme including:

- Lectures on experimental physics at collider experiments by Anna Sfyrla.
- Lectures on theoretical physics and Monte Carlo event generators by Torbjörn Sjöstrand.
- Hands-on lessons in machine learning by Maurizio Pierini.
- Evening seminars on multimessenger astronomy by Teresa Montaruli and the CERN experimental programme by Jamie Boyd.

The school also directly succeeded the mid-term meeting of the network with the EU Project Officer, a key stage in the lifecycle of the network, wherein the progress and trajectory of the network was evaluated by the European Union.

6.3 Upcoming events

At time of writing, the network still has two years ahead of it, in which further network events are planned. These will guide the governance of the network, develop ESR expertise and deepen collaborations with industry.

The network assembly sits as a cornerstone of network policy and governance.

Accelerator bootcamps in specific aspects of RTA . These are likely to take place in the summer of 2024.

An industry applications school will round off the collaboration with industry. It is intended that most ESRs will have completed their industry secondments by this time.

7 Conclusion

The network will provide valuable contributions in HEP, particularly to the commisioning and operation of LHC experiments throughout Run 3 of the LHC. Additionally, the network serves to further the adoption of RTA approaches in industry and do demonstrate the value of collaboration between HEP and industry.

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References

[1] H. Hu, Y. Wen, T.S. Chua, X. Li, IEEE Access **2**, 652 (2014)

[2] W. Tian, Y. Zhao, in *Optimized Cloud Resource Management and Scheduling*, edited by W. Tian, Y. Zhao (Morgan Kaufmann, Boston, 2015), pp. 17–49, ISBN 978-0-12-801476-9, `https://www.sciencedirect.com/science/article/pii/B9780128014769000021`

[3] J. Jovel, R. Greiner, Frontiers in Medicine **8** (2021)

[4] F. Rosenblatt, Psychological review **65 6**, 386 (1958)

[5] T. Cover, P. Hart, IEEE Transactions on Information Theory **13**, 21 (1967)

[6] P. Abreu, W. Adam, T. Adye, E. Agasi, G. Alekseev, A. Algeri, P. Allen, S. Almehed, S. Alvsvaag, U. Amaldi et al., Physics Letters B **295**, 383 (1992)

[7] K. Albertsson, P. Altoe, D. Anderson, J. Anderson, M. Andrews, J.P.A. Espinosa, A. Aurisano, L. Basara, A. Bevan, W. Bhimji et al., *Machine learning in high energy physics community white paper* (2019), `1807.02876`

[8] R. Aaij, C.A. Beteta, T. Ackernley, B. Adeva, M. Adinolfi, H. Afsharnia, C.A. Aidala, S. Aiola, Z. Ajaltouni, S. Akar et al., Nature Physics **18**, 1 (2022)

[9] A. Sirunyan, A. Tumasyan, W. Adam, F. Ambrogi, T. Bergauer, M. Dragicevic, J. Erö, A.E.D. Valle, M. Flechl, R. Frühwirth et al., Journal of Instrumentation **15**, P06005 (2020)

[10] B. Nachman, *Anomaly Detection for Physics Analysis and Less Than Supervised Learning* (2022), chap. Chapter 4, pp. 85–112

[11] J. Serrano, *Introduction to FPGA design* (2008), `https://cds.cern.ch/record/1100537`

[12] U. Meyer-Baese, *Digital Signal Processing with Field Programmable Gate Arrays* (Springer Berlin Heidelberg, 2013), ISBN 9783662046135, `https://books.google.co.uk/books?id=L6fvCAAAQBAJ`

[13] J. Duarte, P. Harris, S. Hauck, B. Holzman, S.C. Hsu, S. Jindariani, S. Khan, B. Kreis, B. Lee, M. Liu et al., Computing and Software for Big Science **3** (2019)

[14] D. vom Bruch, Journal of Instrumentation **15**, C06010 (2020)

[15] Ł.K. Graczykowski, M. Jakubowska, K.R. Deja, M. Kabus, on behalf of the ALICE collaboration, Journal of Instrumentation **17**, C07016 (2022)

[16] G. Aad, B. Abbott, D.C. Abbott, A. Abed Abud, K. Abeling, D.K. Abhayasinghe, S.H. Abidi, O.S. AbouZeid, N.L. Abraham, H. Abramowicz et al. (ATLAS Collaboration), Phys. Rev. Lett. **125**, 131801 (2020)

[17] Kvapil, Jakub, Bhasin, Anju, Bombara, Marek, Evans, David, Jusko, Anton, Kluge, Alexander, Krivda, Marian, Kralik, Ivan, Lietava, Roman, Nayak, Sanket Kumar et al., EPJ Web Conf. **251**, 04022 (2021)

[18] A. Bocci, on behalf of the CMS Collaboration, Journal of Physics: Conference Series **2438**, 012016 (2023)

[19] G. Aad, T. Abajyan, B. Abbott, J. Abdallah, S. Abdel Khalek, O. Abdinov, R. Aben, B. Abi, O. AbouZeid, H. Abramowicz et al. (ATLAS), Tech. rep. (2013), final version presented to December 2013 LHCC., `https://cds.cern.ch/record/1602235`

[20] R. Aaij, J. Albrecht, M. Belous, P. Billoir, T. Boettcher, A. Brea Rodríguez, D. vom Bruch, D.H. Cámpora Pérez, A. Casais Vidal, D.C. Craik et al., Computing and Software for Big Science **4**, 7 (2020)

[21] A.M. Sirunyan, A. Tumasyan, W. Adam, F. Ambrogi, T. Bergauer, M. Dragicevic, J. Erö, A. Escalante Del Valle, M. Flechl, R. Frühwirth et al. (CMS Collaboration), Phys. Rev. Lett. **124**, 131802 (2020)

[22] R. Aaij, B. Adeva, M. Adinolfi, Z. Ajaltouni, S. Akar, J. Albrecht, F. Alessio, M. Alexander, A. Alfonso Albero, S. Ali et al. (LHCb Collaboration), Phys. Rev. Lett. **120**, 061801 (2018)

[23] M.D. Wilkinson, M. Dumontier, I.J. Aalbersberg, G. Appleton, M. Axton, A. Baak, N. Blomberg, J.W. Boiten, L.B. da Silva Santos, P.E. Bourne et al., Scientific Data **3**, 160018 (2016)