कृत्रिम मेधा

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परिदृश्य पथ-निर्देशन : कण त्वरकों के संबंध में कुछ चुनौतियों के समाधान के लिए मशीन लर्निंग अनुप्रयोग और आधुनिक नियंत्रण तकनीक

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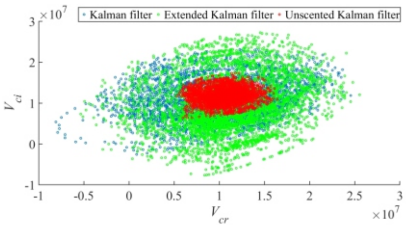

केएफ, ईकेएफ एवं यूकेएफ द्वारा आरएफ गुहिका उद्ग्रहण अनुमानित बनाम कल्पित घटकों का आरेख

सारांश

कण त्वरक विविध घटकों का अंतरसंबंध होता है। त्वरक प्रणालियों में निहित जटिल डेटापैटर्न उच्च गुणवत्तावाले डेटासेट प्रदान करते हैं , जो उन्नत मशीन लर्निंग (ML) एल्गोरिदम के प्रशिक्षण के लिए आदर्श हैं। इस लेखमें त्वरक EPICS SCADA और डेटाआर्काइविंग के साथ ML फ्रेमवर्क के एकीकरण को प्रस्तुत किया गया है। इसके अलावा , लोलेवलआरएफ (LLRF) नियंत्रक के लिए आनुविंशक एल्गोरिदम और पुनरावृत्तिशिक्षणनियंत्रण के अनुप्रयोग के परिणाम भी प्रस्तुत किए गए हैं। विभिन्न आधुनिक नियंत्रण और अनुमान तकनीकों का उन्नयन अत्याधुनिक प्रौद्योगिकी का उपयोग करके उच्च शक्तिवाले त्वरक की कई गुहा ऑपरेशन की विश्वसनीयता, दक्षता और स्थिरता को सुनिश्चित करेगा। डिट्यूनिंग अनुमान और आरएफ स्रोत रैखिकीकरण में प्रयुक्त आधुनिक नियंत्रण तकनीकों को भी पेश किया गयाहै।

Artificial Intelligence

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Navigating the Landscape: Machine Learning Applications and Modern Control Techniques for Mitigating Some Challenges for Particle Accelerators

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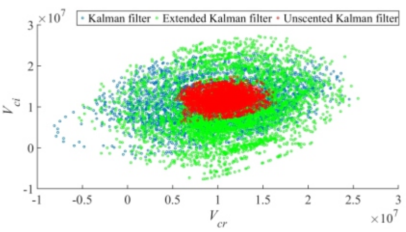

Plot of estimated real versus imaginary components of RF cavity pickup by KF, EKF and UKF

ABSTRACT

Particle accelerators constitute an interconnection of diverse components. Intricate data patterns inherent in accelerator systems provide rich datasets ideal for training sophisticated Machine Learning (ML) algorithms. This article presents integration of accelerator EPICS SCADA and Data Archiving with ML framework. Results in application of genetic algorithm and iterative learning control for Low Level RF (LLRF) controller are also presented. Augmentation of various modern control and estimation techniques using state of the art technology shall lead to reliable, efficient and stable multi-cavity operation of high power accelerator. Modern control techniques employed in detuning estimation and RF source linearization are introduced.

KEYWORDS: *EPICS, Machine Learning, Control, Particle Accelerators*

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Introduction

Accelerator Control Division has successfully designed, developed and commissioned control and instrumentation (C&I) systems, like, Low Level RF (LLRF) [1] for RF cavity control, RF Protection and Interlock (RFPI) [2] system, Beam Position Monitor (BPM) [3] system and Programmable Timing and Control System (PTC) [4] for various accelerators facilities. As accelerators grow in complexity and scale, the demand for efficient, safe and adaptive control systems becomes increasingly crucial. Traditional control systems struggle to adapt to the inherent non-linearity and non-predictable environmental dynamics. The developed C&I systems employ RF and digital signal processing algorithms and provide digital data for logging, monitoring and post-mortem analysis. Data intensive dynamics of C&I systems make them suitable to harness the advances in the domain of ML. In this context, the integration of ML techniques into the control and instrumentation of particle accelerators has emerged as a promising avenue for enhancing performance, optimizing operation and overcoming inherent challenges.

ML integration with Accelerator Controls

Experimental Physics and Industrial Control System [5] (EPICS) is a set of open source software tools, libraries and applications developed collaboratively and used worldwide to create distributed soft real-time control systems for scientific instruments such as particle accelerators, telescopes and other large scientific experiments. Integration of ML analysis tools with accelerator control systems requires interfacing with EPICS Input Output Controller (IOC) and databases. The quality and temporal alignment of accelerator data, encompassing information from various noisy sensors and diverse subsystems, necessitate meticulous and often automated pre-processing and integration efforts. The upgraded version of EPICS - EPICS 7 is more suitable for ML integration as it provides structured Process Variables (PV) database with time stamped metadata. EPICS 7 Soft IOC for LLRF system has been developed and integrated with a Data Archiver, which supports NOSQL database. For ML integration, EPICS 7 Data Acquisition (DAQ) IOC design as shown in Fig.1 is proposed. ML algorithms require extensive datasets, and often there is a limited availability of historical data, especially for rare failure events or off beat operating scenarios. This needs continuous logging of data streams from instrumentation. In EPICS DAQ IOC, PV data stream gets the data from Device Support which is interfaced to underlying LLRF/RFPI/BPM front end equipment. Timestamp information from timing system is crucial for time alignment and is used to populate metadata of PVs. For certain

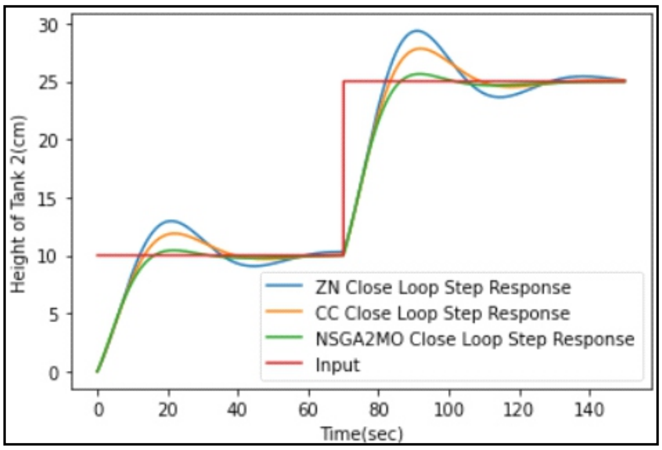

Fig.2: Response of FOPDT system for step change in input.

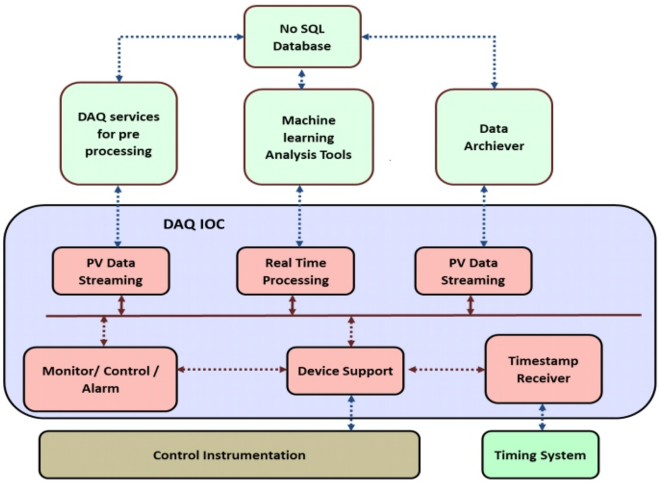

Fig.1: EPICS 7 IOC for ML integration.

PVs pre-processing services such as data merging, temporal alignment and unification is required before storage. ML analysis tools can then interface with the stored data and/or directly with real time processing in IOC.

Control Instrumentation

Performance of LLRF and Resonance Control System (RCS) defines the phase, amplitude and frequency stability of RF cavity. Generally proportional integral (PI) controller is used in LLRF system for amplitude and phase stabilization. Optimizing the performance of controller is pivotal for addressing challenges such as RF amplifier noise, cavity parameter swings, microphonics and beam loading effects. Conventional methods are limited by process modelling error and parametric uncertainties. Adaptive control system can overcome these challenges.

Many of the PI parameters optimization problems are multi-objective in nature, for example, improving both transient and steady state response, and a thorough comprehension of equilibrium between competing choices is desired. The Non-dominated Sorting Genetic Algorithm (NSGA-II) [6] emerges as a potent online optimization technique, providing an optimal set of solutions for competing system parameters, overshoot and settling time in step response. The cost function used in NSGA-II is a weighted combination of Integral Square Error (ISE) for transient response, Integral Time Absolute Error (ITAE) for steady state response and Integral Absolute Error (IAE) for overall error reduction. For evaluating the performance of NSGA-II algorithm, a RF system is modelled as a First Order Plus Dead Time (FOPDT) System and PI parameters are calculated using Zeigler Nichols (ZN), Cohen Coon (CC) and NSGA-II method. A comparative analysis of PI controller performance for a step input change is performed as shown in Fig.2. NSGA-II algorithm provides better transient and steady state response as compared to classical methods. Fig.3 shows that NSGA-II algorithm has significantly improved IAE, ITAE and

Table 1: Comparison of ILCs.

	PID-ILC	FNOILC
Memory requirement	Low	High
Computational complexity	Low	High
Convergence	Slow	Fast
No. of tuning parameters	Less	More

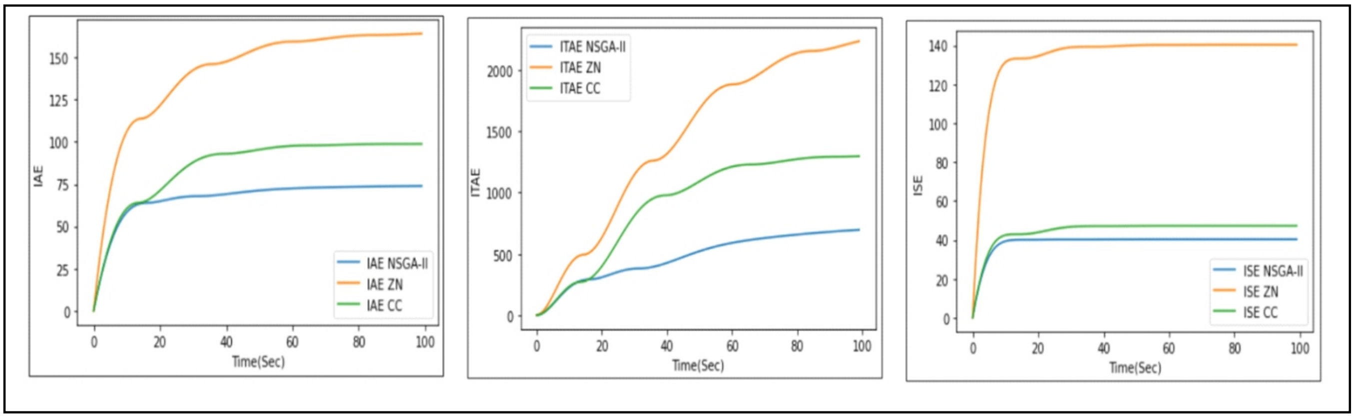

Fig.3: Plot of IAE, ITAE and ISE for ZN, CC and NSGA-II.

ISE as compared to ZN and CC. Further investigations are being carried out by experimental testing using cavity emulator.

In pulsed mode of operation of cavity, disturbances due to beam loading and Lorentz Force detuning, are repetitive in nature. Another modern control method based on Iterative Learning, finds a significant role in such applications and helps achieve high amplitude and phase stabilities, especially in instances where RF-ON times are a few micro-seconds or lower. The addition of Iterative Learning Control (ILC) enhances control loop performance over and above achievable by feedback controller. ILC learns about system dynamics by capturing input and output over previous pulses. In this technique the control output is modified as per pre-defined cost function.

This method has demonstrated huge success in many engineering applications. Though proportional-integral-derivative (PID) type of ILC has been reported as a solution, a more recent Fast Norm Optimal Iterative Learning Controller (FNOILC) [12] is better for fast error minimization with constrained control effort and faster convergence. Table 1 shows comparison of the two candidate ILCs for handling RF cavity repetitive disturbance problems.

System Identification

A number of critical systems in an accelerator are non-linear and have time dynamics evolving over multiple parameter spaces. System modelling with BPM data is another area where ML can handle the online modelling of systems by predicting the parameter space inferred from the measured data. ML can also be used to reduce dimensionality of complex systems for tuning and speedup. In an operational accelerator, ML find an application in identification of model of RF cavity along with its associated RF system. The accurately identified model is important to implement current state of art algorithms based on modern control and estimation theory, detuning estimation and RF power amplifier linearization being a two of the examples. An accurately identified model by ML enhances performance of these algorithms, thus leading to overall improvement in control system performance.

Effective resonance control of RF cavity, especially for superconducting (SC) cavity, needs precise estimation of detuning using cavity model. Conventionally, least squares estimation, linear and non-linear observer based approaches have been used, however estimation based on Kalman filter (KF) and its variants offer practical advantages of robustness in presence of sensor noise and model uncertainty.

In case of normal conducting cavity, detuning estimation based on adaptive KF [9] suffices. Due to non-linear transfer characteristics of SC cavity, a non-linear estimator like Extended Kalman Filter (EKF) or Unscented Kalman Filter (UKF) [10] perform better. A linear estimator when used for a nonlinear system like SC cavity results in more variance as seen in simulated results in Fig.4. Fig.4 also shows that for SC cavity, UKF estimates are better compared to estimates by obtained using KF and EKF. Here, state estimation problem is solved by KF, EKF and UKF for real and imaginary components of the cavity pick-up denoted by *Vcr* and *Vci*, respectively for given cavity input signals and its model parameters subsequently resulting into detuning estimation [9].

At high power operation of RF cavity, amplitude and phase non-linearity of RF power sources like Klystron or Solid State Power Amplifier (SSPA) pose control and operational difficulties. Estimators such as ordinary and recursive least squares capture RF source non-linearity and digitally pre-distort [11] LLRF output to compensate for amplitude and phase non-linearity. A predistortion needs placement of inverse transfer characteristics of SSPA at its input as shown in Fig.5, basically achieved through recursive least square estimation of Volterra model coefficients. A linearly increasing DPD input (x_{DPD}) provides its output (y_{DPD}) such that SSPA output (y_{PA}) is also linearly increasing.

Fault detection

Traditional protection systems like RFPI and Machine Protection System (MPS) are responsible for protection of equipment, personnel and facility. These systems continuously monitor signals from various sensors, compare these with predefined fault thresholds, and generate permit or stop operation of accelerator. The post-mortem data at the fault occurrence is stored and studied for root cause analysis. Unsupervised ML algorithms can be used to enhance the capability of traditional protection systems by a prior identification of detrimental conditions. This results in avoiding false fault conditions and thus, plant availability can be increased. Historic sensor data from diverse systems can be used for anomaly detection and the trained models can be deployed online. Results from the ML algorithms can be used to fine tune the threshold ranges of traditional systems.

ML for instrumentation

The deployment of ML algorithms in control and instrumentation devices for particle accelerators is challenging. Real-time control requirements demand low-latency processing, placing stringent demands on the timing precision of ML algorithms. ML algorithms are computationally intensive requiring high performance computing (HPC) platforms. HPC can be made available at edge-through

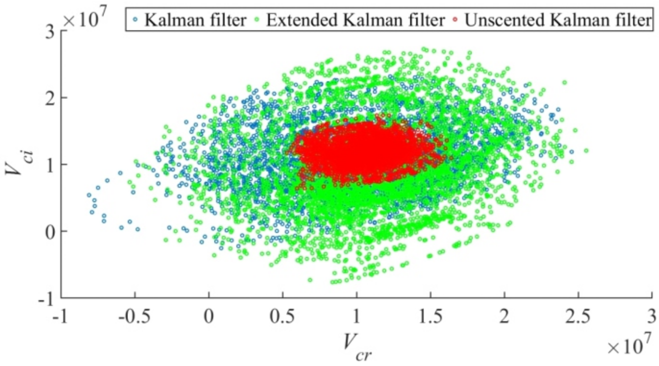

Fig.4: Plot of estimated real versus imaginary components of RF cavity pickup by KF, EKF and UKF.

physical integrated platforms or through cloud. AI at the edge is a solution for many use cases such as integration of ML solutions with embedded control systems like RFPI for protection, RCS and LLRF system for RF cavity control, which are implemented on SoC-FPGA, cPCI-FPGA and VME-FPGA based embedded systems. This needs compatibility and interoperability of ML solutions with FPGA. TinyML [7] is a type of ML that allows models to run on smaller, less powerful devices. TinyML is suitable for FPGA as it employs techniques to convert model weights from floating-point numbers to fixed-point or integer representations, removes unnecessary connections which reduce model size and computational demand. Integration of open source TinyML framework [8] for FPGA with EPICS 7 DAQ is currently under development for embedded control systems.

Conclusions

EPCIS 7 DAQ IOC architecture is proposed for ML integration with accelerator controls. Application of NSGA-II optimization algorithm, and ILC are being pursued. Opportunities and challenges for application of ML in field of machine protection, system modelling, tuning and optimization are presented. An indigenously developed elaborate control system integrated with machine learning, whose output acts as input to model based modern control approaches, seems to be a promising approach for reliable, efficient, stable and safe high power particle accelerator delivering high quality beam.

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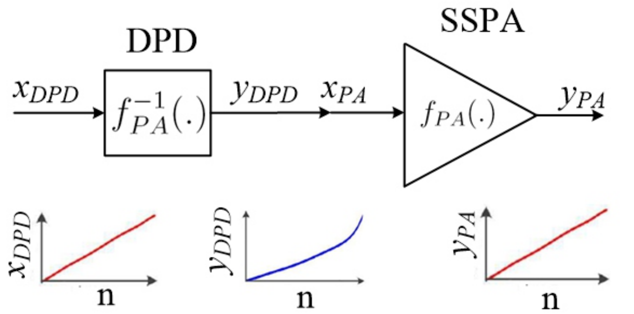

Fig.5: Pre-distortion system for SSPA.

References

[1] Alok Agashe, P.D. Motiwala, S.K. Bharade, Shyam Mohan and Gopal Joshi, "Digital LLRF System for RFQ" Proceedings of InPAC2015, Mumbai, India.

[2] Sujo C.I., Khole S., Shukla Hitesh, Bharade S., Keshwani R., Afaash M., Joshi Gopal, Prieto Peter, "RF protection interlock system for proton linacs under Indian institutions and FERMILAB collaboration", Proceedings of InPAC2018, RRCAT, Indore, India.

[3] Sandeep Bharade, Gurunath Randale, A. Agashe, Paresh Motiwala, Gopal Joshi, Frank Pillion, Djaid Zouaoui, Dominique Touchard, "EPICS DAQ System for beam position monitoring of SPIRAL2 LINAC at GANIL", Proceedings of InPAC2019; IUAC

[4] Shukla Hitesh, Bharade S.K., Sujo C.I., Motiwala P.D. and Joshi Gopal, "Design, development and installation of programmable timing control system for LEHIPA", Proceedings of InPAC2015, Mumbai, India.

[5] Argonne National Laboratory, 28 Feb 2021, "Experimental Physics and Industrial Control System"

[6] Pengzi Chu, Yi Yu, Danyang Dong,Hui Linand Jianjun Yuantiny, "NSGA-II-Based Parameter Tuning Method and GM(1,1)-Based Development of Fuzzy Immune PID Controller for Automatic Train Operation System", 2020 Mathematical Problems in Engineering.

[7] ML Foundation, "https://www.tinyml.org/"

[8] Shvetank Prakash, Tim Callahan, Joseph Bushagour, Colby Banbury, "CFU Playground: Full-Stack Open-Source Framework for Tiny Machine Learning (TinyML) Acceleration on FPGAs", 2023 IEEE International Symposium on Performance Analysis of Systems and Software (ISPASS).

[9] R.T. Keshwani, S. Mukhopadhyay, R.D. Gudi and G. Joshi, "Comparative Investigations on Detuning Estimator for Experimental RF Cavity," in IEEE Transactions on Instrumentation and Measurement, vol. 72, pp. 1-9, 2023, Art no. 2526309, doi: 10.1109/TIM.2023.3311075.

[10] Rajesh Keshwani, S. Mukhopadhyay, Ravindra D. Gudi and Gopal Joshi, "Unscented Kalman Filter as SC cavity detuning estimator", Proceedings of InPAC2023, BARC, Mumbai

[11] Rajesh Keshwani, S. Mukhpadhyay , Ravindra D. Gudi , Gopal Joshi, "Digital Predistortion technique for RF power amplifier linearization: Modelling and Simulations", Proceedings of InPAC2022 VECC, Kolkata, 22-25 March, 2022.

[12] Rajesh T. Keshwani, Siddhartha Mukhopadhyay, Ravindra D. Gudi, Gopal Joshi, "A Novel Tuning Scheme for Fast Norm Optimal Iterative Learning Controller", IFAC-PapersOnLine, Vol. 57, 2024, Pages 179-184, ISSN 2405-8963, https://doi.org/10.1016/j.ifacol.2024.05.031.