Real-Time measurement, simulation, and prediction of the magnetic field for particle accelerators

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Outline

• Problem
• Old B-Train systems
• Requirements for a new system
• New hardware
• New B-Train systems
• Field Simulation
• B-Train lite systems
• Machine learning to predict magnetic field
• Summary
• Future plans
Problem

Magnet Design → Magnet Manufacture → Machine Operation

Offline magnetic measurements and simulations

B-Train systems

Role of measurements and simulations in magnetic design, manufacture and operations
Old B-Train systems

• The CERN’s synchrotrons employ systems so-called B-Train for measuring the dipole field in real-time. The name derives from the discrete positive and negative pulse trains used to distribute incrementally the measured field in out-of-date systems, developed as far back as the 1950s.

• The out-of-date digital transmission (dating from the early 1960s) uses two coaxial cables to distribute 24 V pulses at the maximum frequency of 500 kHz which indicate a ± 0.1 Gauss increase or decrease of magnetic field, i.e. up and down pulses. These pulses are distributed from the reference magnet to several client applications.

• Currently, all six B-train systems in operation have been upgraded in the frame of complex-wide consolidation project.
**Old B-Train systems**

- Measurements are carried out in a reference magnet, which is ideally installed in a dedicated room outside of the synchrotron and is powered in series with the magnets’ ring.

- A combination of two primary sensors:
  - An **induction coil** to measure the rate of change of the field according to Faraday’s law.
  - A so-called **field marker** to provide the necessary integration constant \( B_m \).

\[
V_c = -\frac{d\Phi}{dt} \quad \text{and} \quad \ddot{B}(t) = B_m + \Delta \ddot{B}(t) = B_m - \frac{1}{A_c} \int_{t_k^*}^{t} V_c(\tau) \, d\tau.
\]
Requirements for a new system

• Uniform system across the whole complex.

• System based on CERN-standard components including Linux Front Ends, FPGA Mezzanine Cards (FMC), FESA C++ software, for which CERN guarantees long-term support.

• Industrially made sensors such as PCB fluxmeters and FMR resonators.

• Improved maintainability thanks to uniform components across all machines:
  – Allowing a common spare pool.
  – Improved remote diagnostics capabilities.
  – Simplified training.

• Improved performance in terms of accuracy of the measured field (e.g. high resolution integrators, integral flux loops to capture end effects such as saturation, hysteresis and eddy currents).

• Remote configurability, leading to increased flexibility for accelerator operation.

• Full integration with machine control system and CERN central timing.
Requirements for a new system

- Under certain special circumstances, magnetic field measurement feedback is not the best option. For instance, machine operators may want to replace the measured field temporarily with the simulated one as a beam diagnostic tool:
  - **Simulated field**: Interpolation of data in a database.
  - **Predicted field**: real-time prediction for the magnetic field (neural networks).

- Distribution of the measurement and/or simulated/predicted values over a dedicated optic fiber network thanks to the White Rabbit protocol (up to 1 MHz).

Example of a neural network that can be used to predict the magnetic field in a magnet for particle accelerators

White Rabbit network example  [https://white-rabbit.web.cern.ch/](https://white-rabbit.web.cern.ch/)
New hardware

https://ohwr.org/project/spec/wiki/home

Simple PCI Express carrier (SPEC)

Integrator FMC Board

B-Train crate

SFP Port for WR Fibre Optic Connector

LVDS DIO Connectors

SPEC front view

Integrator Module Transmission Panel

LCD Output & Display Selection

Timing and Field Marker Output Panel

Field Marker Module Transmission Panel

Field Marker Input Connectors

Power Supplies for different voltage rails

Output Connectors providing access to Induction Coil and Field Marker signals

https://ohwr.org/project/spec/wiki/home
New B-Train systems

Block diagram of the novel B-Train Project

Software hierarchy of the Front end Computer
New B-Train systems

Schematic flowchart of the integrator, including offset and gain correction. The green blocks denote analogue processing steps, while the yellow ones the processing in the digital domain.

\[
\Delta V_{in} = V_c + \delta V \quad \Delta V'_{in} = 0.8 \left(0.625\Delta V_{in} + \Delta V_2\right) = \frac{1}{2}\Delta V_{in} + \frac{4}{5}\Delta V_2
\]

\[
V_{out} = G_{cc}V_{ADC} + \Delta V_1 \quad \Delta \Phi_i = \tau_s \sum_{j=i_k^*}^{i} V_{out,j} \quad \bar{B}_i = \gamma(B_m - \alpha \frac{\Delta \Phi_i}{A_c})
\]
New B-Train systems

• marker peak detection algorithm.

\[ j = \min(i) : \begin{cases} 
  t_1 \leq t_i \leq t_2 \\
  |V_{m,i}| \geq \overline{V} \\
  \text{sign}(\dot{V}_{m,i}) \neq \text{sign}(\dot{V}_{m,i-1}) 
\end{cases} \]
New B-Train systems

White Rabbit frame composition.
New B-Train systems

- Monitoring the WR payloads at full speed is an essential part of the commissioning and operation phases.
- Noise and glitches in the field measurement can affect destructively the beams and require full bandwidth to be evaluated correctly.

Block diagram.

Physical object

Labview user interface.
New B-Train systems

Operational rack

Spare rack

Diagnostic rack
New B-Train systems

Operational rack

RF generator
PT2025 teslameter
WR switch
Coils patch panel
B-Train chassis
FEC
New B-Train systems

Spare rack

RF generator
PT2025 teslameeter
Oscilloscope
Coils patch panel
B-Train chassis
FEC
New B-Train systems

- Central timing over WR
- WR multiplexer
- Development equipment
- WR switch
- WR monitoring tool

Diagnostic rack
New B-Train systems

DC characterization

Accuracy of the voltage measurement.

Mean and standard deviation of $\Delta \Phi / \Delta t$ -Vin over the full input dynamic range.
New B-Train systems

DC characterization

- Linearly estimated voltage over 1 second.
- Integrator drift over 120 seconds.
New B-Train systems

Dynamic characterization

Layout for the system dynamic configuration
New B-Train systems

Dynamic characterization

Relative difference between relative and ideal gain

Amplitude frequency response

Relative Gain Diff. ($10^{-4}$)

Frequency (Hz)

Gain (dB)

Ideal Response

Measured Response
New B-Train systems

Dynamic characterization

Layout for the system dynamic configuration
# New B-Train systems

## Dynamic characterization

<table>
<thead>
<tr>
<th></th>
<th>Input to Output at 250 kHz (µs)</th>
<th>Transmission at 250 kHz (µs)</th>
<th>Input to Output at 100 kHz (µs)</th>
<th>Transmission at 100 kHz (µs)</th>
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<td>Average</td>
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<td>7.3</td>
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<td>Minimum</td>
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<td>4.9</td>
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<td>Maximum</td>
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<td>9.9</td>
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<tr>
<td>$\sigma$</td>
<td>2.3</td>
<td>1.2</td>
<td>3.6</td>
<td>1.9</td>
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## Overall system latency at different transmission speeds

<table>
<thead>
<tr>
<th></th>
<th>Without Switch (µs)</th>
<th>With Switch (µs)</th>
<th>$C_0$ to Integrator DAC (µs)</th>
<th>$C_0$ to WR DAC (µs)</th>
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<tr>
<td>Average</td>
<td>1.53</td>
<td>3.93</td>
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<tr>
<td>Maximum</td>
<td>4.32</td>
<td>7.2</td>
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<tr>
<td>$\sigma$</td>
<td>0.13</td>
<td>0.13</td>
<td>1.2</td>
<td>1.7</td>
</tr>
</tbody>
</table>

**Delay across the White Rabbit network @ 250 kf ps**

**Internal FEC propagation time @ 250 kf ps**
Field Simulation

- The image of each cycle is stored in the LSA.
- The vector cycle representation is very compact and a finer resolution is generally required at high field.
- The table of vectors is interpolated to the desired resolution (by default, 4 μs) in real-time in the FPGA, using Bresenham’s line algorithm.

Schematic flowchart of the field simulation.
B-Train lite systems

- Custom solutions for very specific cases:
  - ISOLDE high-resolution separator dipoles (HRS90 and HRS60).
    - Only NMR (PT2025).
    - Other solutions under discussion.
  - LINAC3.
    - Only NMR (PT2025).

- Possibility of new installations for a variety of new clients:
  - Transfer lines.
  - Experiments’ magnets.
  - And all the cases in which the knowledge of the magnetic field is required in operation …

If you are interested in our solutions just contact us:
- BTrain-Team@cern.ch
- BTrain-Support@cern.ch
Machine learning to predict magnetic field

But why machine learning?

• The operation of synchrotrons requires knowledge of the magnetic field within a typical tolerance of 0.01% at any given time during a magnetic cycle. At CERN, the field of the bending dipoles of the Large Hadron Collider (LHC) is predicted by the field description for the LHC (FiDeL) semi-empirical mathematical model [1].

• In the LHC injectors, on the other hand, the current-to-field characteristic of the magnets is dominated by the iron core, which gives rise to non-linear effects such as eddy currents, saturation and hysteresis.

• Recent attempts at mathematical prediction using analytical expressions [2] or Preisach models [3] could not attain better than percent-level accuracy, which is inadequate for normal operation. Other classes of methods, such as Jiles-Atherton differential models, were considered but ultimately deemed unsuitable, with particular respect to their difficulties in handling minor hysteresis loops.
Machine learning to predict magnetic field

Training dataset

Correction quadrupole used as a case study

Ferromagnetic yoke
Magnetic poles
Hall probe
Machine learning to predict magnetic field

Multi layer Perceptron (MLP)

- MLP retains no time information

- How can we introduce this information?

Time Delayed Neural Network
Machine learning to predict magnetic field

- Still no information about the previous outputs of the network
- How can we introduce this information?
Machine learning to predict magnetic field

Non Linear Autoregressive Exogenous Input (NARX) Neural Network

Mathematical description

- \( \phi^{A_1} \) is the activation function of the neurons of the layer (tanh in this case)
- \( W_{ji}^{l} \) are the weights of the interconnections between neurons.

\[
a_j^{1}(n) = \phi^{A_1} \left( \sum_{h=1}^{H} W_{jkh}^{O} y(n - h) + \sum_{k=0}^{K} W_{jlk}^{I} u(n - k) \right)
\]

\[
a_{ji}^{l}(n) = \phi^{A_i} \left( \sum_{i=0}^{A_l} W_{ji}^{l} a_{i}^{l-1}(n) \right)
\]

\[
y(n) = \sum_{i=0}^{A_L-1} W_{ji}^{E} a_{ji}^{L}(n)
\]
Machine learning to predict magnetic field

Hyperparameters definition for the model selection

<table>
<thead>
<tr>
<th>Hyperparameter</th>
<th>Multilayer Perceptron</th>
<th>Time Delay</th>
<th>Autoregressive Exogenous</th>
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<td>$L$</td>
<td>$\theta_{MLP}$</td>
<td>$\theta_{TDNN}$</td>
<td>$\theta_{NARX}$</td>
</tr>
<tr>
<td>$A$</td>
<td>${1,\ldots,15}$</td>
<td>$\tilde{L}_{MLP}$</td>
<td>$\tilde{L}_{MLP}$</td>
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<tr>
<td>$K$</td>
<td>${1,\ldots,10}^L$</td>
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<td>$\tilde{A}_{MLP}$</td>
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<tr>
<td>$H$</td>
<td>0</td>
<td>0</td>
<td>$\tilde{K}_{TDNN}$</td>
</tr>
</tbody>
</table>

Bridge Criterion (BC) for the model selection

$$RMSE(y_i, D_{test}) = \sqrt{\frac{\sum_{n \in N} (y_i(n) - B_{test}(n))^2}{|N|}}$$

$$Score(j) = |N| \ln \left( \frac{1}{R} \sum_{i=1}^{R} Error^2(i) \right) + |N|^{2/3} \cdot \left( 1 + 1/2 + \ldots + 1/|W| \right)$$

- The minimization of the BC term corresponds to the maximization of the evidence of the $j$th model, ensuring a balanced model fit as the first term weights the reconstruction error, while the second term penalizes the number of weights.
Machine learning to predict magnetic field

Four steps model selection

compromise between performance and complexity
Machine learning to predict magnetic field

| Hyperparameters | $L$ | $A$       | $K$ | $H$ | $|W|$ |
|-----------------|-----|-----------|-----|-----|------|
| $\tilde{\theta}_{MLP1}$ | 2   | (10, 9)   | 0   | 0   | 129  |
| $\tilde{\theta}_{MLP2}$ | 4   | (1, 1, 1, 10) | 0   | 0   | 37   |
| $\tilde{\theta}_{TDNN1}$ | 2   | (10, 9)   | 26  | 0   | 379  |
| $\tilde{\theta}_{TDNN2}$ | 4   | (1, 1, 1, 10) | 31  | 0   | 67   |
| $\tilde{\theta}_{NARX1}$ | 2   | (10, 9)   | 26  | 31  | 689  |
| $\tilde{\theta}_{NARX2}$ | 2   | (7, 8)    | 26  | 17  | 381  |
| $\tilde{\theta}_{NARX3}$ | 4   | (1, 1, 1, 10) | 31  | 31  | 98   |
| $\tilde{\theta}_{NARX4}$ | 4   | (1, 8, 5, 4) | 31  | 31  | 153  |

Four steps model selection outcomes

compromise between performance and complexity
Machine learning to predict magnetic field

ANOVA results on Absolute Errors computed for the competing models on Dataset D̄E. The horizontal lines are the 95% confidence interval for each model. Five groups are highlighted: LR group (gray), MLP group and LR+* group (yellow), TDNN1 (pink), TDNN2 (in blue) and the NARX group (orange)
Machine learning to predict magnetic field

Some more performance indicators to facilitate the comparison with the requirements

Normalized RMSE

\[ NRMSE(y, D_E) = \frac{RMSE(y, D_E)}{B_{max}} \cdot 100 \]

Maximum Absolute Error

\[ MAE(y, D_E) = \max \{ |y(n) - B_E(n)| \}_{n \in N} \]

Maximum Percentage Error

\[ MPE(y, D_E) = \frac{MAE(y, D_E)}{B_{max}} \cdot 100 \]
Machine learning to predict magnetic field

<table>
<thead>
<tr>
<th>Architecture</th>
<th>Test Dataset</th>
<th>Hyper-parameters</th>
<th>RMSE [T]</th>
<th>NMRSE (%)</th>
<th>MAE [T]</th>
<th>MPE (%)</th>
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<tbody>
<tr>
<td>Linear Regression</td>
<td>D_E</td>
<td>G, B_0</td>
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<td>D_E</td>
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<td>G, B_0, \hat{\theta}_{MLP1}</td>
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<td>1.90 \times 10^{-3}</td>
<td>1.19</td>
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</table>

Performance comparison among the different architectures, trained and computed on the test dataset at the decimated data rate of 250 S/s.
## Machine learning to predict magnetic field

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<thead>
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<th>MPE [%]</th>
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<td>LR+TDNN2</td>
<td>$D_E$ $G, B_0, \theta_{NARX1}$</td>
<td></td>
<td>$7.98 \times 10^{-04}$</td>
<td>$4.99 \times 10^{-01}$</td>
<td>$1.90 \times 10^{-03}$</td>
<td>$1.17$</td>
</tr>
<tr>
<td>LR+NARX1</td>
<td>$D_E$ $G, B_0, \theta_{NARX2}$</td>
<td></td>
<td>$7.98 \times 10^{-04}$</td>
<td>$4.99 \times 10^{-01}$</td>
<td>$1.90 \times 10^{-03}$</td>
<td>$1.17$</td>
</tr>
<tr>
<td>LR+NARX2</td>
<td>$D_E$ $G, B_0, \theta_{NARX3}$</td>
<td></td>
<td>$7.99 \times 10^{-04}$</td>
<td>$5.00 \times 10^{-01}$</td>
<td>$1.90 \times 10^{-03}$</td>
<td>$1.17$</td>
</tr>
<tr>
<td>LR+NARX3</td>
<td>$D_E$ $G, B_0, \theta_{NARX4}$</td>
<td></td>
<td>$8.00 \times 10^{-04}$</td>
<td>$5.00 \times 10^{-01}$</td>
<td>$1.90 \times 10^{-03}$</td>
<td>$1.17$</td>
</tr>
<tr>
<td>LR+NARX4</td>
<td>$D_E$ $G, B_0, \theta_{NARX4}$</td>
<td></td>
<td>$8.00 \times 10^{-04}$</td>
<td>$5.00 \times 10^{-01}$</td>
<td>$1.90 \times 10^{-03}$</td>
<td>$1.17$</td>
</tr>
</tbody>
</table>

Performance comparison among the different architectures, trained on the test dataset at the decimated data rate of 250 S/s. and computed at the full data rate of 2.5 kS/s.
Machine learning to predict magnetic field

Hysteresis comparison measured vs predicted (by NARX4)

20 ppm prediction accuracy

Measured vs predicted magnetic field of the non-linear component of the field
## Machine learning to predict magnetic field

<table>
<thead>
<tr>
<th>Architecture</th>
<th>Metric</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Deep Neural Network (MLP with two hidden layers), Ref. 10</td>
<td>Root Mean Square Error</td>
<td>0.13 %</td>
</tr>
<tr>
<td>Preisach + Feed-forward neural network (one hidden layer), Ref. 8</td>
<td>Maximum Absolute Error</td>
<td>13 %</td>
</tr>
<tr>
<td>Preisach, Ref. 16</td>
<td>Relative Error</td>
<td>0.2 %</td>
</tr>
<tr>
<td>Preisach + Recurrent Neural Network, Ref. 43</td>
<td>Normalized Root Mean Square Error</td>
<td>0.7%</td>
</tr>
<tr>
<td>Neural Network, Ref. 44</td>
<td>Relative Error</td>
<td>&lt; 8 %</td>
</tr>
<tr>
<td>Genetic Algorithm + Neural Network, Ref. 45</td>
<td>Mean Square Error</td>
<td>&lt; 5 %</td>
</tr>
</tbody>
</table>

Litterature comparison
Summary

• 16 individual systems belonging to 8 accelerator facilities were commissioned and are now in operation for the RUN 3.

• The new systems overcome the performance of the previous systems in terms of accuracy and resolution.

• A new tool to monitor the WR payload in real time was developed and used for debugging and troubleshooting.

• A new neural network based algorithm to predict the magnetic field and its non-linearities starting from the input current opens new scenarios for the future.
Future plans

• Continue the development of the system in order to satisfy all the new requests coming from the clients (check EDMS:2637275 for the full details).

• Extend the B-Train like systems for other facilities (new clients).

• Adapt the system to follow the upcoming changes of drivers and operating system supported by CERN.

• Test the new SPEC cards (SPEC7) for the next generation.

• improve the diagnostic features and the alarms in LASER for the operators.

• Real time implementation of the NN approach to integrate it in the current B-Train systems.
Not only me…


  * = former colleague

- Warm welcome to the new members of the team:
  - Matthias Bonora, Regis Chritin, Unai Martinez Hernandez, Guillaume Pichon.
Thanks for the attention

Any questions?