ISBN: 978-3-95450-214-1 ISSN: 2673-5490 doi:10.18429/JACoW-IPAC2021-TUPAB198

ESS DTL TUNING USING MACHINE LEARNING METHODS

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Abstract

The European Spallation Source, currently under construction in Lund, Sweden, will be the world's most powerful neutron source. It is driven by a proton linac with a current of 62.5 mA, 2.86 ms long pulses at 14 Hz. The final section of its normal-conducting front-end consists of a 39 m long drift tube linac (DTL) divided into five tanks, designed to accelerate the proton beam from 3.6 MeV to 90 MeV. The high beam current and power impose challenges to the design and tuning of the machine and the RF amplitude and phase have to be set within 1% and 1° of the design values. The usual method used to define the RF set-point is signature matching, which can be a time consuming and challenging process, and new techniques to meet the growing complexity of accelerator facilities are highly desirable. In this paper we study the usage of Machine Learning to determine the RF optimum amplitude and phase. The data from a simulated phase scan is fed into an artificial neural network in order to identify the needed changes to achieve the best tuning. Our test for the ESS DTL1 shows promising results, and further development of the method will be outlined.

INTRODUCTION

The European Spallation Source (ESS) is a state of the art neutron science facility under construction in Lund, Sweden [1]. The basic process used by the facility is spallation, wherein one impinges a high neutron material, in this case Tungsten, with high energy protons, causing the target to shed excess neutrons. The high energy protons are provided by the ESS linear accelerator (linac), a 600 m long accelerator consisting of many different sections utilizing varied accelerator technologies in order to raise the proton energy from the 75 keV source output to the final 2.0 GeV arriving on the target. A crucial part of this machine is the 39 m long drift tube linac (DTL) divided into five tanks, designed to accelerate the proton beam from 3.6 MeV to 90 MeV. As the machine is expected to deliver beam of high current and power, a primary concern is to avoid slow beam losses, as these lead to radiation activation of surrounding equipment. In order to avoid such losses, proper and careful tuning of the RF fields is crucial. As a result the requirement for accuracy of the RF set point is to be within 1% in RF amplitude and 1° in phase [1]. In order to achieve this type of accuracy, much work has been performed in the last decades to develop new techniques to meet the growing scale and complexity of facilities [2–4]. Within this paper we will investigate how Machine Learning (ML) may serve this purpose. This paper presents our current strides in the development of a tuning technique using ML and a comparison of our current results with those of the Signature Matching (SM) technique, a more established methodology for RF tuning [1–4].

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RF PHASE SCAN

In order to be able to quantify how the beam responds to changes to the RF set-point, a diagnostic sensitive to the beam time of flight through the cavity must be used. For those cases a Beam Position Monitor (BPM) can be used. As the beam passes a BPM, not only is the transverse position measured, but also the amplitude and phase of the fields excited by the passing beam on the BPM sensor. Although this phase alone doesn't hold much information, by comparing two BPM phases we can get a fast measurement which is proportional to the time-of-flight, or looking with respect to acceleration in a RF cavity, the energy gain between the two devices. It is important to stress that this measurement is relative and that extracting the absolute values of the energy is not an easy task. For this technique, using only the relative phase changes has proven to be enough.

In order for clear signatures to emerge, it is not uncommon to use subsequent unpowered accelerating structures as drift space for the beam, and to extract the relative phase change from BPMs in these locations [2]. It simplifies tuning when the energy is not varying between BPMs, as in a non-accelerating cavity, but it is not a requirement. Initial commissioning of the ESS DTL will be done with only the first DTL tank, and as such it is required to reach the RF field requirements using only the BPMs inside this tank for tuning. Thus the relative phase change needed to be extracted from internal BPM pairs within the accelerating structure for the results in this article.

The BPMs on this structure are then used to measure the energy gain (or time-of flight) as a function of the set points in the accelerating cavity. As the BPM's measured phase is closely dependent on the energy of the beam, scanning RF amplitude and phase in a cavity and plotting out the resulting phase differences will give rise to different curves depending on the proximity to the ideal set point for the cavity. A few of these signature curves can be seen in Fig. 1, where the ideal set point can be found from the signature for the ideal amplitude A_0 = 6.89 kV, the ideal input beam energy E_0 = 3.62 MeV and the -35° offset phase set point.

Much work has been done to find efficient and fast methods for extracting and identifying this ideal signature.

Simulations

OpenXAL was used to simulate the first tank of the ESS DTL during acceleration and to reproduce the signals from the six BPMs [5, 6]. As phase difference is the data of interest, this results in 15 different BPM combinations, each producing a phase scan for each amplitude set point of the

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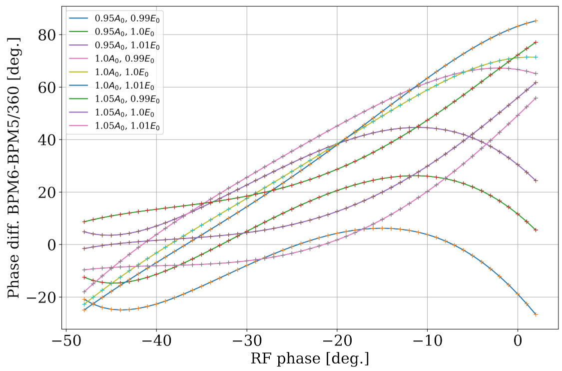

Figure 1: The phase curves for different RF amplitude and input energy set points. BPM phases simulated as comparison between two BPMs in the first DTL tank in the ESS linac.

cavity, which was varied in RF amplitude and input beam energy. Both techniques outlined below require training or fitting of some type and for this purpose a large data set was produced for a machine free from errors. This consisted of 110 different amplitude set points, with a variation of ±5.5% around the design RF cavity amplitude A_0, and 60 different input beam energy set points, with a variation of ±1.5% around the design input energy E_0. Each phase scan consisted of 55 phase points, spread evenly around the -35° set point.

To this perfect machine four different types of errors were then applied. BPM longitudinal position within the machine was adjusted, potentially caused by installation and construction, as well as the phase readout from these BPMs, produced by electronic limitations. There are also errors arising from production limitations when constructing the cavities. Such limitations could give rise to errors in both RF amplitude and phase gap-to-gap. The different types of errors and their magnitudes are summarized in Table 1.

Table 1: The Different Types of Errors Used in Simulations and Their Corresponding Magnitude

Error Type	**Magnitude**
BPM Δs	± 100 µm
BPM $\Delta\phi$	±1°
RF Amplitude	±2%
RF Phase	±0.5°

SIGNATURE MATCHING

One method, which is widely used [2–4], is to use a set of simulated data (like the ones shown in Fig. 1) and fit each phase scan set with RF amplitude A and input beam energy ϵ with a polynomial

$$f(\phi, A, \epsilon) = a_0(A, \epsilon) + a_1(A, \epsilon)\phi + ... + a_n(A, \epsilon)\phi^n \quad (1)$$

and at this point we assume that an error in the input phase of the cavity acts as a simple offset on the variable ϕ of the whole curve. As a result from all the fittings, it is possible to construct a surface $a_n(A, \epsilon)$ for each coefficient of the fitted polynomial. This surface can then be approximated by another 2D polynomial surface so that we have a continuum of coefficients for any given set-point in (A, ϵ).

With the parameters obtained from the fits described above, it is possible to investigate the variance, χ^2, between the simulated model and the corresponding measured data. This variance is defined as

$$\chi^2(\phi_0, A, \epsilon) = \frac{\sum_j^N (f(\phi_j - \phi_0, A, \epsilon) - W_j)^2}{N} \quad (2)$$

wherein f is our fit to the model prediction of the BPM phase difference (Eq. (1)) and W_j is the measured BPM phase difference at some unknown RF phase, RF amplitude and incoming beam energy. One then optimizes the values of ϕ_0, A and ϵ to minimize Eq. (2), thus determining to which set-point the signature curve W_j corresponds to. This method is known as Signature Matching [2–4].

MACHINE LEARNING

Machine learning is a term used to describe a specific field of modern computer algorithms capable of learning from experience. Most often, the algorithm refers to a neural network, a network of individual artificial neurons, wherein the weighted connections between the neurons can be trained to reach an ideal output. This training can be performed in different ways, but the most relevant to this project is the technique of supervised learning. Machine learning algorithms come in many forms and can solve many distinct problems using varying network structures, definitions of loss and optimization algorithms. The problem we are looking at in this project involves reducing larger scans of data down to three dependent variables, RF amplitude, RF phase and input beam energy. This leads us to the use of a network and loss function fitting for linear regression. This network is trained using a mean squared error function as loss, and the ADAM optimization algorithm [7, 8].

This network was defined using the python library Keras. The library comes with predefined versions of our loss function, mean squared error, and our optimization algorithm, ADAM. ADAM has different coefficients which may be tuned to improve the networks performance, although the learning rate is most relevant. Optimization of the network structure and training parameters was done iteratively, looking at generalized performance as the figure of merit. This was quantified as the loss on a subset of data separated during training. Through this process we arrived at a 10-layer structure with 80 neurons in each layer, and a final output layer of three neurons. This was trained for 20 000 epochs with a learning rate of 0.00001. This network was used to produce the results presented in the following section [8, 9].

RESULTS

Figure 2 shows the results for both methods when attempting to produce the correct set point in amplitude. The x-axis

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Table 2: Difference between the Predicted and Expected Value for the RF Amplitude and Phase and the Input Energy

Data Set		σ_A [%]	σ_ϕ [°]	σ_E [%]	μ_A [%]	μ_ϕ [°]	μ_E [%]
No Errors	ML	0.013	0.000	0.006	0.001	0.000	0.002
	SM	0.181	0.154	0.037	0.008	0.001	0.001
All Errors	ML	0.605	0.002	0.510	0.022	0.000	0.013
	SM	0.293	0.557	0.152	-0.004	0.010	0.001

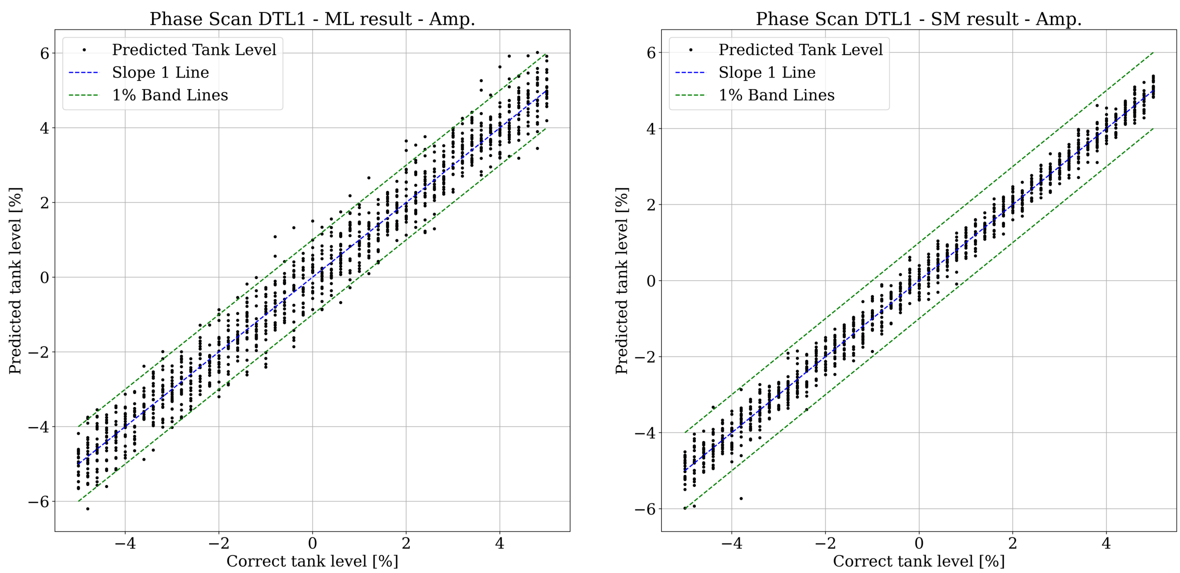

Figure 2: The predicted RF amplitude set points from both methods plotted against the correct amplitudes, along with a slope one line and 1% limits.

represents the correct set points and the y-axis the predictions of the methods. The blue line in Fig. 2 is a slope 1 line which then represents the perfect prediction, and the two green lines represent the ±1% band lines, the minimum amplitude accuracy required for the ESS cavities. Here we can see the spread around the ideal predictions visually, though it is numerically summarized in Table 2.

Table 2 shows the standard deviation (σ) and the mean (μ) of the difference between the predicted and expected value for the RF Amplitude (A) and phase (ϕ), as well as for the input energy (E). The low mean in all rows shows there is little to no systematic offset to the predictions. We see higher accuracy from ML on the training set. If we look at the results with all errors present we see SM performing better on amplitude and energy, while ML performs much better on the phase prediction. It should be noted that the SM predictions take 60 times as long to be calculated as the comparable ML results. Due to the BPM data being extracted from an accelerating cavity, SM is also quite sensitive to which BPM combination is used as input. For the results presented here, the three best combinations (BPM3-BPM1, BPM4-BPM2 and BPM4-BPM3, indexed in order of longitudinal placement) were chosen and averaged.

OUTLOOK

We have managed to produce promising results with a somewhat rudimentary neural network and short training. This suggests that the problem of RF tuning, even with the limitation of using internal BPMs within the accelerating structure, is solvable using ML. In the near future this project will move on to constructing and training more complex neural networks, expanding the scope to include the rest of the DTL, and possibly importing data from other facilities to test this new methodology on real data. The possibility of a hybrid method has also been discussed, using ML to perform the fitting required for SM. This could potentially conserve the advantages of both methods while avoiding their respective drawbacks.

ACKNOWLEDGEMENTS

This study has only been possible with the help of the entire Beam Physics team at ESS, as well as that of other teams at the facility.

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