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AUTOMATED RF-CONDITIONING UTILIZING MACHINE LEARNING

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Abstract

RF-Conditioning of a room temperature cavity is a long and resource intensive process. The need for constant supervision by experienced personal to avoid damage to the cavity and used equipment makes it a very expensive endeavor. To reduce the workload of the experimentalist, it was decided to develop a program utilizing machine learning, which, once finished, should have the probabilities to greatly reduce the need for constant supervision by human personal or even to conduct a full RF-conditioning on its own. After a training with existing data of already conducted conditioning of room temperature cavities and a virtual cavity, it is planned to improve and expand the program during the RF-conditioning of 15 CH-cavities, designated for the MYRRHA project, with similar properties. In this paper, the outline of the program, as well as the existing and planned goals shall be given.

INTRODUCTION

Conditioning is a necessary but slow process, in which the power injected into the cavity is slowly increased until the power levels required by the beam dynamics are reached.

During this process, unwanted and potentially dangerous effects can occur, with outgassing, discharges and multipacting as the most common ones. Since those not only hinder the conditioning progress (for example by making the cavity not accept more power) but also can damage the signal generator, amplifier, measuring equipment and the cavity itself, constant supervision by trained personal is required.

When a conditioning is carried out by IAP Frankfurt, the forward power P_f, the reflected power P_r and the transmitted power P_t are monitored by the experimenter in addition to the pressure p inside the cavity. The control mechanisms on the other hand are the forward Power P_f and the frequency *f*.

The process itself can take from several days to several weeks, with great differences even between structurally identical cavities. In order to reduce the time and surveillance effort needed to perform a successful conditioning, it was decided to develop a supporting program, with the long-time goal of fully automated conditioning.

As a first step, a LabView program was designed by IAP, as described in [1]. To further improve the possibilities of automated conditioning, it was decided to develop a trainable machine learning algorithm, with the long-term goal of fully automizing conditioning and reducing the need of expensive human supervision.

THE PROGRAM

As with all trainable algorithms, the results are always just as good as the data the algorithm was trained with. This poses a great problem for nearly all modern machine learning algorithms.

Essential are all the above-described parameters, P_f, P_r, P_t, p and the frequency *f*. Additionally, a good time resolution is important, so that the later program can react quickly to changes inside the cavity. Nearly all data from previous conditionings available to the IAP didn't fulfill one or more of those requirements, making it necessary to produce new data and find new sources of data.

Conditioning of the LILAC RFQ

As the conditioning of the LILAC RFQ was planned for March 2023, it was decided to use the possibility to collect first training data to develop a first version of a machine learning algorithm. The specifications of the conditioned RFQ are stated in Table 1, while the experimental setup is depicted in Fig. 1.

Table 1: Parameters of the LILAC RFQ as Stated in [2]

Parameter	Value	Unit
Operating frequency	162.5	MHz
Shunt impedance $Z_{eff\,(CST)}$	116	kΩ*m
Quality factor (CST)	5800	

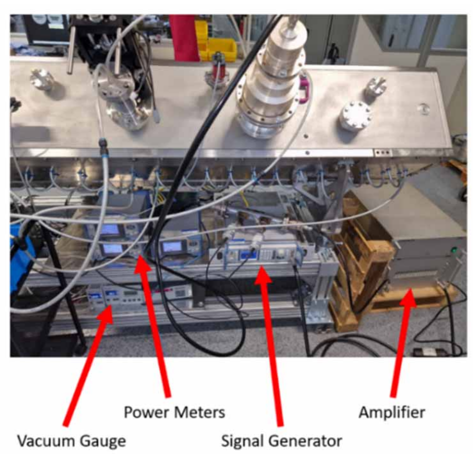

Figure 1: Experimental Setup of the Conditioning of the LILAC RFQ. All Power levels, the pressure inside the cavity and the frequency were recorded.

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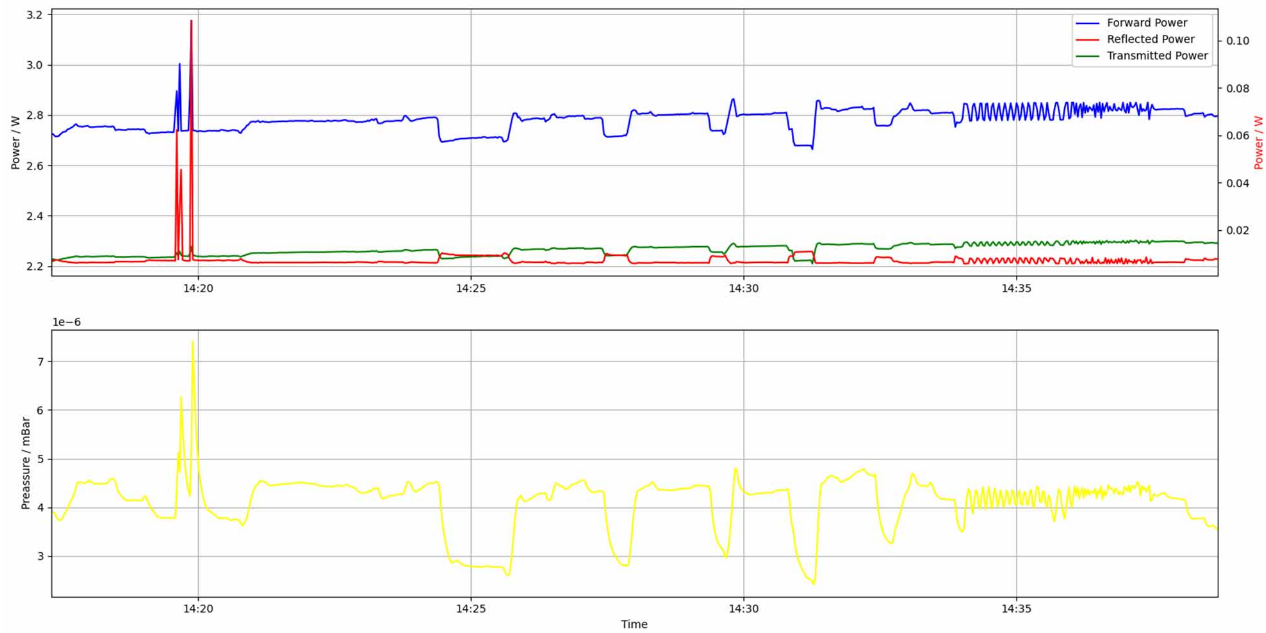

Figure 2: Conditioning process during the first day of conditioning. The progress was very slow, as the cavity didn't accept higher power levels without a drastic decrease of vacuum.

The conditioning of the RFQ proofed to be time consuming, as the power could only be increased in small steps. After two days of conditioning the power level was at only 5 W. The difficult start of the conditioning process is depicted in Fig. 2.

Possible Approaches for Machine Learning Algorithms

Generally, machine learning algorithms can be separated in supervised and unsupervised algorithms. While supervised algorithms are provided with "true values", as to speak the desired results, unsupervised algorithms try to find an underlying structure without any labelling by the programmer. Both approaches were, in different extent, studied for the available training data.

Unsupervised Algorithms: Clustering

During clustering, the algorithm tries to find similarities in the data, which are then ordered accordingly. Theoretically, the clusters can then be associated with an action done by the experimenter, for example a power increase, decrease or frequency shift. Those labels could then be used to train a supervised classification algorithm.

The clustering was done with a TimeSeriesKMeans algorithm utilizing the dynamic time warping metric. This allows the comparison of time series. 15 cluster were identified by the algorithm. Out of them, some are more clearly identifiable as others. One of the clearer identifiable clusters is depicted in Fig. 3.

Even though some clusters are promising, the majority of the 15 clusters is not clearly identifiable and doesn't allow to make a clear assumption what the next step should be.

Nevertheless, with some more optimization it could be possible to automize the labelling process necessary for a classification task by this method, reducing the workload in data preparation significantly.

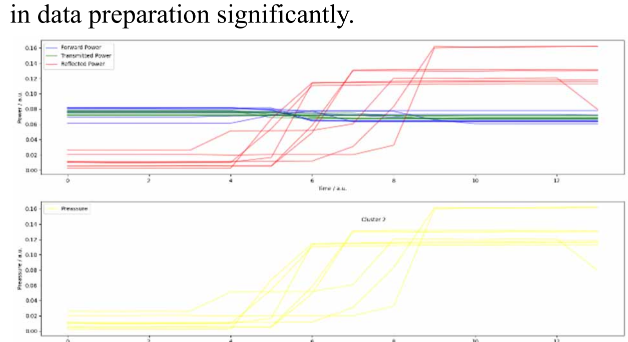

Figure 3: The second of 15 identified cluster. Here, an increase in reflected power with a decrease in vacuum at a nearly constant forward and transmitted power can be seen.

Supervised Algorithms

There are several supervised algorithms suitable for time series. One of the more prominent ones are Recurrent Neural Networks (RNNs). For the first tests with the acquired training data were Long Short-Term Memory (LSTM) RNNs used. The data given to the algorithm were all measurable parameters (P_f, P_r, P_t, f and p at the time t), scaled by their target values, while the labels were the forward power P_f at the time $t+\Delta t$. This was done to make a prediction into the future, as to simulate the actions done by the experimenter reacting on the actual data. As a realistic value for Δt a time skip of 1 second was chosen.

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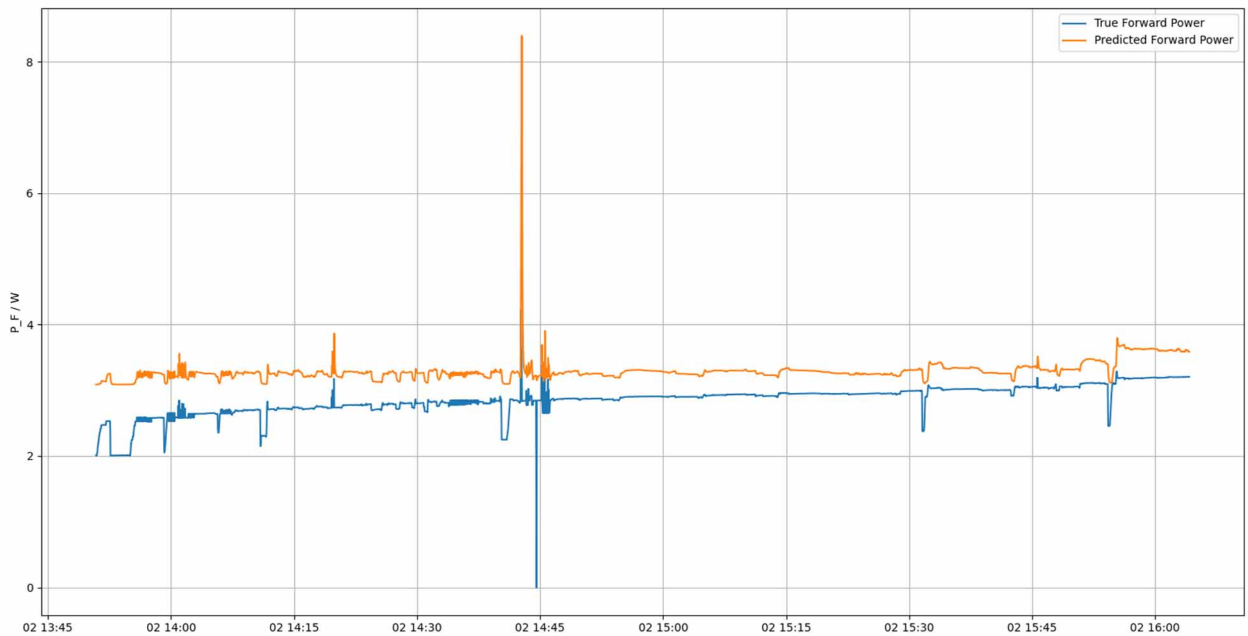

Figure 4: Comparison between predicted and true forward power.

As for the algorithm architecture, a relatively small neural network has been chosen. It consists out of four layers with two LSTM layers and approximately 54 thousand trainable parameters. The number of layers, their output shape and the number of trainable parameters per layer are presented in Table 2.

Table 2: Architecture of the Utilized Network

Layer	Output Shape	Number of Parameters
LSTM 1	(None, None, 64)	16896
LSTM 2	(None, 64)	33024
Dense 1	(None, 64)	4160
Dense 2	(None, 1)	65
Total Parameters		54145

Results of the LSTM Network

Even though the used network is relatively small, and the amount of training data was very restricted, the results look promising (compare Fig. 4). The overall structure is recognizable. The reasons for the offset between the true and the predicted power have yet to be researched, but it is likely a result of the lack of training data.

In a next step, the implementation of a classification algorithm is likely. This would make the implementation of commands possible, like to reduce the power or adjust the frequency. The pure prediction of the future values is an important step to achieve an independently operating system but is not the final goal.

SUMMARY AND OUTLOOK

It has been shown that even with limited data and a small neural network it is possible, to predict the general form of action during a conditioning. With more diverse training data, the performance should further improve.

As the next steps in the development of an automated conditioning algorithm, it is planned to test several other algorithm architectures, most notable of those transformers.

Additionally, it is planned to acquire more training data through several means. By in house conditioning of various prototypes, acquiring additional data from research cooperations of already conducted conditionings and through the planned conditioning process of 15 CH-cavities designed for the MYRRHA project [3].

As a final goal, the algorithm should be capable of performing the conditioning of various types of normal conducting cavities on its own, making the process easier and reducing the time needed by the experimenter.

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