

Long term Coherent stability and diffusion studies for the Future Circular Colliders

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1. Electron Cloud Studies for the FCC-ee to ensure stability

1.1 Motivation

In a circular particle accelerator, mainly machine operating with positively charged particles, the trailing bunches of the train are in a dense electron cloud (e-cloud) that can lead to unwanted effects: transverse instabilities, transverse emittance blow-up, particle losses, heat loads on the beam chambers, vacuum degradation (as observed in several accelerators all over the world [7-9]). For these reasons, the electron cloud (e-cloud) mitigation is a fundamental task in a circular particle accelerator (e.g., synchrotron, cyclotron). The process of the electron cloud formation is complex and depends on a lot of parameters [10]. Electron trajectories are strongly influenced by externally applied magnetic fields, because the electrons spin around the field lines [11]. Moreover, the bunch spacing determines how many electrons survive between consecutive bunch passages. The bunch intensity and bunch length also have an important effect as they affect the acceleration received by the electrons [10]. The chamber geometry influences electron acceleration and time of flight and the surface properties have a primary role in the electron multiplication process. The main quantity involved is the Secondary Electron Yield (SEY), which is defined as the ratio between emitted and impacting electron current as a function of the energy of the impinging electrons [10]. The SEY plays a key role in the e-cloud formation and, therefore, the goal is to reduce this surface parameter. The SEY depends on surface chemical properties and on the accumulated electron dose. The main strategies to reduce the SEY are: (i) to design the FCC vacuum chambers in terms of shape, material, coating or surface treatment by means of extensive simulation studies; (ii) to reduce accumulated electron dose by means of beam induced scrubbing runs [12]. The second strategy is very expensive, because it needs highly



qualified personnel hours and machine weeks, and it is a limited mitigation process. Moreover, there are other collective effects (e.g., impedance and wakefield [13]), therefore, a trade-off among all the requirements for the vacuum chamber is needed [2].

1.2 Research Goal

The final goal is to check the stability limits by means of self-consistent beam stability simulations for the different arc elements with realistic e-cloud distributions obtained from build-up simulations. The beam stability simulations are heavy from the computational point of view and, therefore, a preliminary study to identify the parameters, in the range of the values of FCC-ee case, which play a significant role in the e-cloud formation has been performed.

1.3 Research Activity

An extensive e-cloud build-up simulation study has been carried out using PyECLOUD code, in order to identify the parameters, in the range of the values of FCC-ee case, which play a significant role in the e-cloud formation. FCC-ee is a circular electron-positron collider, the first stage towards a 100 TeV proton-proton collider FCC-hh. The Z configuration of FCC-ee has been investigated, because the strongest e-cloud effects are foreseen for this configuration due to the highest number of bunches and, therefore, the smallest bunch spacing, In the study, the latest version (V22.2) of the parameters of the FCC-ee configuration Z has been used [3]. In this study, 9,450 simulations have been carried out with the following investigated parameters:

- particle: position beams, electron beam;
- beam chamber winglet height (see Fig. 1): from 9 mm to 11mm, with a step of 1 mm;
- particle accelerator device: drift space, focusing and defocusing quadrupole, dipole close to the focusing and defocusing quadrupole;
- bunch spacing: from 10 ns to 30 ns, with a step of 5 ns;
- bunch intensity: from $2.0 \oplus 10^{11}$ particle per bunch (ppb) to $2.8 \oplus 10^{11}$ ppb, with a step of $0.1 \oplus 10^{11}$ ppb;
- SEY: from 1.0 to 1.6, with a step of 0.1.





Figure 1: FCC-ee vacuum chamber transverse section.

Firstly, the electron density versus the bunch passage (see Fig. 2) has been analysed in order to check if there is the multipacting effect in every simulation (by the simulated 500 bunch passages) and a synthetic parameter has been used for the global analysis. The synthetic parameter is defined as the average of the e-cloud density after that the avalanche multiplication is triggered (see Fig. 2) [6].

From the simulation results, the variation of the beam chamber winglet height has made a negligible contribution to the e-cloud density. In the elements, the configuration of the magnetic field is different: in the drift space, there is no magnetic field; the magnetic field in the dipole is 1.415 mT; and, in the quadrupole, there is a quadrupolar gradient of 5.65 T/m. In the focusing and defocusing quadrupole, the only quantities that change are the horizontal and vertical beta functions (see Fig. 3). In the FCC-ee, the beam is flat (the horizontal and vertical emittance are $\sum_{gx} = 0.71$ nm, $\sum_{xy} = 1.42$ pm, respectively) and, therefore, only the flatness of the beam changes among the different elements. The simulation results have shown a negligible contribution of the beta functions, in the range of the FCC-ee parameters, to the e-cloud process [4,5].





Figure 2: Example of e-cloud density versus bunch passage. The bunch passage, after that there is multipacting, is in solid black line; the minimum and the maximum values of the e-cloud density after multipacting are in dashed grey line; the average e-cloud density after multipacting is in dashed red line.



Figure 3: Horizontal (\mathbb{B}_x), in red line, and vertical (\mathbb{B}_y), in blue line, beta functions in the different elements.





Figure 4: E-cloud density versus SEY for different bunch intensity (in different colours) in the elements: drift space on the left, dipole in the centre, quadrupole on the right.

In Fig. 4, the e-cloud density versus SEY for different bunch intensity (in different colours) in the elements is plotted: drift space on the left, dipole in the centre, quadrupole on the right. The value of bunch spacing is 10 ns. In the drift space and dipole, the electron density has a similar behaviour with respect to the bunch intensity: smaller bunch intensity means larger e-cloud density. In the quadrupole, the electron density is smaller than the dipole and drift space case for lower bunch intensity, and the bunch intensity has a negligible effect on the e-cloud density. In all elements, increasing the bunch spacing is stronger in the drift space and dipole and for some cases there is no multipacting by the simulated 500 bunch passages. Increasing the bunch spacing, the dependence of the e-cloud density on the bunch intensity is weaker. Moreover, in the drift space and the dipole, the SEY threshold for multipacting increases with the bunch spacing more than the quadrupole case [4,5].

Considering for the FCC-ee collider a circumference of 91.1 km and a number of bunches per beam of 10,000, the maximum bunch spacing reachable is 30.4 ns, when all the bunches are equally spaced. In this filling scheme, there is no space to put any gaps between bunch trains in order to "clean" the e-cloud between two consecutive bunch train passages and, therefore, even in the case of large bunch spacing and small SEY, the multipacting could occur after a large number of bunch passages. In the simulation results, a finite number of bunch passages (500) has been simulated, but multipacting could occur in the next bunch passages and the saturation value of the e-cloud density could be reached after 500 bunches and, therefore, the e-cloud density



could be higher. To simulate the e-cloud formation process in the case of particular filling schemes (e.g., no gaps between bunch trains), a large number of bunch passages has to be used and it is not feasible from the computational point of view [6].

In the case of electron bunches, the multipacting occurs in a few cases, but the e-cloud density is smaller than the positron bunch cases and the electrons of the e-cloud are mainly located far from the beam chamber centre [4,5].

1.4 Outlook and Future Development

The next step is the investigation of other important parameters in the e-cloud formation process by means of build-up simulations, in particular:

- The simulation studies which are presented are in the collision configuration with the longest bunch length (rms 14.5 mm), where the synchrotron radiation and beamstrahlung effects are considered. The injection configuration also has to be analysed with the shortest bunch length (rms 4.38 mm), where only the synchrotron radiation effects are considered. These simulations need a smaller time step and, therefore, they are heavier from the computation point of view. Convergence studies have to be carried out in order to maximise the time step and, therefore, optimise the computational effort for the future studies.
- Further studies about the vacuum chamber geometry are planned, regarding the winglet depth and the radius (see Fig. 1).
- Check the e-cloud density for a larger range of bunch intensities: from one tenth to the full bunch intensity due to the bootstrapping.
- Analyse the dipole magnets adding a small quadrupolar gradient error (e.g., -9 mT/m).
- Simulation studies in other particle accelerator regions and devices are planned (e.g., interaction regions, solenoids, etc.).
- Simulations with realistic filling schemes of FCC-ee are foreseen.
- Evaluate the heat loads in the different cases.
- Study the e-cloud density movement during the bunch passages, in the electron beam case.

Further studies will be performed in order to check the stability limits by means of selfconsistent beam stability simulations for the different arc elements with realistic e-cloud distributions obtained from build-up simulations.



Another future development is to improve the model of the electron cloud formation based on the current state of knowledge (from both laboratory and the LHC experience). In particular, the energy spectrum model of the emitted electrons could be improved, using lab measurements and the existing numerical tools for e-cloud build-up based on the LHC RUN3 data set.

Moreover, the code development and benchmark of PyECLOUD for Xsuite in the software framework for FCC is foreseen. Xsuite is a project launched to rationalise and modernise software for multiparticle simulations in order to move from a heterogeneous range of programs each with limited capabilities to an integrated modular toolkit (Xsuite) and in order to cover with a single toolkit injectors, LHC, HL-LHC and design studies (e.g., FCC framework). In this project, the exploitation of modern computing platforms (e.g. GPUs) for a wide range of applications and a strong simplification of the development and maintenance process, removing several duplications, are planned.

The final goal is to contribute to the development of a framework for comprehensive beam dynamics simulations on the combined effect of persisting electron cloud, beambeam and impedance aiming at the prediction of stability limits.

1.5 List of presentations:

1. Presentation at EPFL-LPAP FCC-ee Software Framework Meeting 2022/05/11 https://indico.cern.ch/event/1160125/contributions/4872192/attachments/2441680/4182938/2022 05 10 Sabato Luca FCCweek.pdf

2. Presentation at CHART Workshop 2022 2022/06/09 https://indico.psi.ch/event/12727/contributions/35124/attachments/21949/37860/2022_06_09_Sa bato_Luca_CHART_Workshop.pptx

3. Presentation at EPFL-LPAP Activity Meeting 2022/09/23 https://indico.cern.ch/event/1200207/contributions/5046762/attachments/2514699/4323463/2022 09 23 Sabato Luca EPFL-LPAP.pdf

4. Presentation at ECLOUD22 workshop 2022/09/25 – 2022/10/01 <u>https://agenda.infn.it/event/28336/contributions/176811/attachments/97052/133885/2022_09_26</u> <u>Sabato_Luca_ECLOUD22.pptx</u>

5. Presentation at 159th FCC-ee Optics Design Meeting 2022/11/10 https://indico.cern.ch/event/1205924/contributions/5080961/attachments/2544998/4382481/2022 11_10_Sabato_Luca_FCC-ee%200ptics_Design_Meeting.pdf



6. Presentation at FCCIS 2022 workshop 2022/12/07

https://indico.cern.ch/event/1203316/contributions/5125374/attachments/2562368/4416763/2022 12 07 Sabato Luca FCCIS 2022 Workshop.pptx

1.6 List of references:

7. W. Fischer et al., "Electron Cloud Observations and Cures in the Relativistic Heavy Ion Collider", Physical Review Special Topics-Accelerators and Beams, vol. 11, no. 4, p. 041002, 2008.

https://journals.aps.org/prab/abstract/10.1103/PhysRevSTAB.11.041002

8. H. Fukuma, "Electron Cloud Observations and Predictions at KEKB, PEP-II and SuperB Factories", Proceedings of ECLOUD12: Joint INFN-CERN_EuCARD-AccNet Workshop on Electron-Cloud Effects, La Biodola, Isola d'Elba, Italy, 2012.

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https://arxiv.org/abs/1306.5944

 G. Iadarola, "Electron Cloud Studies for CERN Particle Accelerators and Simulation Code Development", PhD thesis, Università degli Studi di Napoli Federico II, March 2014.

https://cds.cern.ch/record/1705520

11. P. Dijkstal, "Electron Cloud Build-up Studies for the LHC", Master's thesis, Technische Universität Darmstadt, October 2017.

https://cds.cern.ch/record/2289439

12. G. ladarola and G. Rumolo, "Scrubbing: Expectations and Strategy, Long Range", Proceedings of Chamonix 2014 Workshop on LHC Performance

https://e-publishing.cern.ch/index.php/CYR/article/view/128

13. A.W. CHAO, "Physics of Collective Beam Instabilities in High Energy Accelerators", Wiley Series in Beam Physics and Accelerator Technology, 1993.

https://www.slac.stanford.edu/~achao/wileybook.html



2. Machine learning applied to the design of future Colliders via surrogate models

2.1 Introduction

The understanding of the beam stability is essential for the operation of existing circular accelerators, such as the CERN Large Hadron Collider (LHC), as well as for the design of future ones such as the Future Circular Collider [3,4].

In a first step we have tried to define a purely data driven model of the LHC collider beam loss rates, Unidentified falling objects losses and the on-set of coherent instabilities. Results have been very promising. A model to describe the beam loss rates at injection energy has been defined and details can be found in References [7,9]. For the identification of the UFO loss mechanisms a model has been developed and has proved to be efficient and reproducing well the machine observations [5]. Very useful and interesting tool developed for the online identification of coherent beam instabilities has also been the subject of a detailed study and results published in References [6]. All these methods have helped in understanding the numerical models behind the ML techniques used and to understand observations from a different view. The models have highlighted beam parameters dependences that were not obvious. In addition, possible use for beam controls and operation have been inspired by the results.

Our second step was to move the predictability of particle loss rates at the design stage of an accelerator as it is for the FCC case. The standard approach for the numerical evaluation of the beam stability of an accelerator relies on the ability to accurately track initial conditions [8], distributed in phase space, for a realistic time scale, and this is computationally demanding (3-5 days).

For this reason, the development of a Machine Learning (ML) model that predicts the time evolution of beam losses of a particle in a specific set of tuning knobs in a few seconds will be extremely convenient in order to explore new accelerator configurations.

2.2 Data sets and simulations

Currently, two datasets are available to test ML models on beam stability studies. In the first dataset, the target is the survival plot for every machine configuration i.e., the target is an image.



While for the second dataset, the target is the Dynamic Aperture (DA) radius, which is a numeric quantity. The DA is defined as the extent of the phase-space region in which the particle's motion remains bounded over a finite number of turns.

In general, the data consist of:

- · Independent features (machine configuration) as the synchrotron tune (Q_x, Q_y) , chromaticity Q', quadrupole magnets current I_{MO} , beam orientation (clockwise or anticlockwise), seeds for magnet errors, and others.
- Dependent features (target): survival plot or Dynamic Aperture (DA).

The first dataset consists of survival plots (uniformly distributed) with about 3 thousand different machine configurations in 2D phase-space of LHC. An example of a survival plot sample is shown in Figure 1. This data was used in the past to train a Generative Adversarial Network (GAN). Despite that this dataset is a good enough for a concept proof the use GANs, the tuning knobs phase-space is limited only on the two most important variables for stability and the amount of sample is small to train Deep Learning (DL) architectures which generally require on the order of millions of samples.



The second dataset consists of DA radius (for particles distributed polar coordinates in 11 different angles) with about 30 thousand different machine configurations in 6D phase-space



 $(Q_x, Q_y, Q', I_{MO}, beam orientation and magnet seeds)$ for High Luminosity LHC (HL-LHC). An example of a DA sample is shown in Figure 2.



2.3 Regression of Dynamic Aperture using Neural Networks

This last dataset was used to train a fully connected Neural Network (NN) to regress the DA radius in a specific angle for a specific machine configuration. The model consists of 4 hidden layers with 1024, 512, 256 and 32 nodes, batch normalisation and dropout (5%) were implemented between hidden layers. The train was performed using NADAM optimizer with adaptive learning rate. In order to measure the performance, 20% of the dataset was not used for the training and instead was used just for testing. The Mean Absolute Percentage Error (MAPE) achieved is 0.06 (0.06) for test (train) dataset and no overfitting was observed during the training (Figure 3).

In order to explore new accelerator configurations, an active framework was implemented to continuously update the model with new simulated data. This adaptive sampling for the DA model is based on another fully connected NN that consists of 4 hidden layers with 512, 256, 128 and 32 nodes, trained on the same dataset (~30k samples) to regress the mean absolute error of the DA model for every single machine configuration. The MAE is 0.08 (0.09) for the test (train) dataset and no overfitting was observed during the training (Figure 4).





The unreliable knobs (machine configurations) are the ones with considerably predicted errors and will be used to run the full accelerator simulation, and by ranking the predicted errors, it is possible to have an adaptive sampling mechanism. Meanwhile the trusted knobs, the ones with small predicted error (MAPE<5%), are used to generate synthetic data through the previous DA model. Some examples of accelerator configuration categorised as good knobs by the model are shown in Figure 5.



In order to test the active learning mechanism, 3 thousands of new machine configurations were generated and classified as trusted knobs. This data was added to the initial training dataset and the DA model was retrained. The MAPE was improved to 0.05 on the test dataset (non-synthetic data).



Figure 5: Knobs categorizes as trusted and their respective DA in function of angles.

Despite the DA model together with the Active Learning prove being able to predict the beam stability for the majority of the accelerator configurations, in some few cases the errors are substantial [1]. One of the main reasons is dataset size that is not adequate to train a DL model. Therefore, new dataset are being generated to improve the model performance and new tools to accelerate the full simulation are being developed such as xboinc, which will be discussed in the next session.

These results were presented at CERN ABP-NDC meeting: https://indico.cern.ch/event/1208772/#31-machine-learning-for-da-sim

2.4 Accelerating Tracking Simulations of Particle Accelerators

The full data simulation of the two datasets discussed in the previous section were generated with MAD for the lattice generation and with SixTrack for the particle tracking. As mentioned, the latter is computational demanding, a single particle simulation of a specific accelerator



configuration could demand up to five days. In order to accelerate the tracking simulation for thousands of particles for every machine configuration, SixTrack was implemented as a BOINC application [11]. BOINC is a system that allows volunteer computing. By sharing processing resources of multiple personal computers, it is possible to accelerate the SixTrack simulation. For the FCC case, a higher computation demand is expected due to the increase in the number of lattices and synchrotron radiation. For this reason, the BOINC system is ideal to submit jobs for the FCC simulations.

However, an improved tracking tool in under development: xtrack [2]. This tool is a package of the Xsuite framework, which researchers from EPFL and CERN are developing. The packages, features and development of Xsuite are shown in the diagram on Figure 6. The red blocks show the CHART contributions to the development for beam dynamic studies of the FCC.



Figure 6 Schematic of XSUITE packages and features for use at the LHC green and light green boxes. Below the necessary developed features in red for beam dynamics studies of Future Circular Colliders for leptons and hadrons. These developments are part of different CHART approved projects. The names of people involved in the developments are also listed.

During 2022 the BOINC application for xtrack was developed: xboinc. The application was implemented on Linux and Windows and available on GitHub [12]. In addition, its validator and assimilator were developed in order to handle the job submission. The xboinc was tested locally as well on a test server by the developers. Currently, the application is being configured in the CERN server to be tested with real volunteers. The application will be available to the collaboration in S 2023.



2.5 Presentations and references

[1] CERN ABP-NDC meeting. <u>https://indico.cern.ch/event/1208772/#31-machine-learning-</u>for-da-sim

[2] CERN ABP-NDC meeting: <u>https://indico.cern.ch/event/1189566/#29-report-on-boinc-setup-for-x</u>

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[11] The BOINC Projects. https://boinc.berkeley.edu/

[12] The xboinc Application. <u>https://github.com/xsuite/xboinc</u>