OPTIMIZATION OF HEAVY-ION SYNCHROTRONS USING NATURE-INSPIRED ALGORITHMS AND MACHINE LEARNING

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Abstract

The application of machine learning and nature-inspired optimization methods, like for example genetic algorithms (GA) and particle swarm optimization (PSO) can be found in various scientific/technical areas. In recent years, those approaches are finding application in accelerator physics to a greater extent. In this report, nature-inspired optimization as well as the machine learning will be shortly introduced and their application to the accelerator facility at GSI/FAIR will be presented. For the heavy-ion synchrotron SIS18 at GSI, the multi-objective GA/PSO optimization resulted in a significant improvement of multi-turn injection performance and subsequent transmission for intense beams. An automated injection optimization with genetic algorithms at the CRYRING@ESR ion storage ring has been performed. The usage of machine learning for a beam diagnostic application, where reconstruction of space-charge distorted beam profiles from ionization profile monitors is performed, will also be shown. First results and the experience gained will be presented.

INTRODUCTION

FAIR—the Facility for Antiproton and Ion Research will provide antiproton and ion beams of unprecedented intensities as well as qualities to drive forefront heavy ion and antimatter research [1]. The multi-turn injection (MTI) into heavy-ion synchrotron SIS18 is one of the bottlenecks for providing unprecedented intensities. The loss-induced vacuum degradation and associated life-time reduction for intermediate charge state ions is one of the key intensity limiting factors for SIS18 [2]. Beam loss during injection can trigger the pressure bump instability. An optimized injection can relax the dynamic vacuum problem, but is also crucial to reach the synchrotron intensity limit by a large multiplication of the injected current [3].

The complexity of the FAIR facility demands a high level of automation to keep anticipated manpower requirements within acceptable levels, as shown in [4]. An example of complexity is the High Energy Beam Transport System of FAIR which forms a complex system connecting among other things seven storage rings and experiment caves and has a total length of 2350 metres [5]. An automatized machine based optimization would improve the time for optimization and control of HEBT.

In the frame of the Swedish in-kind contribution to the FAIR project the storage ring CRYRING@ESR is planned to be used for experiments with low-energy ions and antiprotons. The ring is already installed in the existing GSI target hall and commissioning has started in 2015 [6–8]. Since CRYRING@ESR has its own local injector it can be used stand-alone for testing novel technical developments like automatized configuration of beam line devices. A semi-automatized optimization has been already preformed at the CRYRING in Sweden [9]. Figure 1 shows the CRYRING@ESR and is local injector. Over the second transfer line the CRYRING@ESR can also receive beams form the experimental storage ring ESR.
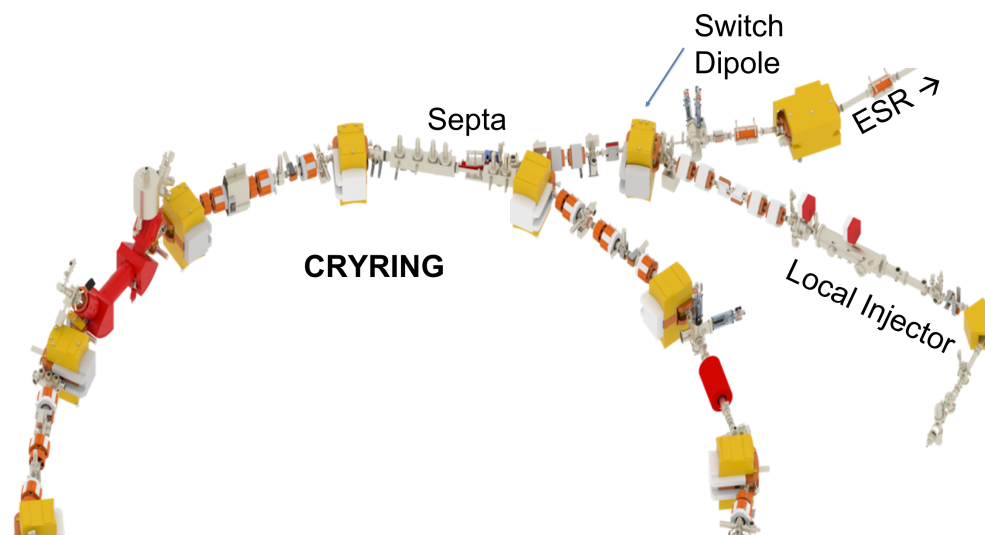
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Figure 1: CRYRING@ESR injection from the local injector has been online optimized with an evolutionary algorithm.

For the optimization and control of synchrotrons the knowledge of beam parameters is a key ingredient. Ionization profile monitors play an important role in non-destructive measurements of the transverse beam profile. They make use of residual gas ionization by the particle beam and collect the ionization products via appropriate guiding fields. However, for the foreseen intensities at heavy-ion synchrotron SIS100 for some beams a profile distortion is expected to be visible. Here the application of machine learning allows the reconstructing of the beam profiles with simulation supported training.

NATURE-INSPIRED OPTIMIZATION

Nature-inspired optimization algorithms often perform well approximating solutions to all types of problems because they ideally do not make any assumption about the underlying fitness landscape. The *fitness* determines the quality of the solution and determines the probability of its survival for the next optimization step. The fitness is evaluated by an objective function, a simulation code or a real running system. In many real-life problems, multi-quantities have to be optimized. In addition, these quantities can be contradicting and there is more than one equally valid solution. These solutions form a so-called Pareto front (PA front) in the solution space. A solution is Pareto optimal if it is not dominated by any other solution. By using a non-dominated selection algorithm one tries to find solutions near the optimal Pareto set.

Evolutionary algorithms

An evolutionary algorithm (EA) is inspired by biological evolution, such as *reproduction*, *mutation*, *recombination*, and *selection*. Genetic algorithms (GA) is the most popular type of EA. In GA terminology, a solution vector is called an *individual* and represents a set of variables; one variable is a *gene*. A group of individuals form a *population*, the following child populations are counted in *generations*. The first population is created randomly. The *crossover* operator exchanges variables between two individuals - the parents - to discover with their offspring promising areas in the solution space (*exploration*). For the optimization within a promising area, the mutation operator changes randomly the characteristics of individuals on the gene level (*exploitation*). Reproduction of individuals for the next generation involves selection. During optimization the most promising individuals are chosen to create the next generation. By allowing individuals with poor fitness to take part in the creation process the population is prevented to be dominated by a single individual. The most popular techniques for a single-objective optimization are proportional selection, ranking and tournament selection [10, 11].

Particle swarm optimization

The initial inspiration for the Particle Swarm optimization (PSO) came from the "graceful but unpredictable choreography of a bird flock" and is a example of alternative algo-
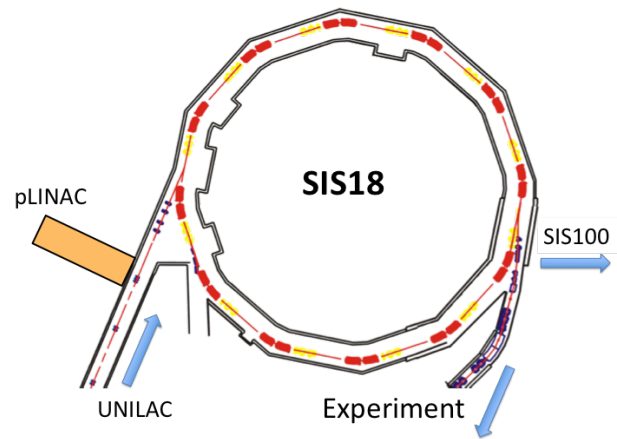

Figure 2: The heavy-ion synchrotron SIS18 and its injectors.

rithms. The key to the swarm success liens in *social influence* and *learning*. Each individual's behavior is influenced by its own *personal experience* and the *social standard* [11]. Within a swarm, each individual refers to a point in the variable space. It is updated by adding a velocity depending on the personal experience and the socially swarm influenced. The "nostalgia" in the individual tends to return to a place it encountered in the past that best fulfilled the objectives reflected by the personal best *pbest*. Simultaneous, the individuals seek to attain publicized knowledge or social norms, reflected by the best position ever for the entire swarm *gbest*. The movements of the swarm a guide by improved positions, which are updated during the optimization. Including in addition stochastic elements in the algorithm allows to search widely and hopefully finding a satisfactory solution. PSO has shown faster convergence than GA optimization [11].

INJECTION OPTIMIZATION

SIS18 (Figure 2) will serve as a booster for SIS100 in the FAIR facility to provide ion beams of unprecedented intensities and qualities. An optimized interface between injector linacs and synchrotron is mandatory to achieve this goal. The new FAIR proton linac (pLINAC) will provide the high intensity primary proton beam for the production of antiprotons. The existing GSI heavy ion linac (UNILAC) is able to deliver world record uranium beam intensities for injection into the SIS18, but it is not suitable for FAIR operation. Therefore an upgrade program is planned to replace the post-stripper section. An evolutionary algorithm based optimization of the multi-turn injection (MTI) of the SIS18 has been performed to define the interface parameters for UNILAC and pLINAC. The goal of the optimization is to stack the beamlets injected from the injector in the horizontal phase space until the synchrotron intensity limit is reached. Thereby injection losses on the septum or acceptance have to be minimized to prevent a synchrotron performance reduction to due loss induced vacuum degradation [3]. However, the required MTI brilliance should be in a reachable value frame for the injector linac. As MTI has to fulfill Liouville's theorem, four bumper magnets create a time variable closed orbit bump such that
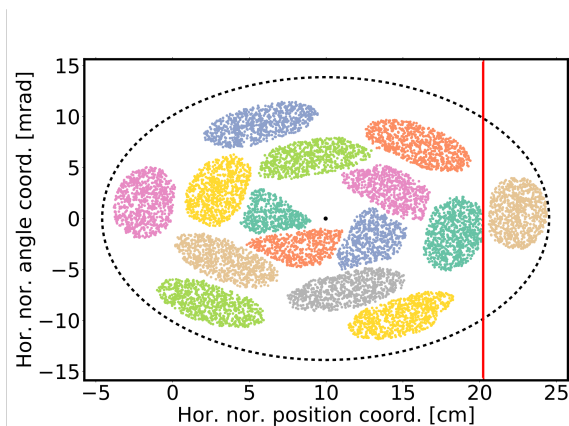
Figure 3: Snapshot of a MTI simulation with loss. The red line indicates the septum and dashed line the acceptance.

Figure 4: The evolution of loss for injected emittance of 7 mm·mrad. GA found a much better injection parameter setting for a low loss injection than the previous simulation studies (dashed lines).

Figure 5: The PA front for gain factor and MTI loss. GA found a much better PA front than the previous studies.

the injection septum deflects the next incoming beamlet into available horizontal phase space close to the formerly injected beamlets. For effective adaptation to the free phase space, for instance, an exponential bump reduction can be chosen. During the nature-inspired optimization the parameters on which the MTI depends are altered in consideration of the limiting technical and physical conditions to find an excellent MTI performance. The MTI performance depends on injector emittance and current, position and angular of the incoming beam, the closed orbit at the septum, horizontal tune, miss-match of the incoming beam and the orbit bump reduction. For the optimization the Distributed Evolutionary Algorithms in Python (DEAP) [12] together with pyORBIT has been used. The SIS18 MTI model has been implemented in the particle tracking code pyORBIT—the Python implementation of ORBIT (Objective Ring Beam Injection and Tracking) code—and was carefully validated against experiments [13–15]. Figure 3 shows a snapshot of a MTI simulation with loss in normalized coordinates. The loss areas—inner and outside of the septum as well as the acceptance—are visible. The inner beamlets lost particles at septum earlier during the injection process and therefore not overlap. The injected beams are spirally arranged. The first injected beams are sitting in the center of the spiral next due to the closed orbit indicated by the black dotted. Figure 4 illustrates the evolution of the injection loss obtained from the GA for different numbers of injected turns. The GA finds a better set of parameters than the previous simulation studies (indicated by the dashed lines [14]). The fact that a longer injection time leads to higher losses also holds for the GA optimization if the available acceptance is filled. However, especially in these cases GA discovers a much better solution. The dependence of the gain factor on the injection loss is of particular interest due to the vacuum degradation problem. In order to define the relationship between both, the gain factor has been included as an optimization objective, i.e. to find a 2D Pareto front of both. Figure 5 shows that multi-objectives genetic algorithms (MOGA) finds a much better set of parameters for an improved MTI performance
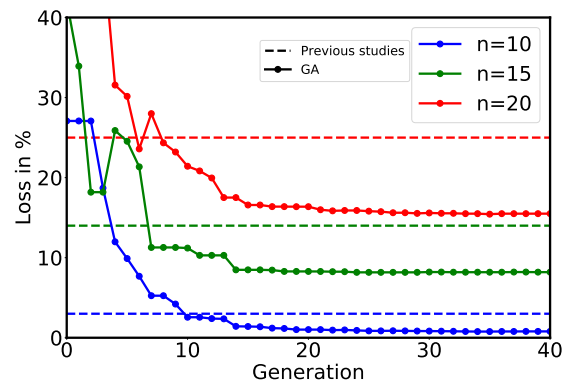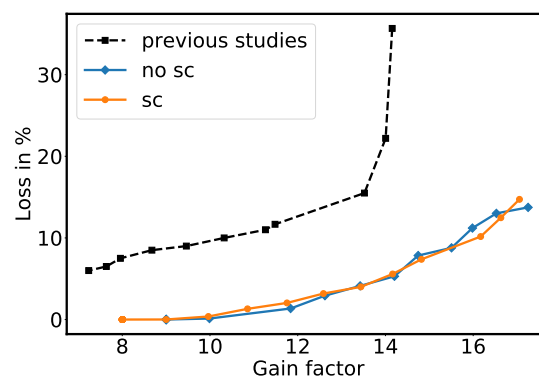
than the previous simulation studies [14]. The influence of space charge on the MTI performance optimization with MOGA is significant even if the discovered PA fronts are similar: The discovered MTI parameters are different with space charge. For the layout of the injector upgrade and the new proton injector is crucial to known the injection dependence on emittance. The demands on the injector could be relaxed if a sufficient MTI performance with a large injection emittance can be discovered. Previous MTI optimization studies [14, 16] clearly demonstrate that the horizontal emittance of the incoming beam has a significant impact on MTI performance. The smaller the injected emittance is, the better the MTI performance gets, which is contradicting to relaxation of the injector demands. A reduction of the horizontal emittance can be achieved e.g. by horizontal collimation [16] or by a round-to-flat transformation [15]. Figure 6 shows in accordance with MTI model and previous studies the trade-off between the objectives over a wide range of parameter variations, which can be summarized as follows: no loss means small injected emittance and low gain factor; a high gain factor implies small emittance with
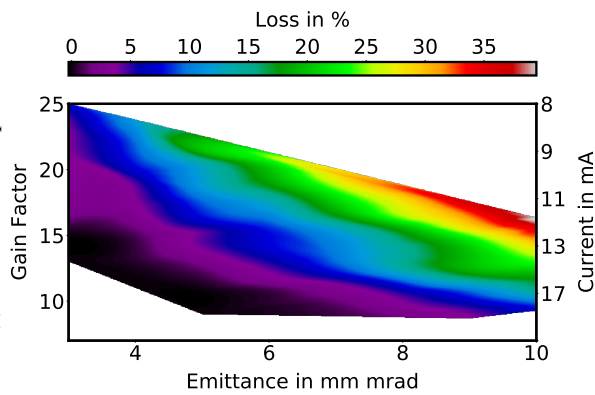
Figure 6: The 3D Pareto front for a simultaneously GA optimization of gain factor, loss and emittance. On the right axes the require injector current is shown to reach the space charge limit in the SIS18.

medium loss; and large emittance means very large loss and small gain factors. This trade-off is a direct consequence of Liouville's theorem. The obtained results for single and double objective optimization are located also on the 3D PA front. Optimization with multiobjective particle swarm (MOPSA) shown similar result with fast convergence. A 3D Pareto front for proton injector has generated shown in [17]. Outcome of this optimization and heuristic analyze of the MTI demonstrate, that a low-loss injection to fill SIS18 up to the space charge limit for several emittance over many turns for various proton currents could be achieved.

ONLINE INJECTION OPTIMIZATION

The multi-turn injection of the CRYRING@ESR from the local injector has been online optimized with a genetic algorithm. The aim of the automatized optimization was to maximize the beam current stored in the CRYRING@ESR. The beam current has been measured with the Schottky diagnose in the CRYRING. An end-user application exploiting the genetic algorithm framework Jenetics [18] to optimize unknown beamline settings through the Java based FAIR control system has been implemented [19]. Jenetics is an end-user ready software library implementing an genetic, evolutionary algorithm, written in modern day Java. Therefore the choice to use Jenetics was obvious although faster algorithm are known. The Jenetics algorithm allows independent variation of the merging dipole magnet and the quadrupoles strengths in the transfer line as well the septa, steerer strengths, and the closed orbit defined by the ring dipols. The result of the successful evolutionary algorithm optimization performance is presented in Figures 7. Shown are two cases of converged genetic scans for the recombination probability of 0.5 and 0.8. The population size was 50 and the offspring fraction 0.5. The tournament size of 15 has been chosen rather large to reach a fast convergence. For large tournament size, weak individuals have less chance of being selected. The first population is created

randomly forming a range around 10–15% of known good values (e.g. from earlier manual settings or beam optics calculations). The performance of the ion source, especially unstable plasma conditions play a crucial role, as it introduces non-deterministic transmission fluctuations which cannot be coped with by the algorithm without further measures. Therefore for each genetic scan step an averaging over ten measurements has been performed. Both scans reached after about 1.5 hours optimization time previous achieved transmission. At present, the time-domain performance is limited by the FAIR control system. Hence, removing performance bottlenecks in the FAIR control system code stack would be a key to fully enable this method's power.

MACHINE LEARNING

A principal characteristic of Machine Leaning (ML) is to implicitly deduce a set of rules from given data, mapping specific input to output, relieving the user from this tedious task. As such ML is especially suited for problems whose solutions require either a lot of manual fine-tuning or involve long lists of (potentially unknown) rules. Relevant for the presented problem is the later case, where supervised machine learning consisting of regression models is used to predict continuous variables from the given data. Supervised ML covers many different algorithms with varying complexity, from linear approximations like Linear Regression (LR) up to "biologically inspired" Artificial Neural Networks (ANN) [20].

Linear Regression

Linear regression is a linear approach modelling the relationship between the scalar dependent variable and one or more explanatory variables. In linear regression, the relationship is modeled using linear predictor functions whose unknown model parameters are estimated from the data. The least squares approach is often used for fitting linear regression models.

Artificial Neural Networks

Artificial neural networks (ANN) are computing systems vaguely inspired by the biological neural networks found in animal brains. The most basic form of ANN typically utilized in supervised learning problems is a fully-connected feed-forward Multi-Layer Perceptron (MLP). It is a specific ANN architecture which is represented by consecutive layers of nodes where all nodes of two consecutive layers are connected to each other. Each node sums all its weighted inputs and transforms the result using an activation function. The activation function should be non-linear in order to represent non-linearities in the data and it must be differentiable in order to comply with the fitting procedure. Weights are usually randomly initialized and then iteratively updated during the fitting procedure in order to minimize the selected loss function.
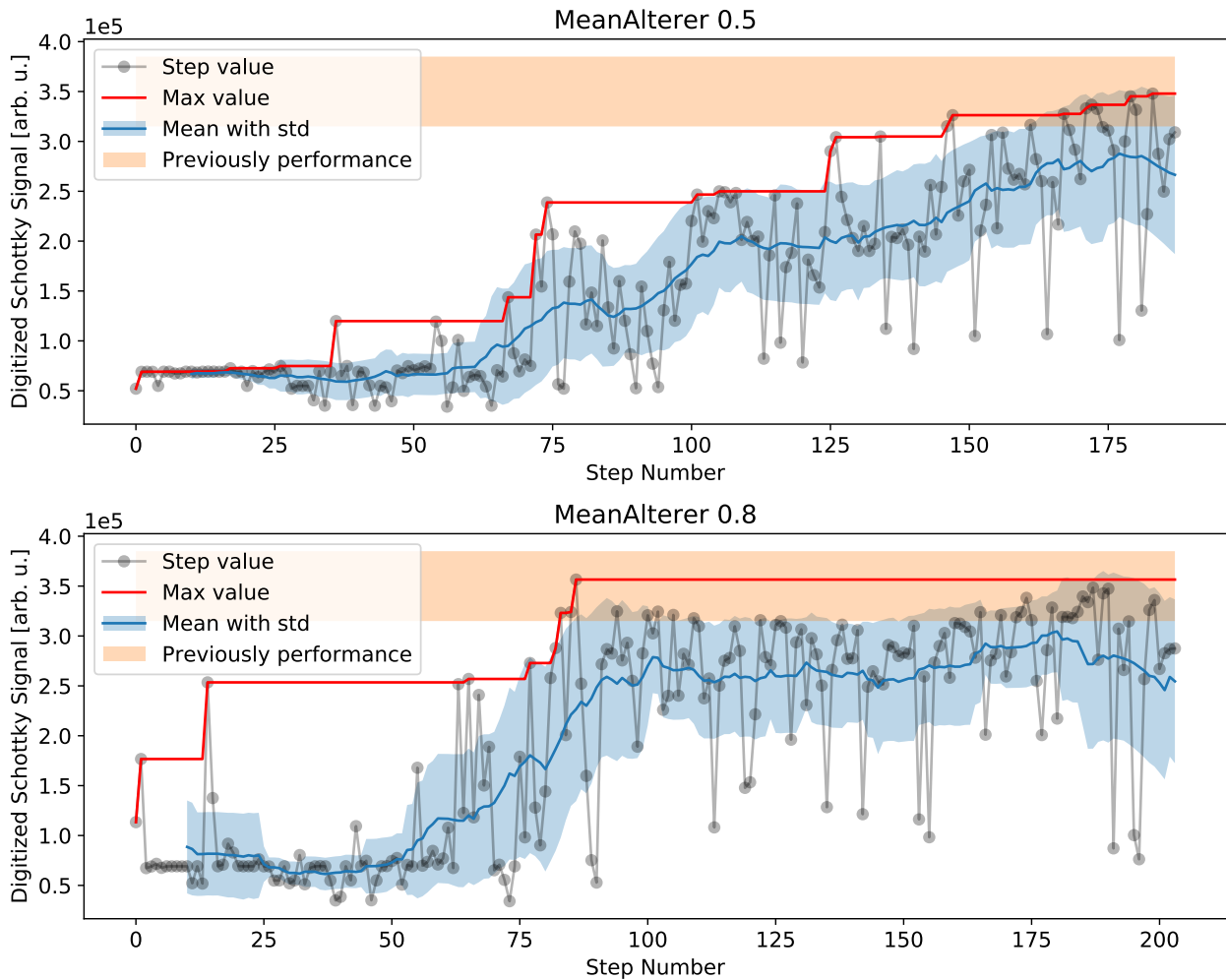
Figure 7: Converged genetic scan driving ten parameters for two different recombination probability. The goal of the optimization has been to maximize the CRYRING@ESR MTI performance. The scans reached the final value after four generations and reached previous good transmission after 89 (upper scan) and 97 minutes (below scan). For each optimization steps an averaging over ten measurements has been performed.

IPM PROFILE RECONSTRUCTION

The principle of IPMs is the following; the primary beam ionizes the residual gas and the ionized particles (ions or electrons) are extracted via electric fields, sometimes in conjunction with magnetic fields to confine the movement of ionized particles in the plane transverse to the electric field [21]. In the ideal case the ionized particles would move on a straight path towards the detector and the profile of the extracted particles reflects the transverse profile of the primary beam. The electromagnetic fields of the primary beam can affect the trajectory of particle movement towards the detector, see Figure 8. As a consequence the beam profile can be significantly deformed compared to the unimpaired wire scanner measurements. Several attempts have been made to correct or describe such effects parametrically, but no satisfactory analytic procedure was found. At that point a machine learning based approach reliant on good simula-

tion model of the IPM along with space charge effects was performed.

The Virtual-IPM simulation tool was used for simulating the movement of electrons inside the IPM region for a typical LHC case [22], where the beam electric field leads to major distortion. The simulated profiles were binned corresponding to the resolution of an acquisition system based on hybrid-pixel detector [23]. Together with the bunch length and the bunch intensity this data were used for fitting various ML models. Even the simple linear regression model showed very promising results for the beam width reconstruction [22]. The complex artificial neural networks can reconstructed the whole beam profiles as shown in Figure 9 [24].

CONCLUSION AND OUTLOOK

A fast beam dynamics simulation model has been developed and used together with a multi-objective genetic
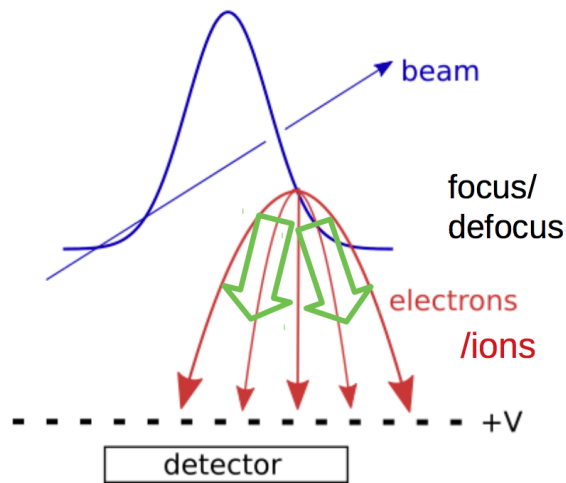
Figure 8: In the ideal case the ionized particles would move on straight lines towards the detector. However the electromagnetic field of the beam can influence the particles movement as shown.
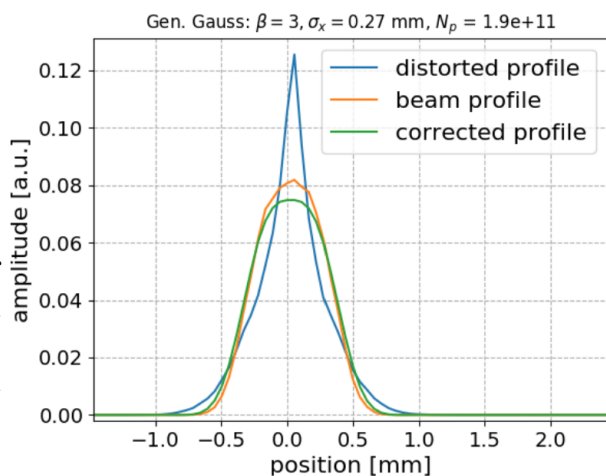

Figure 9: Simulation of profile distortion due to space charge using Virtual IPM together with the ANN corrected profile.

algorithm to optimize the multi-turn injection into SIS18. A loss-free or low-loss injection for several emittance over many turns were identified. Space charge results in a similar PA front, but with different injection settings. With the optimized multi-turn injection a range of injector brilliance could be defined. This crucial information gives more flexibility for the layout of the SIS18 injectors.

An online optimization of multi-turn injection into the storage ring CRYRING@ESR has been presented. After 1.5 hours of optimization time previous transmission could be reached. The nature-inspired optimization has potential to reduce the manpower requirements and variations of quality performance due to the manual procedure. Looking forward, the algorithm shall be applied to SIS18.

A novel method for resolving IPM profile distortion under the influence of magnetic guiding fields based on machine learning has been presented. The first investigations, using simulated data, yield promising results. Next steps include estimation of influence of error sources on predictions, optimization of model selection and application of the method to measured data. The method has a potential to extend usability and reduce cost of IPMs for high brightness beams. The application of machine learning to time-domain signals like the longitudinal Schottky signals is under investigation.

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