ISBN: 978-3-95450-214-1 ISSN: 2673-5490 doi:10.18429/JACoW-IPAC2021-TUPAB052

CURRENT STUDY OF APPLYING MACHINE LEARNING TO ACCELERATOR PHYSICS AT IHEP*

J. Wan[1], Y. Jiao[1†], Institute of High Energy Physics, Beijing, China
[1]also at University of Chinese Academy of Sciences, Beijing, China

Abstract

In recent years, machine learning (ML) has attracted increasing interest among the accelerator field. As a complex collection of multiple physical subsystems, the design and operation of an accelerator can be very nonlinear and complicated, while ML is taken as a powerful tool to solve such nonlinear and complicated problems. In this study, we report on several successful applications of ML to accelerator physics at IHEP. The nonlinear dynamics optimization of the High Energy Photon Source (HEPS) that is a 4th-generation light source is a challenging topic. In this optimization, we use a ML surrogate model to fast select the potentially competitive solutions for a multiobjective genetic algorithm that can significantly improve the convergence rate and the diversity among obtained solutions. Besides, we also tried to apply a generative adversarial net to solve one-to-many problems of longitudinal beam current profile shaping. Unlike most supervised machine learning methods than cannot learn one-to-many maps, the generative adversarial net-based method is able to predict multiple solutions instead of one for a 4-dipole chicane to realize several desired custom current profiles.

INTRODUCTION

Machine learning (ML) has attracted increasing interest in the domain of particle accelerator in recent years. Compared to conventional physical model-based methods, ML methods are considered to be more efficient and more transferable in the vast majority of cases. By learning from the existing data, ML models are able to reveal the correlations hidden in the data which may be strongly nonlinear and complicated. So far, a plenty of applications of ML have been made to various topics of accelerators [1-5]. In this paper, we will discuss several successful ML applications to the issues of accelerator physics at IHEP.

The High Energy Photon Source (HEPS) [6] is a diffraction-limited light source under construction at IHEP. Due to the strong nonlinearities, the optimization of the nonlinear beam dynamics, such as the multiobjective optimization of dynamic aperture and Touschek lifetime, has become very challenging. In previous studies, evolutionary optimization methods like multiobjective genetic algorithms (MOGA) [7] and multiobjective particle swarm optimization (MOPSO) [8] are used to solve such optimization problems. However, these evolutionary methods usually require to evaluate a large number of candidate solutions for evolution. In an actual scenario where computing resources are limited, e.g. the optimization on the Tousheck lifetime of the HEPS lattice that takes about three hours for each evaluation, the optimization time can become too long and even unacceptable.

In the presented study, a neural network-based MOGA (NBMOGA) is proposed [9]. A neural network is trained with the data produced by the early optimization of the MOGA as the surrogate model. This machine learning surrogate model is used to fast screen a large number of offspring generated from MOGA to select the competitively potential solutions. These selected solutions are then evaluated by the actual evaluator and used as the evolutionary candidates for the MOGA. With these high-quality candidates, a faster convergence rate and a better diversity among solutions are expected.

Another application is to use the ML method to solve the one-to-many problems on the temporal shaping of the electron beam. Details of this work will be presented in a separate publication [10]. To control the temporal shape to an electron bunch, a widely-used method is to manipulate the dispersion terms of a magnetic chicane which turns out to be one-to-many problems. Current popular methods to solve such one-to-many problems are stochastic optimization methods that may have great limitation. An important limitation of using these stochastic optimization methods is that the optimization can easily fall into local optimums for a highly nonlinear process where many local optimums exist. Besides, for a one-to-many problem, the stochastic optimization methods normally lead to one solution while with other potential solutions missed.

To overcome above limitations, we use a semi-supervised ML method, the conditional generative neural network (CGAN) [11], to solve one-to-many problems of temporal shaping. We construct a CGAN solver that is trained by the stochastically generated dispersion terms of a chicane-type bunch compressor. By feeding different noise component to the trained CGAN solver, it is expected to simultaneously predict multiple solutions for the same custom temporal profile.

NEURAL NETWORK-BASED MULTIOBJECTIVE OPTIMIZATION ALGORITHM

Details of the Algorithm

With the NBMOGA, the first few generations of the optimization follow the standard MOGA. As the data pool becomes large enough, a neural network is trained with the data generated in the early optimization of MOGA to learn the correlation between the optimized variables and the objectives. In the later optimization, the number of offspring generated with MOGA is increased to *K* times that of a

* Work supported by National Natural Science Foundation of China (No. 11922512).
† jiaoyi@ihep.ac.cn

ISBN: 978-3-95450-214-1 ISSN: 2673-5490 doi:10.18429/JACoW-IPAC2021-TUPAB052

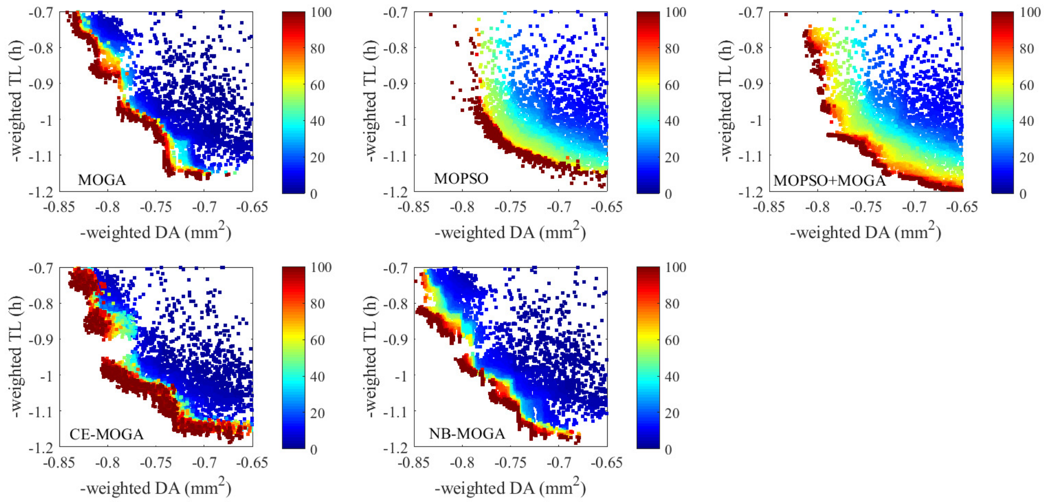

Figure 1: Evolutions of population for optimizing DA and Touschek lifetime with five different optimization methods. The colour from blue to red represents the index of generation from 1 to 100.

standard MOGA. The objective values of the offspring can be estimated quickly with the trained neural network. Based on the estimated results, those offspring are ranked with the non-dominated sorting method. Only N top-ranked solutions are randomly selected and used as the evolutionary candidates. With their objective performance evaluated on the actual evaluator, these N candidates are then combined with their parent individuals and ranked with the non-dominated sorting method again. The N top-ranked solutions are selected from the combination to form a new generation.

Optimization of DA and Touschek Lifetime for the HEPS Lattice

The lattice of the HEPS storage ring has 48 hybrid seven bend achromats (7BAs), which are grouped in 24 periods. After the linear parameters of the lattice were fixed based on the global optimization, optimization of DA and Touschek lifetime by tuning the strength of multipoles is necessary and has been performed for HEPS.

The two objectives are optimized with five existing optimization methods, i.e. MOGA, MOPSO, combination of MOPSO and MOGA [12], CEMOGA [13] and NBMOGA, with the same initial population. In each generation, the time of training the neural network for the NBMOGA is about 10 s, which is much less than the evaluation time (~3 h) and can be ignored. Therefore, the evolutionary time of NBMOGA required for a generation can be considered to be the same as that of other tested optimization methods except the CEMOGA. For the CEMOGA, additional "elite solutions" are needed to evaluate, which will successively call the parallel program twice to evaluate the MOGA offspring and the "elite solutions" respectively, and double the evolutionary time for this problem.

The evolutions of population over 100 generations (~600 hours for the CEMOGA and ~300 hours for the other four methods) are illustrated in Fig. 1. It is found that the NBMOGA results in a better non-dominated front with higher objective performance and more continuous distribution in the objective space than using other four methods. If keeping the DA area approximately the same as the initial solution, the Touschek lifetime can be further improved by about 10% with the NBMOGA compared to the standard MOGA within the same optimization time.

CGAN SOLVER FOR ONE-TO-MANY PROBLEMS OF TEMPORAL SHAPING

Conditional Generative Adversarial Network

The CGAN is an extended version of the generative adversarial network [14] that is an emerging ML technique in the area of image processing. These generative methods are considered to have the potential to handle one-to-many problems. The training of the CGAN is via the competition of a pair of neural networks, called the generator (hereafter referred to as G) and discriminator (hereafter referred to as D). G is trained to create fake data samples as authentic as possible to fool D, and D is trained to distinguish between the fake and real samples. An additional label is also fed to G so that the G can generate samples with user specified content.

How the CGAN Solver Solves Temporal Shaping Problems

In our CGAN solver scheme, the R_{56}, T_{566}, and U_{5666} which are the first-, second- and third-order longitudinal dispersion terms in the transfer map are taken as training data. The corresponding temporal profiles to the training data are taken as labels. The two networks of the CGAN solver are simultaneously trained with the labelled data. The trained solver is expected to predict different potential solutions to realize the same target custom profile when multiple solutions exist.

ISBN: 978-3-95450-214-1 ISSN: 2673-5490 doi:10.18429/JACoW-IPAC2021-TUPAB052

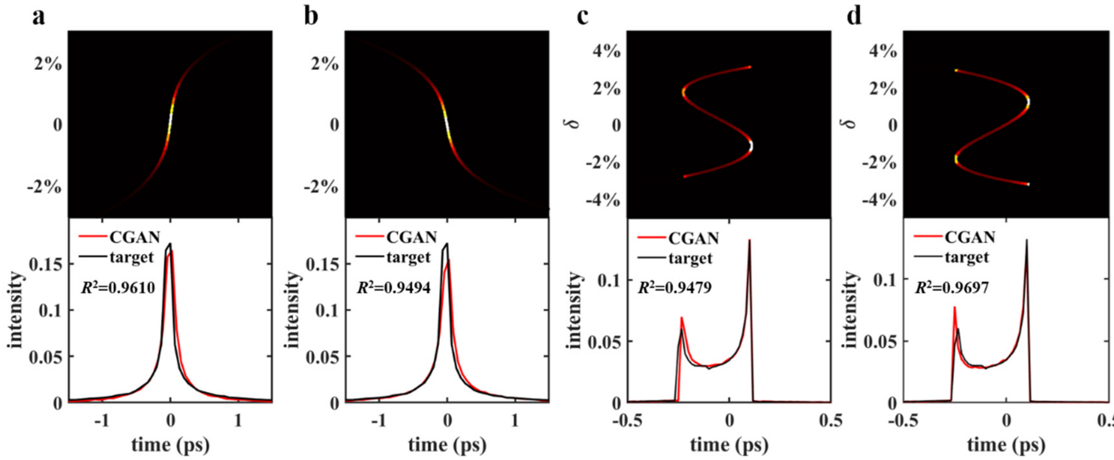

Figure 2: Longitudinal phase space distribution and temporal profiles of two separate CGAN predictions. The left two columns represent the cusp-shaped profile, and the right two columns represent the double-horn profile, respectively. R^2 is the determination coefficient to the target temporal profile.

Two test temporal profiles that are common in bunch compression, i.e. a cusp-shaped profile and a double-horn profile (see Fig. 2) are used to test the performance of the CGAN solver. The CGAN solver is able to simultaneously give multiple sets of R_{56}, T_{566}, and U_{5666} predictions for the same target profile. It is found that these predictions converge to several points in the variable space, which represent multiple solutions to the target. For each of the test temporal profiles, two separate solutions obtained with the CGAN solver are selected and the corresponding longitudinal phase space distributions are shown in Fig. 2. It is found that the beams in Fig. 2(b, d) are over compressed, i.e. the head and tail of the beam are reversed. Nevertheless, the over compressed beam finally results in almost the same temporal profiles as the under compressed beam in Fig. 2(a, c), with a high determination coefficient (close to 1) to the target.

The results in Fig. 2 indicate that with the CGAN solver, one can accurately realize different custom desire temporal profiles. Furthermore, multiple solutions for the same input temporal profile are found with the CGAN solver when multiple solutions exist. The acquirement of the multiple solutions is crucial for temporal shaping since an under compressed beam and an over compressed beam can provide different benefits in scientific applications [15, 16]. Besides, it is found that to realize the cusp-shaped profile, the octupole strength required to achieve the longitudinal dispersion terms of the solution in Fig. 2(a) is significantly higher than that of solution in Fig. 2(b) (-15.7 m^{-3} and 0.4 m^{-3}, respectively). The strong octupoles may bring high sensitivity during the beamline optimization and operation. Additionally, compared to the stochastic optimization methods, the CGAN solver can be several orders of magnitude faster to solve the temporal shaping problems because once the CGAN is trained, it only needs little time (fractions of one second) to directly predict the longitudinal terms of a new temporal profile.

SUMMARY

A neural network-based MOGA is proposed. The converge rate and diversity among solutions of standard MOGA can be significantly improved by using the competitively potential solutions selected by the ML surrogate model to replace its original offspring. This method can be beneficial to the time-consuming optimization of nonlinear dynamics.

A CGAN solver is proposed for one-to-many problems of temporal shaping. The CGAN solver can quickly and accurately predict multiple potential solutions for the same custom temporal profile. This method can be also applied to other similar highly nonlinear one-to-many problems, for instance, photon pulse shaping and transverse phase space manipulation of an electron beam.

REFERENCES

[1] Y. Li, W. Cheng, H. Y. Li, and R. Rainer, "Genetic algorithm enhanced by machine learning in dynamic aperture optimization", *Phys. Rev. Accel. Beams*, vol. 21, p. 054601, 2018. doi:10.1103/PhysRevAccelBeams.21.054601

[2] C. Emma, A. Edelen, M. J. Hogan, B. O'Shea, G. White, and V. Yakimenko, "Machine learning-based longitudinal phase space prediction of particle accelerators", *Phys. Rev. Accel. Beams*, vol. 21, p. 112802, 2018. doi:10.1103/physrevaccelbeams.21.112802

[3] A. Scheinker, A. Edelen, D. Bohler, C. Emma, and A. Lutman, "Demonstration of model-independent control of the longitudinal phase space of electron beams in the Linac-coherent light source with Femtosecond resolution", *Phys. Rev. Lett.*, vol. 121, p. 044801, 2018. doi:10.1103/physrevlett.121.044801

[4] S. C. Leemann and S. Liu, "Demonstration of Machine Learning-Based Model-Independent Stabilization of Source Properties in Synchrotron Light Sources", *Phys. Rev. Lett.*, vol. 123, p. 194801, 2019. doi:10.1103/physrevlett.123.194801

ISBN: 978-3-95450-214-1 ISSN: 2673-5490 doi:10.18429/JACoW-IPAC2021-TUPAB052

[5] X. Xu, Y. Zhou, and Y. Leng, "Machine learning based image processing technology application in bunch longitudinal phase information extraction", *Phys. Rev. Accel. Beams*, vol. 23, p. 032805, 2020. doi:10.1103/physrevaccelbeams.23.032805

[6] Y. Jiao *et al.*, "The HEPS project", *J. Synchrotron Radiat.*, vol. 25, p. 1611, 2018. doi:10.1107/S1600577518012110

[7] L. Yang, D. Robin, F. Sannibale, C. Steier, and W. Wan, "Global optimization of an accelerator lattice using multiobjective genetic algorithms", *Nucl. Instrum. Methods Phys. Res., Sect. A*, vol. 609, p. 50-57, 2009. doi:10.1016/j.nima.2009.08.027

[8] X. Huang and J. Safranek, "Nonlinear dynamics optimization with particle swarm and genetic algorithms for SPEAR3 emittance upgrade", *Nucl. Instrum. Methods Phys. Res., Sect. A*, vol. 757, p. 48-53, 2014. doi:10.1016/j.nima.2014.04.078

[9] J. Wan, P. Chu, and Y. Jiao, "Neural network-based multiobjective optimization algorithm for nonlinear beam dynamics", *Phys. Rev. Accel. Beams*, vol. 23, p. 081601, 2020. doi:10.1103/physrevaccelbeams.23.081601

[10] J. Wan, Y. Jiao, and J. Wu, "Machine learning-based direct solver for one-to-many problems on temporal shaping of electron beams", 2021. arXiv:2103.06594

[11] I. Goodfellow *et al.*, "Generative adversarial nets", 2014. arXiv:1406.2661

[12] Y. Jiao and G. Xu, "Optimizing the lattice design of a diffraction-limited storage ring with a rational combination of particle swarm and genetic algorithms", *Chin. Phys. C*, vol. 41, p. 027001, 2017. doi:10.1088/1674-1137/41/2/027001

[13] J. Wan, P. Chu, Y. Jiao and Y. Li, "Improvement of machine learning enhanced genetic algorithm for nonlinear beam dynamics optimization", *Nucl. Instrum. Methods Phys. Res., Sect. A*, vol. 946, p. 162683, 2019. doi:10.1016/j.nima.2019.162683

[14] M. Mirza and S. Osindero, "Conditional generative adversarial nets", 2014. arXiv:1411.1784

[15] R. J. England, J. B. Rosenzweig, and G. Travish, "Generation and measurement of relativistic electron bunches characterized by a linearly ramped current profile", *Phys. Rev. Lett.*, vol. 100, p. 214802, 2008. doi:10.1103/physrevlett.100.214802

[16] Y. Ding *et al.*, "Beam shaping to improve the free-electron laser performance at the Linac Coherent Light Source", *Phys. Rev. Accel. Beams*, vol. 19, p. 100703, 2016. doi:10.1142/9789813279612_0021