International Journal of Electrical and Computer Engineering (IJECE)
Vol. 16, No. 1, February 2026, pp. 477~487
ISSN: 2088-8708, DOI: 10.11591/ijece.v16i1.pp477-487

Design of a thermionic electron gun of 6 MeV linac by using neural network based surrogate model

Elin Nuraini[1,2], Sihana[2], Taufik[1], Darsono[1], Saefurrochman[1], Rajendra Satriya Utama[2]
[1]Research Center for Accelerator Technology, Research Organization for Nuclear Technology, National Research and Innovation Agency, South Tangerang, Indonesia
[2]Department of Nuclear Engineering and Engineering Physics, Faculty of Engineering, Universitas Gadjah Mada, Yogyakarta, Indonesia

Article Info

Article history:

Received Jun 17, 2025
Revised Oct 2, 2025
Accepted Nov 23, 2025

Keywords:

Accelerator design
Electron gun
Linac
Neural network
Surrogate model

ABSTRACT

High performance electron guns are fundamental components in linear accelerators (linacs), directly influencing beam quality and downstream system efficiency. However, designing electron guns for applications such as a 6 MeV linac presents complex trade-offs between current, perveance, and beam emittance. Traditional simulation-driven optimization methods are computationally expensive and limit rapid prototyping. In this study, we develop a neural network-based surrogate model trained on CST Studio Suite simulation data to predict the electron gun's performance metrics. Our approach significantly accelerates the optimization process by providing real-time predictions of beam current and perveance across a wide design parameter space. The surrogate model achieves high prediction accuracy, with training and validation losses on the order of 10^{-7}. Results demonstrate that neural network models can serve as reliable and efficient tools for electron gun design, offering considerable computational savings while maintaining accuracy. Future extensions include expanding the surrogate model to multi-objective optimization and incorporating thermal and mechanical effects into the design process.

Corresponding Author:

Sihana
Department of Nuclear Engineering and Engineering Physics, Faculty of Engineering, Universitas Gadjah Mada
Jalan Grafika No.2, Sendowo, Sinduadi, Mlati, Sleman, Daerah Istimewa Yogyakarta, Indonesia 55284
Email: sihana@ugm.ac.id

1. INTRODUCTION

Linear accelerators (linacs) rely on high-quality electron sources to achieve their operational performance, with electron guns playing a pivotal role in determining the overall beam emittance, current, and stability. In particular, energy recovery linacs (ERLs) demand electron guns capable of producing high-brightness, low emittance beams to sustain efficient operation at high repetition rates [1], [2]. Such requirements are critical for applications including synchrotron light sources, free electron lasers, and high-energy physics experiments [3].

Designing an electron gun suitable for a 6 MeV linac poses several challenges. Achieving a balance between high beam current and low emittance demands careful optimization of geometrical parameters, electric field distributions, and material selections [4], [5]. Traditionally, such optimization relies on repeated full-physics simulations using software like CST Studio Suite or ASTRA [6], [7]. While these methods offer high accuracy, they are computationally intensive, with each design iteration potentially requiring hours to days of processing time.

Recent advances in machine learning, particularly in the development of neural network surrogate models, offer promising avenues to accelerate design processes in accelerator physics [8]–[12]. Surrogate models can approximate the behavior of complex systems, providing real-time predictions of system responses without the need for time-consuming simulations. Their application has been demonstrated in cavity optimization [13], beam transport systems [14], and accelerator control systems [15], [16]. Recent studies have also applied neural models to predict beam emittance and optimize injector configurations in real time [17], [18].

Despite these advances, there remains a gap in the application of neural networks to the design and optimization of electron guns themselves. Most prior works focus on beamlines or downstream transport systems rather than the injector stage. Motivated by this need, our study presents the development and validation of a neural network surrogate model specifically tailored for predicting the performance of a thermionic Pierce-type electron gun [19]. Our study addresses this gap by proposing a surrogate model dedicated to predicting key performance parameters beam current and perveance based on geometric design inputs. This specific focus is critical, as the initial beam parameters set by the gun fundamentally influence the entire accelerator chain.

By training the model on a comprehensive dataset generated from CST simulations, we enable rapid evaluation of key performance metrics such as beam current and perveance. Our approach not only accelerates the design process but also opens pathways toward more sophisticated, real-time, multi-objective optimizations in future linac developments.

This paper is structured as follows: Section 2 describes the methodology including electron gun modeling, dataset generation, and surrogate model development; Section 3 presents simulation results and model validation; and Section 4 discusses the conclusions and potential future research directions.

2. METHOD

This study employed a two-stage methodological framework combining physics-based simulations and machine learning. In the first stage, a Pierce-type electron gun was modelled and simulated using CST Studio Suite to generate a comprehensive dataset across a wide range of design parameters to be inserted in learning machine. In the second stage, a neural network-based surrogate model was developed and trained using simulation data to enable rapid performance prediction and design optimization. The detailed steps are presented in the following subsections.

2.1. Electron gun design and CST simulations

The design phase commenced with the creation of a three-dimensional (3D) computer-aided design (CAD) model the design parameters of a Pierce-type electron gun as depicted in Figure 1. This design includes a thermionic cathode, a carefully shaped Pierce electrode, and an anode with a focusing nose. Each geometric component was engineered to meet operational goals such as minimizing emittance while sustaining sufficient beam current for the intended 6 MeV linac application. The proposed electron gun was designed according to the following design parameters, namely: 0.25 A of current beam, 4.5 mm of beam diameter, emittance is less than 10^{-5} mm.rad and perveance is less than 10^{-7} A/V$^{3/2}$. The scheme of electron gun design process is depicted in Figure 2. This scheme shows step by step to design the electron gun.

To accurately simulate the electric fields and charged particle dynamics within the gun, CST Studio Suite (version 2022) was employed [20]. CST combines the finite element method (FEM) for solving electrostatic field distributions with the particle-in-cell (PIC) method for self-consistent simulation of particle motion and space charge effects [21]. The Electrostatic Solver module calculated the static electric field distribution arising from applied cathode and anode potentials. Subsequently, the PIC module tracked thousands of electrons emitted from the cathode surface under the influence of these fields, incorporating collective effects such as beam expansion due to mutual repulsion. Boundary conditions were set as perfect conducting electrodes in a full-vacuum environment. The extraction voltage was varied in the range of 20–40 kV, and for each configuration thousands of electrons were tracked to obtain output parameters such as beam current, perveance, emittance, and beam diameter. A systematic parameter sweep was performed, varying critical design parameters including cathode diameter, cathode length, anode-cathode gap, and anode nose length was depicted in Table 1. A total of 1280 unique configurations were simulated, each capturing output parameters such as beam current, perveance, and final beam diameter. The comprehensive dataset, occupying approximately 600 GB of storage, forms the foundation for surrogate model training.

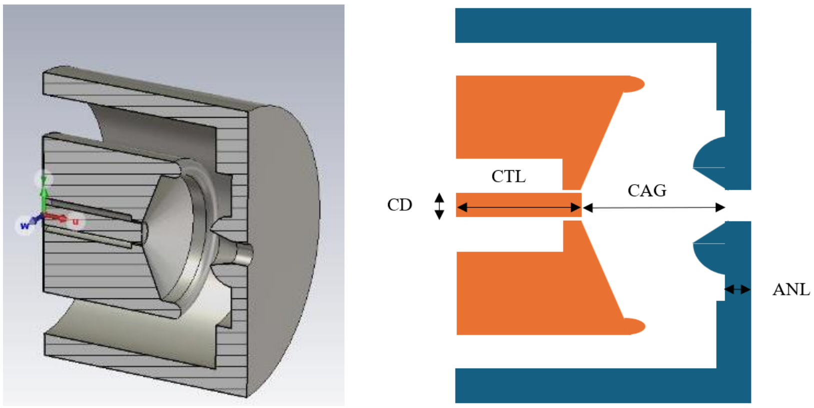

Figure 1. Model of pierce-type electron gun

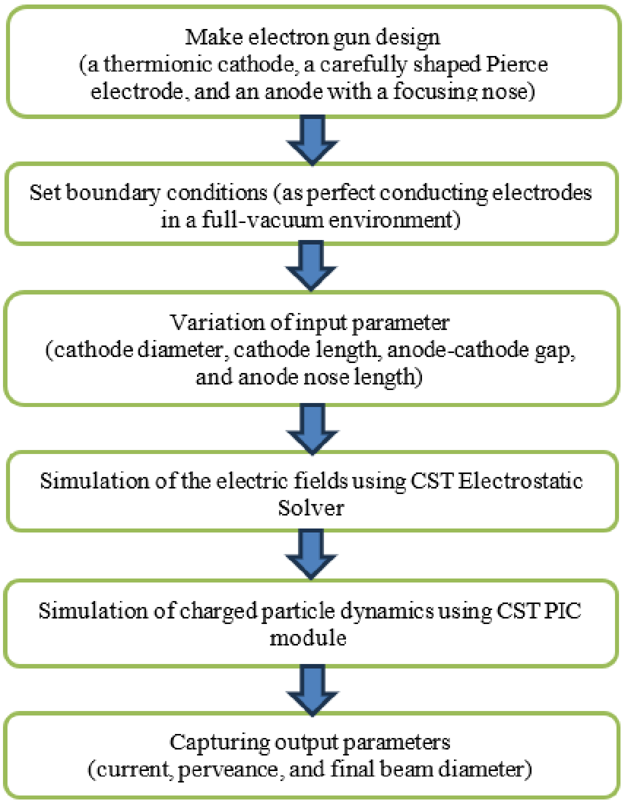

Figure 2. Scheme of electron gun design process

In order to simulation can be conducted well and fast, we used the workstation computer with technical specifications: System manufacturer: Dell, Inc.; System model: Precision 5820 Tower; OS Microsoft Windows 11 Pro for Workstations; Processor Intel (R) Xeon (R) W-2223 CPU@3.60 GHz, 4 Core, 8 Logical Processors; and RAM: 64 GB.

Table 1. Variation of input parameter

Parameter	Number of variations	Minimum (mm)	Maximum (mm)
Cathode diameter (CD)	6	0.21	1.7
Cathode length (CTL)	6	8	13
Anode cathode gap (CAG)	6	6	11
Anode nose length (ANL)	6	1.3	1.8

2.2. Development of the neural network surrogate model

Following data collection, a fully connected feedforward neural network (FNN) was constructed to serve as a computationally efficient surrogate model. The architecture consisted of an input layer corresponding to the four design parameters, three hidden layers with 80, 40, and 20 neurons respectively, and an output layer producing two target values: beam current and perveance. The scheme of surrogate model is shown in Figure 3.

Each hidden layer utilized the rectified linear unit (ReLU) activation function, which promotes sparsity and mitigates the vanishing gradient problem commonly encountered in deep neural networks [22]. Mean squared error (MSE) was employed as the loss function to quantify the deviation between predicted and true output values, while network weights were updated using the Adam optimization algorithm [23].

Training was conducted over 20,000 epochs with a learning rate of 0.0002, a choice made based on preliminary convergence studies to balance speed and model stability. Input and output data were normalized to zero mean and unit variance prior to training to enhance learning dynamics and accelerate convergence [22]. The dataset was split with an 80/20 ratio between training and validation sets to assess generalization performance and detect potential over fitting.

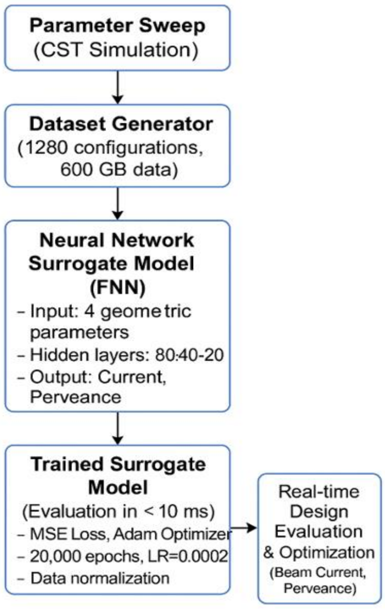

Figure 3. Scheme of surrogate model

2.3. Computational resources and challenges

The high computational cost of generating the simulation database was addressed by leveraging a high-performance computing (HPC) cluster equipped with large memory nodes to handle the memory-intensive FEM-PIC simulations. Neural network training was performed on a dedicated workstation equipped with GPU acceleration (NVIDIA RTX series), reducing training time by approximately an order of magnitude compared to CPU-only training.

Despite the upfront investment in simulation time and data storage, the trained surrogate model dramatically reduces the computational cost for future design evaluations. Predictions for new configurations can be obtained in milliseconds, facilitating real-time exploration of the design parameter space and enabling rapid optimization cycles that were previously infeasible with traditional methods.

2.4. Computational resources and considerations

Due to the high computational demands of both CST simulation and neural network training, simulations were conducted on a high-performance computing cluster. The large memory footprint required for CST parameter sweeps (approximately 600 GB) necessitated efficient data management practices. For neural network training, training time and convergence were optimized by tuning the learning rate and number of epochs, ultimately achieving an accurate and efficient surrogate model capable of replacing traditional full-scale CST simulations for subsequent design iterations.

3. RESULT AND DISCUSSION

3.1. Electric field and electron beam path simulation

Electric field and electron beam path of electron gun were simulated using CST software as depicted in Figures 4 and 5 respectively. As shown in these figures, the results were in accordance with design parameters. The optimum results were obtained as follows in Table 2. In order to simulation can be conducted well and fast, we used the workstation computer with technical specifications: System manufacturer: Dell, Inc.; System model: Precision 5820 Tower; OS Microsoft Windows 11 Pro for Workstations; Processor Intel (R) Xeon (R) W-2223 CPU@3.60 GHz, 4 Core, 8 Logical Processors; and RAM 64 GB.

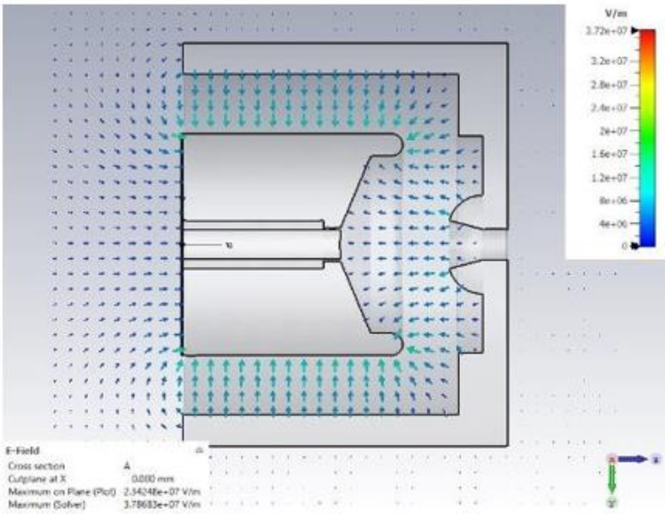

Figure 4. Electric field simulation

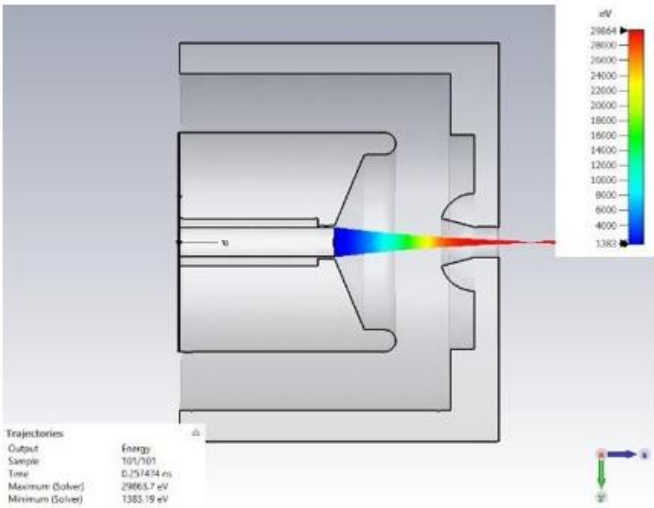

Figure 5. Electron beam path

Table 2. Optimum design of electron gun

Parameters	Value	Unit
Beam current	0.51	A
Perveance	9.80×10^{-8}	$A/V3/2$
emittance (x)	9.41×10^{-6}	mm.rad
emittance (y)	8.30×10^{-6}	mm.rad
beam size (Diameter)	0.3024	mm
operating voltage	30	kV

3.2. Neural network training performance

The training process of the surrogate model was monitored using both training and validation loss curves. As shown in Figure 6, the model achieved convergence within the first few thousand epochs, and both loss values remained stable with no signs of divergence throughout the entire 20,000-epoch training schedule. The final training loss reached 2.2143×10^{-7}, while the validation loss settled at 3.9560×10^{-7}, indicating excellent generalization performance. The closeness of training and validation curves suggests that overfitting was successfully mitigated [24].

The low MSE values reflect the model's ability to accurately learn the mapping between geometric design parameters and output beam metrics. These metrics include beam current and perveance, two parameters that are highly sensitive to electron gun geometry and electric field distribution. The performance of the model confirms that even relatively shallow neural networks, when properly configured and trained on high-fidelity simulation data, can provide highly reliable predictions for complex physical systems [25], [26].

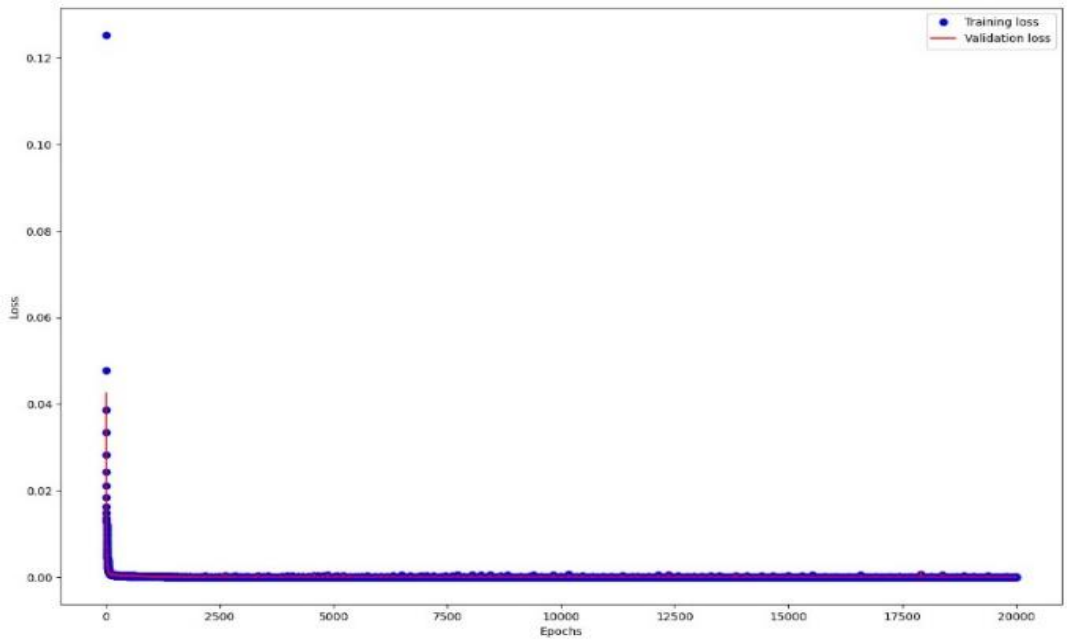

Figure 6. Training performance of neural network surrogate model

3.3. Prediction accuracy of beam parameters

Figure 7 presents a scatter plot comparing the predicted beam current against the ground truth values obtained from CST simulations. The strong linear alignment of points along the diagonal line (y = x) demonstrates a high degree of prediction accuracy across the full range of input conditions [25], [26]. This capability is particularly valuable in practical design workflows, where predicting how small changes in geometry influence the beam current can accelerate the refinement process.

Similarly, Figure 8 shows the performance of the neural network in predicting beam perveance. The close agreement between predicted and actual values further supports the robustness of the trained surrogate model [27]. Accurate prediction of perveance is crucial in electron gun design because it captures the relationship between current and accelerating voltage, serving as a diagnostic indicator for space charge-limited emission.

The beam current, emittance, and perveance are crucial performance indicators that directly reflect the physical behavior of the electron gun. Beam current is primarily influenced by the cathode-anode voltage and the emission area, which are governed by electrode geometry. A higher extraction voltage and larger emission area lead to increased beam current. Emittance, which quantifies the spread of the beam in phase space, is affected by the focusing properties of the geometry; sharp curvature or abrupt changes in field lines tend to degrade emittance. Meanwhile, perveance is a function of both the beam current and extraction voltage, serving as a measure of space-charge effects. By analyzing how these parameters vary with geometry inputs such as electrode angle, gap distance, and voltage, we provide a deeper physical understanding of the design-performance relationship in thermionic electron guns.

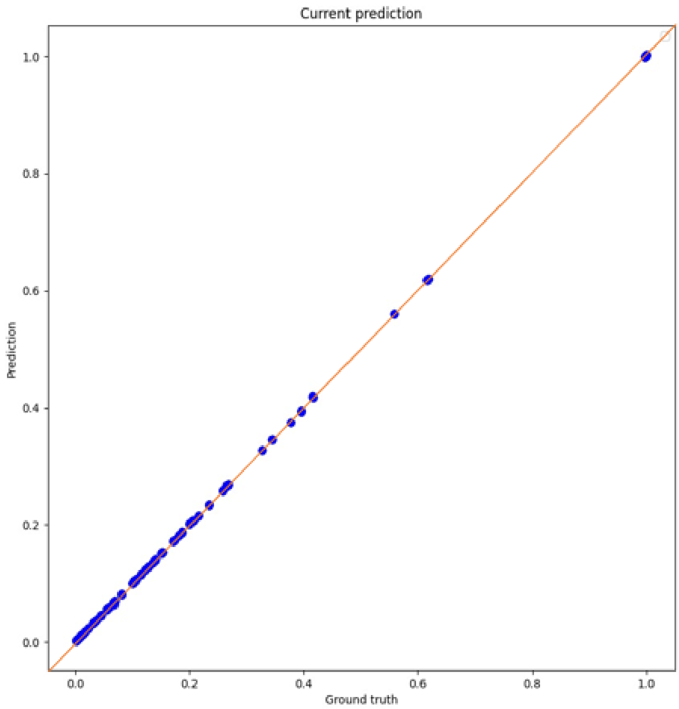

Figure 7. Current prediction vs truth values

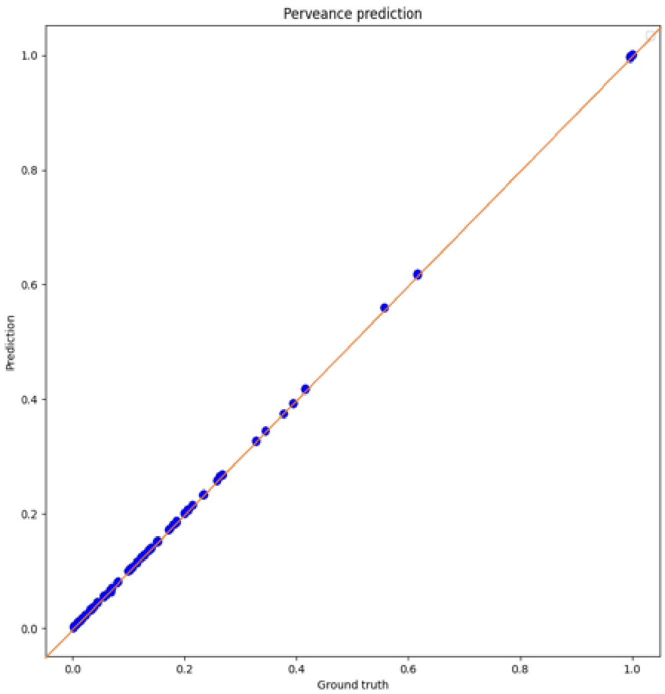

Figure 8. Perveance prediction vs true values

An additional important output, beam diameter at the gun exit, was also monitored across configurations. Although not used as a training target, its correlation with predicted current and perveance indirectly validates the physical consistency of the model. In almost all configurations, the beam diameter remained below the 5 mm threshold, indicating the focusing components in the Pierce geometry was functioning as expected.

3.4. Sources of error and model limitations

Despite the strong overall performance, minor deviations were observed in a few high-current configurations, where the predicted values slightly underestimated the ground truth. These errors are likely due to sparse representation of such configurations in the training dataset. Increasing the density of samples in high-current regimes could improve prediction accuracy in future studies [28].

Moreover, the surrogate model is limited to the parameter ranges seen during training. Extrapolation to unseen regions of the design space may yield unreliable results, which highlights the importance of thoughtful dataset construction. Integration of uncertainty quantification techniques or active learning strategies could further enhance model reliability, particularly for high-risk operating points.

3.5. Computational efficiency and practical implications

From a computational perspective, the surrogate model significantly outperforms traditional FEM-PIC simulations in terms of evaluation time. Once trained, the model predicts beam characteristics for new configurations in under 10 milliseconds on a standard GPU, compared to hours of processing required by CST simulations. This speed enables rapid iterative design, global sensitivity analysis, and real-time multi-objective optimization that would otherwise be infeasible.

These results underscore the value of combining high-fidelity simulation tools with data-driven surrogate models in accelerator design. While the simulation process remains essential for initial dataset generation, the trained surrogate allows for fast design exploration and deeper physical insight. Similar multi-objective frameworks have been implemented successfully in recent surrogate-assisted injector designs [29], and their efficiency has been benchmarked in review studies of neural-based optimization in beamline components [30], [31].

These findings are built upon previous research in the field. For instance, Ahmadiannamin *et al.* [32] demonstrated the challenges of balancing beam emittance and current in thermionic sources using semi-analytical methods such as the Vaughan approach, which our model addresses with automated, data-driven predictions. Liu *et al.* [33] focused on beam transport tuning using surrogate-augmented optimization (ASTRA combined with NSGA-II), but did not incorporate injector-level surrogate design for cathode geometry, a gap our work fills. Similarly, Kane *et al.* [11] applied neural networks to predict output beam properties from laser-plasma interactions but did not address initial beam quality parameters such as perveance, which are central to our study. By focusing on geometry-to-beam output mapping at the gun stage, our method extends surrogate modeling to earlier and more critical design stages in the accelerator chain.

4. CONCLUSION

This study successfully applied a neural network surrogate model to predict the performance of a Pierce-type electron gun using data generated from CST Studio Suite simulations. The surrogate model accurately predicted key beam parameters namely beam current and perveance and demonstrated rapid convergence during training. These results indicate strong generalization performance and confirm that data-driven models can capture the essential physics of electron gun behavior. The approach significantly reduced the simulation time required for each design evaluation, enabling real-time parametric exploration and accelerating the design iteration process. This capability is particularly valuable for complex accelerator systems, where computational cost often becomes a limiting factor. Future directions of this work include expanding the surrogate model toward multi-objective optimization, integrating uncertainty quantification, and incorporating thermal and mechanical effects to increase robustness. These enhancements would further solidify the role of machine learning-based surrogate modeling as a generalizable and efficient strategy for designing high-performance components in modern particle accelerators. Overall, this methodology provides a promising tool for improving the speed, flexibility, and intelligence of accelerator design workflows, and has strong potential for broader application in high-precision beamline component development.

ACKNOWLEDGMENTS

The authors would like to express their sincere gratitude to National Research and Innovation Agency or BRIN for providing educational funding for the author’s Master’s degree.

FUNDING INFORMATION

This research was supported by the RIIM LPDP Grant and BRIN, grant 272 number B-4131/II.7.5/TK.01.03/02/2025 and B-1703/III.2/TK.01.03/1/2025. We also extend our gratitude to the Research Center for Accelerator Technology - Research Organization for Nuclear Energy.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Elin Nuraini	✓	✓	✓	✓	✓	✓		✓	✓	✓			✓	✓
Sihana		✓		✓		✓	✓	✓	✓	✓	✓	✓		
Taufik	✓		✓	✓			✓	✓		✓	✓	✓	✓	✓
Darsono	✓	✓		✓			✓	✓		✓				
Saefurrochman			✓	✓						✓	✓			
Rajendra Satriya Utama			✓	✓	✓		✓	✓		✓	✓			

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

REFERENCES

[1] M. Akemoto *et al.*, "Construction and commissioning of the compact energy-recovery linac at KEK," *Nuclear Instruments and Methods in Physics Research, Section A: Accelerators, Spectrometers, Detectors and Associated Equipment*, vol. 877, pp. 197–219, Jan. 2018, doi: 10.1016/j.nima.2017.08.051.

[2] M. Arnold *et al.*, "First operation of the superconducting Darmstadt linear electron accelerator as an energy recovery linac," *Physical Review Accelerators and Beams*, vol. 23, no. 2, Feb. 2020, doi: 10.1103/PhysRevAccelBeams.23.020101.

[3] L. Faillace *et al.*, "High field hybrid photoinjector electron source for advanced light source applications," *Physical Review Accelerators and Beams*, vol. 25, no. 6, Jun. 2022, doi: 10.1103/PhysRevAccelBeams.25.063401.

[4] P. Petrov and M. Tongov, "Study of the cathode emissivity in generators for electron beam systems," *Optik*, vol. 209, May 2020, doi: 10.1016/j.ijleo.2020.164358.

[5] A. Krauze, J. Virbulis, and A. Kravtsov, "Modeling electron beam parameters and plasma interface position in an anode plasma electron gun with hydrogen atmosphere," in *IOP Conference Series: Materials Science and Engineering*, May 2018, vol. 355, no. 1, doi: 10.1088/1757-899X/355/1/012008.

[6] C. Saisa-ard, J. Saisut, and S. Rimjaem, "Electron beam dynamics in the 3D magnetic field of alpha magnet at the PBP-CMU Electron Linac Laboratory," *Nuclear Instruments and Methods in Physics Research, Section A: Accelerators, Spectrometers, Detectors and Associated Equipment*, vol. 916, pp. 102–115, Feb. 2019, doi: 10.1016/j.nima.2018.11.034.

[7] G. U. Islam, A. Rehman, M. Iqbal, and Z. Zhou, "Simulation and test of a thermioic hairpin source DC electron beam gun," *Optik*, vol. 127, no. 4, pp. 1905–1908, Feb. 2016, doi: 10.1016/j.ijleo.2015.11.132.

[8] J. Villarreal, D. Winklehner, D. Koser, and J. M. Conrad, "Neural networks as effective surrogate models of radio-frequency quadrupole particle accelerator simulations," *Machine Learning: Science and Technology*, vol. 5, no. 2, Jun. 2024, doi: 10.1088/2632-2153/ad3a30.

[9] C. Garcia-Cardona and A. Scheinker, "Machine learning surrogate for charged particle beam dynamics with space charge based on a recurrent neural network with aleatoric uncertainty," *Physical Review Accelerators and Beams*, vol. 27, no. 2, Feb. 2024, doi: 10.1103/PhysRevAccelBeams.27.024601.

[10] C. K. Huang *et al.*, "Symplectic neural surrogate models for beam dynamics," in *Journal of Physics: Conference Series*, 2024, vol. 2687, no. 6, doi: 10.1088/1742-6596/2687/6/062026.

[11] G. Kane *et al.*, "Surrogate models studies for laser-plasma accelerator electron source design through numerical optimisation," 2024.

[12] J. Kaiser, C. Xu, A. Eichler, and A. Santamaria Garcia, "Bridging the gap between machine learning and particle accelerator physics with high-speed, differentiable simulations," *Physical Review Accelerators and Beams*, vol. 27, no. 5, May 2024, doi: 10.1103/PhysRevAccelBeams.27.054601.

[13] A.-K. S. O. Hassan, H. L. Abdel-Malek, A. S. A. Mohamed, T. M. Abuelfadl, and A. E. Elqenawy, "RF cavity design exploiting a new derivative-free trust region optimization approach," *Journal of Advanced Research*, vol. 6, pp. 915–924, 2015.

[14] B. Mustapha, J. Martinez, B. Blomberg, C. Peters, and C. Dickerson, "AI-ML development for the ATLAS ion linac facility," *Proceedings of IPAC2021*, pp. 4122–4125, 2021, doi: 10.18429/JACoW-IPAC2021-THPAB181.

[15] L. Mei *et al.*, "Automation of superconducting cavity cooldown process using two-layer surrogate model and model predictive control method," *Cryogenics*, vol. 139, p. 103824, 2024.

[16] J. St. John *et al.*, "Real-time artificial intelligence for accelerator control: A study at the Fermilab Booster," *Physical Review Accelerators and Beams*, vol. 24, no. 10, Oct. 2021, doi: 10.1103/PhysRevAccelBeams.24.104601.

[17] L. Gupta, A. Edelen, N. Neveu, A. Mishra, C. Mayes, and Y. K. Kim, "Improving surrogate model accuracy for the LCLS-II injector frontend using convolutional neural networks and transfer learning," *Machine Learning: Science and Technology*, vol. 2, no. 4, Dec. 2021, doi: 10.1088/2632-2153/ac27ff.

[18] D. Meier, L. V. Ramirez, J. Völker, B. Sick, J. Viefhaus, and G. Hartmann, "Optimizing a superconducting radiofrequency gun using deep reinforcement learning," *Physical Review Accelerator and Beams*, vol. 25, p. 104604, Mar. 2022, doi: 10.1103/PhysRevAccelBeams.25.104604.

[19] K. Ellis, N. Banerjee, and C. Pierce, "Modeling a thermionic electron source using a physics-informed neural network," 2023.

[20] C. Saisa-ard and S. Rimjaem, "Design and beam dynamic simulation of the thermionic RF electron gun with external resonant cavity for transverse emittance reduction," *Nuclear Instruments and Methods in Physics Research, Section A: Accelerators, Spectrometers, Detectors and Associated Equipment*, vol. 940, pp. 243–253, Oct. 2019, doi: 10.1016/j.nima.2019.06.035.

[21] S. V Langellotti, N. M. Jordan, Y. Y. Lau, and R. M. Gilgenbach, "CST particle studio simulations of coaxial multipactor and comparison with experiments," *IEEE Transactions on Plasma Science*, vol. 48, no. 6, pp. 1942–1949, 2020, doi: 10.1109/TPS.2020.2981257.
[22] A. F. Agarap, "Deep learning using rectified linear units (ReLU)," *arXiv preprint arXiv:1803.08375*, pp. 2–8, 2019.
[23] I. K. M. Jais, A. R. Ismail, and S. Q. Nisa, "Adam optimization algorithm for wide and deep neural network," *Knowledge Engineering and Data Science*, vol. 2, no. 1, pp. 41–46, 2019, doi: 10.17977/um018v2i12019p41-46.
[24] J. Straub, "Machine learning performance validation and training using a 'perfect'' expert system,'" *MethodsX*, vol. 8, p. 101477, 2021, doi: 10.1016/j.mex.2021.101477.
[25] A. P. Hemmasian, F. Ogoke, P. Akbari, J. Malen, J. Beuth, and A. Barati Farimani, "Surrogate modeling of melt pool temperature field using deep learning," *Additive Manufacturing Letters*, vol. 5, p. 100123, 2023, doi: 10.1016/j.addlet.2023.100123.
[26] P. Ghafariasl *et al.*, "Neural network-based surrogate modeling and optimization of a multigeneration system," *Applied Energy*, vol. 364, p. 123130, 2024, doi: 10.1016/j.apenergy.2024.123130.
[27] D. Sturek and S. Lazarova-Molnar, "Surrogate modeling: review and opportunities for expert," *Procedia Computer Science*, vol. 257, pp. 826–833, 2025.
[28] A. I. J. Forrester, A. Sóbester, and A. J. Keane, *Engineering design via surrogate modelling: A practical guide*, 1st ed. West Sussex: John Wiley & Sons Ltd., 2008.
[29] M. M. Nasr, W. Ameen, A. Dabwan, and A. Al-Ahmari, "Machine learning-based multi-objective optimization for enhancing the performance of block support structures for electron beam additive manufacturing," *Metals*, vol. 15, no. 6, pp. 1–25, 2025, doi: 10.3390/met15060671.
[30] I. Kante, "Machine learning for beamline steering," *arXiv preprint arXiv:2311.07519*, pp. 1–9, 2023.
[31] J. Wan, P. Chu, and Y. Jiao, "Neural network-based multiobjective optimization algorithm for nonlinear beam dynamics," *Physical Review Accelerators and Beams*, vol. 23, no. 8, p. 81601, 2020, doi: 10.1103/PhysRevAccelBeams.23.081601.
[32] S. Ahmadiannamin, F. A. Davani, R. Ghaderi, F. Ghasemi, M. L. Rachti, and S. Zarei, "Simulation study of electron gun for six MeV Linac for X-ray cargo inspection," *IPAC 2014: Proceedings of the 5th International Particle Accelerator Conference*, pp. 3847–3849, 2014, doi: 10.18429/JACoW-IPAC2014-THPRI038.
[33] L. Liu *et al.*, "Simulation study of high-quality electron beam injector for external injection of laser plasma wakefield acceleration," *Nuclear Engineering and Technology*, vol. 57, no. 7, p. 103531, 2025, doi: 10.1016/j.net.2025.103531.

BIOGRAPHIES OF AUTHORS

Elin Nuraini graduated for undergraduate program in Physic from 10 November Institute of Technology, Indonesia, in 1990. Currently, she is a Senior researcher at the Research Center for Accelerator Technology, Research Organization for Nuclear Technology, National Research and Innovation Agency (BRIN). She is also studying at Department of Nuclear Engineering and Engineering Physics, Faculty of Engineering, Universitas Gadjah Mada, Yogyakarta, Indonesia. Her research interests include accelerator technology and application. She can be contacted at email: elin001@brin.go.id.

Sihana graduated for undergraduate program in nuclear engineering from Universitas Gadjah Mada, Yogyakarta, Indonesia, in 1990. He has graduated for Graduate program at Institut of Energy Engineering, Technical University, Berlin, Germany in 1993. He received the Ph.D. degree in Fakultaet fuer Prozesswissenschaften (Faculty of Process Science), Instituet fuer Energietechnik (Institut of Energy Engineering), Technical University Berlin, Germany in 2000. Currently, he is a Lecturer at the Department of Nuclear Engineering and Engineering Physics, Faculty of Engineering, Universitas Gadjah Mada, Yogyakarta, Indonesia. His research interests include analysis of safety, security and safeguard for nuclear system. He can be contacted at email: sihana@ugm.ac.id.

Taufik graduated for undergraduate program in Physics from Universitas Padjajaran, Bandung, Indonesia, in 2004. He has graduated for Graduate Program at Department of Physics, Universitas Gadjah Mada, Yogyakarta, Indonesia in 2013 and received the Ph.D. degree in Sokendai, Tsukuba, Japan in 2019. Currently, he is a senior researcher at the Research Center for Accelerator Technology, Research Organization for Nuclear Technology, National Research and Innovation Agency (BRIN). His research interests include accelerator science. He can be contacted at email: tauf009@brin.go.id.

Darsono graduated for undergraduate program in Physics from Universitas Gadjah Mada, Yogyakarta, Indonesia, in 1982. He has graduated for Graduate program at Department of Physics, Queens University, Ontario, Canada in 1990. Currently, he is a Research Professor at the Research Center for Accelerator Technology, Research Organization for Nuclear Technology, National Research and Innovation Agency (BRIN). His research interests include the accelerator science, accelerator technology and accelerator application. He can be contacted at email: dars001@brin.go.id.

Saefurrochman graduated for undergraduate program in electrical engineering from Indonesia Institute of Technology, South Tangerang, Indonesia. Universitas Gadjah Mada, Yogyakarta, Indonesia, in 2005. He has graduated for Graduate program in Electrical Engineering, Universitas Gadjah Mada, Indonesia, in 2017. Currently, he is a Junior researcher at the Research Center for Accelerator Technology, Research Organization for Nuclear Technology, National Research and Innovation Agency (BRIN). His research interests include accelerator technology, DC high voltage engineering and control engineering. He can be contacted at email: saef005@brin.go.id.

Rajendra Satriya Utama studying in Department of Nuclear Engineering and Engineering Physics, Faculty of Engineering, Universitas Gadjah Mada, Yogyakarta, Indonesia. His research interests include particle accelerator technology, especially electron beam generation and optimization. He can be contacted at email: rajendrasatr00@gmail.com.