

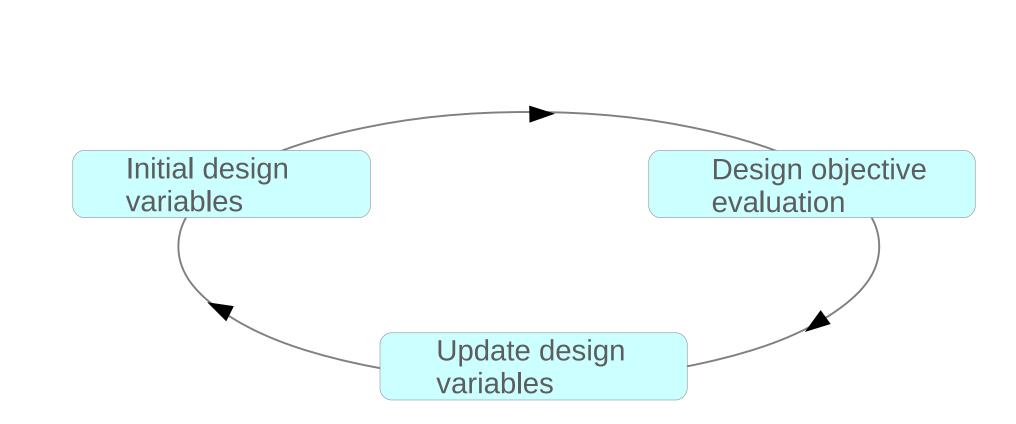


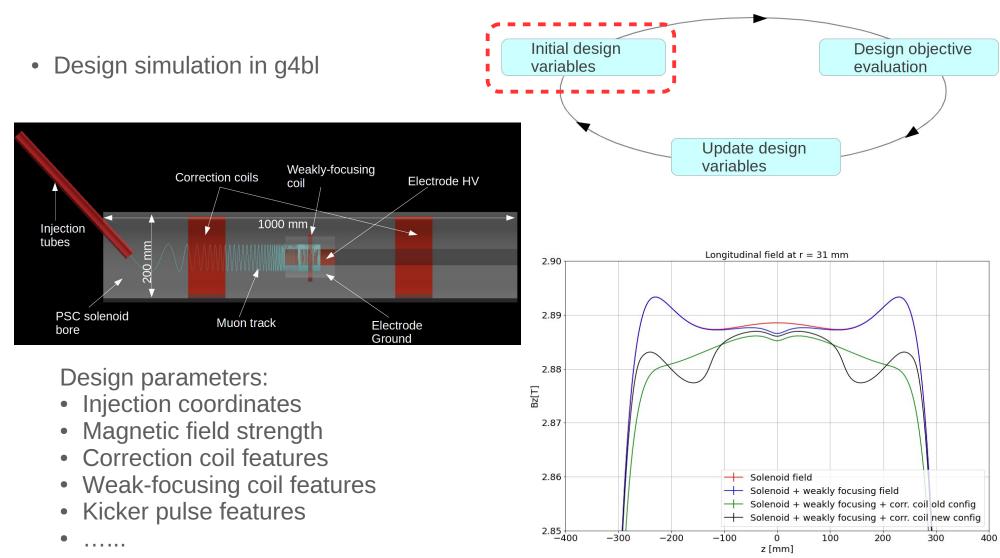
# **Muon Injection Optimzation in Simulations**

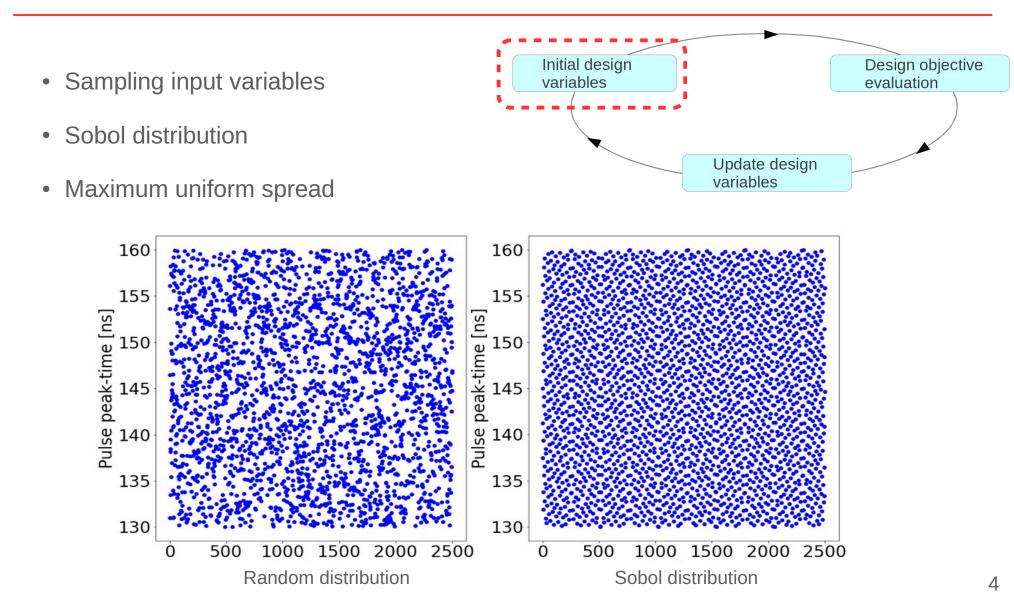
Ritwika Chakraborty (PSI)

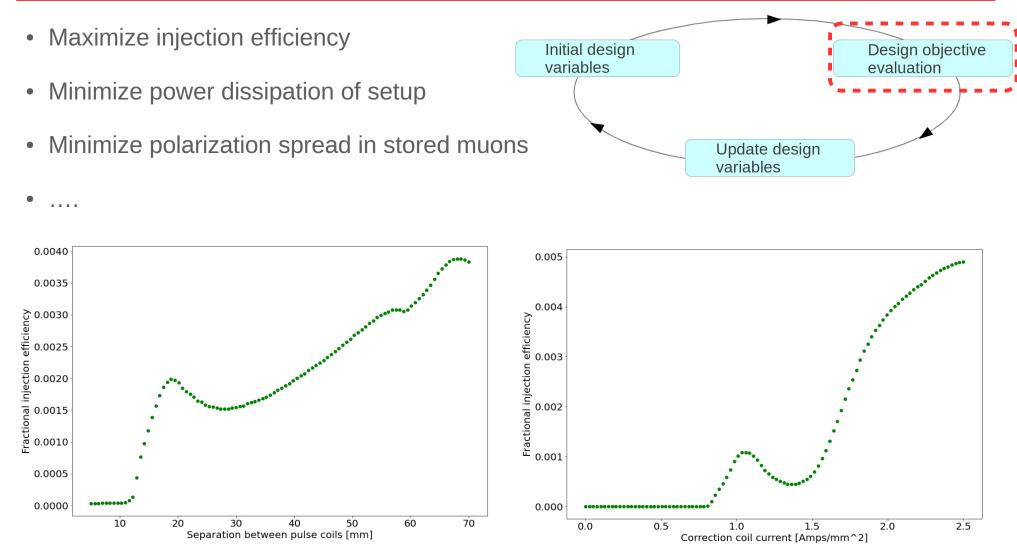
**MuEDM collaboration Spring Meeting** 

04.04.2024

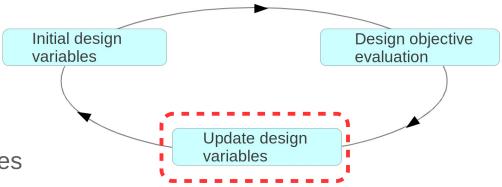


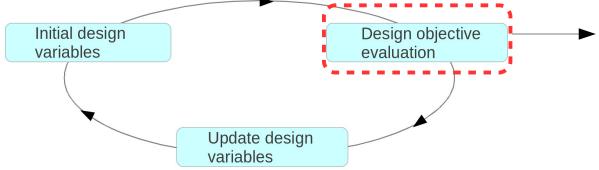






- Update design variables based on objective evaluation
- Repeat until optimal solution found
- Required to run simulation thousands of times
   → computationally expensive
- Replace physics simulation with approximation  $\rightarrow$  surrogate model





- Surrogate model for objective evaluation
  - → Many ways
  - $\rightarrow$  PCE and NN models explored

• Polynomial Chaos Expansion (PCE) :

$$Y = \sum_{i=0}^{\infty} \alpha_i \Psi_i \left( \vec{x} \right)$$

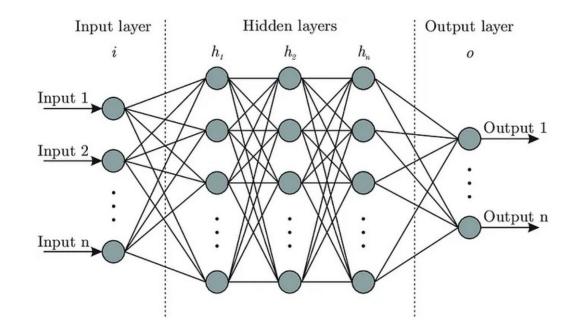
 $\mathbf{Y} \rightarrow \text{Model response (injection efficiency)}, \mathbf{\Psi}_i \rightarrow \text{Orthogonal polynomials}$ x  $\rightarrow$  input variables,  $\mathbf{\alpha}_i \rightarrow \text{expansion coefficients}$ 

- Polynomial basis based on input variable distribution
- Coefficients determined using regression based methods

$$\vec{\alpha} = \operatorname{Argmin} \frac{1}{N} \sum_{j=1}^{N} \left\{ f(\vec{\xi}^{j}) - \sum_{i=0}^{P-1} \alpha_{i} \Psi_{i}\left(\vec{x}^{j}\right) \right\}^{2}$$

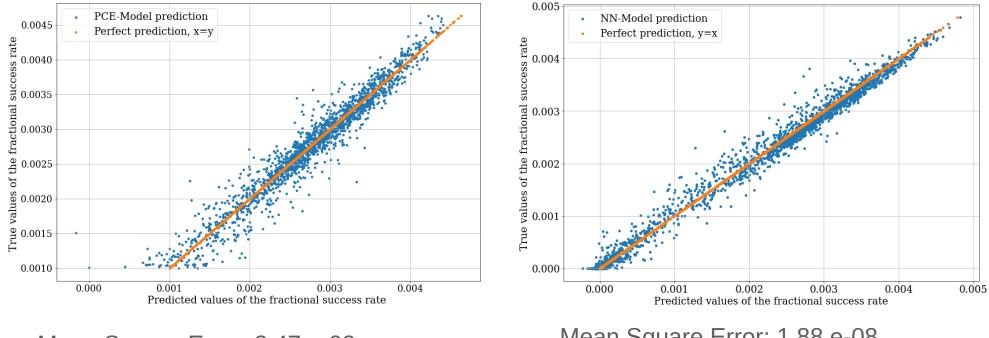
# **NN Surrogate Model**

- Use the input (design) and output (objective) to train a neural network
- Need to make choice for hyper parameters:
  - $\rightarrow$  no. of hidden layers
  - $\rightarrow$  no. of neurons
  - $\rightarrow$  learning rate
  - $\rightarrow$  optimizer
  - $\rightarrow$  scheduler
  - $\rightarrow$  activation functions
  - $\rightarrow$  ....



## **Model Performance**

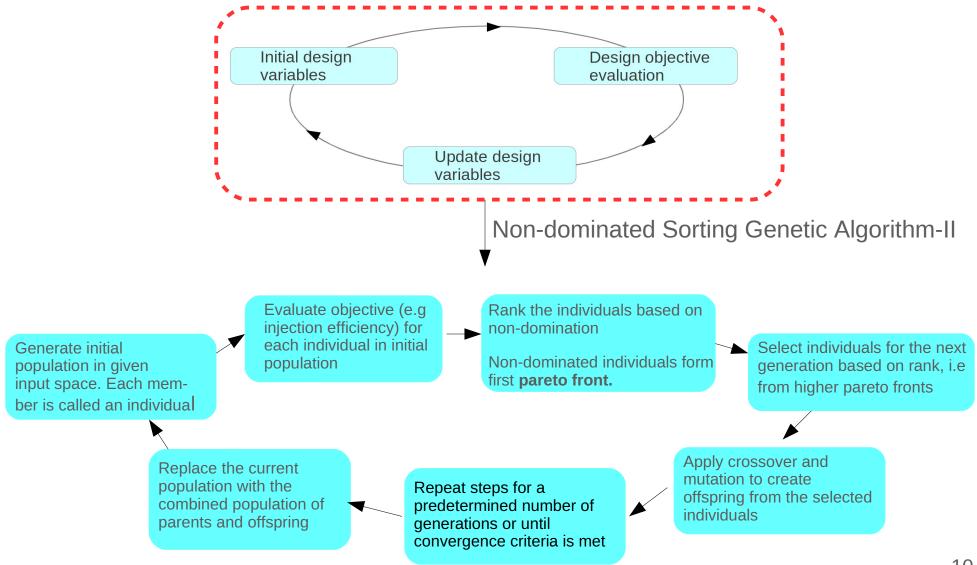
#### Model performance for a 6 dimensional input space



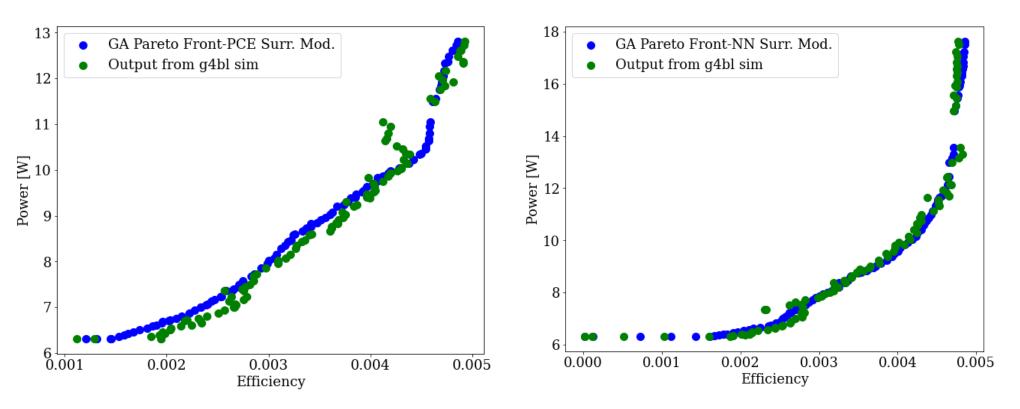
Mean Square Error: 3.47 e-08

Mean Square Error: 1.88 e-08

#### **Genetic Algorithm: NSGA-II**



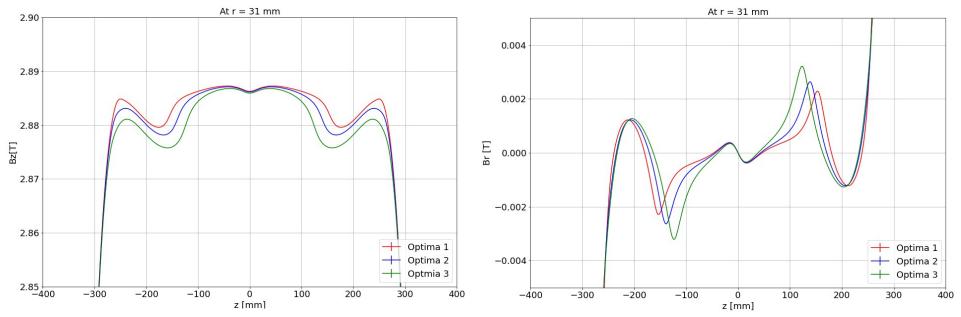
## Surrogate model based NSGA-II performance



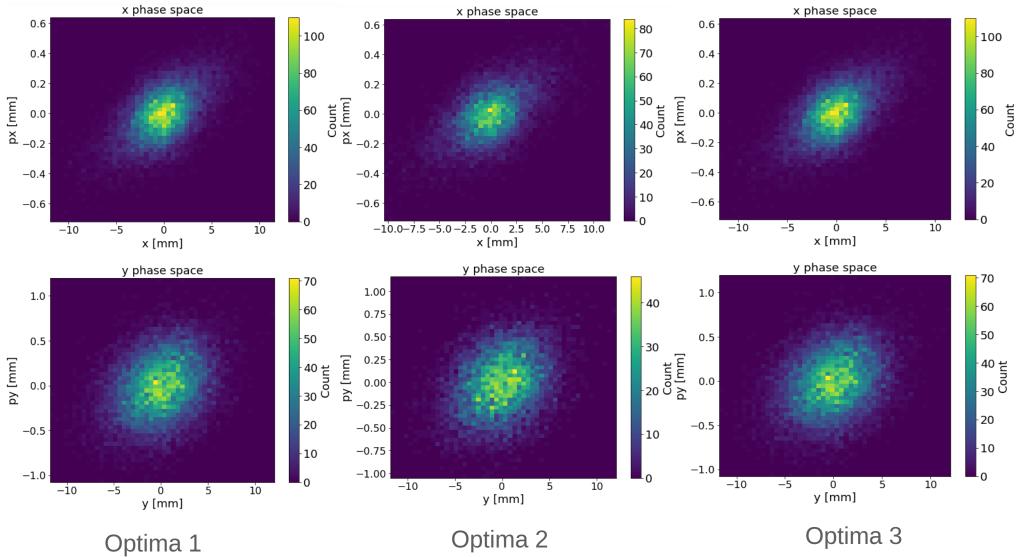
• 5% vs 2% agreement for PCE/NN based GA performance for average eff 0.35%

## A look at Solutions: Magnetic Field Profile

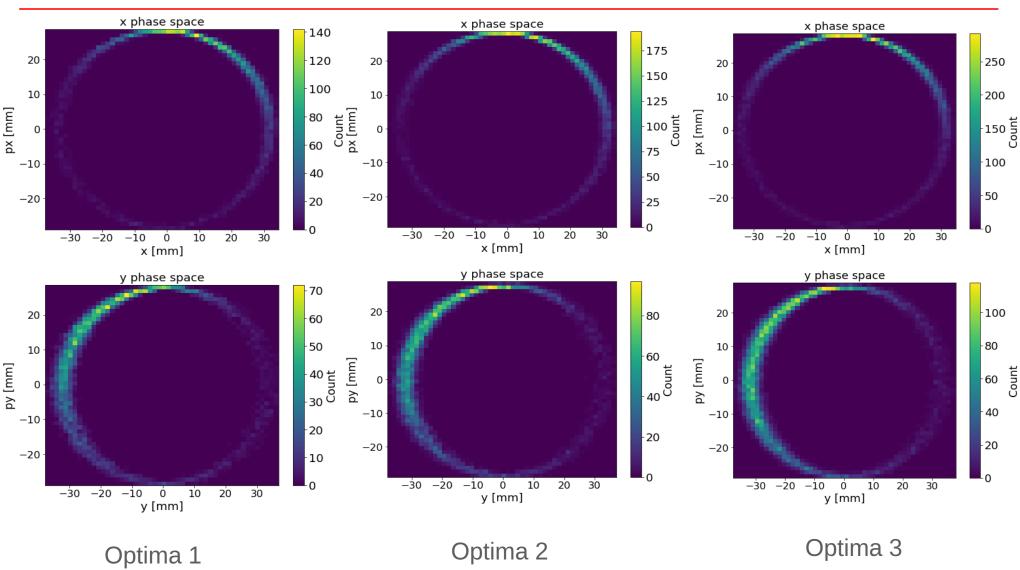
|          | Efficiency | Kicker<br>Timing<br>[ns] | Kicker<br>strength | Corr coil<br>Length<br>[mm] | Corr coil<br>InnRadius<br>[mm] | Corr coil<br>OutRadius<br>[mm] | Corr Coil<br>Pos [mm] |
|----------|------------|--------------------------|--------------------|-----------------------------|--------------------------------|--------------------------------|-----------------------|
| Optima 1 | 0.0022     | 97.99                    | 0.80               | 95.93                       | 40.01                          | 7.00                           | 202.40                |
| Optima 2 | 0.0032     | 91.80                    | 0.72               | 118.31                      | 40.01                          | 7.10                           | 198.90                |
| Optima 3 | 0.0048     | 81.27                    | 0.69               | 140.96                      | 40.00                          | 8.00                           | 194.57                |



## A look at Solutions: Storage phase space at Injection



## A look at Solutions: Transverse Storage Phase Space



# Summary

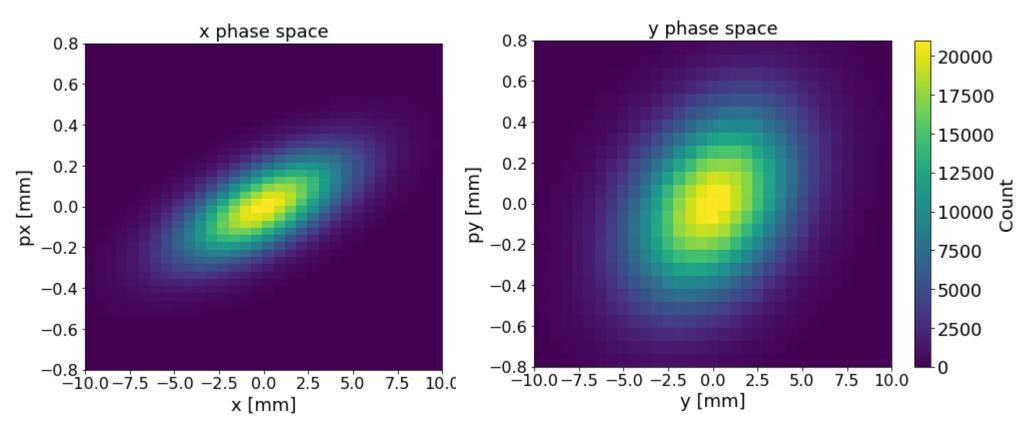
- Running simulations iteratively is bottleneck in optimization process
- Orders of magnitude speed up can be achieved by replacing physics simulation by surrogate model
- Genetic algorithm NSGA-II used to run multiobjective optimization
- PCE and NN surrogate models based GA investigated;  $\sim 10^3$  speed up for PCE,  $\sim 10^4$  for NN
- No significant difference in storage phase space at injection or storage for 3 kicker timings
- Possibility to improve efficiency with bigger pulse coil separation
- Plan to expand into optmization where higher dimensional input space can be implemented with straightforward uncertainty quantification techniques

# Acknowledgments

- Computational resources: PSI Local High Performance Computing cluster, Merlin6, Siyuan-1 cluster supported by the Center for High Performance Computing at Shanghai Jiao Tong University and the Euler cluster operated by the High Performance Computing group at ETH Zürich.
- Accelerator Modeling and Advanced Simulations (AMAS) group at PSI: A. Adelmann, S. Heinekamp and P. Juknevicius
- NN surrogate starting point: A. Holmberg Bachelor's Thesis ETH Zurich 2021

#### Extra

#### **Total phase space after collimation**



#### **Neural Net hyperparameters**

```
def init (self, input dimension, output dimension, n hidden layers,
            neurons, regularization param, regularization exp):
    super(net, self). init ()
   # Number of input dimensions n
   self.input dimension = input dimension
   # Number of output dimensions m
   self.output dimension = output dimension
   # Number of neurons per layer
   self.neurons = neurons
   # Number of hidden layers
   self.n hidden layers = n hidden layers
   # Activation function
   self.activation = nn.LeakyReLU()
   self.regularization param = regularization param
   self.regularization exp = regularization exp
   self.input layer = nn.Linear(self.input dimension, self.neurons)
   self.hidden layers = nn.ModuleList([nn.Linear(self.neurons, self.neurons) for in range(n hidden layers)])
   self.output layer = nn.Linear(self.neurons, self.output dimension)
   self.dropout = nn.Dropout(0.1)
```

# Xavier weight initialization
init xavier(my network, retrain)

```
optimizer = optim.Adam(my_network.parameters(), lr=le-3)#, weight_decay=le-5)
#optimizer = optim.LBFGS(my_network.parameters(), lr=0.1, max_iter=1,
# max_eval=50000, tolerance change=1.0 * np.finfo(float).eps)
```

scheduler = optim.lr\_scheduler.ReduceLROnPlateau(optimizer\_, mode='min', factor=0.5, patience=500000)
#scheduler = optim.lr scheduler.StepLR(optimizer=optimizer, step size=50, gamma=0.5)

#### **Neural Net activation function**



#### **6-d optimization parameter bounds**

bounds = {"T\_Offset": [80, 98], "BPI": [0.35,0.80], "CC\_Len": [88, 150], "CC\_Ir": [40, 84], "CC\_Thick":[7,15], "CC\_Pos":[166,241]}