EECE 502 Final Year Project
Group Final Presentation

Optimal Power Flow via Machine Learning

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Motivation

Cost & Time

- OPF plays a heavy role in the determination of the cost of operation of a power system.
- The utility incurs enormous losses due to inaccurate software tools with approximations.
- No fast solution exists without sacrificing accuracy.

Total **Losses** due to inaccurate solvers	Estimated **Savings** with only **5% increase** in optimality of solvers
10s of billions of Dollars	**$12 billion** in United States **$87 billion** World Wide

Desired Needs

New solvers that are:

- **Faster:**
Can handle a new instance of OPF problem in less than a second.
- **More robust:**
Can handle rapid fluctuations and stochasticity.

Requirements & Specifications

Should reach accurate results within 1% of the actual solution.

Designed Model

Should solve OPF problem in real-time

Should not violate any of the constraints of the problem

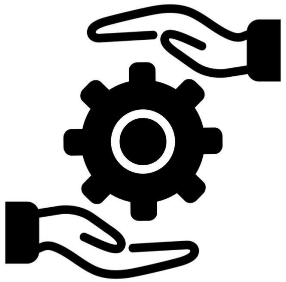
Deliverables

Ease of Use:

Software Implementation of a user-friendly OPF solver with a relevant graphical user interface (GUI).

Practicality:

Validation of the solver performance under different operational scenarios.



Compliance:

Confirmation of IEEE standards.

IEEE SA STANDARDS

Technical Constraints

Voltage Limit	Voltages at nodes must be maintained within bounds
Thermal Limit	The current in the transmission line must not exceed an upper limit
Stability Limit	The load angle must be below 30°
Power Constraints	Power generated and transmitted in transmission lines is bounded

Non-Technical Constraints

Economic — **Gives the economical operation of the generating units**

Environmental — **Allows the integration of renewable energy**

Literature Review

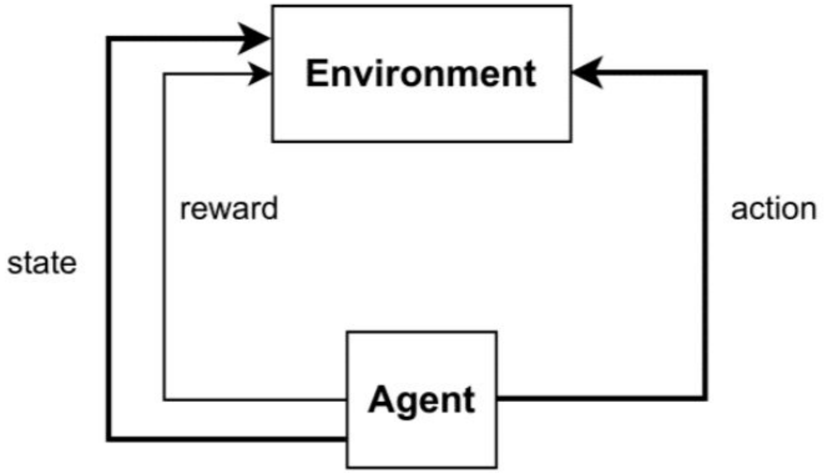
Methods for solving OPF

Learning-Based		Traditional	
Neural Network	Reinforcement Learning	Probabilistic	Deterministic
Requires large amount of historical data	Requires extensive training Tuning of many hyperparameters	Require a lot of time on new instance Can be computationally expensive	

Design Alternatives

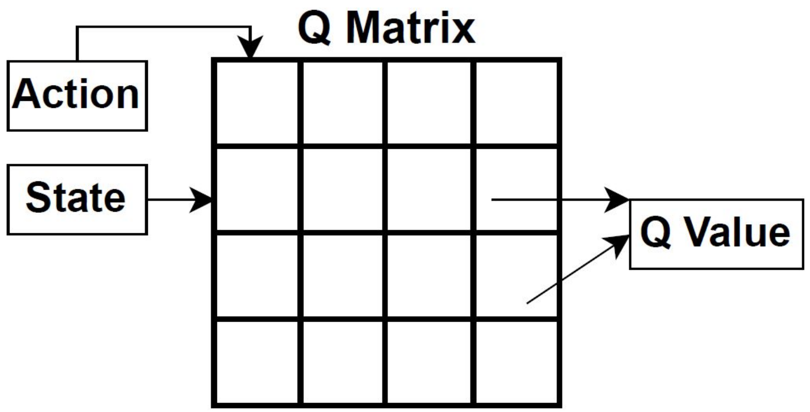
Reinforcement Learning

- Agent learns solution through solving a MDP.
- Consists of the state, action, state transition probability, and reward.



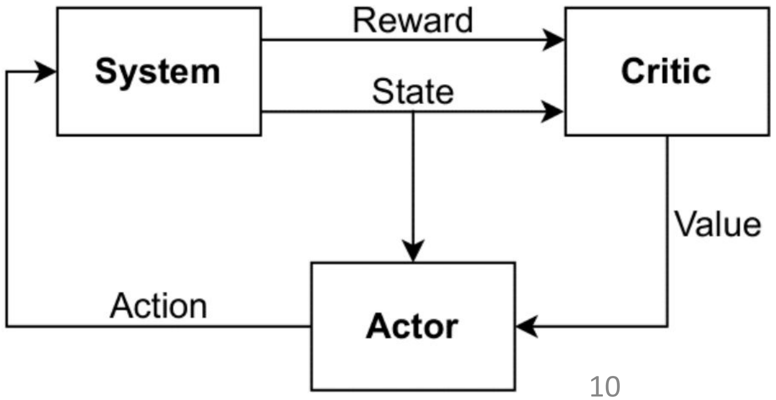
Q-Learning

- Agent learns optimal policy through evaluating actions it takes while interacting with environment.



Actor-Critic Models

- Actor: Decides on the action.
- Critic: Evaluates the quality of the action.



Design Alternatives

Supervised Learning

Shallow Models

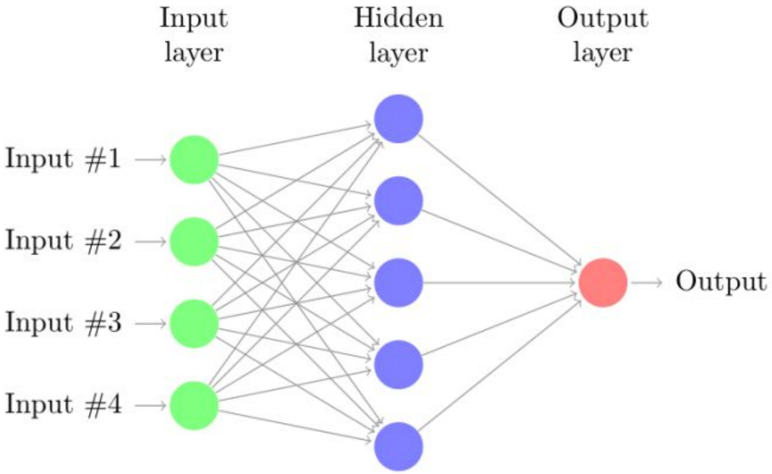
- Linear regression
- Support vector machines
- Unable to learn complex data points

Deep Models

- Neural networks
- Function approximators

Design Decision

Neural Networks



Descent Method:

for iterations **do**
  for batch size **do**
    randomly select a sample
    perform forward propagation using the sample
    perform back propagation using the sample
  end for
end for

$$a_i = \sigma(w_{i-1}\, a_{i-1} + b_{i-1})$$

Error propagates back from output to input

Mean Squared Error:

Minimize W,B $\frac{1}{N}\sum_{i=1}^{N}(\hat{\mathbf{y}}_i - \mathbf{y}_i)^2$

Mean Squared Error function is minimized

where W,B are weights and biases

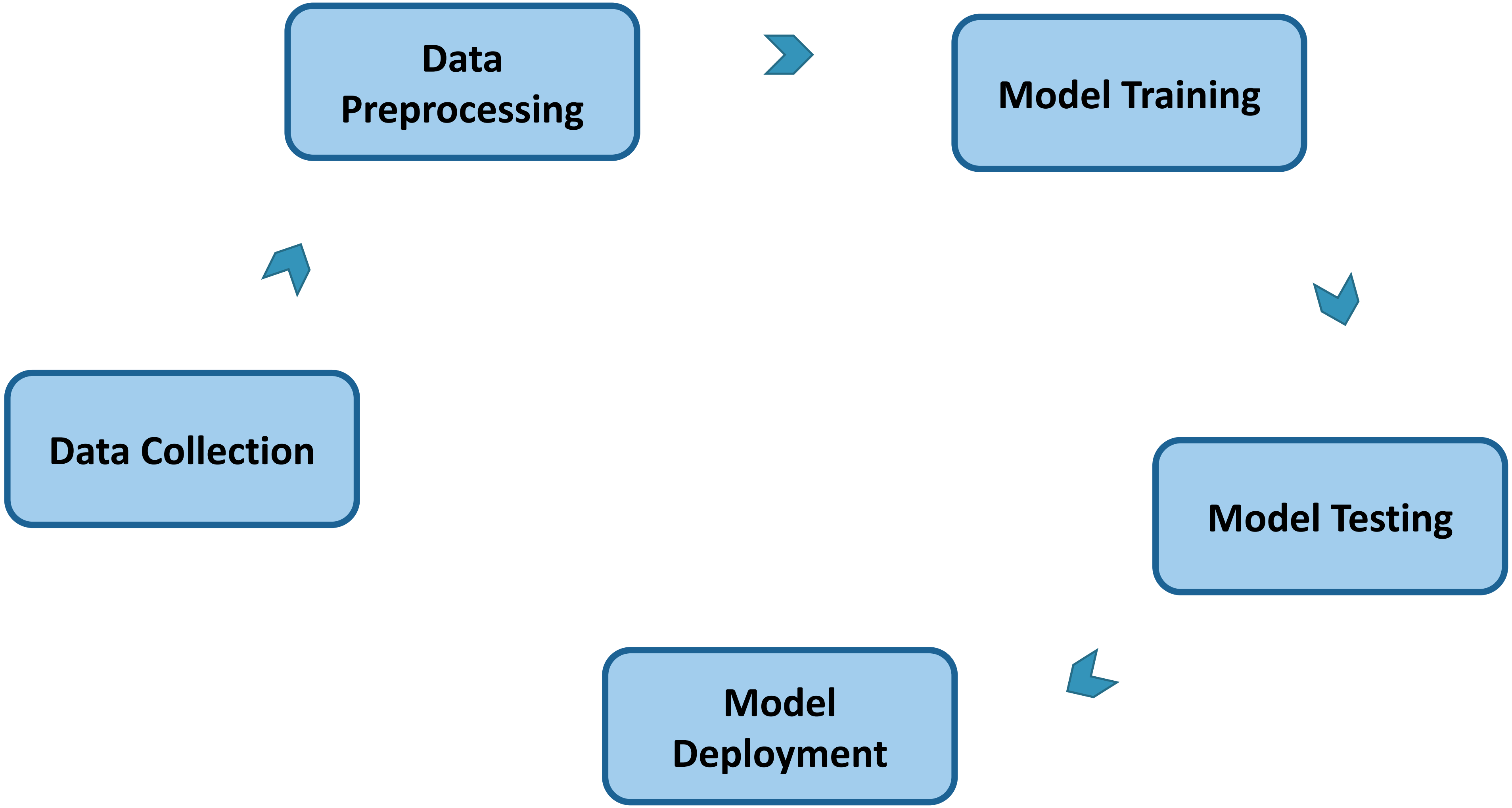
Universal Approximation Theorem

$$f(\mathbf{x}) \approx \sum_{j=1}^{N_L} v_j \phi(\mathbf{w_j x} + b_j)$$

where,

f	function to be approximated
x	input vector
NL	number of layers
vj	constant in R
wj, bj	weights and biases for layer j

NN Methodology



OPF Formulation

OPF Objective Function:

Minimize $$\sum_{i \in G}(c_{2i}P_{gi}^2 + c_{1i}P_{gi} + c_{0i})$$

Maps amount of power generated to associated cost

Inequality Constraints:

$$V_{G_i}^{min} \leq V_{G_i} \leq V_{G_i}^{max} \qquad \forall i \in N$$

$$P_{G_i}^{min} \leq P_{G_i} \leq P_{G_i}^{max} \qquad \forall i \in G$$

$$Q_{G_i}^{min} \leq Q_{G_i} \leq Q_{G_i}^{max} \qquad \forall i \in G$$

$$|S_{flow_{i,l}}| \leq S_{flow_{i,l}}^{max} \qquad \forall (i,l) \in L$$

Equality Constraints:

$$P_{G_i} - P_{D_i} = V_i \sum_{j \in N} V_j (G_{ij} \cos \delta_{ij} + B_{ij} \sin \delta_{ij}) \qquad \forall i \in N$$

$$Q_{G_i} - Q_{D_i} = V_i \sum_{j \in N} V_j (G_{ij} \sin \delta_{ij} - B_{ij} \cos \delta_{ij}) \qquad \forall i \in N$$

where,

- **PGi**, **PDi**, **QGi**, **GDi**: real and reactive power generated and demanded for node *i*
- **Gij**, **Bij**: conductance and susceptance of line (*i*,*j*)
- **δij**: voltage phase angle difference between nodes *i* and *j*

DC - OPF

I. **Objective Function:**

$$min \sum_{i \in G} (c_{2i} P_{gi}^2 + c_{1i} P_{gi} + c_{0i})$$

Power Generation Limits: $$P_{G_i}^{min} \leq P_{G_i} \leq P_{G_i}^{max} \qquad \forall i \in G$$

Line Flow Limits: $$|\frac{1}{x_{i,l}}(\theta_i - \theta_l)| \leq P_{flow_{i,l}}^{max} \qquad \forall (i,l) \in L$$

Power Balance: $$P_{G_i} - P_{D_i} = \sum_{j=1}^{N} B_{ij} \theta_j \qquad \forall i \in N$$

Implementation

II. Data Generation Scheme:

Algorithm Data Generation Scheme

```
Specify case file, N and δ
P_D ← default demand values
for N do
    for i ∈ demand nodes do
        P̃_{D_i} ~ U(P_{D_i} − δP_{D_i}, P_D + δP_{D_i})
    end for
    P̃_G ← run (DC-OPF | P̃_D)
    Save P̃_D, P̃_G
end for
```

III. Data Pre-processing:

Standard Normalization for the input:

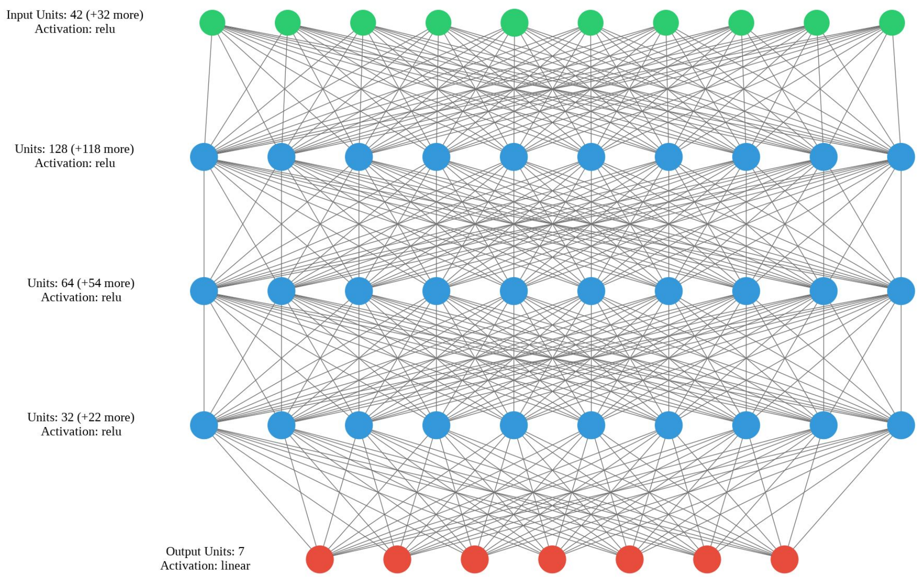
$$P_{D_{n_i}} \leftarrow \frac{P_{D_{n_i}} - \mu_n}{\sigma_n} \qquad \forall i \in N \qquad \forall n \in S_L$$

Normalization Scheme for the output:

$$P_{G_{n_i}} \leftarrow \frac{P_{G_{n_i}} - P_{G_{min_n}}}{P_{G_{max_n}} - P_{G_{min_n}}} \qquad \forall i \in N \qquad \forall n \in G$$

IV. NN Construction:

Input P_D



Output P_G

Loss Function:

$$min_{W,b} \frac{1}{N} \sum_{i=1}^{N} \frac{1}{|G|} \sum_{j=1}^{|G|} (\widehat{P_{Gij}} - P_{G_{ij}})^2$$

NN Hyperparameters:

No. of Iterations	300
Batch Size	32
Learning Rate	0.001

Design Iterations

Iteration 1

Input data was not normalized

Model failed to learn and performed like a dummy model

- Data was normalized
- Model converged 80% of the time

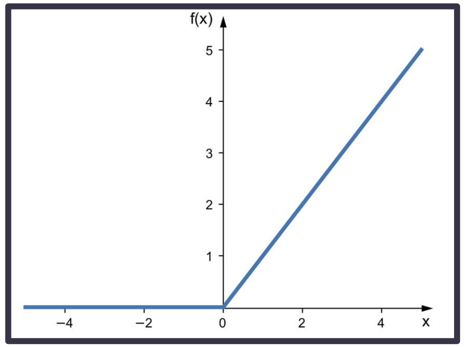
Iteration 2

Final activation function was ReLU

NN failed to converge a fifth of the time

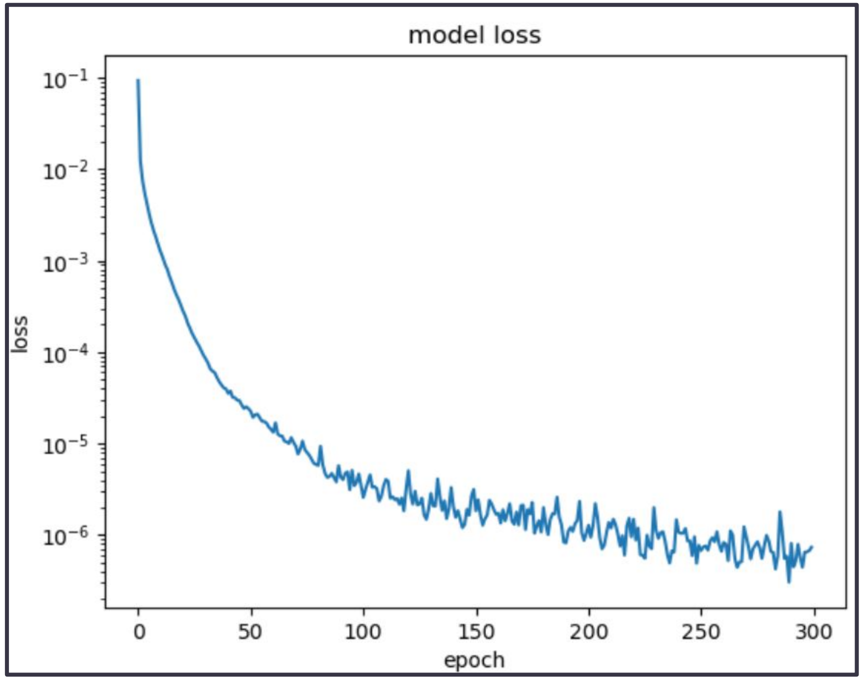
- Final ReLU was replaced by a linear function
- Model converged 100% of the time

ReLu Activation Function:



Results

I. Training Results:

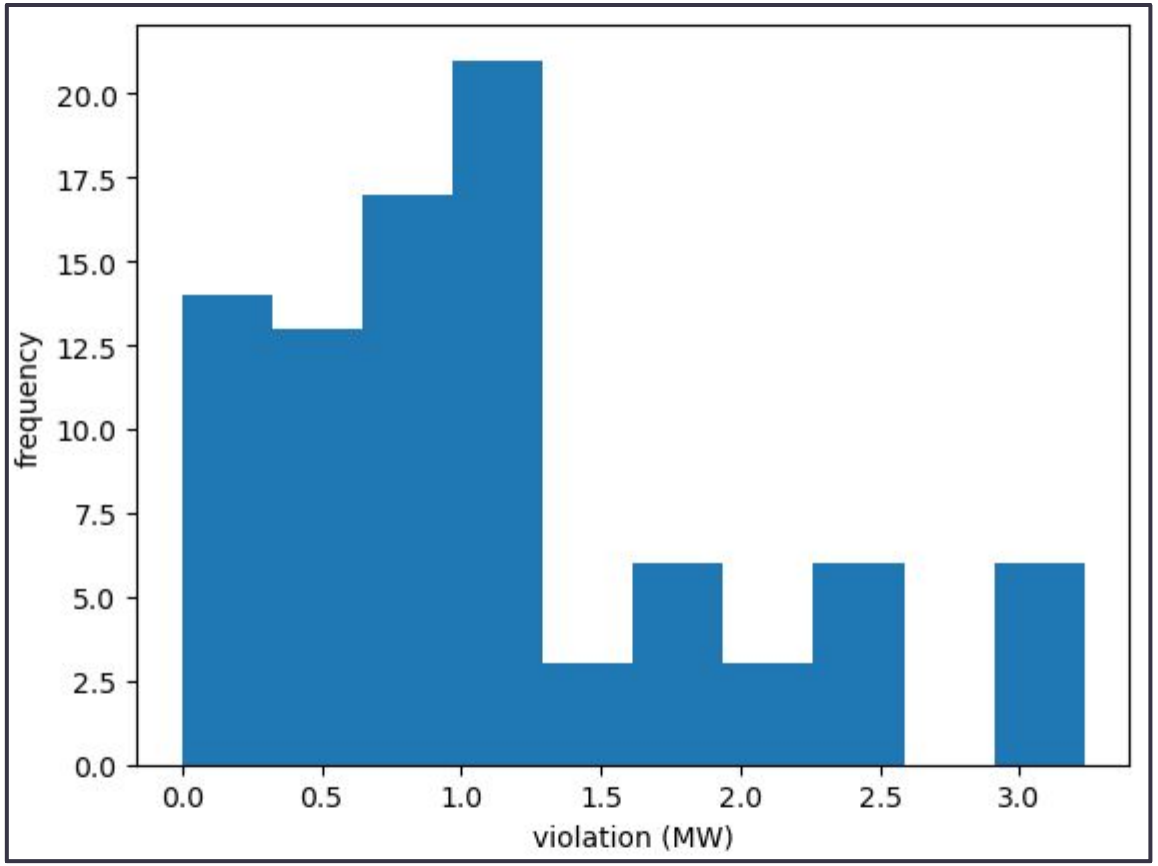


II. Testing Results:

Power Network	MSE	MAPE(%)	Speed-up
IEEE-30	2E-8	0.007	x6
IEEE-57	5.2E-6	0.09	x11
IEEE-118	4.7E-8	0.01	x23
IEEE-300	1.5E-7	0.02	x43

Loss Function Modification

Distribution of Violations:



New Loss Function:

$$\mathcal{L}_{new} = w_{MSE}\mathcal{L}_{MSE} + w_{pen}\mathcal{L}_{pen}$$

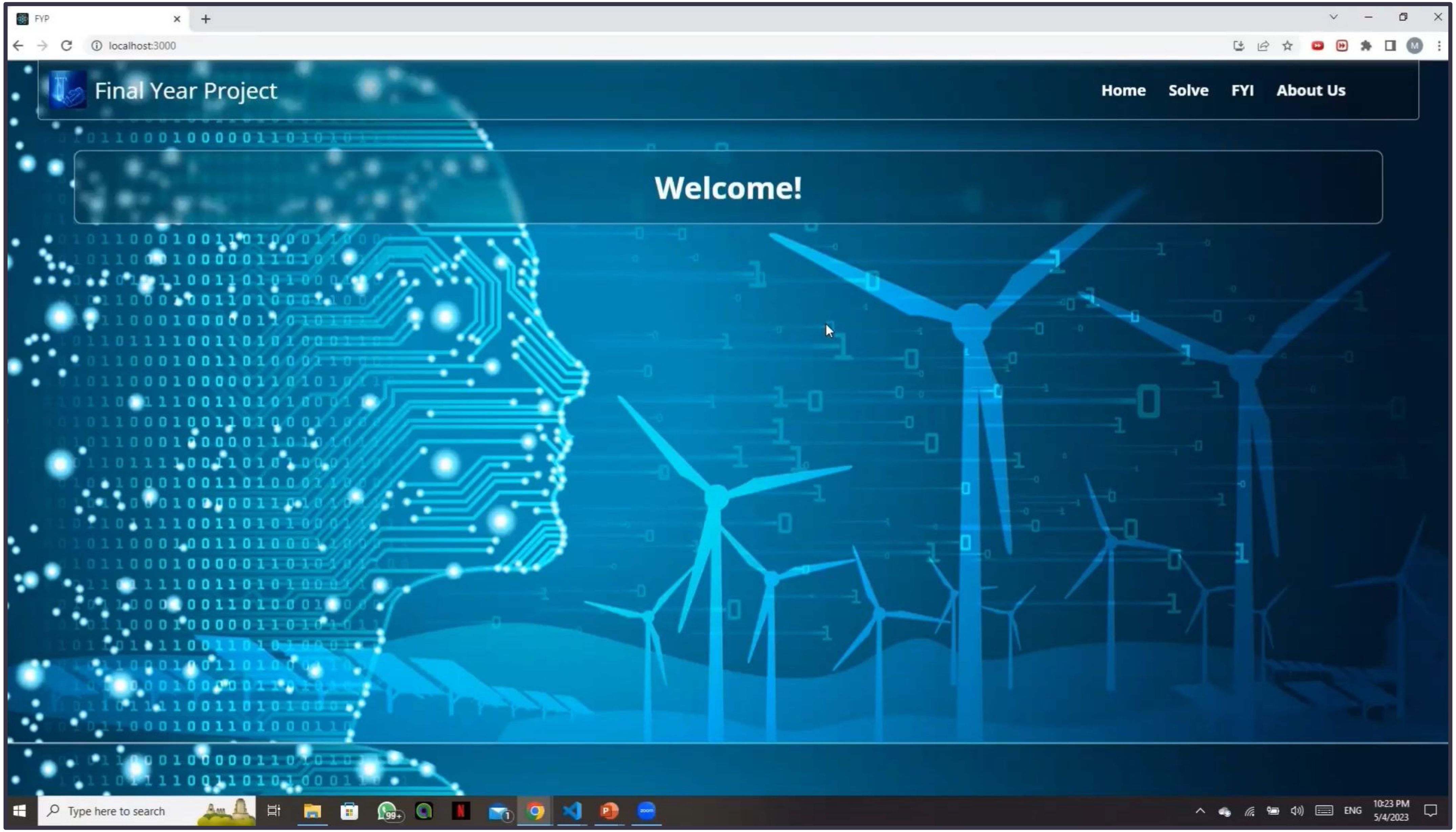
$$\mathcal{L}_{\mathcal{MSE}} = \frac{1}{N}\sum_{i=1}^{N}\frac{1}{|G|}\sum_{j=1}^{|G|}(\widehat{P_{Gij}} - P_{G_{ij}})^2$$

$$\mathcal{L}_{pen} = \frac{1}{N}\sum_{i=1}^{N}\frac{1}{|G|}\sum_{j=1}^{|G|} max(\hat{P}_{ij} - P_{ij}^{max}, 0) + max(P_{ij}^{min} - \hat{P}_{ij}, 0)$$

where, $w_{MSE} = 1 \text{ and } w_{pen} = 5$

Metric	Score
MSE	4.7E-6
MAPE	0.1%
no. of generator limits violation	0

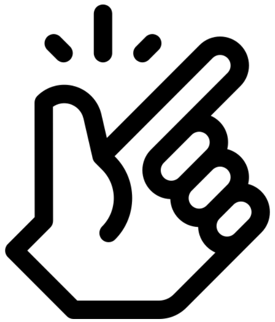
Graphical User Interface



Our GUI Advantages

Ease of Use:

- User-friendly interface
- No prior knowledge of machine learning or programming required



Convenience:

- Significant speed-up when compared to traditional solvers
- Can be trained once and reused for testing

Brief Overview

I. Software Used:

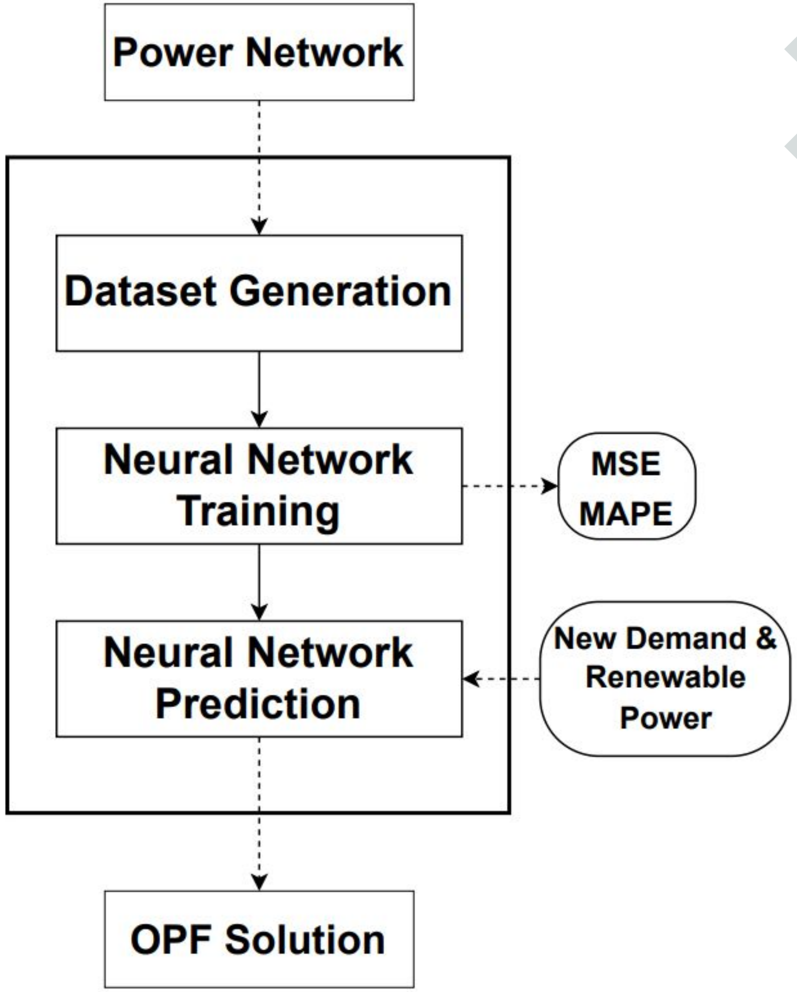
Front-end:

- **React** for building interactive elements
- **CSS** for design

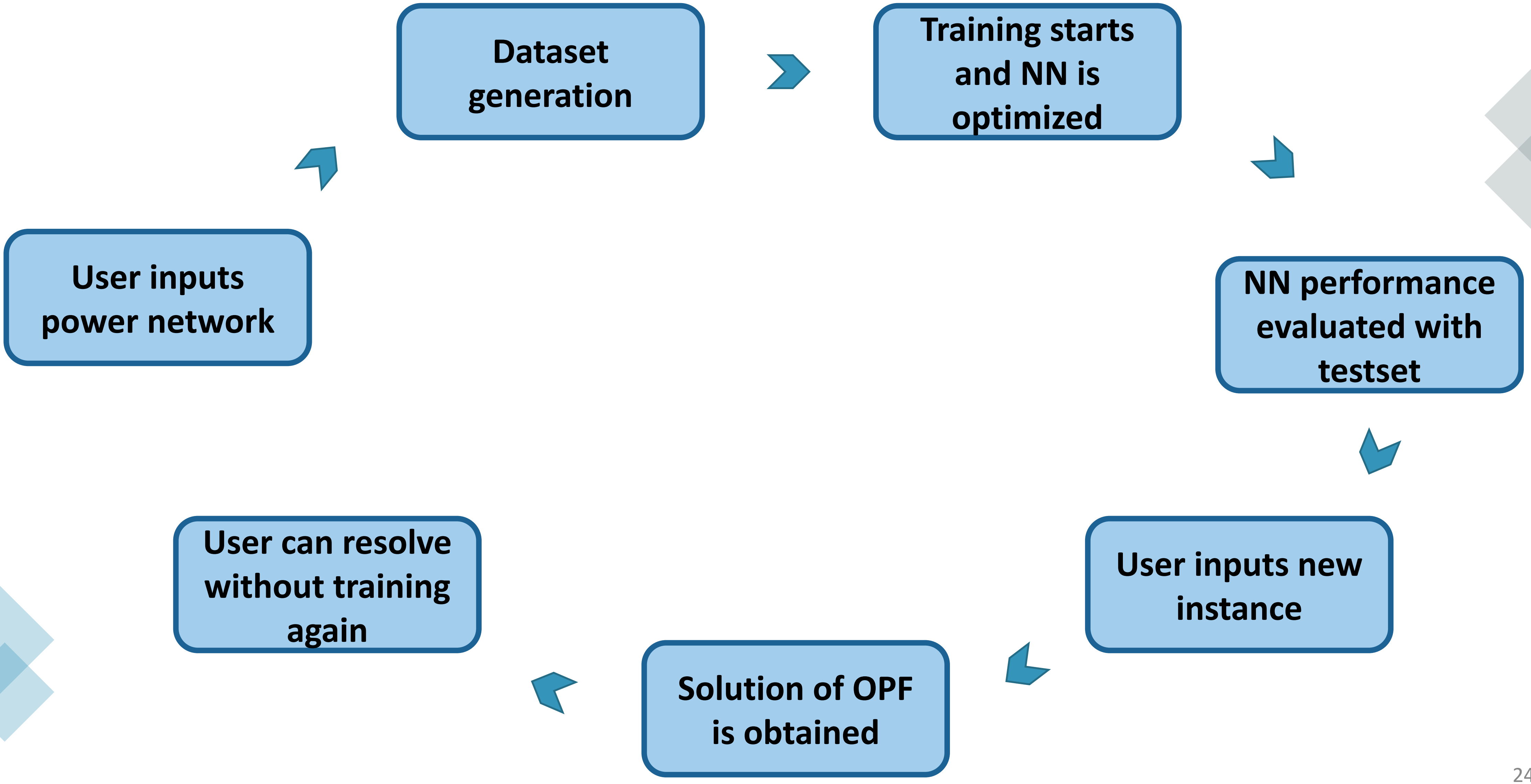
Back-end:

- **Flask Python** microframework

II. Process:



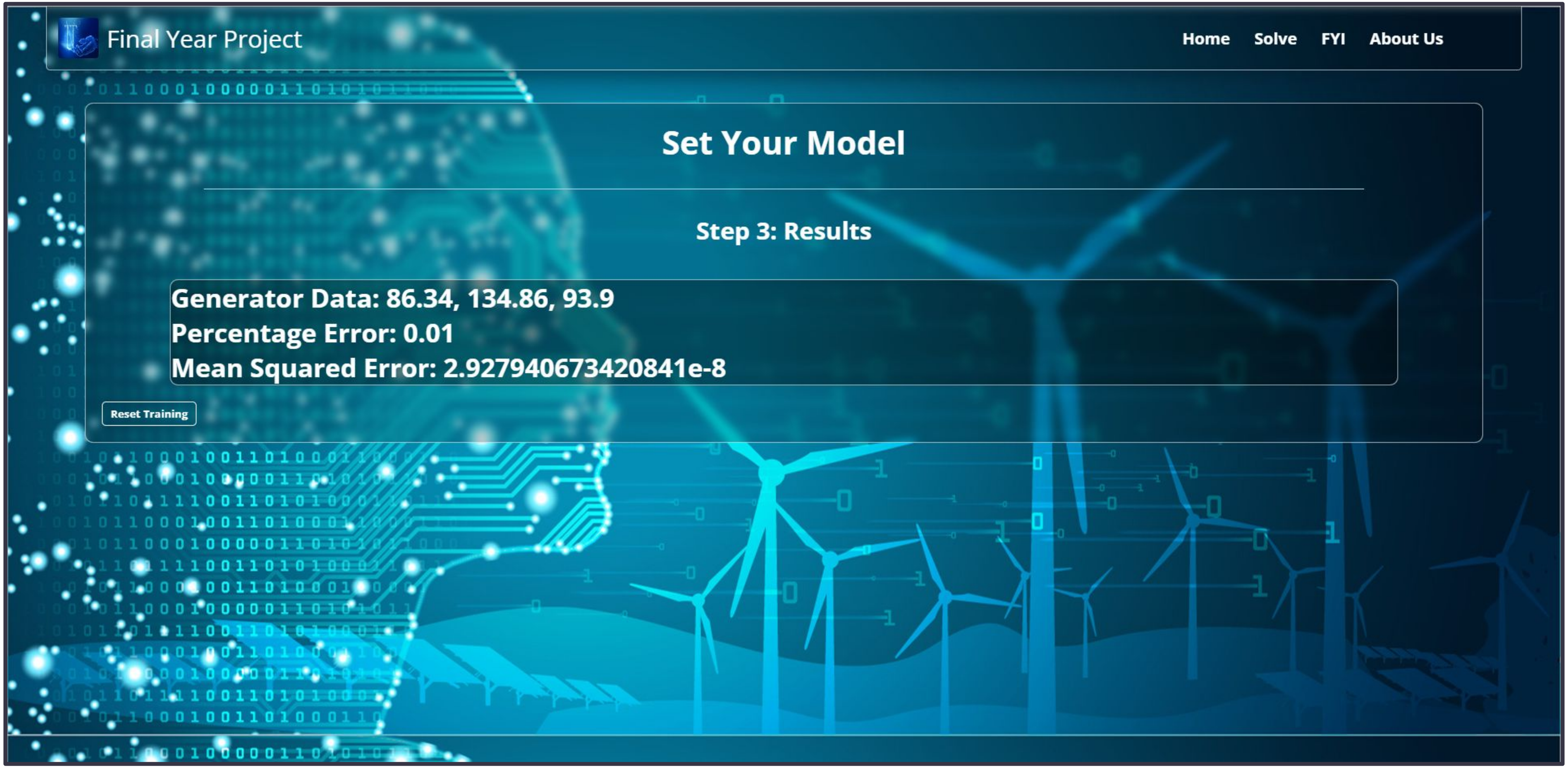
Software Steps



Step 1 - Training

Step 2 - Solving

Step 3 - Displaying Results



GUI Demo

Sustainable Development Goals

Enables the integration of renewable energy sources

Responds to rapid fluctuations in renewable power generation

Gives the most economic scheme for electric power production

Enables the integration of renewable energy sources

Can include minimization of emissions in its objective function

Conclusion

Overall,

- Presented a NN approach to solve the OPF problem
- Trained and tested the NN ⇒ accurate and faster than traditional solvers
- Proposed a custom loss function where constraints are not violated
- Created a user-friendly interface that does not require expertise in programming or machine learning

Optimal Power Flow via Machine Learning

EECE 502 Final Year Project

Mohammad F. El Hajj Chehade, Mohamad Al Tawil, Karim Khalife

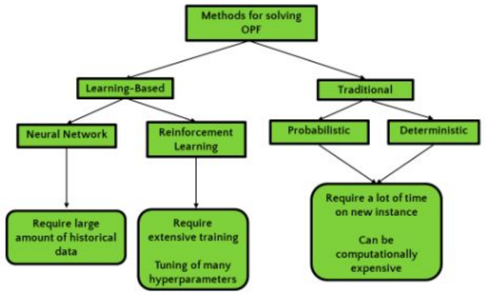
Department of Electrical and Computer Engineering

Abstract

The optimal power flow (OPF) problem is fundamental to ensuring the efficient and reliable operation of a power system. The problem's objective is to minimize the operating costs of thermal resources within a power system. The recent integration of renewable energy sources into the power grid has led to rapid fluctuations in power generation, necessitating the presence of a faster OPF solver capable of balancing accuracy and speed. This paper proposes Artificial Neural Networks (ANNs) as a viable solution to the OPF problem. An algorithm is introduced to generate the necessary dataset, while a custom loss function is implemented to ensure that constraints are not violated. The results demonstrate a high level of accuracy for the solver, as well as a significant improvement in speed when compared to traditional solvers. Finally, a user-friendly platform is developed for solving the OPF problem using ANNs, which eliminates the need for knowledge of programming or machine learning.

Key words: optimal power flow, Artificial Neural Networks (ANNs), custom loss function, user-friendly platform

Background



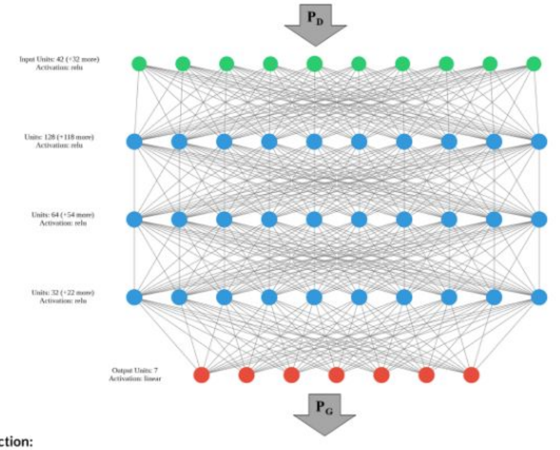
Objectives

Our project aims to develop an efficient neural network solver that meets the following requirements:

- Accelerate the solution process compared to traditional solvers
- Deliver highly accurate results
- Ensure that the solver does not violate any problem constraints
- Integrate the solver into a user-friendly graphical user interface (GUI) for ease of use.

Method

Neural Network Architecture:



Loss Function:

$$\boxed{\mathcal{L}_{new} = w_{MSE}\mathcal{L}_{MSE} + w_{pen}\mathcal{L}_{pen}}$$

$$\boxed{\mathcal{L}_{MSE} = \sum_{i=1}^{N} \frac{1}{|G|} \sum_{j=1}^{|G|} (\widehat{P_{Gij}} - P_{G_{ij}})^2}$$

$$\boxed{\mathcal{L}_{pen} = \frac{1}{N} \sum_{i=1}^{N} \frac{1}{|G|} \sum_{j=1}^{|G|} max(\hat{P}_{ij} - P_{ij}^{max}, 0) + max(P_{ij}^{min} - \hat{P}_{ij}, 0)}$$

Algorithm Data Generation Scheme

Specify case file, N and δ
$P_D \leftarrow$ default demand values
for N **do**
  for $i \in$ demand nodes **do**
    $\tilde{P}_{D_i} \sim U(P_{D_i} - \delta P_{D_i}, P_D + \delta P_{D_i})$
  end for
  $\tilde{P}_G \leftarrow$ run (DC-OPF | $\tilde{P}_D$)
  Save $\tilde{P}_D, \tilde{P}_G$
end for

Results

Testing Results:

Power Network	MSE	MAPE(%)	NN(M)	MATPOWER(ms)	Speed-up
IEEE-30	2x10	0.007	50	322	x6
IEEE-57	5.2x10	0.09	50	522	x11
IEEE-118	4.7x10	0.01	50	1131	x23
IEEE-300	1.5x10	0.02	50	2166	x43

Graphical User Interface (GUI):

Step 1: Enter the power network to train:

Step 2: Enter the demand data to solve for new examples:

Step 3: The solution of the OPF with the performance metrics of the neural network:

Conclusions

- This study presents a neural network approach to solve the optimal power flow problem.
- The neural network is evaluated using the DC-OPF case, and it provides accurate solutions and faster speed compared to traditional solvers.
- A custom loss function is proposed to ensure that the constraints are not violated.
- The developed solver is presented and tested.
- A user-friendly platform is created for the solver, which does not require expertise in programming or machine learning.

We would like to thank our advisor and dear professor *Dr. Rabih Jabr*.

His consistent guidance and constructive feedback were instrumental to the success of the project.

Even during the darkest times when our project was sinking, his advice and words of wisdom were the rescue boat.

We would also like to thank our committee members, Dr. Chaaban and Dr. Chedid, for attentively listening to our presentation, and our FYP coordinator Dr. Tawk.

Questions ?