



Differential Evolution Techniques: A Critical Review

Subita Bhagat¹, Nikhil Prakash²

Assistant Professor¹, Assistant Professor²
Department of Chemical Engineering
SLIET, Longowal

Abstract: For efficiency in polymerization the structure of metallocene polymer particle plays an important role. To control and optimize the structure of metallocene particle a support vector machine was designed which had a different set of algorithmic patterns. This technique was known as DIFFERENTIAL EVOLUTION TECHNIQUE. A software was adopted to run this machine and carry out simulations of the model. After some research work scientists were able to discover optimized conditions and structure of polymer to be altered. Differential revolution technique has proved to bring a lot of improvement in a polymer formation through metallocene based catalysts structural inspection. All such processes are based upon artificial intelligence. DE technique is widely used for complex processes like polymerization of styrene. It depends on many conditions like temperature, amount of initiator and time.

Keywords: Differential Evaluation, polymer, metallocene catalyst

I. INTRODUCTION

Artificial neural networks(ANN) are tools used for modifying complex non-linear processes as they only require output-input data to perform their functions especially on metallocene catalysts(Zhang et al., 2008).

SVM machine's are used to perform high dimension problems because of its good generalization capability.

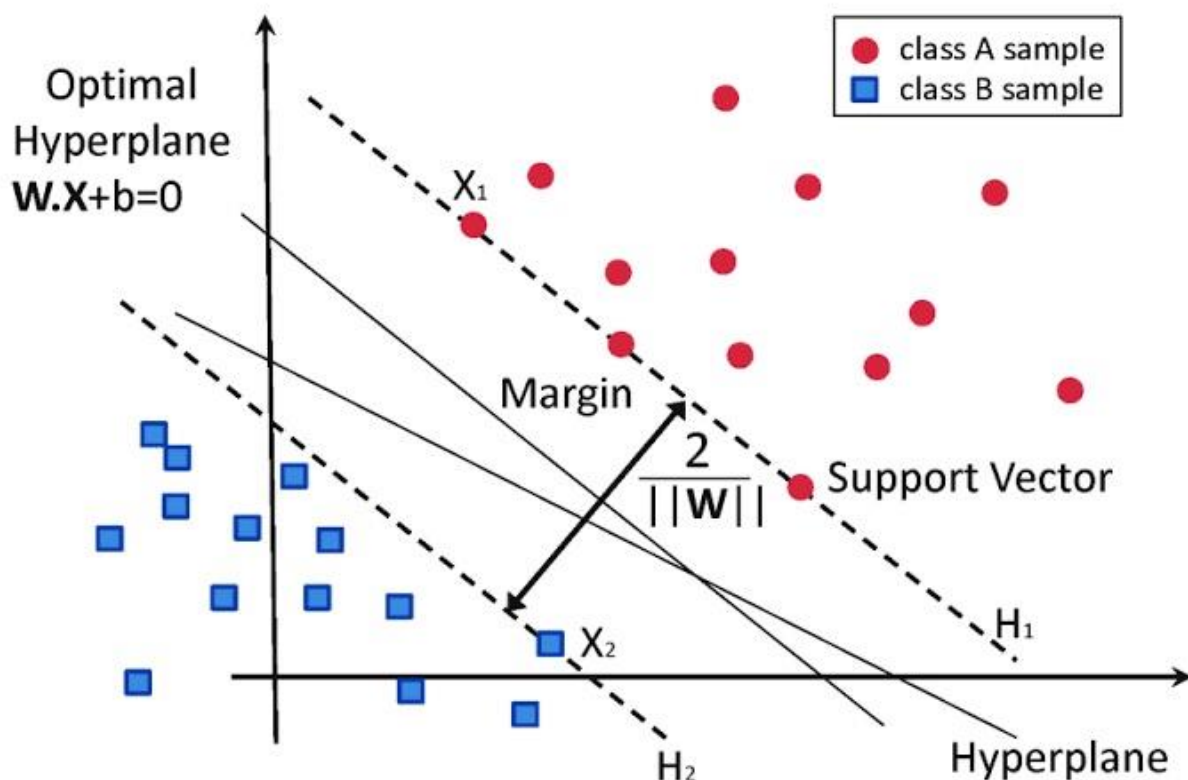


Figure 1: SVM MACHINE ALGORITHMIC PATTERNS

Architecture of Artificial Neural Network

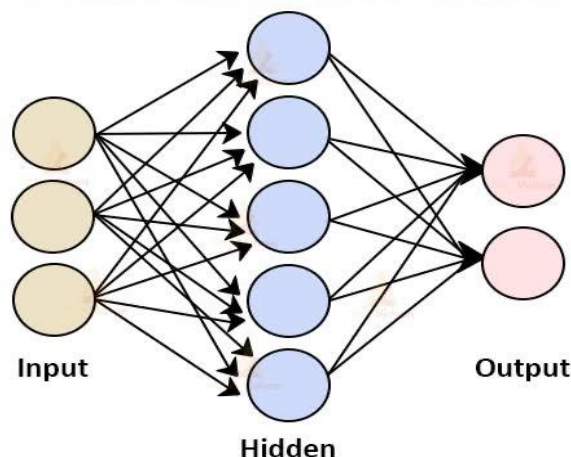


Figure 2: Artificial Neural Network

Evolutionary algorithms(EA) are used to optimize both architecture and internal structure of an ANN parameter. Among all evolutionary algorithms , Differential evolution is best EA and the most powerful one(L. Wang & Li, 2010). It is highly recommended for non-linear objectives. Lahiri and Ganta in 2009 designed a method to incorporate ANN and DE technique together. An algorithm was designed to hold up solid liquid slurry flow(Liu et al., 2010).

II. DE USED IN POLYMERIZATION OF STYRENE

Polymerization of styrene is performed using batch suspension technique(Soriano-Disla et al., 2014). A mathematical model is used as a simulator for styrene polymerization. It contains balance equations for monomer conversion, initiator concentration, distribution moment of radicals and dead polymer and equations that deal with diffused constraints are also featured(Ji et al., 2007). It's difficult to accurately operate and satisfy all such conditions. Therefore input-output models are used for accurate polymerization of Styrene(Sauter et al., 2016).

Initiator concentration and temperature used in polymerization of styrene are 10-55 mol/l and 60°C – 90°C. Reaction time taken in this process was 0-2000 minutes as for lower concentration and lower temperature the reaction time is longer(Coates, 2000).

For styrene polymerization process the model input variables are:

- Io- Initial concentration
- T- Temperature
- t- Reaction time
- x- monomer conversion
- Mn- Numerical average molecular weight.

This technique tends to predict the main properties like molecular mass and reaction characteristics as a function working conditions.

III. OPTIMIZING NEURAL NETWORKS WITH DIFFERENTIAL EVOLUTION:

DE algorithm is simultaneously used to structurally and functionally optimize neural network for styrene polymerization. SADE-NN-2 is the variant used in this polymerization and it is a combination of adaptive DE with ANN's and black propagation(BP). DE is used to perform a global search and BP is used to locally improve the best solution found in each generation. This property of both the algorithms exist only because all DE individuals are ANN(Resconi et al., 2000).

For all the evolutionary algorithms the evolution of population is brought by mutations, recombination and selection steps until a all conditions are matched to stop the process. Firstly By random approach some solution sets prepared . Gaussian distribution is used in this process(G. Wang et al., 2018).

Mutations has a role to play in diversity. Then the mutants are combined with crossover. In DE there are two crossovers to create a trial population which are:



- BINOMIAL- In this crossover each characteristic are copied from one of the parents.
 - EXPONENTIAL- In this crossover block of characteristics are inherited alternatively from parents.
- SADE-NN-2 is a self adaptive method where optimization is done using F and Cr control parameters. Like this the evolution takes place simultaneously so a separate method to optimize is not required. In other methods the optimization takes place layer wise but in SADE-NN-2 the variation is done at neuron level.

DE AND SUPPORT VECTOR MACHINES:

SVM uses small number of parameters which gives it an added advantage. This is done to maintain a balance between training errors and generalization capability. A novel algorithm is combined with DE to perform styrene polymerization. In this process DE acts as an optimizer and SVM models this process differently from SADE-NN-2. The classic method is used for training procedure in SVM machine.

The same DE is used in this procedure which was used in SADE-NN-2 method. So the performance results depend upon the performance of the model and not the performance of optimizer. In this case the population was designed using different list of SVM parameter like

- SVM type (u-SVR and e-SVR)
- Kernel type (linear, polynomial, RBF, and sigmoid.
- Degree (applicable to polynomial kernel only)
- The cost of parameter.

IV. CONCLUSION

In this paper we studied about two methodologies which were developed for radical free polymerization of Styrene.. These methods are ANN and SVM as models and the structural and parameter optimization is carried out by DE and CS. Both ANN and SVM can be used for the process of polymerization and the choice depends upon the user experience. Although we can say that SVM-DE can be a more preferable because of it's accessibility and accuracy in results.

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