International Journal of Innovative Technology and Exploring Engineering (IJITEE)
ISSN: 2278-3075 (Online), Volume-9 Issue-8, June 2020

Realtime Cost and Performance Improved Reservoir Simulator Service using ANN and Cloud Containers

M.V.S Phani Narasimham, Y.V.S Sai Pragathi

Abstract: ***Real time reservoir simulation is growing demand while drilling to find new energy resources. Especially during drilling when the test data differs from actual data due to fault injections. This paper proposes a methodology using modified ANN scheduler using task characteristics and optimal cloud containers. Our methodology optimizes cost and end to end delay to achieve real time reservoir simulations. Realization of the paper is done using azure cloud resources and open porous media (OPM) reservoir simulator code. ANN based scheduling of cloud containers make the simulator energy efficient and scalable. Methodology uses microservice based architecture which gives the advantage of real time modifications, pluggability with minimum validation costs. Patent is demonstrated on 3-phase black oil well reservoirs - Input pod, Grid pod, Solver pods, Upscale pods, Output pods, 3D PODs. ANN scheduler with Ant Colony Optimization (ACO) will classify the input tasks based on task characteristics and schedule the POD containers on the optimal virtual machines (VMs). Proposed architecture is realized using Kubernetes docker containers on Microsoft azure linux VMs.***

Keywords **:** ***Oil & Well Modeling, Microsoft Azure, Kubernetes, Reservoir Simulators, dockers, Load Balancer, Cloud Simulators.***

I. INTRODUCTION

Typical reservoir simulator architecture, consisting of key modules used in reservoir simulation is presented in Fig.1. Velocity modeler builds a flow model using seismic velocities, seismic data, well velocity and structural details. Petrophysical provides interpretation of well data, logs, core, images and photos from different simulation tools. Grid modeler consists of formation of structured, un-structured grids and corner point grids. Fluid flow equation are solved at discrete grid points. Facies modeler helps in finding rock bodies using pattern recognition technologies for improved estimation of hydrocarbon, fracture distribution and reservoir hetero-genocity. Upscale component upscales porosity by averaging, permeability upscaling using facies. 3D viewer consists of visualization of reservoir properties in 3D grids. There is very high demand for real time reservoir simulations especially when drilling new well surrounded by multiple oil wells. Real time reservoir service solves the problems of neighborhood well interactions, regional fluxes and contact movements. The rest of the paper is organized as follows: Related work is discussed in section 2, cloud reference architecture is illustrated in section 3, ANN based real time cloud architecture is summarized in section 4, Evaluation methods and mathematical models are discussed in section 5, simulation results are discussed in section 6.

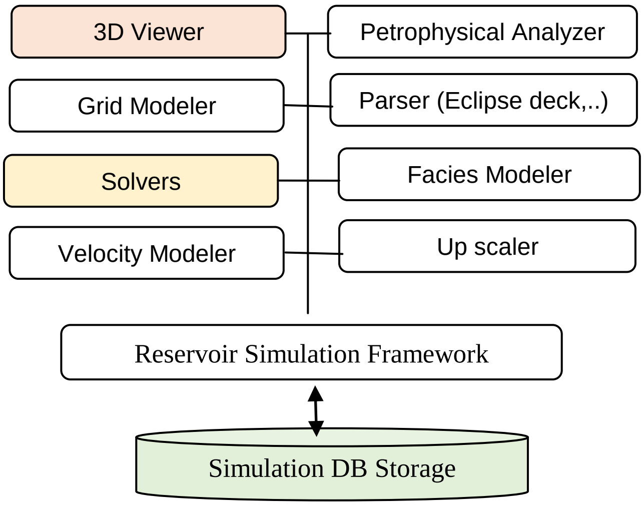

Fig.1 General Reservoir Simulator Architecture

II. LITERATURE REVIEW OF RELATED WORK

Morgan E.E in their paper "Reservoir Simulations in a High Performance cloud computing Environment" discusses cloudifying the industry standard Eclipse Reservoir simulator using Amazon cloud [1]. This paper recommends Amzon High performance cloud computing as low capital investment. M.Th Kotouzal in their paper "A dockerized framework for hierarchical frequency-based document clustering on cloud computing infrastructures" presented dockized hierarchical clustering framework using the usage of topics in the document and multi metrics [2]. S.N. Kayum et.al in their paper "High-Performance Computing Applications Transition to the cloud in the Oil & Gas industry" has proposed hybrid cloud to mitigate the challenges faced by the Oil & Gas industry [3].

Revised Manuscript Received on June 30, 2020.
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Assessment tool was used to analyze the computing parameters a) Application peaks b) Data security c) Capital expense are analyzed. Hybrid cloud model is suggested for spike in compute requirements is handled by the public cloud and routine simulations are run on-premises cloud. S.K. Tesfatsion in their paper "PerfGreen: Performance and Energy Aware Resource Provisioning for Heterogeneous Clouds", presented dynamic tuning of resource management system, designed to improve energy efficiency in a heterogenous cloud environment [4]. A 53% saving of energy is achieved using energy aware scheduler and resource allocator. S.K. Tesfatsion et.al in their paper "A combined frequency scaling and application elasticity approach for energy efficient cloud computing" [5] has achieved 34% energy saving by tuning the number of virtual machines, number of cores and scaling the CPU frequencies. Jyh-Shing, Roger Jang in their paper "ANFIS: Adaptive-Network-Based Fuzzy Inference System" presented the architecture and learning procedure underlying ANFIS, a fuzzy inference system implemented in the framework of adaptive networks [6]. Briefly, ANNs are designed based on simulation of the human brain with the purpose of determining the relationship between outputs and inputs of a system. An ANN is trained with the available experimental data throughout the training step and is employed for estimating the unknown data. Neural networks include, simple synchronous processing components that are known as nodes or neurons located throughout layers. Usually, an artificial neural network has three layers: an output layer, a hidden layer, and an input layer. ANFIS modeling is used to solve the non-linear problems. An adaptive neuro-fuzzy inference system (ANFIS) is a kind of artificial neural network that is based on Takagi–Sugeno fuzzy inference system. It integrates both neural networks and fuzzy logic principles and captures the benefits of both in a single framework [6]. Ghofrane Rehaiem, Hamza Gharsellaoui, Samir Ben Ahmed in their paper "A Neural Networks Based Approach for the Real-Time Scheduling of Reconfigurable Embedded Systems with Minimization of Power Consumption" have used ANN based back propagation technique to model the real time scheduling of tasks in embedded systems to achieve minimum cost [7].

ANN with proper number of input, output and hidden neurons is able to identify and classify complex regions. . S.Agatanovic-kustrin, R. Beresford, "Basic concepts of artificial neural network (ANN) modeling and its application in pharmaceutical research" has applied ANN to find optimal dosage of the drug and analyzing chromatographic data[8]

The most common type of artificial neural networks (ANN) in oil well simulation applications is multi-layer perceptron (MLP) which is trained with aim of a back propagation (BP) approach [9]. M.V.S Phani Narasimham et. al in their paper, "Development of realistic models of oil well by modeling porosity using modified ANFIS technique" have used ANN based neutron porosity model will give reliable static reservoir models for oil well simulation frameworks [10].

Divya Doraya, "A Review Paper on Green Cloud Computing-A New form of Computing". Stresses the importance of green computing by utilizing the available resources in an eco-friendly manner [11]. Alberto Nunez et.al in their paper "iCanCloud: A Flexible and Scalable Cloud Infrastructure Simulator" propose cloud simulator to model cloud based large simulations by varying number and type of virtual machines [12].

III. REAL TIME RESERVOIR SIMULATION METHODOLOGY

T Horvath in their paper, "Dynamic Voltage Scaling in Multitier Web Servers with End-to-End Delay Control" have proved experimentally that dynamic voltage scaling will give power saving in non-trivial scenario. They concluded that optimal savings occur when load balancing uses weighted transformed utilization instead of perfectly balanced [13]. T.Ahmed et.al have discussed advanced reservoir simulation techniques in [14] which gives deep understanding of simulation modules. Existing Reservoir simulation application will be broken into microservices which will be containerized as docker containers. The microservices will use service bus queue to communicate between the containers. The docker containers are deployed to pods which are managed by the Kubernetes cluster.

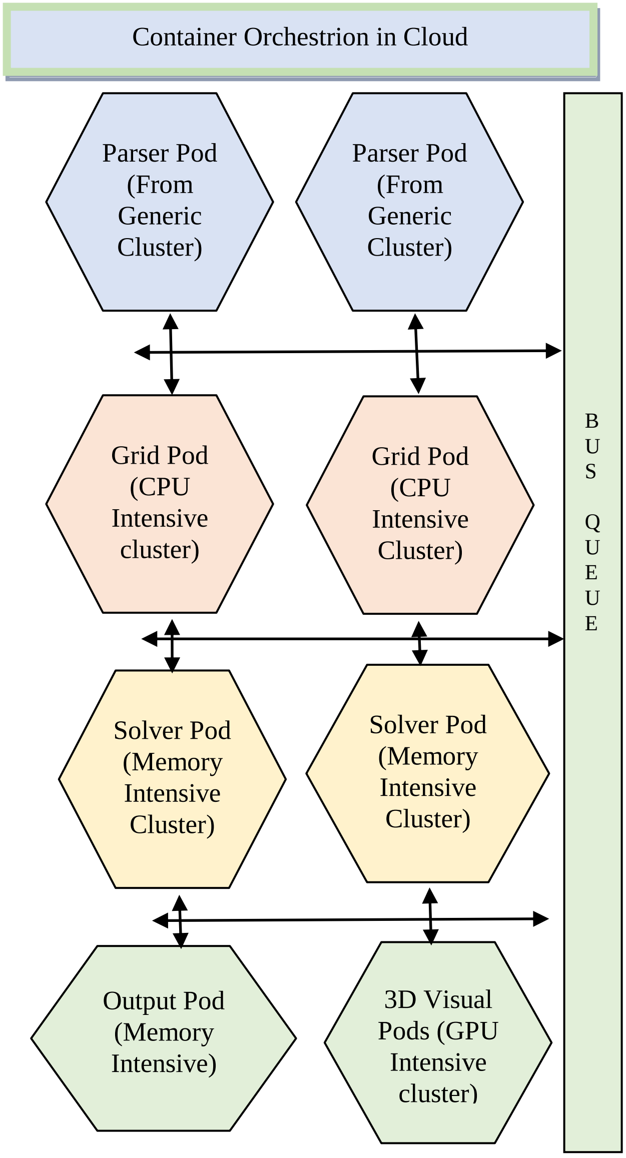

Fig.2 OPM POD Containers in normal workflow.

Bus queue can be azure bus queue or rabbitMQ for exchanging of messages between reservoir containers. Kubernetes Orchestrion can be Azure Kubernetes service or Amazon ECS . The optimal number of containers and pods to achieve real time response will be determined based on optimized cost and end to end delay scheduling scheme. This approach has added advantage as it replaces the heavy weight VMs with docker containers giving more granularity to task scheduling to achieve the real time elastic requirement of modern simulator.

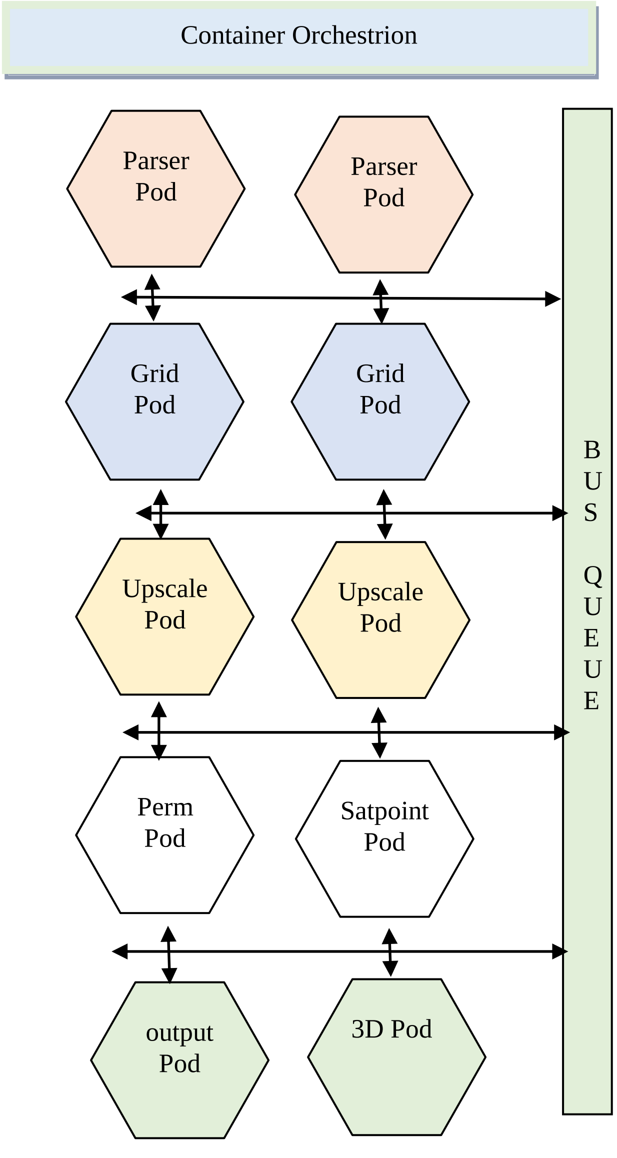

Fig.3 POD Containers in upscale workflow

Upscale workflow of reservoir simulation will have upscale pods which will do the permeability approximation. All the containers are pluggable modules giving the flexibility of easy deployment with new reservoir classification algorithms. Simulator POD can be dune pod or PETsc pod.

IV. MODIFIED READ TIME RESERVOIR TASK SCHEDULER PROCESS

ANN Supervised learning model with various backpropagation algorithms, hybrid algorithms are explored to develop optimal ANN based cloud reference model.

ANN perceptron network with input layer, hidden layer and output layer classifies input reservoir simulation tasks.

Input batch of simulator tasks of a real time scenario are classified based on the task features obtained from the training batches. Reservoir task characteristics in json file are fed to the ANN modeler.

Training batch measures the following VM container characteristics CPU Speed, GPU, Memory Intensive and Generic. The ANN classifier will identify the most suitable containers for execution

Class 1 containers - are CPU intensive.

Class 2 containers - are GPU intensive.

Class 3 containers - are memory intensive.

Class 4 Generic containers.

Ant colony optimizer will find the optimal schedule for execution of the tasks on the containers that will have the minimum timespan and cost for execution. Reducing the cost reduces the power usage and this is validated by the energy consumptions of the Green cloud simulator.

V. MATHEMATICAL MODEL

Modified ANN Back Propagation Mathematical Model

Input task characteristic are input to 4 input perceptron layer followed by two output neurons. The perceptron network weights are tuned using back propagation based on reducing the cost from the training set.

$t = \{ t_1, t_2, t_3, t_4 \}$; is the expected target value set.

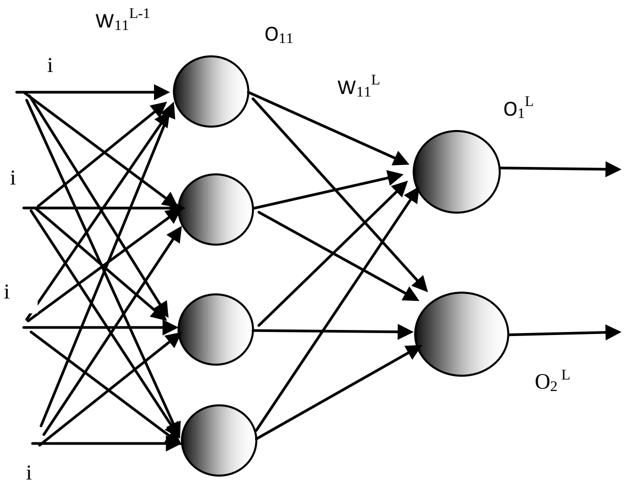

Fig.5 4-input and 4-hidden neurons perceptron network.

Eq.1 gives the cost of the network model using mean square error of output and expected target.

$$C = \Sigma_{j=0}^{K=0,n} (o_{kj} - t_{kj})^2 \text{ -----------------------(Eq. 1)}$$

$$z_j^L = w_{j0}^L o_1^L + w_{j1}^L o_2^L + w_{j2}^L o_3^L + w_{j3}^L o_3^L + b^L \text{ --(Eq.2)}$$

$$o_j^L = f(z_j^L) \text{ -- (Eq.3)}$$

Eq.2 calculates the input to the output neuron of the final layer. Eq.3is the activation function output from input z.

$$\frac{\partial c_0}{\partial w_{jk}^{L}} = \frac{\partial z_j^{L}}{\partial w_{ik}^{L}} \times \frac{\partial o_j^{L}}{\partial z_j^{L}} \times \frac{\partial c_0}{\partial o_j^{L}} \quad \text{-------------------------(Eq. 4)}$$

Eq.4 gives the backpropagation effect of the weights coefficient from the cost which will be tuned using gradient descent of the training set.

Modified ACO Mathematical Model

In ACO the pheromone component η is computed using (1/ (ETC_{ij} + Pod_j + $Cost_j$), Where ETC_{ij} is the expected time to compute task on the Pod, number of $Pods_j$ running in the VM and cost is cost per hour charged for the VMs.

The pheromone of ant k mapping task i to container j is given by

$$\tau_{i,j}^{k} = (1-p)\ \tau_{i,j} + \Sigma_{k=1}^{m}\ \Delta\ \tau_{i,j}^{k} \quad \text{-------------(Eq. 5)}$$

probability of mapping task i to container j is given by

$$P_{i,j}^{ant\ k} = \frac{(\tau_{i,j})^{\alpha}\ (\eta_{I,j})^{\beta}}{\Sigma((\tau_{i,j})^{\alpha}\ (\eta_{I,j})^{\beta})} \quad \text{-----------------(Eq. 6)}$$

β represent the influence factor of heuristic value. Cumulative probability of a task i mapping to the container is calculated. { P_1, P_{1+2}, $P_{1+2+3,\dots}$ }. Random number between 0 to 1 is selected to map the task to container.

VI. SIMULATION

Open porous media reservoir simulator is used as testbed to test the reference architecture. OPM is architected using kubernetes docker containers on Microsoft azure. Training batch of resource tasks is used to measure the makespan of the tasks on CPU intensive, GPU Intensive, Memory Intensive and Generic container VMs.

Relative timespan characteristic of each task is measured using the below formulas.

TCPU = Time Span of the task on CPU intensive VM.

TGPU = Time Span of the task on GPU intensive VM.

TGU = Time Span of the task on Generic VM.

TMI = Time space of the task on Memory Intensive VM.

Relative TimeSpan of CPU

$$RTCPU = 100 * \frac{TCPU}{TCPU+TGPU+TGU+TMI}$$

Relative Timespan of GPU

$$RTGPU = 100 * \frac{TGPU}{TCPU+TGPU+TGU+TMI}$$

Relative Timespan of TGU

$$RTGU = 100 * \frac{TGPU}{TCPU+TGPU+TGU+TMI}$$

Relative Timespan of TMI

$$RTMI = 100 * \frac{TMI}{TCPU+TGPU+TGU+TMI}$$

Relative timespan parameters of the tasks are used as inputs to the ANN models of Perceptron networks trained using back propagation.

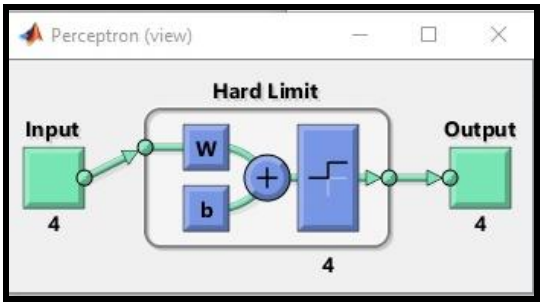

Fig.6 4-Input, 4-Output ANN Perceptron Network.

Input parameters of the task characteristic needed for the real time reservoir simulator service are given as input json file. Input reservoir training data is used to model the ANN classifier at desired rate of 1e-4 and learning rate of 0.1.

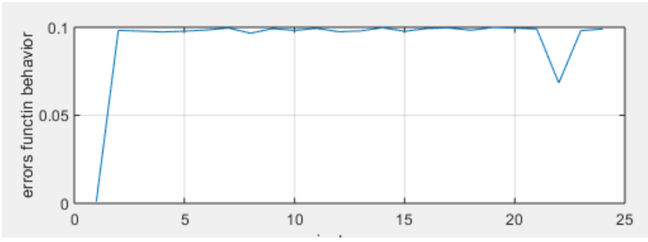

Fig.7 MSE error of output in the final iteration of ANN.

.Net core based docker container images of reservoir architecture described in section 3 are saved in azure private registry. Container VMs are deployed on the azure linux VMs, orchestred using azure kubernetes cluster service. Reservoir tasks are scheduled on the container pods using the modified ANN+ACO schedulers.

VII. CONCLUSION

From the mathematical model and simulation results it is concluded that reference cloud architecture proposed in this paper will give time optimized and cost effective solution using modified ANN and cloud containers for real time reservoir simulation using cloud containers. Integrating improved scheduling algorithms using genetic scheduler will further improve the performance of the reservoir simulator service. The architecture proposed in the paper can be used to determine real time life analysis of building and bridges. Future work will be done to achieve real time reference architecture for game engines in multiplayer scenario.

REFERENCES

1. M. E. Eldred, A. Prangi, A A. Al-Emadi, A. A Ahmad, T. J. OReilly, N. Barghouti, M. Oil, “Reservoir Simulations in a High Performance Cloud Computing Environment”, Society of Petroleum Engineers, SPE-167877-MS, 2014.
2. M. Th. Kotouza1, F. E. Psomopoulos and P. A. Mitkas1, “A dockerized framework for hierarchical frequency-based document clustering on cloud computing infrastructures”, Journal of cloud computing, 2020, 9:2.
3. S N. Kayum, M. Rogowski, “High Performance Computing Applications Transition to the Cloud in the Oil & Gas Industry”, Sept 2019, IEEE High Performance Extreme Computing Conference, At Waltham, USA.

4. S.K. Tesfatsion, E. Wadbro and J.Tordsson “PerfGreen: Performance and Energy Aware Resource Provisioning for Heterogenous Clouds”, 3-7 Sept 2018, IEEE International Conference on Autonomic Computing.
5. S.K. Tesfatsion, E. Wadbro and J.Tordsson “A combined frequency scaling and application elasticity approach for energy efficient cloud computing”, Vol.4, Issue 4, Dec 2014, pg 205-214, Sustainable Computing: Informatics and Systems.
6. Jyh-Shing Roger Jang, “ANFIS:Adaptive-Network-Based Fuzzy Inference System”, IEEE Transactions on Systems Man and Cybernetics, June 1993.
7. Ghofrane Rehaiem, Hamza Gharsellaoui, Samir Ben Ahmed, "A Neural Networks Based Approach for the Real-Time Scheduling of Reconfigurable Embedded Systems with Minimization of Power Consumption.", ICIS Conference, At Okayama, Japan, June 2016, 10.1109/ICIS.2016.7550777.
8. S. Agantonovic-kustrin, R. Beresford, “Basic concepts of artificial neural network (ANN) modeling and its application in pharmaceutical research”, Journal of Pharmaceutical and Biomedical Analysis”, 22(2000) 717-727.
9. Mohammad A Ahmadi, “Comparison of machine learning methods for estimating permeability and porosity of oil reservoirs via petrophysical logs”, ScienceDirect, Petroleum, 14 June 2018, https://www.sciencedirect.com/science/article/pii/S2405656117301633.
10. M.V.S Phani Narasimham, Dr. Y.V.S Sai Pragathi, “Development of realistic models of oil well by modeling porosity using modified ANFIS technique”, International Journal on Computer Science and Engineering, Vol.11, No.07, July 2019.
11. Divya Doraya, “A Review Paper on Green Cloud Computing-A New form of Computing”, International Journal of Advanced Research in Computer Science and Software Engineering, Vol.5, Issue 7, July 2015 ISSN: 2277 128X.
12. Alberto Nunez, Jose L.Vázquez-Poletti, Agustin C. Caminero, Gabriel G. Castañé, Jesus Carretero, Ignacio M. Llorente, “iCanCloud: A Flexible and Scalable Cloud Infrastructure Simulator”, J Grid Computing (2012) 10:185–209.
13. Tibor Horvath, Tarek Abdelzaher, Kevin Skadron, "Dynamic Voltage Scaling in Multitier Web Servers with End-to-End Delay Control" IEEE Transactions on Computers, Vol. 56, No. 4, April 2007.
14. Tarek Ahmed, Paul D. McKinney, Advanced Reservoir Engineering", Book, ISBN 978-0-7506-7733-2, 2005, https://www.sciencedirect.com/book/9780750677332/advanced-reservoir-engineering.

ACKNOWLEDGMENT

Thankful to Stanley college of Engineering & Technology for women, Principal Dr. Satya Prasad Lanka for encouraging to pursue new research areas. Grateful to Dr. S.P Setty, Professor Andhra University, in providing valuable insights on modelling. Thankful to Wipro management, Ganesh Bukka, Ramakrishna Kashikar, Ganeshan Kailasam, Product Engineering Services, Wipro Technologies in encouraging and helping with relevant environment for working on this paper.

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