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Comparative Study of Multi Neurons & Multi Layers Artificial Neural Network in Knowledge Management

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Abstract

Knowledge transfer impacts the firm's performance and its ability to respond to changing landscape. Various knowledge management models capture the process of knowledge transfer. ANN can help simulate and predict the knowledge transfer outcome. However, ANN has various algorithms. This study discusses and develops a model based on the Artificial Neural Network (ANN) framework to transfer knowledge. Virtual reality based simulated animation study is explored as preferred knowledge transfer methodology. ANN offers multiple algorithms to train the model. Levenberg Marquardt (LM) is found to be one of most effective ANN algorithms with accurate and faster output. We further explore LM ANN algorithm and compare the same for efficacy and ability to train the Knowledge model with different combinations of Layers and Neurons. Further the study explores application of LM algorithm with layer-Neurons combinations for most optimum methodology for transfer of knowledge applications. Thus, the most optimum methodology to transfer knowledge is explored using ANN.

Keywords : Knowledge Transfer, Artificial Neural Network, Neurons, ANN layers

1. Introduction:

We studied Knowledge management literature with keywords such as "knowledge transfer" or "KM", "Manufacturing". We also covered papers in the area of "Artificial Neural Networks" and "Virtual Reality", "Simulation" with keywords "ANN" or "Virtual Reality" or "VR" or "Simulation". We studied for literature covering five ANN algorithms "Levenberg Marquardt", "Gradient descent with momentum and adaptive learning rate backpropagation", "Random order incremental training with learning functions", "Sequential order incremental training with learning functions". "Conjugate gradient backpropagation with Fletcher-Reeves updates". The literature was studied from Scopus and Science Direct. Study done at top education institute and industry set up shows that the best method of knowledge transfer from amongst hands on lab, animated videos, lab video and lecture mode is animated videos (Singh et al, 2020). ANN has been widely used in Industry. It has been used in Ontology-based neural network for patent knowledge management in design collaboration (Trappey et al, 2013), electrical grids power system (Singh et al, 2019), Knowledge Warehousing (Nemati et al, 2002) etc . Knowledge outcome would improve the firm's output and profitability. This can be done using ANN. However, there are various algorithms for ANN training of a model and further each algorithm works differently with different layers and Neurons.

2. Theoretical Background

2.1 Knowledge management in manufacturing

Over time, the textile sector has been globally represented and characterized by increasingly demanding customers, thus Lean Manufacturing model, bolstered by knowledge management to guarantee its viability over time with simulation using the Arena software reduced non-compliances with companies' production schedule up to 80% (Cortez et al, 2020).

The ability for workers to connect in real-time with an expert system to get the assistance they might need while also having access to rich, animated step-by-step instructions in one, a unified interface has the potential to transform the way people work especially in small and medium-sized (SME) companies to close the knowledge gap between experienced workers and new employees (Driate et al, 2019). The voluntary use of private devices by employees without the formal approval of the IT department, commonly termed Shadow IT, is an increasingly widespread phenomenon. The rise of Shadow IT in a manufacturing context which takes place in a self-organized way without knowledge of the management may lead to Knowledge drain (Richter et al, 2019).

The influence on knowledge sharing among workers within Polish manufacturing enterprises using the Customer Relationship Management (CRM) systems (Patalas-Maliszewska & Kłos, 2019) and Additive Manufacturing Technology and Knowledge Management (Godina et al, 2019), requires innovative solutions.

A study of SMEs in the Manufacturing Sector across the UK and Thailand from 36 manufacturing companies from the UK and Thailand shows knowledge management is influenced by geographic and cultural differences (Tikakul & Thomson ,2018). Design for additive manufacturing (DfAM) application of KM (Wang et al, 2018) and stages and examples of processing production knowledge for building knowledge management system (KMS) using decision rules describing production knowledge. (Paszek ,2018). The analysis of the process of knowledge management at the operational level in the manufacturing enterprise of high-tech sector, which produces parts using additive Manufacturing (AM) (Zimmer & Madeja ,2018).

Applying the Unified Theory of Acceptance and Use of Technology (UTAUT) in organizations. Factors which affect KMS usage were performance expectancy, effort expectancy, social influence, facilitating conditions, behavioral intention and behavior usage (Kamprom et al, 2017). The effect of cognitive skills, technical skills, and social skills of the knowledge workers on the knowledge management system (including information technology, human resource, and sharing behavior) and the decision-making process of manufacturing SMEs in Malaysia (Razali et al, 2017).

Artificial Neural Networks are computational techniques that belong to the field of Machine Learning. There are various algorithms for optimization of ANN and Levenberg–Marquardt is one of most effective one.

2.2 Levenberg–Marquardt algorithm (LMA)

The Levenberg–Marquardt algorithm (LMA) (Levenberg, 1944; Marquardt, 1964) is a hybrid technique that uses both Gauss–Newton and steepest descent approaches to converge to an optimal solution. Levenberg-Marquardt algorithm is one of the most efficient training algorithms for neural network modelling, having the updating rule, the Jacobian matrix needs to be computed and a training process should be designed. Considering a single neuron (designated j) with p inputs in a hidden layer of a network with a total number of r neurons, $y_{j,i}$ means the ith input of neuron j, weighted by $w^h_{j,i}$ while y_j is the output of neuron j:
In the Levenberg-Marquardt method, a damping factor λ is typically used in the training process which is adjusted at each iteration until the sum of squared errors decreases. Thus, the algorithm solves equation 1 (Levenberg, 1944):

$$w_{k+1}=w_k-(J_k^TJ_k + \lambda I)^{-1}J_ke_k \quad (1)$$

3. Research Methodology:

In this study we designed an experiment among 450 subjects who have different aspirations and motivation levels, are from related and unrelated backgrounds, have different interpretation and learning abilities and also have different skill sets etc. Training is imparted through virtual reality augmented reality animated video mode. Pre and post tests were conducted based on four specific KPI's viz Safety, Quality, Productivity and Cost. Output of these results were captured into an ANN model and system trained to learn from these inputs. LM algorithm is coded and different layer and Neurons combinations are studied. Simulated environment allowed feeling at height and doing the actual work on VR platform in an industry set up.

4. Experimental Study:

The experimental study was conducted at an industry in India and 450 subjects were studied. The results were of pre and post test were compiled on four KPI's as above. . The experiments conducted were in the area of storage height working operation using equipment. This process is difficult to understand and involves a variety of skill sets due to the processing intricacies involved. It also has safety risks, affects the quality, and impacts overall productivity and cost. The staff chosen was a group with 10 years of education followed by basic technical study of two years. All participants were semi-skilled or skilled with two years of technical education.

5. Experiment Methodology

5.1 Demographic Mapping

The age group was set into 4 groups as below

Table 1 Age vs. Experience of experiment subjects

Age (years)	18-20	20-25	25-30	30-40
Nos	175	202	51	22
Experience (years)	**Nil**	**Upto 1 year**	**1-5 years**	**5-10 years**
Nos	32	73	272	73

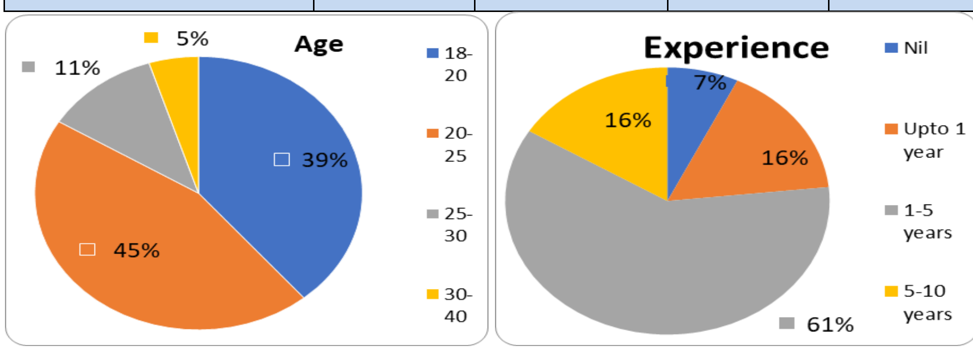


Fig. 1 : Age and experience of the participants

5.2 Formulation of the questionnaire

The questionnaires of pre-as well as post tests were based on 4 test attributes viz Safety, Productivity, Quality and Cost and each of these parameters were indexed based on a detailed study conducted**.** The first part contained questions to know details about the members like their age, experience and whether they were aware of the process involved of working with target equipment at height. It also contained an assessment of overall experience in industry. The second part of the questionnaire or test contained questions about the target process with specific focus on the equipment to work at height.

5.3 Experimental setup

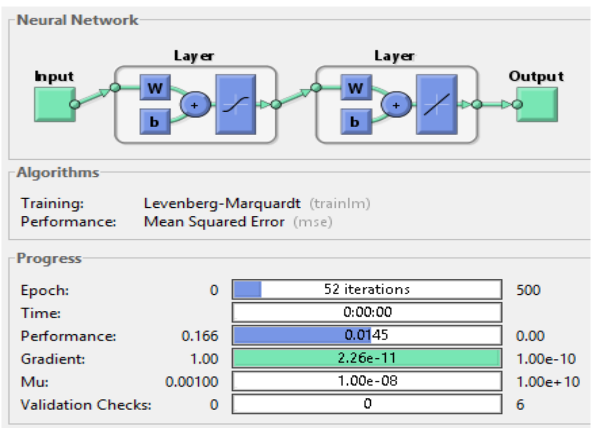
All the 450 participants were assessed before and after the virtual reality animated video augmented reality simulation session. After obtaining the answers from all the participants through the questionnaire tests the results were fed into Artificial Neural Network (ANN) model using MATLAB using version 7.10.0.499

5.4 ANN Training using MATLAB and Results

Pre-test and Post test data is normalized for safety, quality, productivity and cost. Thereafter we do coding using Levenberg Marquardt algorithm as base for the four different KPI's and with different combination of layers and neurons for each KPI. The algorithm is run of MATLAB and model is trained.

5.5 Safety KRA Bilayer LM ANN Optimization with 5 Neurons

The figure 2 shows a bilayer model for the ANN tool for the Safety KRA with 5 Neurons for which the individual errors in predicting the outcomes from the realistic post-test recordings are shown in figure 3. It is targeted in this case that the network mean squared error must go below 10^{-2} which happens in case of the safety dataset at the end of the 52nd training epoch out of the 11 training cycles made out of the training dataset of 450. This error behavior for the productivity KRA is plotted in Figure 4 . The added total errors of the training of the test sets come out to be 6.5151. Further, Fig 4 shows the best training performance achieved and Fig. 6 shows the behavior of the network properties like gradient, mu and validation checks. The R value for the productivity KRA in this case also indicates high value of correlation between the input and the target respectively



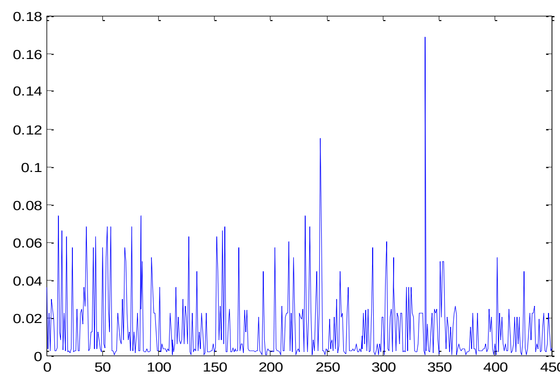
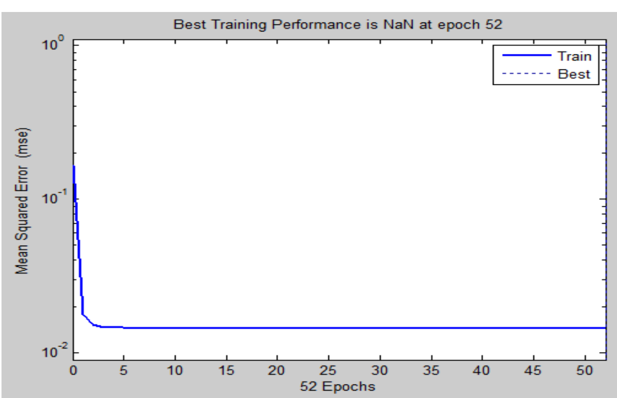


Fig. 2 : Bilayer ANN Training using LM for Safety; Fig. 3 : Safety Error Plot for 450 subjects using LM



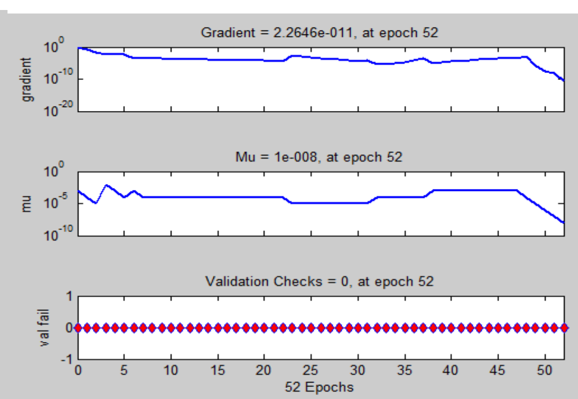


Fig. 4: Performance Plot for Safety KRA; Fig. 5 : Gradient, Mu and Validation for Safety KRA

Similar MATLAB based programming was done with different layers and Neurons for other Key Performance indicators (KPI's) viz. Quality, productivity and cost

6. Results, Discussion and Conclusion

ANN Optimisation using different methods are tabulated below

Table 2: Comparison of ANN Optimisation using LM with layers- Neurons Combination

S.No	ANN LM No of layers	No of Neurons	Sum of Error-Safety	Sum of Error-Quality	Sum of Error-Productivity	Sum of Error-Cost	Performance, Training State and Remarks
1	Two layers	5 Neurons	6.5151	6.9474	5.5541	7.1560	Productivity and Quality not trained even after 5000 iterations
2	Two layers	6 Neurons	--	--	5.5297	--	Trained
3	Two layers	7 Neurons	--	--	5.5297	--	Trained
4	Two layers	8 Neurons	--	--	5.5297	--	Trained
5	Two layers	10 Neurons	--	6.9421	5.5297	--	Quality- 6 iterations, Productivity- 6 iterations
6	Three layers	5 Neurons	6.5151	6.9421	5.5297	8.7153	Trained
7	Four Layers	5 Neurons	6.5423 7.7076 (681 i)	6.9421	7.4178	8.7153	Safety not trained after 100 iterations, 681 iterations
8	Four layers	10 Neurons	6.5151	--	--	--	Trained
9	Five layers	5 Neurons	6.5151	6.9421	5.5297	7.1560	Trained
10	Ten layers	5 Neurons	6.5151	6.9421	5.5297	7.1560	Trained

Interpretation is based on an overall sum of errors with all four parameters embedded as a weightage and thus combination of the TWO no. of layers and 5 no. of neuron layers works out to yield minimum error as per Table 2. Its observed from Safety KPI that there is no improvement in overall error with changing layers however at 4 layers system does not get trained. With increased neurons the system can still be trained as seen in Safety 4 layer and also in case of productivity 2 layers and thus our finding is that over training of the network means creating error instability which is detrimental to the prediction of a value.

The table 3 show comparison of processing time and iterations required . We could deduce that including too much of complexity like 5 layers 5 neurons per layer is overkilling the error and the network starts showing up stability issues. Further we can conclude that use of ANN does not mean that we leave everything to the machine and thus leads to overtraining issues. It is evident from the case of 4 layers 5 neurons where the parameter safety is not getting trained even after 100 iterations. Perhaps in the next 5-layer 5 neuron case the error instability in prediction is low and the error is not propagating between the fourth and fifth layer easily. Thus, LM achieves the purpose of training the model for most optimum knowledge transfer and we further identify and understand that same needs to be done with best combination of neurons and layers.

Table 3: Comparison of ANN Optimisation on Processing and Iterations

S.No	ANN LM No of layers	No of Neurons	Safety-Iterations/ Processing Time	Quality-Iterations/ Processing Time	Productivity-Iterations / Processing Time	Cost-Iterations/ Processing Time	Performance, Training State and Remarks
1	Two layers	5 Neurons	52/ 0 sec	5000/ 36 Sec	5000/ 35 sec	59/ 0 sec	Productivity and Quality not trained even after 5000 iterations
2	Two layers	6 Neurons	--	--	92/0 sec	--	Trained
3	Two layers	7 Neurons	--	--	61/0 sec	--	Trained
4	Two layers	8 Neurons	--	--	7/0 sec	--	Trained
5	Two layers	10 Neurons	--	6 /0 sec	6/0 sec	--	
6	Three layers	5 Neurons	86/ 1 sec	344/ 3 sec	45/ 0 sec	183/ 1 sec	Trained
7	Four Layers	5 Neurons	100/ 1 sec 681/ 7 sec	27/ 0 sec	5/ 0 sec	10/ 0 sec	Safety not trained after 100 iterations, 681 iterations
8	Four layers	10 Neurons	13/ 0 sec	--	--	--	Trained
9	Five layers	5 Neurons	8/ 0 sec	12/ 0 sec	67/ 1 sec	15/ 0 sec	Trained
10	Ten layers	5 Neurons	6/ 0 sec	12/ 0 sec	16/ 0 sec	18/ 0 sec	Trained

7. Limitations of Study and Future Research

The limitations of the study are that we have compared different layers and neurons combination with Levenberg Marquardt algorithm while other algorithms may behave differently. Further we have considered output from a single industry in a specific demographic location. Additionally, the impact of pre-skills and gender has not been considered.

Thus, it offers future research opportunities in the area of science, technology and literature learning and knowledge transfer. It can attempt to predict the language knowledge transfer where respective augmented reality animation videos are made for these languages. It would also help in international travel through use of augmented reality and how the learning from the same can be used in present context when pandemic situation has limited the international travel across the world. Another interesting study could be in the area of disability and how the methodology can assist in knowledge transfer in people with special needs. Finally, we would like to explore the application in the area of Alzheimer and how our knowledge ANN can assist in memory retention and retrieval in such cases.

Bibliography

1. Cortez, C., Di-Laura, N., Viacava, G., Raymundo, C., & Dominguez, F. (2020). Lean Manufacturing Model Based on Knowledge Management to Increase Compliance in the Production Process in Peruvian SMEs in the Textile Garment Sector. *Advances in Intelligent Systems and Computing*, 103-111.

2. Driate, A., Minoufekr, M., & Plapper, P. (2019). Knowledge management for manufacturing SMEs using industrial IoT Proceedings. *15th Annual International Conference on Distributed Computing in Sensor Systems, DCOSS*, 355-361.

3. Godina, R., Ferreira, I., Brás, I., Espadinha-Cruz, P., & Matos, F. (2019). Knowledge management and additive manufacturing technology: A literature review. *Proceedings of the European Conference on Knowledge Management, ECKM*, 398-404.

4. Kamprom, K., Lertworaprachaya, Y., & Lertwongsatien, C. (2017). Factors influencing the use of knowledge management systems: A case study of the manufacturing and service sectors in Thailand. *International Journal of Applied Business and Economic Research*, 3(2), 413-431.

5. Levenberg, K. (1944). A method for the solution of certain non-linear problems in least squares. *Quarterly of Applied Mathematics, 2*(2), 164-168.

6. Marquardt, D. W. (1963). An Algorithm for Least-Squares Estimation of Nonlinear Parameters. *Journal of the Society for Industrial and Applied Mathematics, 11*(2), 431-441.

7. Nemati, H. R., David, S. M., Lakshmi, I. S., & Richard, H. T. (2002). Knowledge warehouse: an architectural integration of knowledge management, decision support, artificial intelligence and data warehousing. *Decision Support Systems, 33*, 143-161.

8. Paszek, A. (2018). Processing of production knowledge for building knowledge management systems (KMS) in manufacturing companies. *Proceedings of the 32nd International Business Information Management Association Conference, IBIMA 2018 - Vision 2020: Sustainable Economic Development and Application of Innovation Management from Regional expansion to Global Growth*, 4494-4503.

9. Patalas-Maliszewska, J., & Kłos, S. (2017). A Study on Improving the Effectiveness of a Manufacturing Company in the Context of Knowledge Management. *Research Results Foundations of Management*, 149-160.

10. Razali, N. B., Mamun, A. A., Zakaria, M. N., Malarvizhi, C. A., & Nawi, N. B. (2017). Decision centric knowledge management system for manufacturing SMEs: A conceptual framework. *Advanced Science Letters*, 2938-2941.

11. Richter, S., Waizenegger, L., Steinhueser, M., & Richter, A. (2019). Knowledge management in the dark: The role of shadow IT in practices in manufacturing. *International Journal of Knowledge Management*, 1-19.

12. Singh, A., Badoni, M., & Singh, B. (2014). Application of least means square algorithm to shunt compensator: An experimental investigation. *2014 IEEE International Conference on Power Electronics, Drives and Energy Systems (PEDES), Mumbai,*, 1-6.

13. Singh, S., Bhattacharya, S., & Saddikuti, V. (2020). An application of AHP and fuzzy AHP with sensitivity analysis for selecting the right process to impart knowledge. *Int. J. Knowledge Management Studies, 11*(3), 258-277.

14. Tikakul, C. T., & Thomson, A. (2018). International lessons in knowledge management: A study of western & eastern manufacturing SMEs. *Electronic Journal of Knowledge Management*, 113-130.

15. Trappey, A. J., Charles, V. T., Tzu-An, C., & Yi-Hsuan, H. (2013). Ontology-based neural network for patent knowledge management in design collaboration. *International Journal of Production Research, 51*(7), 1992-2005.

16. Wang Y., B. R. (2018). A Knowledge Management System to Support Design for Additive Manufacturing Using Bayesian Networks Journal of Mechanical Design. *Transactions of the ASME*.

17. Zimmer, J., & Madeja, M. (2018). Operational knowledge management in a manufacturing enterprise in the high-tech sector - Case study. *Proceedings of the 32nd International Business Information Management Association Conference, IBIMA 2018 - Vision 2020: Sustainable Economic Development and Application of Innovation Management from Regional expansion to Global Growth*, 2456-2469.