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Application of Artificial Neural Network into Manufacturing Processes

Ernest Mnkandla[1], Ndala Mhlongo[2]
mnkane@unisa.ac.za
[1,2] School of Computing, University of South Africa, Johannesburg, South Africa

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Abstract

The neural network model is an advanced and effective tool aims at simulating the manufacturing operations. An important number of researchers have utilized artificial neural network (ANN) to optimising multiple response metrics in manufacturing applications. In the majority of situations, the use of ANN enables the prediction of the mechanical and physical properties of manufacturing goods based on provided technical data. To this end, the deployment of ANN in manufacturing sector is tremendously significant in terms of cost and material resource savings. Thus, Artificial neural network as a key component regarding the optimization of the manufacturing processes.

A. Introduction

Manufacturing is "a collection of linked functions and operations concerning the industrial sectors, including product development, equipment specifications, scheduling, assembly, certification, maintenance, and marketing of the goods." Computer systems were widely utilized in contemporary production. Computers were originally utilized regarding the direct control of clusters of industrial machinery in the mid-1960s. The notion of flexible manufacturing systems (FMS) was proposed in the 1970s. An FMS is defined as "a computer-controlled collection of semi-independent workstations connected by autonomous material-handling systems [1]." These types of systems are able of autonomously generating a wide variety of goods. They are currently extensively utilized in production. Presently, computer-aided manufacturing systems have evolved to the point that computer integrated manufacturing (CIM) systems are spreading rapidly around the world. A CIM platform is created when the design objectives incorporate the utilization of computer system to create a merged stream of production processes, built on a merged data stream that connects all organizational activities [2]. The next step, it is becoming obvious, seems to be that of smart production environment. The mechanisms within this phase "might well be identified by their capacity in solving problems without performing a comprehensive, overt algorithm for every optimization procedure or without knowing all the details, mathematical relationships, and models in perfect order and comprehensive structure necessary to find a predetermined response [4]." Due to the rising complexity and overload of decision-making in a technologically advanced system setting, artificial intelligence (AI) is frequently used to help human work. “Artificial intelligence is an awful reference for an inadequately system that, in the long term, may be the single most critical and ubiquitous component of genuine computer-integrated manufacturing (CIM) [5].” Expert systems based on knowledge were the most prominent AI method in the 1980s. There has been a surge in interest in using artificial neural networks to be manufacturing in recent years. Artificial neural networks are a subset of artificial intelligence that have the ability to improve quality of the product, decrease a manufacturing system's reaction time, increase system resilience, and enhance its cognition [6]. Since the late 1980s, dozens of articles on neural network applications in manufacturing have been published. The majority of them are dispersed throughout several fields and publications. This makes it extremely difficult to obtain all of the information required for manufacturers to use artificial neural networks. A study that will assist researchers and practitioners in the application of this new technology is greatly sought. Thus, this study used Artificial neural network as a key component regarding the optimization of the manufacturing processes.

B. Research Method

The application of artificial intelligence, more precisely artificial neural networks, has enabled significant advancements in manufacturing industry. Yet, the majority of artificial intelligence applications in the manufacturing sector have focused on expert system, with less emphasis devoted to neural network. The most relevant features of ANN model are:

• Self-adaptive response, which enables the prediction to react to different environmental conditions, thereby improving the networks' potential to understand and anticipate; and

• Parallel computing design, which has a massive effect on a wide variety of disciplines and applications, ranging from speaking and natural language computation to image analysis and concerns in biology.

As a result, they may be extremely beneficial in today's modern computer-merged production and in intelligent manufacturing, as defined by the Industrial revolution 4.0 concept. Presently, the production process is evolving at a breakneck pace, becoming more complex as a result of changing consumer needs and a shorter product life cycle. This necessitates the development of production methods that are easily adaptable to such shifts. Artificial neural network is a strong technology that can be deployed to tackle this issue in this setting. Additionally, ANN is frequently utilized in process tracking and monitoring systems. The only way to ensure the quality of a process is to conduct in-process monitoring using appropriate measures. To guarantee a process's excellent performance, the following technological guidelines should be followed [11]:

• Identifying process characteristic changes;

• Estimating product quality changes;

• Correcting any process activities as a consequence of any abnormalities discovered during the comparison of obtained and intended quality.

These procedures should be carried out with minimum operator monitoring and help, if feasible in an autonomous way. Additionally, all operations should have unique characteristics such as data storage, decision-making, learning, and integration. It should be emphasized that the majority of industrial processes are governed by a large number of variable factors, giving such systems a random, complicated, and unpredictable nature.

This may be due to the fact that they are frequently subjected to parameter changes and are exposed to external disturbance and noises. Additionally, there is frequently a high degree of interplay among factors, making it impossible to accurately describe both the ultimate quality of the items and the components that impact it. Due to these features, the quality of the product frequently changes, affecting its consistency and reducing the product's yield. As a result, not all changes that takes place in manufacturing environments can be easily noticed by an individual, the utilisation of neural network for process monitoring and control has garnered considerable interest in recent years. Similarly, it has been demonstrated that the application of artificial intelligence may resolve the aforementioned issues [18]. In the future, research activities in this area will be intensified and will result in the creation of genuinely smart manufacturing technologies able to produce items without the aid or observation of operators [19]. The figure 1 categorizes the functions required for the integration of artificial neural network into industrial processes and highlights recent advancements in manufacturing application areas. In manufacturing, practical applications include process modeling, monitoring and control, diagnosis, scheduling, and forecasting.

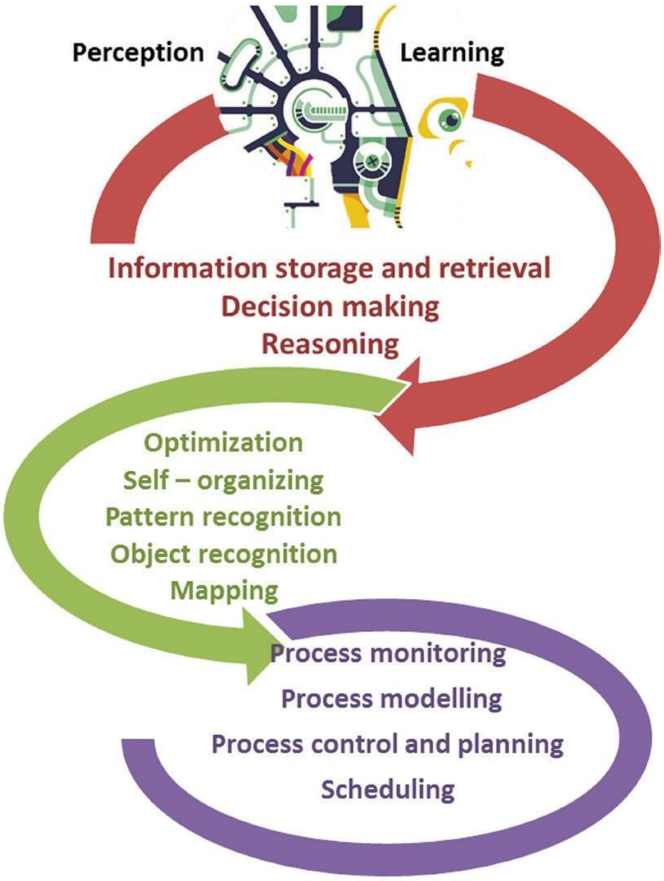

Figure 1. Artificial Neural Network's function and industrial applications

Artificial neural network for tracking, regulating, and optimizing metalworking operations. Experiments were conducted to train the network and establish quantitative correlations between process variables and the mechanical characteristics of welded joints. Finally, an assessment of the process's time-cost parameters is done utilizing the Artificial neural network model's control in order to determine the costs and advantages of the prediction model used.

A. Manufacturing Applications

Numerous manufacturing processes are intricate and demanding because of multiple external disruptions and countless fluctuations in processing parameters. As a result, it is often not feasible to establish a link between the product's quality and the process's input factors. As a consequence, there is demand in integrating artificial intelligence into manufacturing processes for the purposes of data storage, learning, reasoning, and decision making. These technologies are capable of adapting to changing environments and are capable of truly automating activities. The neural network may be used to monitor and forecast many factors in a wide variety of industrial fields in order to resolve issues related to manufacturing system design, process planning, and operational decision making. Manufacturing data, like operation sequences and batch sizes; and different process plans were all taken into account in their approach to solving the extended component family formation issue. Numerous authors also emphasize the method's adaptability and ability to be seamlessly integrated with other production operations. Several significant uses of artificial intelligence to certain manufacturing processes are detailed here, culled from the literature.

• Process of injection molding

Injection moulding techniques have dynamic features, since the melting heats, the cylinder's motion, the retention tension, and the stresses that enables the polymers to stream into the modeling chamber all fluctuate in a challenging way. The processes themselves are immensely difficult, time-varying, multidimensional, and unpredictable. This intricacy complicates the relationship between input operational parameters and output quality characteristics like geometrical correctness and geometrical area quality. Such techniques have been integrated and optimised using artificial intelligence, namely the multi-layer perceptron network, which has been shown to be the most popular network for modeling process dynamics and predicting component quality. [3–9].

• Welding procedures utilizing a gas metal arc

The stream of the electricity is created in gas metal arc (GMA) welding procedures [10–12] because of an arc welder generated between the disposable conductive material and the welding material, as seen in Figure 2.

A wire feeding apparatus supplies both the filler metal and the consumable electrode instantaneously. The considerably large height to breadth proportion of the liquid weld stream contributes to the welds' quality. Thus, monitoring and controlling welding design and heat flow, which are directly connected to the creation of the molten material, are critical for layer thickness and back bead width. Heats were determined in this manner using non - intrusive techniques. Thermal temperature sensing technologies and current researchers have emphasized that the ANN multi-layer perceptron can successfully detect and regulate all surface temperature information.

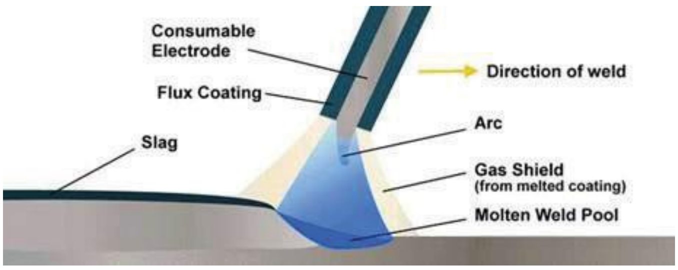

Figure2. Characteristics of the GMA welding process [19]

• Process of arc welding

The intricacy of the connection between the different parameters and the welding quality is a prevalent element in all industrial applications, but especially in metal forming processes. For such grounds, the literature review reveals, via several noteworthy studies, the application of Artificial neural networks for process quality management and surveillance. The ANN inputs information for this sort of welding process are typically the temperature coefficient, the weld volt, the welder's electricity, and the blistering velocity. Again, the multilayer perceptron was the most often used ANN in this situation [10, 13–21]. Their usage was shown to be extremely effective in predicting weld flaws, geometrical parameters such as bead width, head level, and penetrating.

• Machining operations

To provide proper quality management throughout all manufacturing technologies, it is critical to monitor certain data like the milling cutter status, oscillations, tensions, and heat collected throughout real-time manufacturing. To maximize this sort of metal cutting condition monitoring, several researchers have documented in the literature the utilisation of Artificial neural networks to categorize the condition of wear resistance, anticipate durability, and identify tool breakdown in an on-line way using the aforementioned process data. Common detectors include dynamometers for tools, acoustic emission detectors, inertial measurement units, and thermocouples. The multilayer perceptron and Kohonen networks are frequently used in this procedure. [22–23].

• Manufacturing techniques for semiconductors

Due to the intricacy of plasma etch methods used in merged system production, ANNs are used to monitor and manage the process. Artificial intelligence has capabilities in this field that are not possible with conventional open loop controls. Where multi - layer perceptron neural network, which are the most often utilized for this procedure, were deployed. The Neural network models make advantage of essential process factors like electricity, gas flow rate, dc bias voltage, and ignition timing. In this sector, effective usage of networks enables real-time monitoring and calculation of quality factors such as etching thickness and etching time. [14–16].

B. Artificial Neural Network design and implementation

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Artificial neural networks were developed as a tool for simulating the organic learning process occurring in the brain. Neural networks provide a strong method for predicting an actual value following a learning activity using a sample set [19]. ANNs are based on a notion that combines a collection of computational methods with a theoretical foundation in order to forecast the unknown output parameter in a variety of processes. Generally, neural networks are used to subordinate knowledge to observations or when the data or activity is sufficiently complicated that an ideal solution cannot be identified in a fair amount of time. It is difficult to compare the use of neural networks versus other prediction techniques (e.g., statistical methods or a support vector machine) in each application field and even for each task because, in contrast to conventional computational techniques, they are capable of solving nonlinear and ill-defined problems. Numerous variables contribute to this tendency, the most of which are connected to the predictability of the predictions, the durability and adaptability of the findings, as well as the neural process's learning ability. In many situations, if the ANNs are built appropriately, the forecasts made by them increase considerably as the dataset used as training subset grows larger. Consistently, during the last few years, the use of ANNs in a wide variety of commercial sectors has expanded rapidly, as has the number of publications in high-level journals.

A 'good' ANN, from an engineering standpoint, is built on models capable of simulating the properties of natural systems, such as cognitive skills, adaptability, resilience, learning capacity, and fault tolerance. At this level of analysis, the structure and behavior of the ANN needed investigation at several hierarchical levels of organization, including neurons, layers, synapses, and cognition-behavior functions. The ANNs are interested in a variety of applications, including astronomy, mathematics, physics, chemistry, earth and space sciences, life and medical sciences, and engineering. In recent years, the United States of America and the European Union have approved several programs for the study of the human brain. In each of these situations, the ANN has been included into thesis research projects in various forms and at various levels. The interdisciplinarity conferred by the system used for dataset analysis and the computational complexity necessary for data elaboration enables the creation and simulation of systems capable of meeting the demands and difficulties of the actual world. Japan launched a project dubbed Brain Mapping by Integrated Neuro-technologies for Disease Studies (Brain/ MINDS) in 2014 [21], which will combine modern biomedical technologies and neural network systems. In Australia, a separate initiative with an initial investment of around $250 million over ten years has been established with the objective of building the world's first prosthetic brain [14] based on the multilayer perceptron (MLP) technology. Additionally, China has launched another ambitious effort (Brainnetome) [18] with the objective of simulating the brain networks responsible for perception, memory, emotion, and related diseases, as well as developing sophisticated technology to accomplish these goals.

• Designing the ANN

An artificial neural network is a type of computer model that develops a connectivity among process variables and output variables. Weight values, which act as changeable factors, are used to connect artificial neurons. There are large number of applications and paradigms that are either general-purpose or replicate features or neural frameworks, however there is no single simulation software that is presently employed by the entire community, as certain strategies are more appropriate than others for the research task at hand. Additionally, the majority of simulators can fully exploit their computing abilities based on the characteristics of the computing devices on which they are installed [6]. Such relationship is determined by the network's core characteristics, which govern how input and outcome are coupled [9]. The network is comprised of an input layer, an output layer, and a number of hidden layers. The network's essential characteristics are as follows:

• Database partitioning, which specifies the portion of input to be used for training, testing, and verification purposes during the ANN development process;

• Architectural style that governs how layers and neurons are connected;

• A learning algorithm is used to calculate the weights of the connections between neurons.

The next parts discuss the data separation technique, the architectural design methodology, and the method for identifying the learning algorithm.

• Dataset splitting

The suitable data partitioning can be approached as an issue of statistical sampling. Thus, different classical sample approaches may be used to divide the data into three groups based for training, validation, and testing of Artificial neural networks. The most often used techniques include simple random sampling (SRS), trial-and-error methods, systematic sampling, and convenience sampling. The dividing approach trying to address the SRS's high degree of variability by repeatedly doing large sample in order to decrease the ANN's mean square error (MSE) [17]. This approach is extremely demanding and has a high computational cost. For ANN training, a fraction (usually up to 60% of the experimental data consisting of input/output pairs) is employed. Network nodes are connected to weight vectors, which are the connections between neurons, at this phase. They are updated on a regular basis in order to minimize the difference between experimental outcomes and related predictions. A sample (usually up to 20% of the data obtained) is used to validate the ANN [15]. The evaluation sets, in particular, enable the identification of the underlying trend in the training data sample. A sample (usually up to 20% of the experimental findings) is used to evaluate the ANN's forecasting reliability throughout the learning phase. To address the fitting problem, which happens when the network memorizes the training sets and therefore does not learn to make generalisations to new situations, various approaches are recommended: reducing the amount of hidden layers, improving the 'quality' of the training subset used, introducing a few data redundancy into the training set, and so on. In [8], an effective technique for model creation is given that utilizes principal component analysis to identify a low-dimension ANN learning matrix (PCA).

- Network architectures

An artificial neural network is a type of computational model that builds relationships between process variables and output units. Weight values, which act as adjustable variables, are used to connect artificial neurons. This relationship is contingent upon the network's core aspects, which determine the manner in which input and output are coupled [3]. The network is composed of an input layer, an output layer, and a number of hidden layers (Figure 4). The basic steps in the advancement of an ANN are as follows:

- Set of data partitioning, which recognises the set of information to be used for training, testing, and validation;
- Architectural style, which specifies the relationships among layers and neurons; and
- Training algorithm, which specifies the weights of the connections between neurons.
- Artificial neural networks can be classified into two types based on their correlation sequence (architecture):
- Feed-forward networks (e.g., single-layer perceptron, multilayer perceptron, radial basis function nets), in which no network connections act as loops; and
- Repetitive networks, in which distinct circuits take place in network connections (e.g., competitive networks, Kohonen's networks).

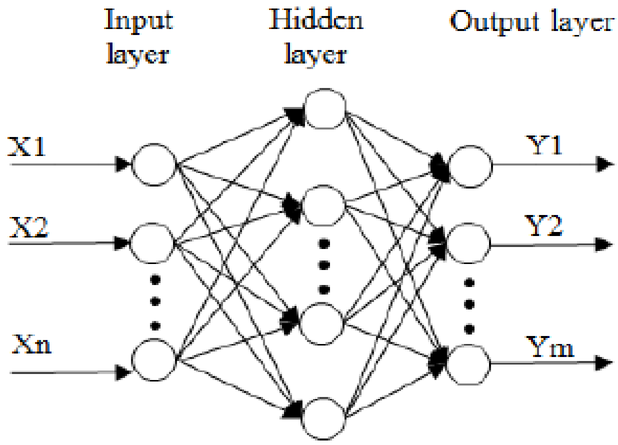

Figure 3. Basic structure of Artificial Neural Network [16]

A "static" network is one that generates just one set of output values instead of a sequence from an input signal, and it functioned under memory-less situation. This implies that its reaction to an input is independent of the prior network state. When fresh input is added into a "recurrent network," the network goes into a new state, rather than staying in the same state. The multilayer perceptron neural network (feed-forward network) is the most often used network design today since the result of one-layer feeds into the input of the next. It is thus possible to determine the activation level that, when combined with a transfer function, yields the desired output. To simplify things, the network may be seen as an input-output model with weights and thresholds (biases) serving as free parameters. Designing an artificial neural network (ANN) architecture begins with determining the kind of structure (feed-forward or recurrent) and the number of hidden layers and neurons in each layer. Having a large number of neurons can contribute to memorization of the training sets, however this results in less generalization capacity of the ANN [12]. Conversely, a deficiency in neurons impairs the ability to correctly classify patterns. Many software programs let you use a "trial-and-error" technique to figure out how many hidden layers and neurons (for each layer) are ideal. In this example, software iteratively tests several designs and provides a "fitness bar" based on the inverse of the mean absolute error (MAE) computed on the testing set for each one. When it comes to architecture, the higher the "fitness bar," the better the design.

C. Result and Discussion

A. Operations in a feed mill

[18] pointed out that there are several sorts of feed producing plants, each with its own distinct qualities. The features of the feed mill, the configuration of the components, and the overall structure all contribute to the variance in feed mills. Nevertheless, the feed production process is divided into eight distinct processes. The feed mill under consideration in this case has a vertical architecture, with materials being moved from top to bottom during operations. This method was

adapted from [18] since it is argued that it makes excellent use of gravity, which minimizes needless transportation expenses.

• Raw ingredient receiving

Usually, feed mills acquire materials through railway and lorry. Wheat and soya are received separately through railroad and lorry. Secondary raw materials are transported to storage bins using large lorries and pneumatically shifted.

• Raw ingredient distribution and storage

Screw conveyor is generally used in feed mills as it offers many advantages over other types of conveyors. Screw conveyors not only transport the materials very fast, but also additional functionality of accurate measurement of the ingredients during the transfer process. This leads to significant savings in the production time in the long run. If the raw materials are greater than 60 kg, bins are used for the purpose of storage. Otherwise, bins are not used.

• Grinding

Grinding is the process of reducing irregularly formed raw material particles to tiny powders. The benefit of grinding is that the finer particles generated during this stage aid in the proper mixing of the components, resulting in the creation of pellets with precise formulation. Grinding mills are often housed in a separate apartment within the mill building, beneath whole grain storage bins. The most often used type of milling equipment is the hammer mill.

• Batching

To create customized feed mixtures, some components should be delivered to the blender in samples. Batch processing is the term used to describe this procedure. This is a critical activity prior to mixing and demands that all raw ingredients are batched in precise amounts in order to create high-quality feed. This is accomplished through the use of screw conveyors with excellent measurement control and scale hoppers positioned above the mixers. Additionally, bulk bag and hand dump stations are utilized to include items into the feed mix. Proper venting between the mixer and scale hoppers is required to provide a constant flow of materials to the mixers.

• Mixing

In a feed processing facility, mixing is a critical activity. The space between the mixer's body and the blades must be kept as narrow as possible to ensure consistent mixing. Another aspect of this procedure to consider is the mixing time. 4–6 minute mixing periods are most frequently employed to achieve uniform mixing. In our investigation, mixing times are irrelevant because they are already optimum. Mash is stored until it is required for mixing operations. Ribbon mixers are available in a variety of sizes and are frequently utilized. They work at a pace of around 40 revolutions per minute. The result of the mixing process is mash. The size of the mash feed has a major impact on the feed's quality and production time.

• Conditioning

Conditioning and pelleting are key processes in feed production. The previous stage's mixture is transferred to the conditioning. The mash is combined with water at a specific temperature for a specified amount of time in the conditioning. This technique maximizes the moisture content of the final meal.

Otherwise, the pelleted feed may have a low moisture level, reducing its nutritional value. Additionally, the rate of pellet manufacturing decreases fast.

• Pelleting

Pelleting is a method to enhance the thickness of feed, which benefits storage, transportation, and ability to handle. Additionally, the increase in feed efficiency and palatability is substantial. Rotating rollers press the conditioned feed materials through die holes in this procedure. Additionally, the feeder rate or feed rate should be regulated at an optimal level to enable constant granule manufacturing at a quicker pace. To avoid wastes, the pellets are cooled to bring the pellet temperature to a safe level. Additionally, they are inspected to eliminate broken pellets from the mix before packing.

• Final product storage and load out

Bulk feed supplies are kept in bins, while packaged feed products are transported to the warehouse for distribution. Production capacity, available space, and facility usage all have an influence on the kind and design of warehouses. In general, load out systems employ reversible screw conveyors and weigh lorry systems. Appropriate clearance and platforms must be given in both systems to provide servicing.

D. Methodology

A. Training function

As argued by [18] the training algorithm modifies the weights associated with each arc in the neural network. Ten alternative back propagation algorithm algorithms are evaluated to determine the optimum method for changing weights effectively to enhance the performance measure and resulting in optimized weights. Ten alternative training algorithms are evaluated using a variety of performance metrics in order to choose the one that best fits the provided data.

B. Performance measures

The different performance measures considered are root mean squared error (RMSE), coefficient of determination (R2), The amount of iterations, the time spent on each cycle, and the maximum number of iterations performed during each cycle. On the basis of mistakes, the first two performance metrics are used to compare neural network parameters. The remaining performance metrics are compute-based.. The equations for RMSE and R2 are presented in Eqs. (1) and (2).

Table 1. Weights and biases for optimal ANN configurations

IW(s,k)	-1.183	0.362	--1.041	-0.002		
	-1.32	-0.619	2.334	1.339		
	-0.535	1.447	0.897	-0.009		
	-1.771	-0.468	1.541	1.087		
	-1.147	-1.136	-1.494	0.467		
	-0.723	1.787	-1.777	-0.022		
	-1.883	-0.417	-1.168	-0.992		
	1.678	-1.093	0.615	1.391		
	1.223	-0.851	-1.615	-1.177		
	-0.659	-1.584	-2.221	0.618		

W_0(s)	0.592	0.184	0.634	-0.148	-0.953	0.178
b1(s)	-2.579	-1.947	1.394	-0.838	-0.287	-0.287
b2	0					

Table 2. Optimal values for input variables in order to maximize throughput.

Input considerations	Yield consideration
Mash feed size = 1.6 mm	Production rate = 13.82 tons/h
Steam temperature = 82 ^{0}C	
Feed rate = 17 tons/hour	
Conditioning time = 34s	

(2)

where n is the average amount of observations, xi;net is the network's expected output values, xi;act is the experimentally determined output value and xavg is the mean of experimentally determined values.

C. Number of layers and neurons

The amount of layers and neurons must be maintained to maximize the network's computational effectiveness and failure mitigation. One concealed layer and one output layer are fixed in this scenario. Additionally, the amount of neurons is set to ten. Thus, there is no change in this problem owing to the number of layers and neurons. If somehow the amount of layers is doubled, a proportional rate of 10 neurons occurs, significantly increasing the network's computing cost. Thus, the constant number of layers and neurons reduces the complexity of the issue to some amount.

D. Transfer function

Transfer functions are input–output functions that are compared to see which combination of transfer functions produces the greatest outcomes. Transfer functions exist between the hidden layer and the output layer. In this example, the combinations log sigmoid – pure linear and tan sigmoid – pure linear are examined. The arcs linking the input–hidden and hidden–output layers include weights. Weights are adjusted to minimize error throughout all iterations. Bias is the neuron's extra input, which improves the neuron's characteristics but adds complexity. The weights and values of the transfer functions can be changed during a neural network's learning process. This is not feasible, and it would be preferable if only one of the variables were changed. As a result, a bias neuron is used to resolve this issue. Only if the transfer function is fixed to a certain value may the weights be altered. The bias neuron contributes to the fixation of the transfer function on a particular value.

E. Discussion

Despite the presence of several variables, each algorithm does not match the provided data. For instance, a training algorithm may exhibit reduced inaccuracy for a certain set of data. The same training algorithm, on the other hand, might not even be precise and accurate for another database. This brings us to the point of comparing the various elements based on training and transfer characteristics, while keeping the amount of layers and neurons constant.

A. Comparison of neural network parameters

Ten distinct training algorithms are examined for two distinct combinations of transfer function (hidden–output layer) – log sigmoid – pure linear and tan sigmoid – pure linear. All training functions have their epochs set to 1000 and their iterations set to 5. Two sets of transfer functions and training functions are compared, and it is determined that the combination of the Polak–Ribiere conjugate gradient backpropagation training function with the log sigmoid – pure linear transfer function produced the best results with the lowest root mean square error and highest positive R2 at a reasonable computation time. These parameters are used to simulate and determine the optimal parameter values for the highest possible production rate.

B. Prediction of optimum parameters

Sample data is used to determine the input variable levels that result in the highest production rate. The solution's accuracy improves as the number of levels of each of these input variables rises. Thus, by correctly controlling the input process variables, a maximum output rate of 13.82 tons/h may be obtained in a feed mill. This would result in considerable cost savings due to the enhanced quality and lower energy use. It should be emphasized, however, that the findings obtained are recipe-specific and should be interpreted with caution.

Table 3. Data regarding the input parameters

S. No	Mash feed size (mm)	Steam temperature (degrees)	Feed rate (tons/h)	Conditioning time (s)	Production rate (tons/h)
	6	82	17.5	34	13.4
	6	83	18	34	13
	6	62	6	33	5.6
	6	83	17.5	34	14
	6	82	17.5	32	14.2
	6	82	18	33	13
	6	83	18	33	14.4
	6	83	18	34	12.9
	6	82	18	32	13.3
	6	62	6	32	4.8
	6	83	18.5	34	14.7
	6	83	18.5	33	13
	6	83	18.5	33	14.2

	6	62	7	34	5
	6	83	18.5	33	13.2
	4	83	9.5	34	7.8
	4	83	9	34	8
	4	62	6	32	4.9
	4	82	9	34	7
	4	83	9	32	6
	4	83	9	34	6
	4	83	9	32	7
	4	82	9	32	7
	4	82	9	34	7
	4	83	9	34	7
	4	83	9	33	7.4
	4	82	9	33	7
	4	50	5.5	34	4.3
	4	82	10.7	33	8.9
	4	83	10.9	34	9
	1.6	67	15.2	34	4.8
	1.6	82	15.4	32	12.7
	1.6	82	15.3	32	13
	1.6	82	15.2	32	12.8
	1.6	82	15.2	34	13.4
	1.6	62	6	32	5
	1.6	82	15	33	11.5
	1.6	82	15	33	11.3
	1.6	62	6	33	4.7
	1.6	82	15	34	12.3
	1.6	62	6	34	5.3

	1.6	84	15	34	13.5
	1.6	84	14.5	34	13.8
	1.6	85	14.3	34	13.2
	1.6	62	5.5	34	4.3

F. Conclusion

Optimizing process parameters for a single recipe in feed production is a positive step toward increasing the productivity of feed operations. The prediction of production rate using neural networks for a given recipe serves as a valuable guideline for information exchange between upstream and downstream members of the animal feed supply chain, assisting in cost reduction and improved performance. Similarly, the study examines the advantages and disadvantages of multiple period planning and its economic implications. Thus, inventory management is a critical management issue that demonstrates sufficient potential in the feed supply chain. Additionally, the scope of the current problem might be broadened by taking various objectives into account and connecting it with other difficulties in the animal feed supply chain. The production rate settings might be synced and optimized in conjunction with the inventory in order to fulfil customer demand and minimize material and financial losses.

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