Research Article

Advanced approach Using Neural Network for Intelligent Automated Production System

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Article History: Received: 10 January 2021; Revised: 12 February 2021; Accepted: 27 March 2021; Published online: 28 April 2021

Abstract: The use of cutting-edge tooling and processes is regarded as an important component in bridging the gap between design and output. The most significant advantage of a fully automated computer-aided planning approach has been Intelligent Automated Planning System (IPS) To investigate how artificial neural networks can be used to assist IAPS in solving problems. A collection of strategies suitable for all applications is defined here, as well as how far they are from a potential implementation of a universal IAPS algorithm. Intelligent development with advanced LSTM neural network algorithms and automation

Keywords : Neural Network, Intelligent Automated Production System

I. INTRODUCTION

Today, Production system design (PSD) seems to be a more extensive procedure, with several different models to-be-validated iterations. This technique has a lot of space for automation in it. It is on the opposing sides, but PSD itself represents an artistic method and idea, which is difficult to formalise (due to conceptual complexity) As a result, it

Seem to be the realm of academics and are largely unappreciated by the general public. PSD development must often react to changes in product and project design in the early stages. Analyses have also shown that 80 percent of the time is expended on ineffective functions such as data gathering, data analysis, and preparation. About 20% of the time spent on the mechanism is spent on the individual PSD. Anyone may improvise at any time; the more critical issue is: What is improvising appropriate? According to researchers, a high degree of process automation and original planning is inherent in activities like this [6], so production automation reduces designers' workload, allowing them to focus on value-added tasks. For high-level process performance, artificial intelligence (AI) is becoming increasingly relevant in car manufacturing. Hagemann and Stark [5] used various approaches in previous studies on intelligent device development issues. However, the same study found that data are very important in the market world so you can't be sure your assumptions and priorities are the same from one process to the next.

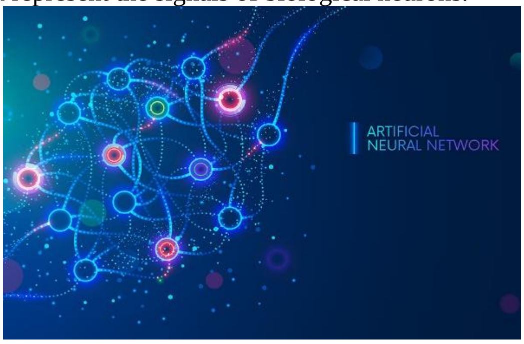
True, however BIW (Body-in-White) is seldom consistent, right, total, and error-free.This study introduces an LSTM (Long Short Term Memory) with Neural network technology that combines all uses machine learning to adapt machine setups to evolving data and modifies such configurations on-the-the-fly. If the current production process has continued to morph into an increasingly Smart Automated System, so has the volume of data, no matter what kind of data, become significantly larger, which, particularly because of Internet of Things (IoT) technologies and communication technologies. cloud providers have recently enabled the use of more precise and flexible forecasts for demand and resource allocation while using the capabilities of cloud centres for long-term equipment storage and maintenance In the other side, there are concerns with broad data transmission and poor efficiency in the networks. One new computer paradigm, known as "edge computing," has been put to use in many instances to address cloud constraints. When response time, expense, safety, and battery life are all factors to consider, edge computing has the ability to do more than just address these issues. It may also be used to spot production defects. For many decades, the two study disparities have overshadowed existing studies. Furthermore, knowledge on mechanical/vibration signals is often added to pipeline signal prediction, and how to implement energy consumption information is still in the early stages of exploration. Energy evidence derived from previous measurements were now interpreted using experimental processes. Real-time energy monitoring poses a difficulty because real-time data is challenging to extract and interpret. Several openings in separated workspaces must be covered using edge anomaly detection and energy-efficient techniques. The methodology relies on two significant contributions: 1) Anomalies help recognise innovation in the timely implementation of innovative concepts 2) Edge computation is used to determine the precise solution to supply anomalies that the long-term memory network considers, and it is combined with Long Short Term Memory (LSTM).

M. Metzner, et al[1] Benchmark a commercial AOI (Automated Optical Inspection) framework for an adaptive methodology that uses convolutional neural networks with custom completely linked layers based on a pre-trained VGG-16 algorithm. With optimised labelled data from the current AOI scheme, supervised learning is used for each static area of interest.

O. Protalinskiy, et al [2] The balanced scorecard and simulation planning and algorithmic decision support systems proposed
D. Lavro, et al [3] describes the function of the whole model, and identifies specific process parameters that make up the model's flow. GRU network teaching was hired.
E. Vitenburg et al [4] To increase performance, it is suggested to use a decision framework and an artificial intelligence system. The authors built a highly creative and efficient project selection algorithm based on an intelligent method of decision support model using the selection process of a neural network.
D. A. Poleshchenko, et al [5] This ANN uses the multiplying loop characteristics of the object, the functional interdependence of raw materials and disruptions, and functional relationships between input and output.
K. Schmidt et al.[6] demonstrated. When it comes to 2D-grayscale videos, one may successfully train deep learning networks to do specific tasks,
A. V. Milov, et al [7] work to enhance the level of regulation on this technological process, as well as reduce the collateral and non-standard errors associated with it.
K. Dmitri, et a[8] 'The precision of preparation is a challenging job that is based on estimation methods. This paper presents a comparison of regressive and neural network models for solving the issue of everyday power usage forecasting.

ARTIFICIAL NEURAL NETWORK

Neural networks are a branch of machine learning and are central to deep learning algorithms, which are also known as artificial neural networks (ANNs) or simulated neural networks (SNNs). Its name and structure are inspired by the human brain and represent the signals of biological neurons.



Artificial neural networks (ANNs) include the node layers, which include one or more hidden layers, the input layer, and the output layer. Each node connects to another node, or artificial neuron has a corresponding weight and threshold. If a node's output is above the threshold value defined, the node is enabled and the data is forwarded to the next network layer. If not, no data will be transmitted to the next network layer.

III. PROPOSED METHODOLOGY

It is a hybrid system since it combines both statistical methods and neural networks. During the planning and model construction phases, a regression algorithm is applied to application setups, whereas a clustering methodology is used in development. The construction of a vector is an essential step for each assembly system and station's function. Categorizing processes and workstations based on their properties creates a group. A shift in the properties selected would have an impact on the structure of the vectors themselves. For example, process approaches are classified by form (welding vs. brazing), length of line, and number of joints. Using a similar approach, assembly methodology, different assembly stations are classified by properties such as the number of components they include and the assembly technique: (due to privacy only a fraction of all relevant properties are mentioned). The regression algorithm scans to see if there are those that can be identified before deciding which assembly processes and stations can go with which assembly processes. The second direction is taken in the primary algorithm, which implements neural networks. Unlike mathematical methods, neural networks are concerned with technical and creative knowledge and provide a clear relation between stages. The neural network's hidden layers connect the processes and terminals. Any training method that operates on a training algorithm queries between the input and output layers to find the best direction. Once educated, the AI will begin to "recognise" related components (e.g. manufacturing resources). Getting this information broadens the system's configuration capability. Algorithms generate new factories by testing suitable assembly methods rather than comparing them to pre-existing ones.

Neural Network Intelligent Production Automation

To compete with other industries, the production chain would need to react to the arrival of robotics. In order to deal with predictive analytics, every manufacturer must be willing to utilise machine learning. Since machine learning has been slow to permeate in automotive and manufacturing facilities, it is yet to be shown that it is important to their respective industries. Today's manufacturers are unable to keep up with sudden changes in consumer tastes for customization and product continuity, making it difficult to reprogram or retool production

processes. As a result, machine learning plays an important role in assisting manufacturers. The machine learning system will optimise processes and maintain supply chains on track by reading and interpreting equipment results. Several well-known businesses have successfully utilised numerous machine learning frameworks in engineering and manufacturing facilities, culminating in industry achievements. There are a couple of these manufacturing facilities, one of which uses neural networks and IoT systems to unify design, growth, sourcing, distribution, production, and logistics.
These findings show the adaptability of the LSTM network, since this form of RNN is capable of detecting long-term dependencies without the need for gradient descent plus backpropagation. RNNs have been shown to relate previous information to the current task, but they perform poorly when confronted with long-term dependencies [17]. When there are long-term dependencies in the results, the corresponding information which be stored well away from the current time phase. LSTM-based networks can be deemed a real and solid solution to the long-term prediction problem in this respect since they have the ability to track the amount of information that passes through 'gates' in a single cell. As a result, LSTMs are well suited for DNN architectures in which several LSTM layers and other types of layers may be connected, and are thus used as a key component of the prediction scheme in this paper. Let's start with the basic univariate process, which is used for benchmarking and serves as the basis for the subsequent models. Furthermore, it is important to investigate the sequence samples are relevant to the prediction task in a time series forecasting questionnaire. Picking samples by embedding the sequence is an important approach in this regard. S = S[n], n > 0 is the scalar time series to be calculated. Assume that the current sample at n and all previous samples are established, and that the predicted sample is S[n + k], where k > 0. In a univariate system, this prediction problem can be interpreted as a regression problem using past samples of the only time series under analysis. There are two forms of input data to consider in this situation. The first implies that eS[n + k] is obtained by determining the parameters of a regression model using the so-called "embedding process," under which the input vector of the regression model is based on previous samples of the time series:

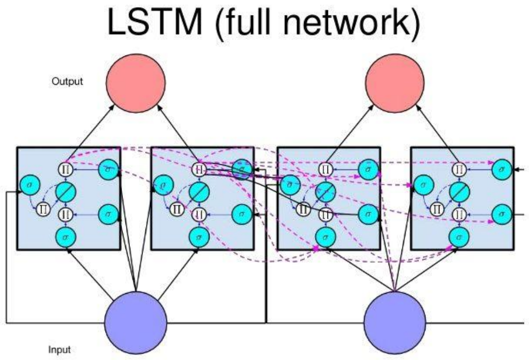


Figure 1 Neural Network for Intelligent Automated Production System

Secondary hypothesise: The univariate approach obtains an estimated value by utilising the current sample as a scalar parameter. The regression model is developed using a multi-layered DNN (stacked LSTM for learning, normalisation, and so on) with one or more dropout layers. Figure 1 depicts one simple network, while Figure 2 depicts another: The first figure depicts the simplest single-input embedding network, while the second depicts a multivariate network of several inputs. There are many layers in this style, including: The LSTM receives the time series as input and outputs the sample; the FC layer binds the LSTM's H hidden states to the predicted value.

Industrial automation 2.0: Immediate positives for manufacturing Industry

Improved production volume: Enhanced usage of machine learning and analytics would allow manufacturing to maximise process efficiency. To minimise raw material costs while preserving product quality, programmes that help predict supply chain yield reduction are given. Effective data collection would result in fewer rework and better efficiency to a greater degree of continuity and operational stability. Prediction-based production capacity is needed for long-term sustainable and profitable yield. What machine learning technologies enable schedule optimization, saving the consumer time, enabling operators to be more efficient, and improving our tracking of supply chain performance?
As part of the asset management approach, the AI software provides real-time enterprise analytics, lifecycle process monitoring, automation, collaboration reviews, and project monitoring.
When Finance is trying to ruin the competition, Tech is looking to gain. Another problem with multi-industry data optimization is that several agencies are not expected to cooperate on it. The data-driven methodology lends itself well to production and logistics management. It reflects a deeper understanding of production workflows, cost information, on-shoring execution, product optimization, and delivering projects on time while fulfilling consumer expectations for less capital.

The electrical Smart of databases and programmes on a single server allows businesses to glean additional details from enterprise processes and equipment knowledge for both repairs and maintenance. This streamlined architecture makes communication between Intelligent System agents, on-site support personnel, and travelling experts easier for integrated service management. We have an outstanding example of the productivity increases achieved by IoT services when paired with Microsoft Azure.

Use an air thermometer more often and faster to get a good understanding of the temperature of the air inside a building. It specifically helps to improve system performance and process efficiency by connecting sensors to production machinery using machine learning analytics. The strength of the liquid, as well as the temperature and other operational parameters such as oil pressure, are examples of operating parameters." These parameters make it easy to spot vulnerabilities and bottlenecks.

Finding new and innovative ways to improve or maximize product or service efficiency is a huge challenge for any manufacturing line. It also uses statistical machine learning to evaluate the factors affecting the output of industrial products, especially for companies with high volume manufacturing operations. This segment demonstrates the tech prototype's modular form. The program modules have several tasks and are connected by data interfaces, as seen in Figure 2.

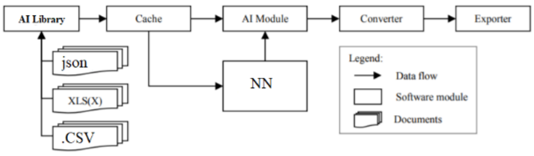


Figure 2: NN based production module

As previously stated, the NN module generates specifications for the output unit in a machine-only readable format. The transfer module decodes the configuration data and optimizes the components of stations that have the correct library IDs. The software is still unaware of the necessary layout of the desired AML file for the production system's setup. The exporter, the final module in the general program algorithm, transforms the output system's configuration information into a pre-existing NN structure. Finally, the configuration is saved as a NN file.

IV. CONCLUSION

Such Neural Network methods are critical to today's industry's strong productivity. Meanwhile, these tactics dispel misconceptions and boost employee morale. For quite some time, the theory of artificial intelligence in manufacturing has been around. Having said that, there are no comprehensive and sufficient support services available to assist in the development of production processes. This is the research gap that we are attempting to fill in this paper. Neural Networks has a revolutionary artificial intelligence architecture that was created to help in the early stages of growth while planning out all of the PS configurations. These issues, such as missing connectivity or incorrect data points, have also been addressed using a hybrid approach. Future studies will seek to determine algorithm capability, as well as research and data quality. Data processing from a digital twin, such as a Neural Network, would be streamlined or at least partly aided as part of our research system's exploration and pilot production plan.

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