BOTTLENECK IDENTIFICATION AND PREDICTION IN A MULTI JOB MANUFACTURING PLANT

JINISH VARGHESE[1], Dr. JAYASREE N[2]

[1]Student, Department of Production Engineering, GEC Thrissur, Kerala, India
[2]Associate Professor, Department of Production Engineering, GEC Thrissur, Kerala, India

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Abstract - *Bottleneck is a junction in a production system which cause a largest effect on slowing down or stopping the entire system. Consequences of bottleneck in production are possible stalls in production, supply overstock and machinery getting damaged. The predicting the bottleneck will reduce the probability of system performance degradation due to random machine failure. Objective of the paper is to study the bottlenecks including detection, prediction them in a multi job manufacturing plant. A multi job manufacturing company model is designed using plant simulation and data related to blockage time and starvation time has been generated from different product mix cases of the same model to analyze the bottleneck for the designed model. Using neural network data is predicted for identification of bottleneck. Identification of bottleneck is carried on both predicted data and simulated data. Bottleneck machine obtained from the predicted and simulated data is compared using confusion matrix. Prediction data accuracy is calculated using RMSE (Root Mean Square Error) and MAPE (Mean Absolut Percentage Error). The practical implications of these results are that shop-floor production and maintenance teams can be forewarned, before a production run, about bottleneck locations, thus forming a prescriptive approach. This approach will enhance the understanding of bottleneck behavior in production systems and allow data-driven decision making to manage bottlenecks proactively.*

Key Words*: *bottleneck, identification, prediction, neural network, turning point

1.INTRODUCTION

A congestion point in a production system or in an assembly line that occurs when workload arrive too quickly for the production system process to handle is termed as bottleneck. Identifying bottlenecks is critically important for improving efficiency in the production line because it allows operations management to determine on which area where accumulation occurs. In an ideal condition, the production progress follows the original schedule, and jobs are processed as the planned routes. Due to various stochastic disturbances, the bottleneck is formed in manufacturing systems and delay will be caused in the original schedule, which delays the regular production progress and order delivery.

A process can experience primary bottleneck, secondary and tertiary bottlenecks. It is important for proposed method find out the primary bottleneck. If secondary or tertiary bottleneck is detected, then solution proposed to reduce/eliminate the bottleneck will be pointless. Bottleneck can be static and dynamic in nature. In static bottleneck there are short and long-term bottlenecks. shifting bottlenecks in a systems shift from one machine to another machine due to change in the machine parameters required for the different variants. The shifting bottleneck method can be further distinguishing between a momentary bottleneck, describing the bottleneck at any given point in time, and an average bottleneck, which describes the bottleneck behavior over a selected period of time.

The current research is aimed at addressing these issues by providing a monitoring system. Most common bottleneck detection methods are Process Time, Average Active Period and Active Period, Lowest production rate, Longest Waiting Time, Longest Queue, Inactive Period, Utilization, Shifting Bottleneck, Bottleneck Walk, Turning Point, Queue Time, Flow Constraint Analysis, Criticality indicators, Inter-departure time variance, Overall Throughput Effectiveness, value stream mapping methods. The detection of a bottleneck and the implementation of improvement actions will result in the improvement of the efficiency of a production system. next step to consider is to predict bottlenecks to improve proactive measures rather than reactive. ANN, ARMA and ARIMA algorithms are to be the most commonly chosen and tested methods for predicting both bottlenecks and throughput in manufacturing systems.

The turning point method is one of a method to identify the bottleneck which takes measurable production data in account to calculate blocking and starving states of the machine along with the respective buffer levels to identify the constraints without modelling any analytical or simulation model. The turning point method achieves an accurate result for short-term bottleneck detection and better performance improvement measures during any production run. This method cannot identify true bottlenecks within a system consisting of large buffers and frequent small stoppages.

2. LITERATURE REVIEW

Lai [1] proposed a systematic framework for a two-layer Long Short-Term Memory (LSTM) network suitable for dynamic bottleneck prediction problem in multi-job manufacturing automotive underbody assembly line systems to predict system bottlenecks dynamically considering the future production planning inputs. The prediction result of the proposed LSTM model is compared with the existing ARMA time series method. The result shows that the proposed LSTM model improves testing accuracy by 35.7%. The proposed method improves prediction accuracy by considering both manufacturing system time series trend and production events.

Roser [2] combined the active period method with the buffer inventories and free buffer spaces of the neighboring inventories to predict a rising change of the bottleneck or shifting bottleneck. By examining the buffers before and after the current bottleneck, the bottleneck shift may take place to process with the second longest active period before the shift. The results are accurate and this changes only when a bottleneck shifts approaches. Hence, the proposed method aids in the identification and the prediction of bottleneck shifts in real time. comparing to the normal active period method, the approach is very accurate and intuitive, but large process data of all processes in the system are required

Subramaniyana [3] tried to investigate the root causes of bottlenecks and suitable specific measures to be implemented based on a data-driven prognostic algorithm which predict the time taken of individual active states of bottleneck machines from machine event-log data from the manufacturing execution system. The proposed prognostic algorithm can locate upcoming bottlenecks and forecasting the duration of active state for the consecutive production run are made. However, the algorithm can pinpoint changes in machine states. This can further lead to investigate other changing trends and factors using other data sources.

Huang [5] proposed a Bottleneck-based dispatching method (BDM) based on future bottleneck prediction for a smart factory that manufactures valve. the bottleneck was predicted based on FBP and ANFIS on data collected during simulation for an experimental period and by the bottleneck identification method the bottleneck stage was also identified. Better bottleneck prediction accuracy, it was observed that the proposed FBP method could accurately predict the future bottleneck stage at most time.

Li [6] proposed a method for predicting the throughput bottlenecks on a production line under dynamic and stochastic conditions using autoregressive moving average (ARMA) model. Blockage and starvation times of each station to be a time series used to predict throughput bottlenecks. It is found that ARMA models can predict blockage and starvation times accurately, which then lead to an accurate prediction of throughput bottlenecks. By understanding the relationship between the ARMA models and the change in machine status. It is observed that the ARMA model order for a machine increases with the increase in its downtime. For the non-bottleneck machines ARMA model order for machine decreases with downtime increment of the bottleneck machine.

Critical features effect on bottleneck dynamics such as production sequencing, and maintenance activities should be evaluated [1]. Root-cause analysis and the best decision for throughput improvement once the bottleneck is predicted should be reconsidered [1]. Prediction of in line buffer level in the manufacturing systems to gain a deeper understanding of production performance to form a unified framework for production prediction and control [6]. The research should focus on combining sensor information from components in the bottleneck machine with machine-state information. This will allow root causes of bottlenecks to be better described and measures to be prescribed [3]. Doing this allows prescriptive algorithms to be used to recommend even more detailed specific, proactive measures for the shop-floor production and maintenance teams and promoting to store detailed digital work records on bottlenecks [3].

There is no further exploration into factors that affecting each machine state [3]. There are some working limitations that to be factored while considering the institutionalization of this algorithm [3]. If the algorithm is based only on machine states, then it can only explain predicted bottlenecks only in relation respect to those states; There is no other information available. The algorithm assumes that the present historical patterns will be present into the future and that accounting for other causal factors of external events will be factored into future work [3].

Furthermore, in order to reduce the effects from the predicted bottleneck, the condition that makes decision during production runs should be studied first to determine when to make decisions [4].

3. METHODOLOGY

A multi job manufacturing company has been modelled using a plant simulation software. A simulated model has been designed which manufactures wood furniture products. The designed model produces 49 parts for 20 products. The model consists of 11 machines ,25 buffers, 12 assembly stations and 26 workers. Each products subparts goes to specific machines to get processed in order to deliver a final product. First in- first out queue service is applied. Processing time of products for each individual machine is taken as random uniform distribution values. Setup time of each machines are given a random uniform distribution values. Failures are designed for each machines. 26 workers in the model is divided into 5 groups and each group of workers have different efficiency ranging from 75 to 85%. For achieving deterministic nature, product mix is changed in the same model for 5 cases. Data generated after the simulation from the model of the 5 different product mix cases are taken separately and is then combined in ascending order. Data generated from the simulation consists of entry and exit time of a product from the buffers and machines. The entry and exit time of products from the buffer is removed. The rearranged data is used as input for prediction. Prediction of data for bottleneck identification is done with application of neural network. Predicted data is used as an aid for identifying the bottleneck in the simulated manufacturing plant.

Levenberg marquardt algorithm was used which typically requires more memory but less time. the performance of the same network is tested on another set of time series data of another machine. The results were satisfied; The number of neurons or delays is given to the network is 10 neurons and 2 delays. Identification of bottleneck from the predicted and simulated data is carried out. In actual data, first the data is arranged based on product order from the source. Initial data shows product name, location of the product and entry or the exit time of the product from the machine. With Initial data, bottleneck identification is difficult. So the data has to be arranged in such a way that each row of the excel sheet shows the individual product entry and exit time from the machines they are assigned. If the product does not enter a machine it will be indicated as zero. After rearranging the entire initial data, blockage and starvation time of each machine has to be calculated. Blockage time is calculated by the time difference between the entry and exit time of the product from a single machine. Starvation time is calculated by the time difference of entry time of upcoming product and exit time of previous product from the same machine. Third step is to calculate the difference of blockage time and starvation time for each machine additional to calculating the difference, sum of blockage and starvation has to be calculated. Finally, the time at which bottleneck occurs is obtained using the turning point method. Turning point method is used on the machine or station where blockage being higher than starvation changes to starvation being higher than blockage. Then the machine is identified as a bottleneck machine. The bottleneck machine causes a change in blockage and starvation. A bottleneck machine has the ability to cause the upstream machines to be blocked and the downstream machines to be starved. Also, a bottleneck machine will have sum total of blocking plus starving time less compared to adjacent machines. To identify whether second machine in a process chart is the bottleneck using turning point method. Check (TB1-TS1) > 0 and (TB2-TS2) < 0 and (TB2+TS2) < (TB1+TS1), where TB1 and TS1 represents the blockage time, starvation time of the first machine. TB2 and TS2 represents the blockage time, starvation time of the second machine respectively. If the condition is true, then the second machine is identified as a bottleneck. Similarly, this condition is used to identify whether the rest of machine possess a bottleneck characteristic. Similarly, the following steps is done for the predicted data to identify the bottleneck. After identifying bottleneck machines from both simulated and predicted data. The bottleneck results are compared.

4. RESULTS AND DISCUSSION

A multi job manufacturing wood product industry is simulated and data generated from the model is used to predict the next value and used it to identify the bottleneck in the system. The neural network by using 10 neurons and 2 delays and Levenberg marquardt algorithm can be effectively used to predict the time series data for the given combined ascending order data of 5 cases of different product mix model.

The accuracy of prediction is evaluated in terms Root Mean Square Error(RMSE) and Mean Absolute Percentage Error (MAPE).

RMSE value of 8.70769 X 10^-05 for n= 42240 using the equation

$$RMSE = \sqrt{[\Sigma (P - O)^2 / n]}.$$

Where Σ is the aggregate sum, P represents the predicted value of the data, O is the observed value of the data and n is the number of observations. the smaller the RMSE, the better a model is able to fit the data.

Mean Absolute Percentage Error (MAPE) is a common method used to measure the forecasting accuracy of a model. The smaller the MAPE the better the forecast.

This model has obtained MAPE value of MAPE= 0.12563 % for n= 42240 using the equation.

$$MAPE = (1/n) * \Sigma (|A-F| / |A|) * 100.$$

Where Σ is the aggregate sum, n is the number of observations, "A" represents the actual data value and "F" represents the forecasted data value

Confusion matrix is also called as matching matrix is shown in Table 1. Each row of the matrix displays the occurrences in an actual class while each column displays the occurrences in a predicted class, or vice versa.

Table-1: Confusion matrix

N=21120	Predicted not bottleneck	Predicted bottleneck
Actual not bottleneck	20870	26
Actual bottleneck	26	248

True positives (TP): These are cases in which predicted bottleneck are actual bottlenecks.
True negatives (TN): These are cases in which not bottleneck cases are predicted as not bottleneck cases.
False positives (FP) or Type I error: These are cases in which not a bottleneck case is predicted as bottleneck cases
False negatives (FN) or Type II error: These are cases in which bottleneck cases are predicted as not a bottleneck case.
Accuracy: Accuracy of the prediction system to predict bottleneck. Accuracy can be calculated using following equation: (TP+TN)/total. Accuracy of 0.999905303030303 is obtained
Misclassification Rate: Rate at which the prediction will be wrong. Misclassification Rate of 0.00246212121212121 is obtained using following equation: (FP+FN)/total.
True Positive Rate: When it's actually bottleneck, how often does it predict bottleneck. These are cases in which predicted bottleneck are actual bottlenecks. True Positive Rate of 1 is obtained using following equation: TP/actual yes.
False Positive Rate: When it's actually not a bottleneck, how often does it predict it as bottleneck. False Positive Rate of 0.104838709677419 is obtained using following equation: FP/actual no.
True Negative Rate: When it's actually not a bottleneck, how often does it predict not a bottleneck True Negative Rate of 0.999904177845918 is obtained using following equation: TN/actual no.
Precision: When it predicts bottleneck, how often is it correct Precision of 0.905109489051095 is obtained using following equation: TP/predicted yes.
Prevalence: How often does the bottleneck condition actually occur in our sample. Prevalence of 0.0117424242424242 is obtained using following equation: actual yes/total
The algorithm is 99.99% accurate. The terms in confusion matrix shows that the algorithm predicts both actual bottleneck and non-bottleneck. The algorithm predicts actual bottleneck accurately and predicts non bottleneck at a few rate of 0.104.

5. CONCLUSION

Suggested an integrated framework for identification and prediction of bottleneck in a multi job manufacturing system. By the identification and prediction of primary bottleneck will improve the throughput of the process and constrains that affects the productivity of a production line. Predicting the future bottlenecks provides a great support for decision-making, which can help to foresee and formulate appropriate actions before production to improve the system throughput in a cost-effective manner. Bottleneck prediction enables the mitigation of resulting production constraints. Companies should implement bottleneck prediction and identification systems to improve its throughput and reduce bottleneck in the process in the near future due to machine degradation, machine failures or planned maintenance. By simulating the plant model before production or before introduction of new product mix or design, bottleneck can be identified and corrective actions can be taken thus saving time, money and worker efforts. Causes of bottleneck can be identified so appropriate actions can be taken by operations management or the maintenance department. Companies should store data related to bottleneck which could aid in future prediction of bottleneck. Limitation of the paper are Bottlenecks Mitigation are not directly addressed in the studies. The proposed method can identify and predict bottleneck for only flow shop production. Study is only limited to simulation. The validation is carried out using the simulated data. Validating with real data from MES or Shop floor data will allow further investigation on limitations of the proposed method.

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