APPLYING A HYBRID MACHINE LEARNING APPROACH TO THE PRODUCTION FLOOR: A CASE OF PAPER COUNTING SYSTEM IN PRINTING INDUSTRY

Paronkasom Indradat[1] and Anirut Kantasa-ard[2]

[1,2]Lecturer, Faculty of Logistics, Burapha University,

169 Long-hard Bangsean Road, Saensuk, Mueang, Chonburi 20131, Thailand,

[1]paronkasom.in@buu.ac.th, [2]anirut.ka@buu.ac.th

ABSTRACT

To satisfy the requirement of quality control in printing and packaging industry, a sheet counting apparatus is developed, which adopts a hybrid machine learning approach and is able to provide a real-time and noncontact measurement of its quantity. With a brief introduction of the system architecture, our main work focuses on the forecasting approach using neural network in different environment. The basic principle is to identify each paper profile from various attributes from the company's Enterprise Resource Planning (ERP) system together with measured heights of the pallet and provide workers an estimated sheet paper count. According to experiments and tests in real production lines, our hybrid approach can reach a very high measuring accuracy for printing papers or cards with any thickness.

KEYWORDS: Recurrent Neural Network, Forecasting, Printing Industry, Estimation

1. Introduction

Despite the digital technology disrupting the customer trend of the printing media, the growth rate of the printing industry is increasing continuously from time to time. The packaging demands are increased in many industrial sectors during this new normal period. For example, the printing of paper packaging is augmented following the growth rate of e-commerce around the world. The market share of printing media is around 313.28 million US dollars in 2021 [1]. The growth rate of market share is around 8.8 percent bigger than in the year 2020. In addition, the largest printing media market is Asia-Pacific region. Thailand is also the largest paper packaging exporter in Southeast Asia. The export revenue from paper packaging is around 6,520 million THB in the year 2018, which is bigger than the year 2017 approximately 7.6 percent [2].

The challenge of the printing industry is how to control the production cost. In general, most printing companies are considered a job shop manufacturing as orders are varied due to different requirements of customers. Some paper packages are manufactured using many machines and complex processes. Also, packaging printing requires a high standard of quality check. Therefore, the efficiency of the production process is very important and impacts the production cost and the variety of customer demands.

The estimation of the paper count on the pallet is one of the most important parts of the printing production process and affects the production cost in the printing house. For instance, the coating process discovers that the number of paper packages is not sufficient to deliver to customers after finishing the printing process. In this case, the printing department is required to re-setup the machine to re-print the remaining packages to cover shortages. This activity will increase the production cost and waste production time. Also, this loss will affect the overall performance of the production process and the competitiveness in the printing industry. Therefore, the printing house is required to focus on the estimation of the paper counter before starting the production process. Manual counting is a time-consuming process, especially in large-scale printing where there are large number of copies required (e.g., one million copies). Several methods of the estimation of the paper counter are implemented recently, such as the use of the counter to count papers manually at the precedent machine before starting the production, using a light sensor, and calculating from the total weight of papers. However, some limitations occur with these methods due to production conditions. For example, the counter does not support the case of pallet partitioning or splitting the number of finished packages after quality checking. These mentioned processes will affect the number of papers on each pallet. Also, paper counting using the light sensor still makes the number of papers vary from the actual quantities regarding different machines and production processes.

Based on all investigated problems mentioned above, we propose a new solution for paper counting. The new solution implements the forecasting concept for paper counting in the production process. The demand forecast is one of the most common methods implemented to estimate or predict the number of resources in many business sectors. In this case, the height and other specifications of papers will be used as the input component to predict the number of papers in the production process. This solution is the simplest for operators and relevant staff without any special requirements as they will measure the height of the papers using only a tape measure.

However, there are some challenges when using the height of the paper to predict the paper counter on the pallet.

1) The thickness of prepared papers is different due to the varieties of paper characters and specifications (more than 20 types of papers).

2) Related operations in the production process impact the height of the paper. For example, finished papers after the printing process will be higher than work-in-process papers.

3) How to stack the paper on the pallet also impacts the height of papers because of the compression force of different paper types.

Regarding the challenges above, it is very essential to measure the height of prepared papers before the paper counting prediction. If we have a good preparation of the paper's height measurement, it will impact the performance of paper counting prediction. Also, a good prediction will help the operators prepare enough papers before the production process.

Machine learning approaches have been proved to be a successful approach in analyzing large scale data. We have seen some fruitful contributions in many research venues, such as e-commerce analytics [3]. However, we have not yet seen many applications in the production floor. This research paper aims to provide the case study of applying the machine learning methodology, especially recurrent neural networks, to support operators in managing their inventory in the printing house. Consequently, the leaner process and cost reduction are achieved. The paper is organized as follows. Section 2 describes the related literature. Section 3 describes our methodology in data preparation process, as well as presenting our proposed hybrid predictive analytics for the case study. Section 4 compares our results with other existing methodologies and concludes our managerial implications for printing industry.

Figure 1 The example of collected paper on the pallet before transferring to production process

2. Literature Review

The literature review is structured as follows. Firstly, some work-in-process inventory management case studies are presented. Secondly, the concept of Paper Counting in printing production are reviewed. Thirdly, the application of forecasting techniques is proposed and demonstrated in counting estimation cases. Lastly, the research gaps in existing works are provided. These reviews will be the starting point to construct the hybrid machine learning approach in this study.

2.1 Work-in-Process Inventory Management in Printing Industry

Managing work-in-process inventory level is crucial for the printing industry. In this industry, there are many parts of WIP inventory throughout the production floor, such as printed papers, coated papers, folder papers, hard cover, sewn book contents, etc., that require continuous monitoring to ensure the availability before entering the next production processes. As a result, cost management in various logistics activities is reduced and more appropriate [4].

The first study [5] examined the concept of inventory management from a case study of printing industry. Inventory management vulnerabilities cause the total cost of the organization to increase. The researcher suggested that such companies should have good strategies for managing and controlling the intake of raw materials used in production. Another work [6] also showed the application of Lean system to reduce wastage in the printing production process, such as reducing the time to change jobs through work measurement, visual control or preparing and managing material areas. The research has shown that Lean-based methodologies have increased efficiency in the production process, such as reducing printer set-up time by 57%, reducing the time required for writing customer claims by 37%, and reducing the number of times required to set up a printer. Subsequent research [7] has brought innovations to upgrade the production process to be more business-friendly and sustainable. By applying several innovations, for example, the use of Flexographic printing technology, energy and raw material consumption during the production process can be reduced by 10-12%, which is suitable for mass production of the same job.

From the research mentioned, we found that inventory management is crucial to the printing industry, as cost control is the sustainable solution for the industry.

2.2 Paper Counting in Printing Production

Paper counting is a mandatory and important operation in printing and packaging industry. The first work **[**8**]** proposed a line-scan camera system that can be used to count number of sheets in the paper. The experiments show achievements in a very high accuracy for various sheet like stacks with a thickness > 0.2 mm. However, in real industry conditions, paper thickness can be as small as 0.08 mm or 80 grams of paper sheet. The method cannot be adopted in all cases in the printing production. Another work **[**9**]** proposed a new stacked-sheet counting method with a deep learning approach on images of stacked papers which can provide 99% accuracy in counting various thickness. However, the study shows challenges in quality of images in different environments, which cause limitation in various lighting conditions.

2.3 Application of Forecasting Techniques in Counting Estimation

Recently, there are various kinds of forecasting techniques that have already been implemented in many industrial sectors including the printing. Due to the main contribution in the paper counting estimation, all relevant forecasting techniques are categorized into two groups: statistics-based, and recurrent neural network. All details are demonstrated below.

2.3.1 Statistics-Based

The first study [10] examined and compared forecasted data and actual data. The factors studied consisted of paper demand, price and total cost in the paper manufacturing industry. The researchers suggest that techniques for forecasting factors in the paper industry should be developed to provide accuracy and forecast information that is closer to the real data. Subsequently, a second study [11] examined predictive techniques using convolutional neural network (MLP) and traditional forecasting techniques (ARIMA, SES, DES, HWES) applied to forecasting the rate of printing and writing paper usage in Iran. Comparing the techniques, MLP provides higher accuracy than other techniques. It is suitable for use in 5-year forecasts, and another work [12] studied the paper boxes and packaging using ABC Classification principles to group products based on consumptions. The researcher then randomly draws 2 items with inventory problems for forecasting using traditional forecasting techniques (SMA, WMA, SES, HWES), and using the forecast results to calculate the order quantity. From the experiments, it was found that the SMA, HWES techniques were more accurate than other forecasting techniques and the cost of inventory storage is reduced by 72-81 %.

2.3.2 Recurrent Neural Network (RNN)

Neural network models are inspired by studies of the information-processing abilities of the human brain. A recurrent neural network (RNN) is a class of artificial neural networks where connections between nodes form a directed or undirected graph along a temporal sequence. This allows it to exhibit more temporal dynamic behaviour. The models have been successfully applied in a variety of business fields including management information systems [13-15], marketing [16, 17], and production management [18-20, 21].

Long Short-Term Memory (LSTM) Neural network is one of the most successful recurrent neural networks that usually be implemented in various applications. LSTM model is constructed by backpropagation through time (BPTT) [22], which is different from feed-forward neural network. In addition, LSTM model requires to setup hyper-parameters such as number of epochs, number of hidden layers and neural units, activation functions, and optimizers to make better prediction [23, 24]. LSTM model will also be implemented in this study. The example structure of LSTM blocks is shown in figure 2.

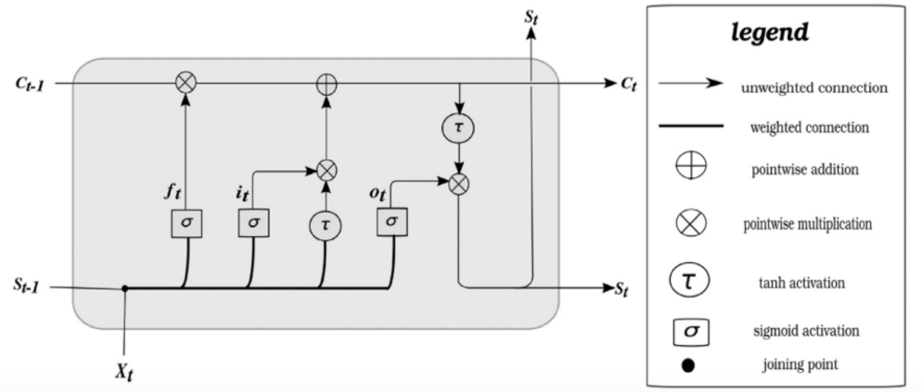

Figure 2 The example structure of LSTM model [23]

2.4 Research Gap

From the literature review on two issues: inventory level management; and demand forecasting, we found that there are theoretical principles and interesting research examples that can be applied to this research. This research will focus on data clustering using principles of partitional clustering process and data prediction with fixed-answer learning. The technique to be used is Reverse LSTM neural network and results will be compared with traditional forecasting techniques. After that, the acquired forecast value will be used in the process of cost calculation and planning the amount of printing and writing paper that will be used in the next production.

3. Research Methodology

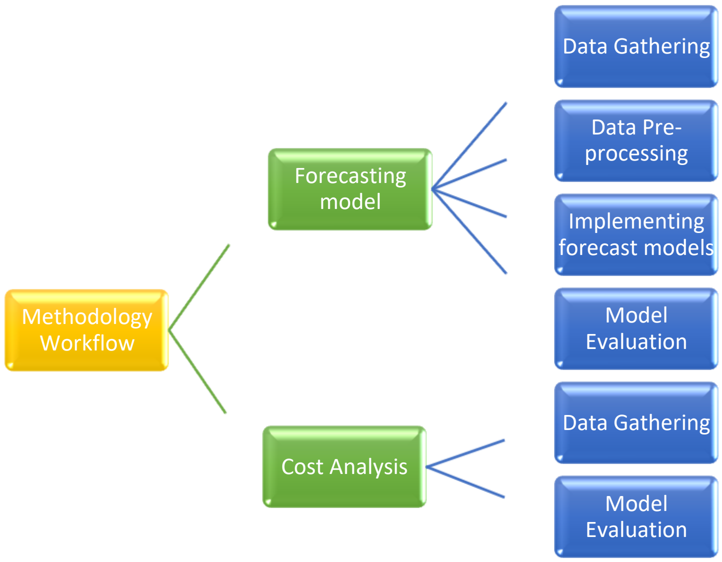

Figure 3 Methodology workflow of this research

3.1 Forecasting Model

3.1.1 Data Gathering

The data acquiring procedure is as follows. We recorded various types of data that are assumed to be related to the sheet counts which are:

1) Paper Type (e.g., Woodfree, Art, Duplex board)
2) Paper Brand
3) Paper GSM (Grams per Square Meter)
4) Paper Source (Customer Supplied, Supplier, Own cutting machine)
5) Printing Status
6) Stacked Sheet Height (cm.)
7) Remarks (other conditions that might affect the height of the paper stacks, such as a stack of more than 1 pallets)

The parameters above are collected from the order planning system. For stacked sheet counts and stacked sheet heights, we modified the time sheet system for the operators to record stacked sheet counts and stacked sheet heights at the end of each production process. For example, at the paper cutting process where the rolls of paper are being cut into sheets, at the printing machines where the printed sheet papers are produced. The operators were asked to use the measuring tape to measure the height and put the information into the timesheet system, while the paper count can be recorded by the machine counters and the operators were asked not to manually remove papers out when the records occurred. In addition, regarding the large dataset, we implement a partitional clustering, which is K-Means, to group the data based on similar characters of input parameters. We choose a cluster data that has high volume of printed sheet papers to train and evaluate forecasting models. More than 5,000 of data points were collected. To summarize, we have 12 paper categories from 3 different sources, 90 different paper brands, the paper GSM ranges from 60 gsm. to 500 gsm. with various paper heights from 1 cm. to 204 cm. at an average of 90.5 cm. The data is used further in data pre-processing.

3.1.2 Data Pre-processing

All pre-processing (such as data cleaning and data transformation) required input and output data that make the data applicable and reduce bias in the dataset [25, 26]. There are many solutions to transform data. Data normalization is chosen to transform all required data in this study. The concept of data normalization is to normalize all input data being the same scale before training a model. In this study, the fit_transform method in the MinMaxScaler function from Python is implemented to normalize data. After finishing this step, all transformed data will be transferred to train forecasting models in the next step.

3.1.3 Implementing Proposed Forecasting Models

There are three steps to implement proposed forecasting models. All details are described as shown below.

1) Firstly, we divide the dataset into 75% of training data and 25% of validating data. In addition, we split dataset randomly using 10-fold cross validation technique.

2) Secondly, the dataset is trained and validated using both statistic and recurrent neural network forecasting models.

2.1) For statistic models, Seasonal Autoregressive Integrated Moving Average with exogeneous factors (SARIMAX) and Multiple Linear Regression (MLR) are proposed due to the forecast characteristic as mentioned in the literature above. These two models are proper statistical techniques to forecast linear behaviours and trends in complex problems [27, 28].

2.2) For a recurrent neural network model, Long Short-Term Memory (LSTM) is considered to forecast the prepared number of printed sheet papers in the production process. LSTM model works well with non-linear trends and captures the forecast pattern using historical data [23, 29]. We configure four hyper-parameters: number of hidden layers, number of hidden neurons, activation functions, and optimizers. The algorithm in [24] will automatically choose the configuration that provide the lowest MAPE, RMSE and highest R^2 scores.

3) Thirdly, we propose hybrid forecasting models by combining two single models. The objective is to support the forecasting trend, both linear and non-linear. Therefore, one hybrid forecasting model will be composed of a statistic model and a neural network model. Regarding the mentioned criteria, two hybrid models are investigated in this study.

3.1) The first model is the hybrid LSTM-MLR.

3.2) The second model is the hybrid LSTM-SARIMAX.

These two hybrid models are inspired by [30], which provided the combination between feedforward neural network and statistic forecasting models. However, the recurrent neural network exhibits good performance with complex forecasting problems such as production capacity and complex time-series data after comparing with the feedforward neural network [31, 32]. Therefore, it would be an interesting perspective to enhance the forecasting performance using the combination between recurrent neural network and statistic models.

After finishing the experiment with all five forecasting models, we will evaluate the forecasting performance. All details will be presented in the model evaluation section.

3.1.4 Model Evaluation

We perform all five forecasting models in both accuracy and correlation aspects. For the accuracy aspect, we implement the Mean Absolute Percentage Error (MAPE), the Mean Absolute Error (MAE), and the Root Mean Square Error (RMSE) to evaluate the error gaps in quantity and percentage [33, 34]. For the correlation aspect, the coefficient of determination (R^2) is considered to evaluate the correlation between forecast and actual quantities [35]. The formula of these indicators will be described below.

1) Mean Absolute Percentage Error (MAPE)

$$MAPE = \frac{1}{n}\sum_{i}^{n}\frac{|X_i - Y_i|}{|X_i|} * 100 \qquad (1)$$

2) Mean Absolute Error (MAE)

$$MAE = \frac{\sum_{i}^{n}|X_i - Y_i|}{n} \qquad (2)$$

3) Root Mean Square Error (RMSE)

$$RMSE = \sqrt{\sum_{i}^{n}\frac{(X_i - Y_i)^2}{n}} \qquad (3)$$

4) Coefficient of determination (R^2)

$$R^2 = 1 - \frac{\sum_{i}^{n}(X_i - Y_i)^2}{\sum_{i}^{n}(X_i - \bar{X}_i)^2} \qquad (4)$$

where X_i is the actual demand for order i, Y_i is the forecast demand for order i and n is the forecast period

Additionally, we implement all forecasting models to forecast the number of prepared papers at the production process in three different datasets.

1) Small dataset with 104 samples
2) Medium dataset with 440 samples
3) Large dataset with 5188 samples

In each dataset, we implement the featured selection method, which is Backward Elimination [36], to choose some input parameters that impact the quantity of prepared paper. These input parameters are chosen based on the p-value of less than 0.05 (confident interval at 95%). Then, paper category, paper brand, grams of paper (GSM), paper source, and the tall size of paper are considered as input parameters. The quantity of prepared paper is considered as an output of each dataset.

3.2 Cost Analysis

3.2.1 Data Gathering

To conduct cost analysis, we use actual historical data, i.e., machine speed, material cost, labor cost, and overhead cost to calculate the cost of shortage and overproduction. The shortage cost occurs when the amount of sheets processed is less than the required amount. The previous process has to be fulfilled to cover the shortage before going to the next process. The cost analysis does not concern the wait time that occurs during the shortage. The overproduction cost is calculated using the paper cost and the material consumption used in the process.

3.2.2 Model Evaluation

To conduct model comparison, we calculate the cost from each forecast output and summarize whether the forecast output causes overproduction or shortage. The cost from all outputs is summarized. As number of data points are different based on the size of the dataset, we normalize the data to the range of 0 to 1 and compare the performance.

4. Results and Analysis

4.1 Evaluation of the Forecasting Model Performance

We experiment all forecasting models in three main datasets, which are small, medium, and large datasets. All details are described below. In addition, the results in Table 1-3 and Figure 4-6 will be demonstrated at the end of section 4.

4.1.1 Result of small dataset:

Regarding the results mentioned in Table 1, we experiment with the forecasting performance in five forecasting models. Also, we consider five forecasting inputs: Paper Type, Paper Brand, Paper GSM, Paper Source, and Stacked Sheet Height. The forecasting output is the number of printed sheet papers. The data proportion is divided into 75% training data and 25% validating data. The hybrid LSTM-SARIMAX provides the best performance with accuracy aspect, which is measured by the lowest MAE and RMSE, while the hybrid LSTM-MLR provides the best score of MAPE. For the coefficient of determination (R^2), the hybrid LSTM-SARIMAX still provides the highest score after comparing with other models.

We can see the performance of the Hybrid LSTM-SARIMAX via Figure 4. For the overall performance, we can see that both hybrid models outperform than single models.

Table 1 The forecasting models' comparison with a small dataset (104 observations)

Forecasting Model	MAPE	MAE	RMSE	R^2
SARIMAX	65.18	1,235.82	1,790.74	0.908
MLR	58.66	1,468.44	1,771.55	0.895
LSTM	20.99	855.37	1,157.85	0.970
Hybrid LSTM-MLR	**10.45**	**698.13**	1,070.50	0.976
Hybrid LSTM-SARIMAX	12.51	679.68	**987.29**	**0.980**

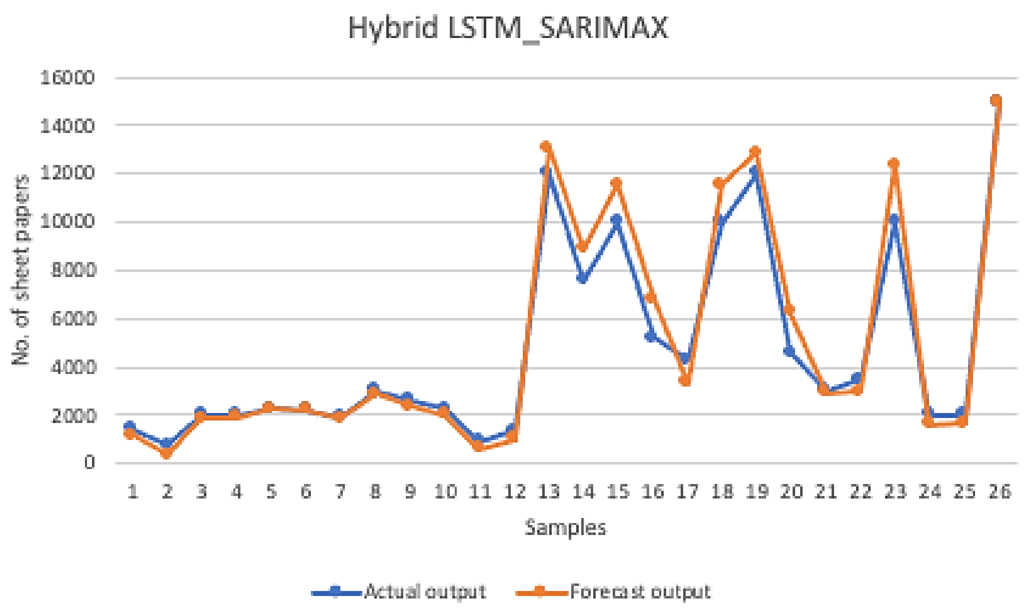

Figure 4 The comparison between actual and forecast outputs with the hybrid LSTM-SARIMAX with a small dataset

4.1.2 Result of medium dataset:

Regarding the results mentioned in Table 2, we experiment with the forecasting performance in five forecasting models. Also, we consider five forecasting inputs and one output the same as the small dataset. The proportion of training and validating data is the same as a small dataset. The hybrid LSTM-MLR provides the best performance with accuracy aspect, which is measured by lowest MAPE, MAE, and RMSE, while the hybrid LSTM-SARIMAX provides the best score of R^2. However, the hybrid LSTM-MLR has similar score of R^2 with LSTM-SARIMAX. We can see the performance of the Hybrid LSTM-MLR via Figure 5. The performance of these two hybrid models is quite similar and outperform after comparing with single models.

Table 2 The forecasting models' comparison with a medium dataset (440 observations)

Forecasting Model	MAPE	MAE	RMSE	R^2
SARIMAX	65.81	2,072.88	2,316.93	0.883
MLR	63.67	1,498.32	1,776.03	0.896
LSTM	15.11	652.46	954.01	0.959
Hybrid LSTM-MLR	**14.36**	**500.46**	**760.34**	0.975
Hybrid LSTM-SARIMAX	16.85	623.14	847.70	**0.978**

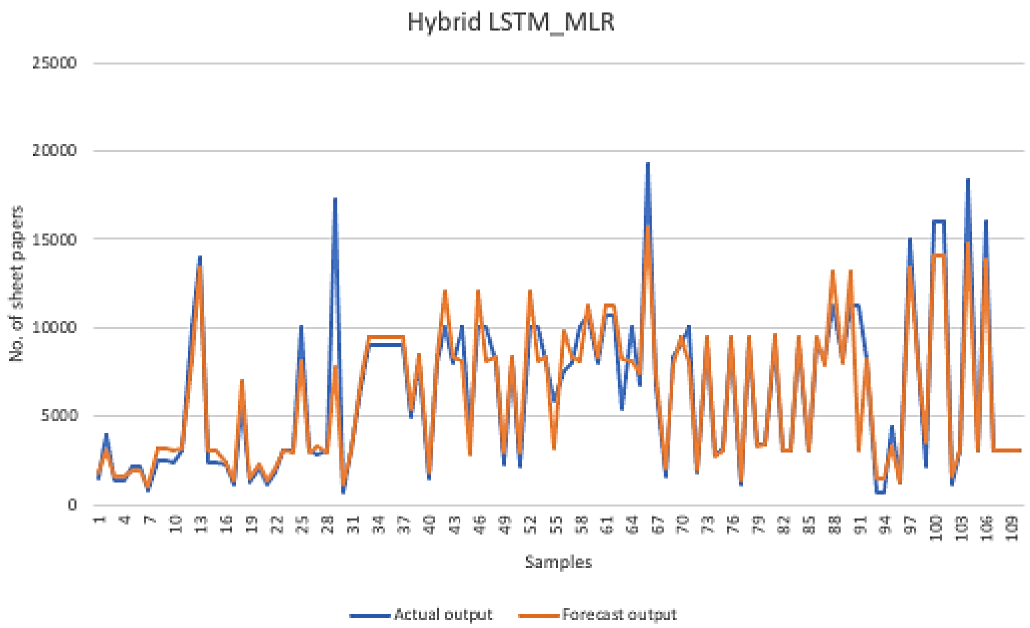

Figure 5 The comparison between actual and forecast outputs with the hybrid LSTM-MLR with a medium dataset

4.1.3 Result of large dataset:

Regarding the results mentioned in Table 3, we experiment with the forecasting performance with five forecasting models. Also, we consider five forecasting inputs and one output the same as the small and medium datasets. The proportion of training and validating data is the same as a small dataset. The single LSTM provides the best performance in both the accuracy (MAE, MAPE) and the coefficient of determination aspects. We can see the performance of the LSTM via Figure 6. Nevertheless, the performance of hybrid LSTM-MLR and LSTM-SARIMAX are similar to the single LSTM model based on all accuracy indicators and the coefficient of determination.

Table 3 The forecasting models' comparison with a large dataset (5188 observations)

Forecasting Model	MAPE	MAE	RMSE	R^2
SARIMAX	125.26	1,939.23	2,838.99	0.533
MLR	137.80	2,105.22	3,003.88	0.539
LSTM	**20.39**	**401.47**	705.85	**0.978**
Hybrid LSTM-MLR	27.89	429.41	**656.00**	**0.978**
Hybrid LSTM-SARIMAX	31.69	463.33	704.16	0.973

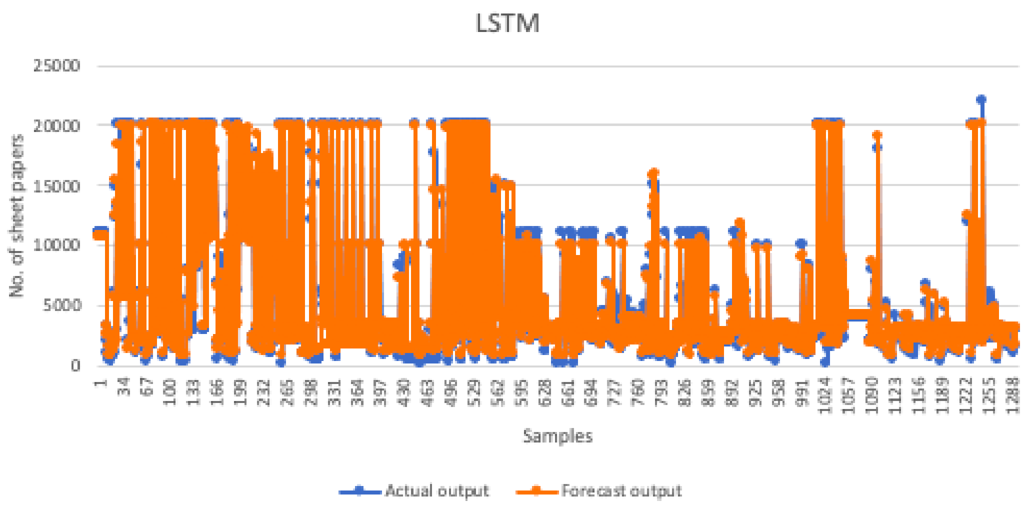

Figure 6 The comparison between actual and forecast outputs with the LSTM model with a large dataset

Based on the investigation of forecasting performance from three datasets, we can find that the hybrid models, both LSTM-SARIMAX and LSTM-MRL, provide the best performance on both small and medium datasets. However, for the large dataset, the single LSTM provides the best performance in both the accuracy and the coefficient of determination scores. Both hybrid models still provide similar performance to the single LSTM model in the large dataset. One of the interesting reasons why the hybrid model indicates higher error gaps and lower correlation in the large dataset is the large error gaps on both MLR and SARIMAX. These error gaps from these two models will impact the performance of hybrid forecasting models. Conversely, the hybrid models achieve better forecasting performance for overall results after comparing with single forecasting models. The advantage of hybrid models in this study show that they deliver good forecasting results with both linear and non-linear trends for counting printed sheet papers.

The forecast output from three datasets will be implemented to do the costing analysis. In this case, we would like to demonstrate how the forecast output impact the total cost in the production process. All details will be described in the evaluation of the costing performance section.

4.2 Evaluation of the Costing Performance

In addition to forecasting accuracy, we compare the process cost that occurs when using different forecasting systems. The cost can be categorized into 2 different groups: underestimate and overestimate costs. The underestimate cost occurs when the prediction amount is less than the actual amount of paper on the pallet. This causes the problem in the next production process. If the worker finds out later that the amount of paper is less than the required amount during the consequent production process, the worker must rework the previous processes all over again to compensate the paper shortage. On the other hand, overestimate cost represents the cost that occurs when the prediction amount is more than the actual one. The surplus of the paper is therefore an overproduction cost. We can summarize the additional cost that occurs from both overestimate cost and underestimate cost as shown in Table 4 and Figure 7. Our proposed hybrid approaches show promising results. Hybrid LSTM&MLR model shows the lowest cost in small-sized and large-sized datasets, while the hybrid LSTM&SARIMAX model shows the lowest cost in medium-sized dataset.

These results demonstrate that both hybrid models can help the company reducing both overestimate and underestimate costs in the production process.

Table 4 Cost Comparison

Forecasting Model	Cost			Normalized Cost		
	Small	Medium	Large	Small	Medium	Large
SARIMAX	816,440.19	1,373,386.30	40,952,587.61	1.00	0.46	1.00
MLR	656,762.91	2,339,267.15	31,287,155.14	0.76	1.00	0.67
LSTM	212,539.82	594,108.07	12,005,481.17	0.09	0.03	0.01
Hybrid LSTM-MLR	151,377.71	542,278.55	11,587,522.81	-	0.00	-
Hybrid LSTM-SARIMAX	172,725.61	534,812.96	11,870,174.28	0.03	-	0.01

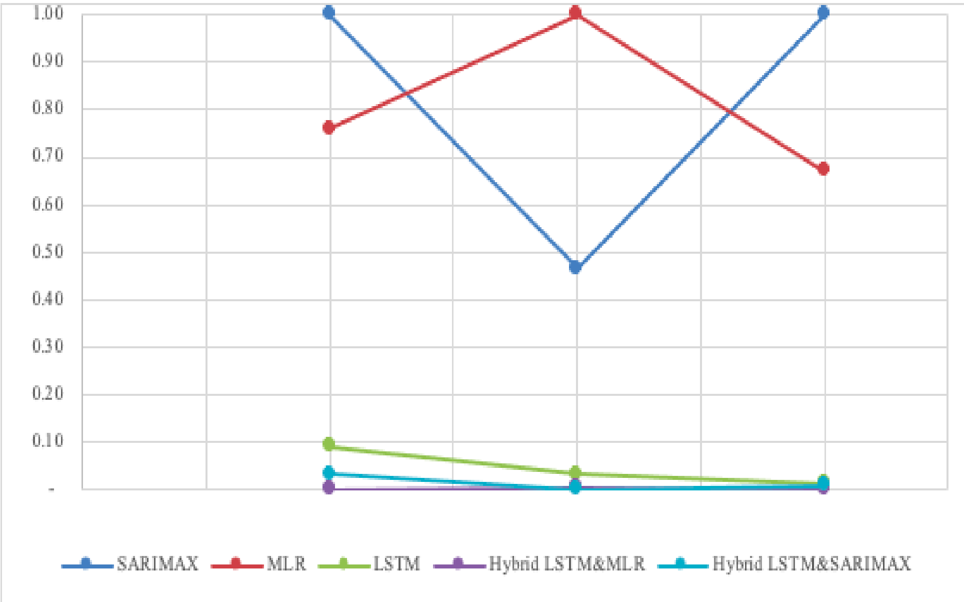

Figure 7 The cost comparison with different forecast models

4.3 Managerial Implications

The current production procedure can be summarized in Figure 8. Without the hybrid forecasting model, the operator at the consequent production process has to confirm the quantity of the stacked sheet on the pallets before starting the production process. If the shortage occurs at this stage, the operator has to inform the production planner to schedule rework. With the hybrid forecasting model, as shown in Figure 9, the operator at the consequent production process does not need to confirm the stacked sheet quantity, thus the production process will be more continuous without unnecessary wait time.

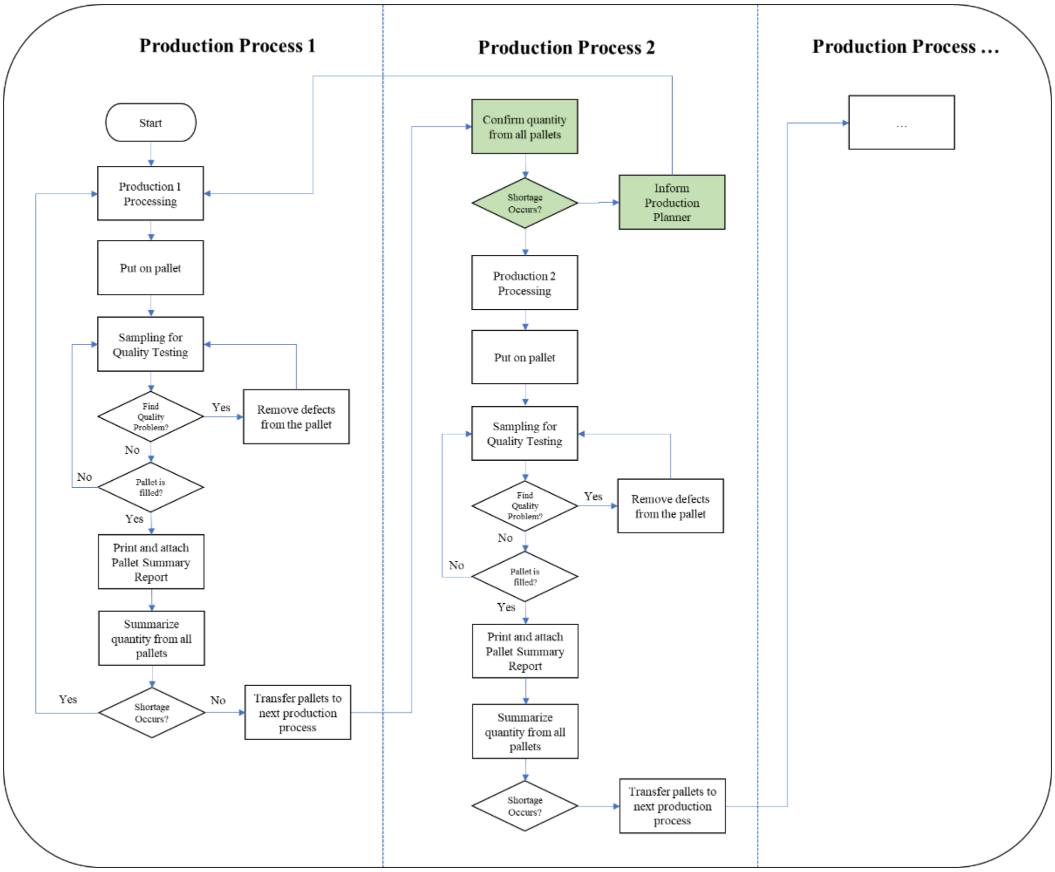

Figure 8 Operation Processes (Before Improvement)

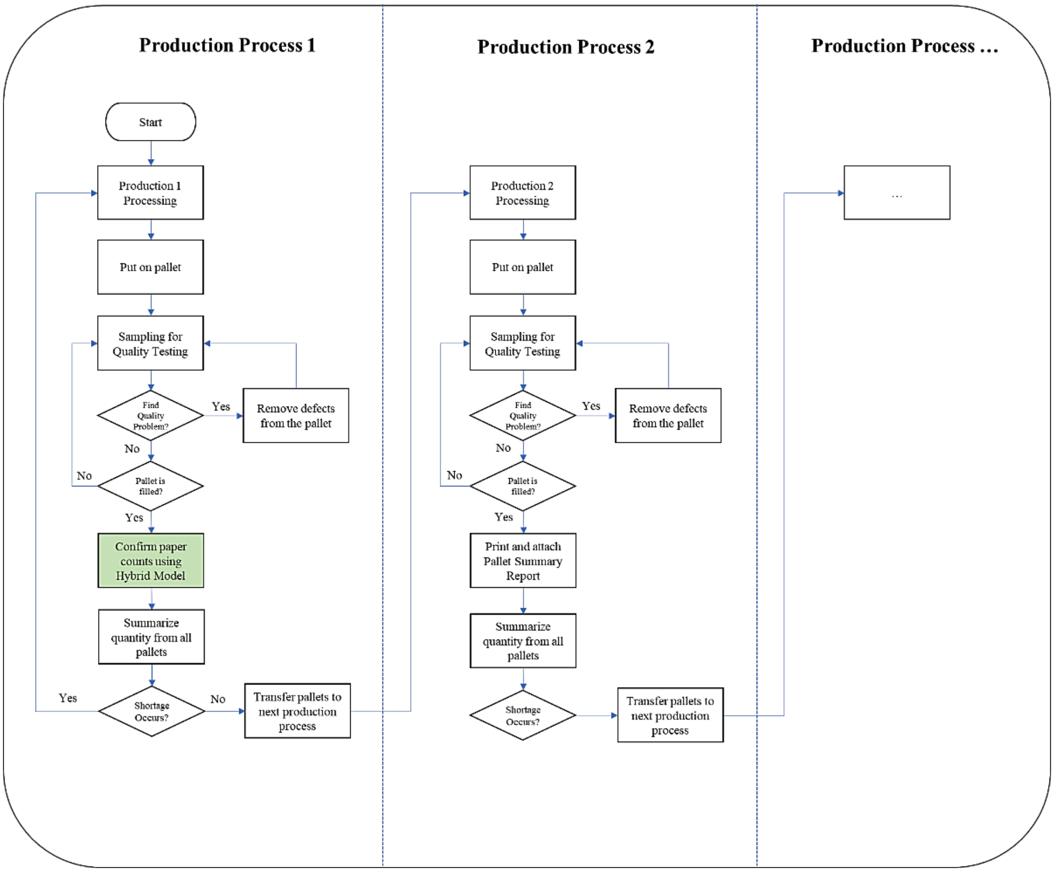

Figure 9 Operation Processes (After Improvement)

5. Conclusions

In this study, we propose a hybrid forecasting approach to support production floor operation in printing industry. The forecasting techniques can help operators to easily determine the quantity of stacked sheet papers by using a simple technique like measurement tapes. Moreover, the hybrid approach can reduce the problem of overestimate and underestimate costs in the production process. The system can be implemented in any stacked sheet papers throughout the company's production processes without concerning various lighting conditions like other novel concepts, such as image processing and laser counter. It is by far one of the most cost-effective options to handle this problem. In addition, this approach does not limit with paper counting only. This approach can be applied in the counting process of other types of raw materials and finish goods that require precise quantity, but the counting process is too complicated and time-consuming, such as, plastic sheets, aluminum sheets, etc.

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Author's Profile

Paronkasom Indradat

Lecturer at Faculty of Logistics, Burapha University. 169 LongHad Bangsean, Seansuk, Muang, Chonburi 20130, Thailand

Email: paronkasom.in@buu.ac.th

Domain: Supply Chain Optimization, Simulation, Decision Support

Anirut Kantasa-ard, Ph.D.

Lecturer at Faculty of Logistics, Burapha University. 169 LongHad Bangsean, Seansuk, Muang, Chonburi 20130, Thailand

Email: anirut.ka@buu.ac.th

Domain: Supply Chain Optimization, Forecasting, Decision Support

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