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Material cost reduction using Cutting Optimization Pro5 and enhanced N-BEATS deep learning forecasting: a case study

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Abstract

Manufacturing industry is constantly looking for ways to improve the efficiency of production processes to lower production costs, maintain product quality, and improve production planning. This study aims to provide an integrated optimization and forecasting framework that combines Cutting Optimization Pro5, linear programming, and an Enhanced N-BEATS deep learning model to minimize material waste and manufacturing cost and to predict the number of production items with a price-reduction strategy. The real industrial case study is based on production and pricing data from the Akad factory of the General Company for Electrical and Electronic Products in Iraq for the period from 2014 to 2025, concerning the manufacture of 80 l and 120 l electric water heaters. That is, Cutting Optimization Pro5 was used to specify optimal sheet sizes and cutting plans, minimizing waste and reducing production costs. At the same time, the Enhanced N-BEATS deep learning model was implemented to forecast future production quantities. The optimization results showed a significant reduction in wasted materials and production costs, allowing lower product prices. Thus, the forecasting results proved that the performance of the Enhanced N-BEATS model was much better than that of SARIMAX and Simple Linear Regression since the model showed the lowest prediction errors (pMAPE value for the 120-l product is equal to 0.040 and nMSE is equal to 0.016, while pMAPE for the 80 l product equals 0.091, and nMSE equals 0.007). The results show that combining cutting optimization and deep learning can create an efficient decision-support framework to improve production efficiency, lower production costs, and enhance production planning in industrial environments.

Keywords: Cutting Optimization Pro5, Deep learning, Enhanced N-BEATS algorithm (neural networks), Reducing prices, Predicting production quantities

1. Introduction

The manufacturing industry is developing at an increasingly rapid pace. As a result, various new intelligent systems have emerged that ensure both operational efficiency and cost-effectiveness for organizations [1, 2]. At present, the industry's competitive nature means manufacturers must use raw materials carefully without compromising product quality or failing to meet customers' needs [3, 4]. Hence, combining optimization tools with forecasting methods appears reasonable and justified [5, 6].

The cutting process produces large amounts of waste, a major contributor to the overall cost of sheet-metal production [7, 8]. The cutting optimization procedure allows manufacturers to save materials, increase efficiency, and contribute to sustainability by reducing waste generated by production processes [9, 10]. Linear programming is a frequently used optimization tool to support planning, scheduling, and allocation in manufacturing processes. In addition, certain software solutions provide manufacturers with practical ways to obtain optimal cutting layouts (Cutting Optimization Pro5 is one example) [11, 12].

Furthermore, artificial intelligence (AI) and deep learning (DL) technologies have substantially changed how manufacturing forecasting is done. The deep learning approach makes it possible to recognize interdependencies and non-linear relationships among mixed variables over time. N-BEATS is a prominent deep learning mechanism that enables reliable, effective forecasting. Modified N-BEATS mechanisms have provided reliable forecasts because they can identify trend and seasonal components [1, 13].

Studies provide evidence that optimization and deep learning are two important directions for development in modern manufacturing. For instance, in material consumption and waste reduction, smart cutting algorithms provide excellent performance as explained by Chen et al. [5]. Paraschos et al. [8] discuss the application of DL for the effective scheduling and production planning in production processes. The modified N-BEATS is an important milestone in time-series forecasting [8]. But, in the current literature, the relationship between the two areas is not considered and only optimization techniques are studied or manufacturing forecasting using AI technologies [3, 4].

With all the above information it must be reiterated that although the field has progressed nicely, there is a major gap. The existing literature either discusses the automatic cutting optimization methods, or manufacturing prediction methods based on AI technologies. Nevertheless, it doesn't provide any solutions for the integration of the two approaches within a single framework. Furthermore, the results of previous research cannot be validated in real scenarios [6].

To reach these goals, this research offers a comprehensive framework, which is a combination of Cutting Optimization Pro5, Linear Programming and an Enhanced N-BEATS deep learning model for intelligent decision making in industry. The feasibility of the approach is tested for the actual production data of Akad Factory, General Company for Electrical and Electronic Products in Iraq. The proposed framework can simultaneously optimize the material usage, reduce the production cost, and predict the future production volumes by incorporating the cost-based pricing strategies. This study contributes in the following ways:

- Creation of an integrated decision support framework that uses cutting-edge optimization, mathematical programming, and deep learning forecasting together.
- Offering a practical approach that combines waste reduction and manufacturing cost reduction.
- Analyzing the forecasting abilities of Enhanced N-BEATS against traditional forecasting techniques.
- Proving that the suggested framework has a real-life application.

2. Methods

2.1. Linear programming and cutting optimization

Linear Programming (LP) has been adapted to maximize material usability throughout the cutting process while keeping raw material wastage to the lowest possible level, considering manufacturing requirements and demand limitations. The optimization model finds an optimal combination of cutting patterns that maximizes material usage while ensuring minimum production costs [4, 5]. The LP model was implemented in Cutting Optimization Pro5, which generated the best cutting layouts used as a basis for cost reduction and further production forecasting using the Enhanced N-BEATS model [6, 7].

2.2. Predicting by deep learning neural network style (DLNN):

The data used includes yearly samples from 2014 to 2025 (N = 12), which is not enough time-series to achieve forecasting objectives. As a result, traditional statistical forecasting procedures cannot model non-linear patterns or provide reliable forecasts. For this reason, the research presented uses Enhanced N-BEATS as a forecasting technique [9, 10].

Enhanced N-BEATS applies deep learning techniques for single-series forecasting through residual learning blocks. Unlike other techniques, this solution does not study the signal simultaneously; instead, it processes each part of the input series independently. Each block processes the previous output, enabling consistent signal modeling.

Step 1: Preparing input

The first step in using the original time series is converting it into an overlapping input series. Each sequence includes records for future prediction. To create proper initial conditions for model training, convert all input values to the interval [0, 1] to normalize the variables.

Step 2: Extracting hidden features

All normalized input series are sent to an MLP model to extract hidden features. The input series from the m-th block passes through the model and yields the hidden features.

$$h^{(m)} = MLP\left(x^{(m)}\right) \qquad (1)$$

where $x^{(m)}$denotes the input sequence of the m^{th}block and $h^{(m)}$represents its latent feature vector.

Step 3: Back casting and forecasting

In this stage, the hidden state is transformed through linear layers to restore the historical series and predict future observations. After that, the predicted figures undergo reverse transformation using means and standard deviations, respectively.

$$\hat{x}^{(m)} = Linear\left(h^{(m)}\right) \times Std\left(x^{(m)}\right) + Mean\left(x^{(m)}\right) \qquad (2)$$

$$\hat{y}^{(m)} = Linear\left(h^{(m)}\right) \times Std\left(x^{(m)}\right) + Mean\left(x^{(m)}\right) \qquad (3)$$

where $\hat{x}^{(m)}$is the reconstructed historical sequence and $\hat{y}^{(m)}$denotes the forecast generated by the current block.

Step 4: Residual learning

The next step involves broadcasting residual information obtained by subtracting the reconstructed signal from the original signal.

$$x^{(m+1)} = ReLU\left(x^{(m)} - \hat{x}^{(m)}\right) \qquad (4)$$

This residual-learning mechanism enables successive blocks to concentrate only on the unexplained components of the time series, thereby improving forecasting performance.

Step 5: Obtaining the final forecast

The outputs from all residual blocks are summarized to obtain forecasts on a regular measurement scale.

$$\hat{Y} = \sum_{m=1}^{M} \hat{y}^{(m)} \quad * Max(x) \qquad (5)$$

where Mdenotes the total number of residual blocks in the network. Thus, it is possible to forecast production demand based on limited historical data by using hierarchical feature extraction and residual learning.

3. Result

The study used relevant production and price data for electric water heaters produced by the Akad Factory, a production plant of the General Company for Electrical and Electronic Products operating under the Ministry of Industry of Iraq, for the period from 2014 to 2025. This analysis covers two product types with capacities of 120 l and 80 l, manufactured on one production line. These products were chosen because they have lower market saturation than competing models and are priced higher than competitors. Because these products are produced in compliance with market-required quality standards, the proposed approach is to reduce production costs through material optimization, allowing lower product sales prices. Tables 1-3 show production prices as well as production volumes for concerned products for 2024 - 2025, compiled from production records and pricing data available at a company.

Table 1. Annual demand and price for products for 2024 and 2025

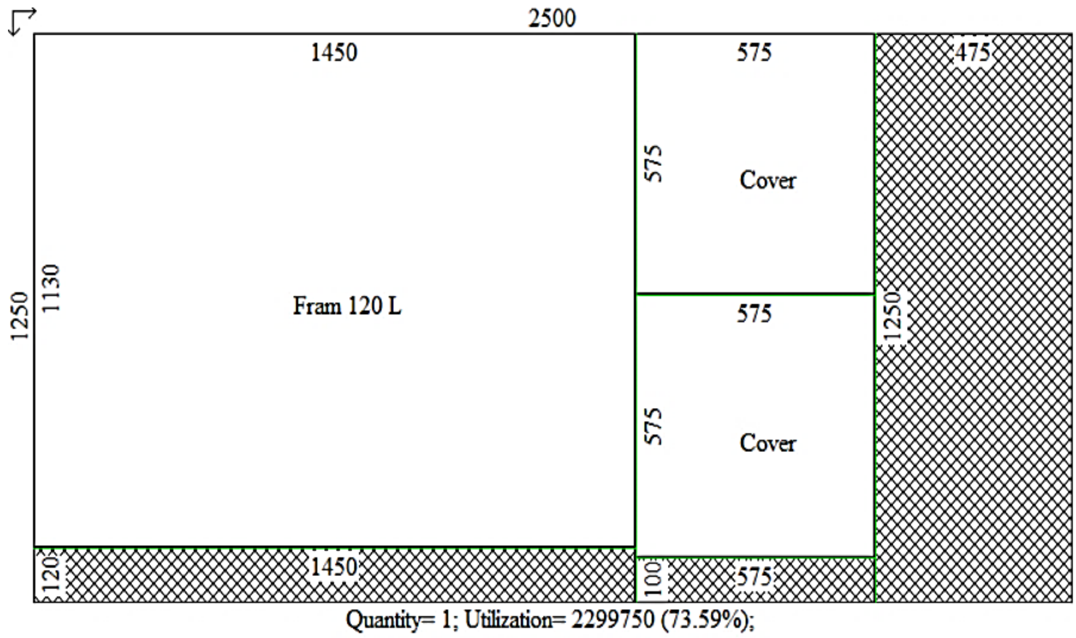
	Annual demand		Price ID	
Water heater	2024	2025	2024,2025	Similar products in local markets in 2025
120 liters	168	145	140000	135000
80 liters	18	11	110000	120000

Analysis of the company's expected production Sales revealed a decline in annual demand and an increase in cost, especially for the 120-l water heater model. Therefore, to improve product positioning and market competitiveness while maintaining the same product quality and raw materials, this research explored ways to improve the cutting process and its material efficiency. Specifically, the existing production line uses a galvanized steel sheet measuring 2500 × 1250 × 0.7 mm to make external parts of the item, including the case and the upper and lower covers. A 2 mm galvanized steel sheet is also used to manufacture internal parts of the product (water tank, upper and lower covers, and base). The sheet is cut into several predetermined parts according to the specified product capacity (either 120 l or 80 l). Table 2 provides the cutting specifications for all products.

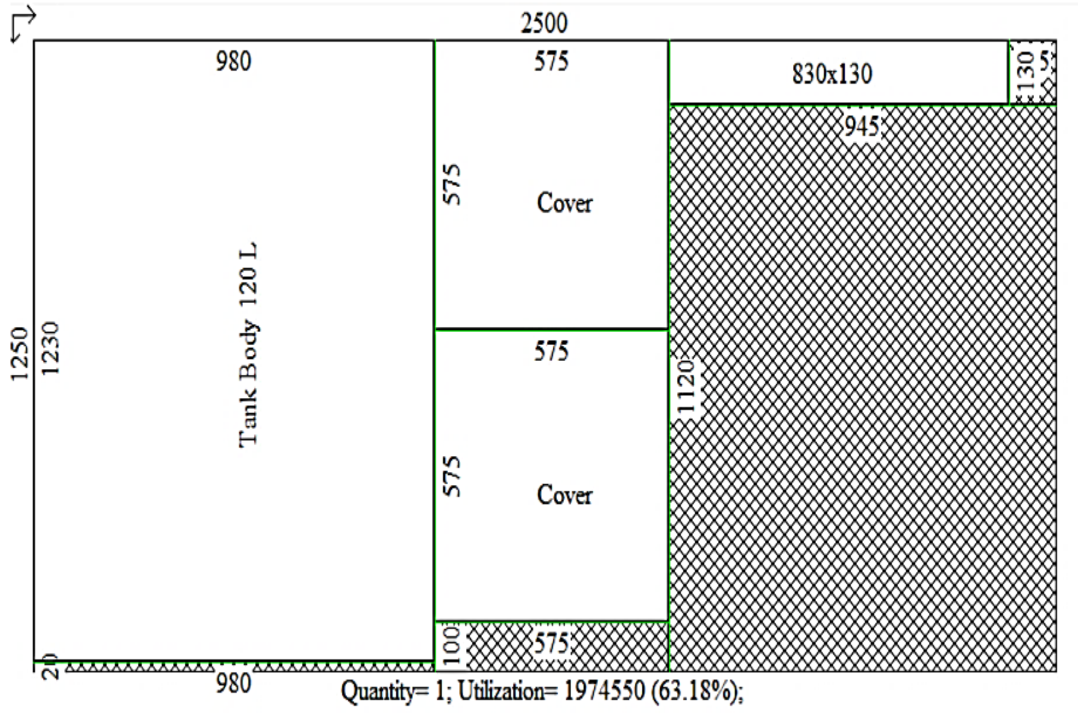
Table 2. Part products cutting

Part products cutting	Outer set thickness 0.7 mm		Indoor set and base thickness: 2 mm		
	Frame	2 Circular cover diameter	Task Body	2 Circular cover diameter	Base
120-liter	1450mm*1130mm	575mm	1230mm*980mm	575mm	830mm*130mm
80-liter	1450mm*780mm	575mm	1230mm*640mm	575mm	830mm*130mm

The cutting process primarily aims to increase sheet surface use and minimize waste material, making it possible to make as many products as possible from one sheet. In general, large sheets allow more freedom in arranging product layouts and offer better opportunities for geometric nesting and material use than small sheets. This optimization method, known as interlock optimization, improves material use by reducing unused areas and increasing the number of complete product sets made from one sheet. Based on this principle, galvanized steel sheets with similar properties but a larger size (3000 mm × 1500 mm) were examined as possible alternatives to the available sheets. The larger sheet provides more opportunities to organize the layout of the necessary components, leading to better material use. To assess the potential advantages of a larger sheet size, the current sheet configuration was compared with the proposed larger dimensions using Cutting Optimization Pro5 software, as shown in Figures 1-2. This software found optimal cutting patterns that maximize material usage while minimizing waste. After creating the new layout in the system for each scenario, we calculated the cut cost, area used, wasted area, efficiency ratio, waste percentage, and number of parts produced per sheet. To conduct the analysis, the program used the dimensions of both the existing and proposed sheets and the size of the various needed parts for each item. After the required information was provided to the software, it defined the optimal cutting layout and the maximum number of complete part sets produced from each configuration. The comparison was conducted separately for 120 l and 80 l water heaters to assess how the newly proposed sheet dimensions would affect manufacturing efficiency. To evaluate the economic impact on the 120 l water heaters, the analysis was based on the company's 2025 purchase prices. Thus, the current 0.7 mm sheet cost around 17,300 IQD, and the 2 mm sheet cost approximately 70,000 IQD. The amended prices for the larger sheets were approximately 26,000 IQD for the 0.7 mm sheet and 90,000 IQD for the 2 mm sheet, based on 2025 market prices. These values were included in the analysis to compare large-sheet acquisition costs, assess savings from waste reduction, and identify the best option for manufacturing the given product.



(a)



(b)

Figure 1. Used sheet for (a) [frame, two covers]; (b) [tank body, base, two covers] to produce 120 l

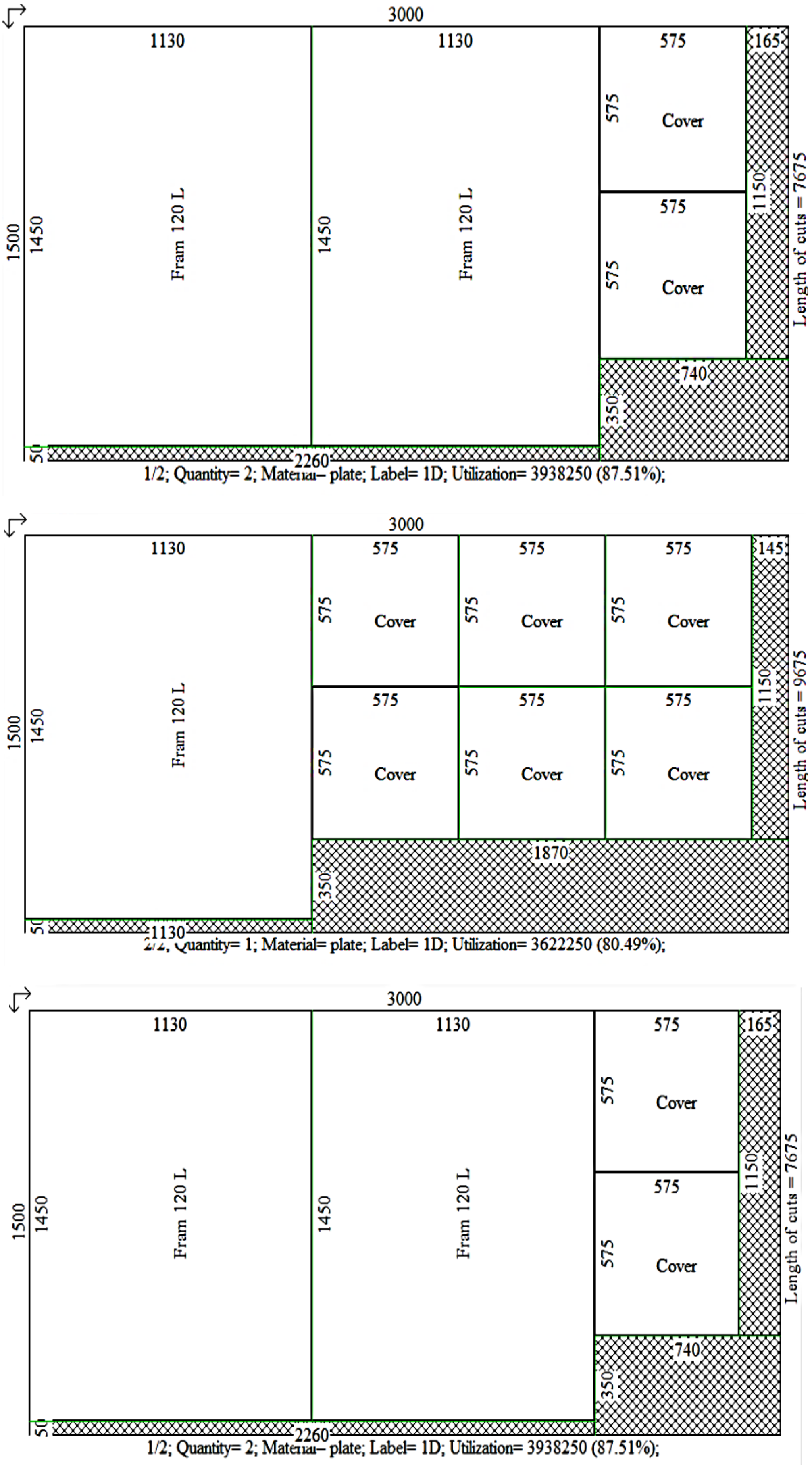


Figure 2(a). Suggested sheet for [five frames, ten covers] product 120 l

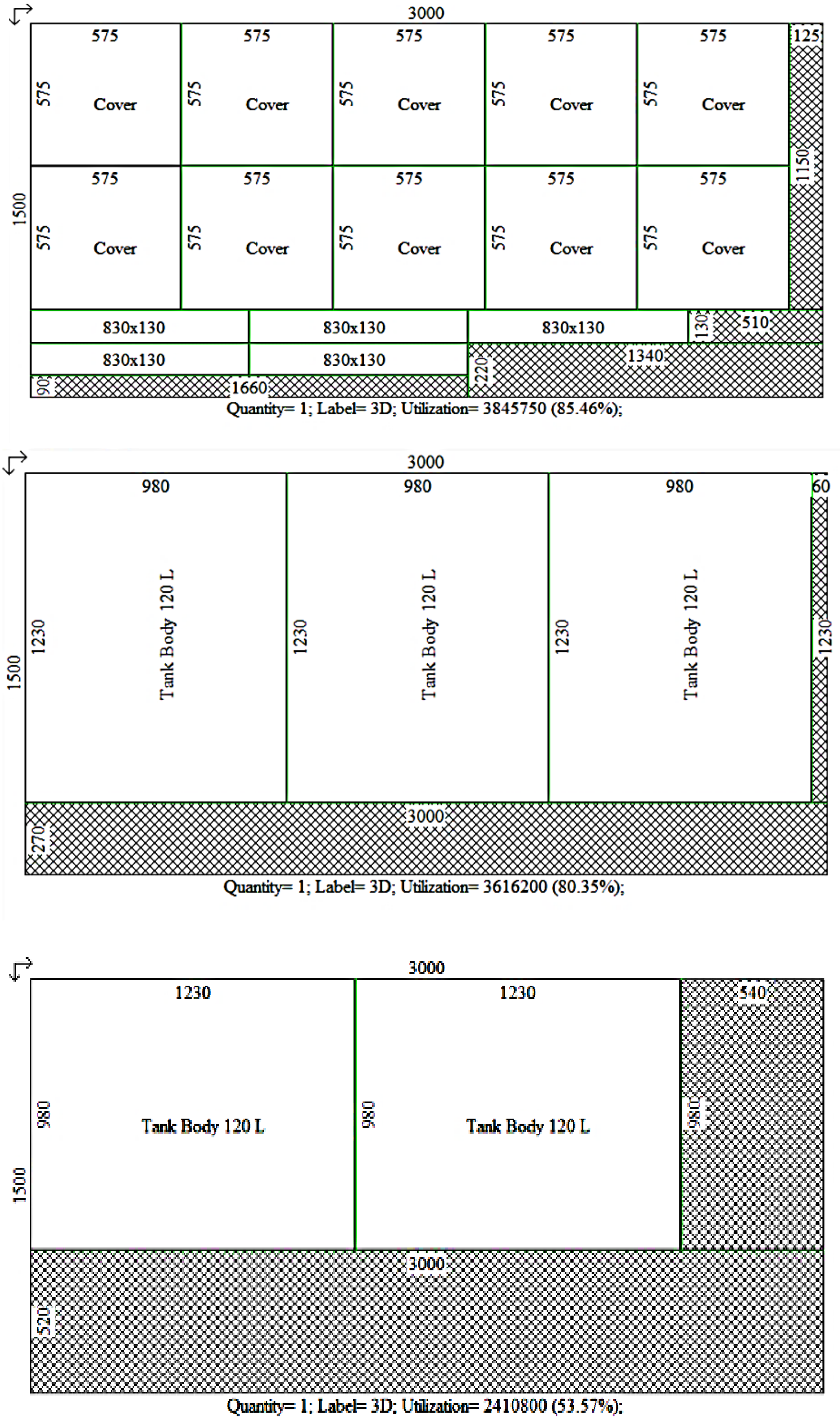


Figure 2(b). Suggested sheet for [five tank bodies, five bases, ten covers] product 120 l

The results are obtained from the program's statistical table for the galvanized iron sheet used and proposed.

Table 3. Results of the statistical program's Cutting Optimization Pro5 for product 120 l

	Galvanized iron sheet used		Galvanized iron sheet proposed	
Parameter	Value outer set	Value indoor set and base	Value outer set	Value indoor set and base
No. of sheets	1	1	3	3
No. of parts of set	1	1	5	5
Total used area	2299750	1974550	11498750	9872750
Total used area %	73.59	63.18	85.17	73.13
Number of utilized parts	3	4	15	20
Area of utilized sheets	3125000	3125000	13500000	13500000
All reused waste	825250	1150450	2001250	3627250
All reused waste %	26.41	36.81	14.82	26.87
Price	12731.42	44229.92	66437.22	197455
Price (Sheet)	17300	70000	78000	270000
Length of cuts	5100	5705	25025	28675
Running time (s)	0.016	0.032	0.094	0.281

The optimization results showed that five comprehensive cutting sets were created with the proposed sheet configuration, compared to only one cutting set produced by the existing sheet. The proposed configuration had a waste rate of 20.845% compared to 31.61% for the existing sheet. The pallet set waste rate also decreased by 11.59% for the 0.7 mm sheet and by 9.00% for the 2 mm sheet due to the proposed sheet dimensions. This indicates that the larger sheet configuration uses raw materials more efficiently and is the best manufacturing solution in terms of material and waste.

To model the cutting optimization problem, a Linear Programming (LP) model was developed to maximize material utilization and minimize waste during the cutting process. The optimization model is presented below.

$$\text{Minimize } Z = A_s - \sum_{j=1}^{n} A_j X_j$$

subject to

$$\sum_{j=1}^{n} A_j X_j \leq A_s$$

$$X_j = n_j,\ X_j \geq 0,\ j = 1,2,\dots,n$$

where:

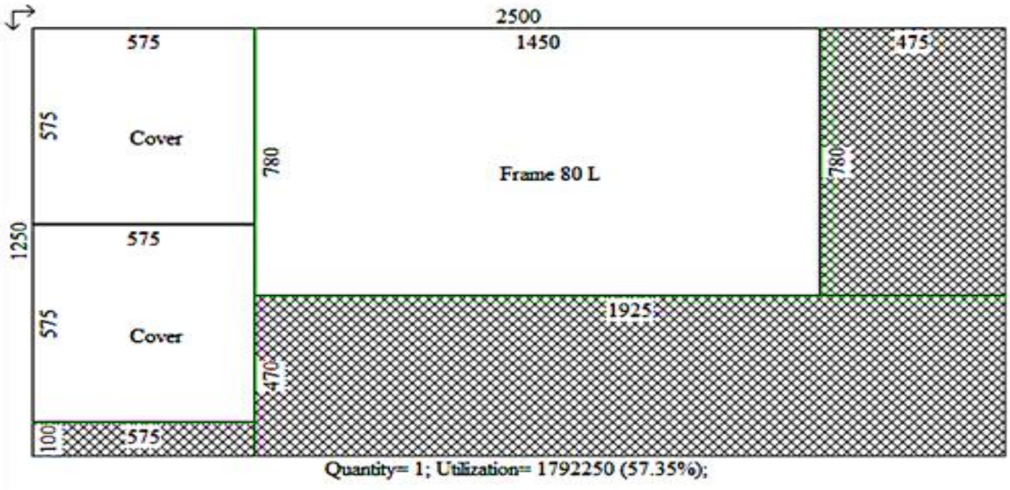
- Z= objective function.
- A_j= area of the j^{th}component.
- A_s= total area of the metal sheet.
- X_j= number of pieces cut from component j.
- n_j= required quantity of component j.

The objective function maximizes the total utilized area of the sheet, or equivalently minimizes the unused (waste) area, while satisfying production requirements and available sheet-area constraints. The optimization model created in WinQSB utilized the dimensions of the parts and their respective surface areas. The software produced the Optimal Solution Report, which revealed the amount of material waste caused by the existing cutting pattern compared with the optimal one. For the 0.7-mm metal plate, the waste area of the current pattern is 825250 mm², while the similarly measured area produced using three large plates from the optimal pattern is 2001250 mm². For the 2-mm plate, the waste area of the existing pattern is 1150450 mm², and the area collected using three plates from the optimal configuration reaches 3627250 mm². Based on these optimization results, the corresponding material areas and costs are calculated for each mentioned thickness and shown in Table 4.

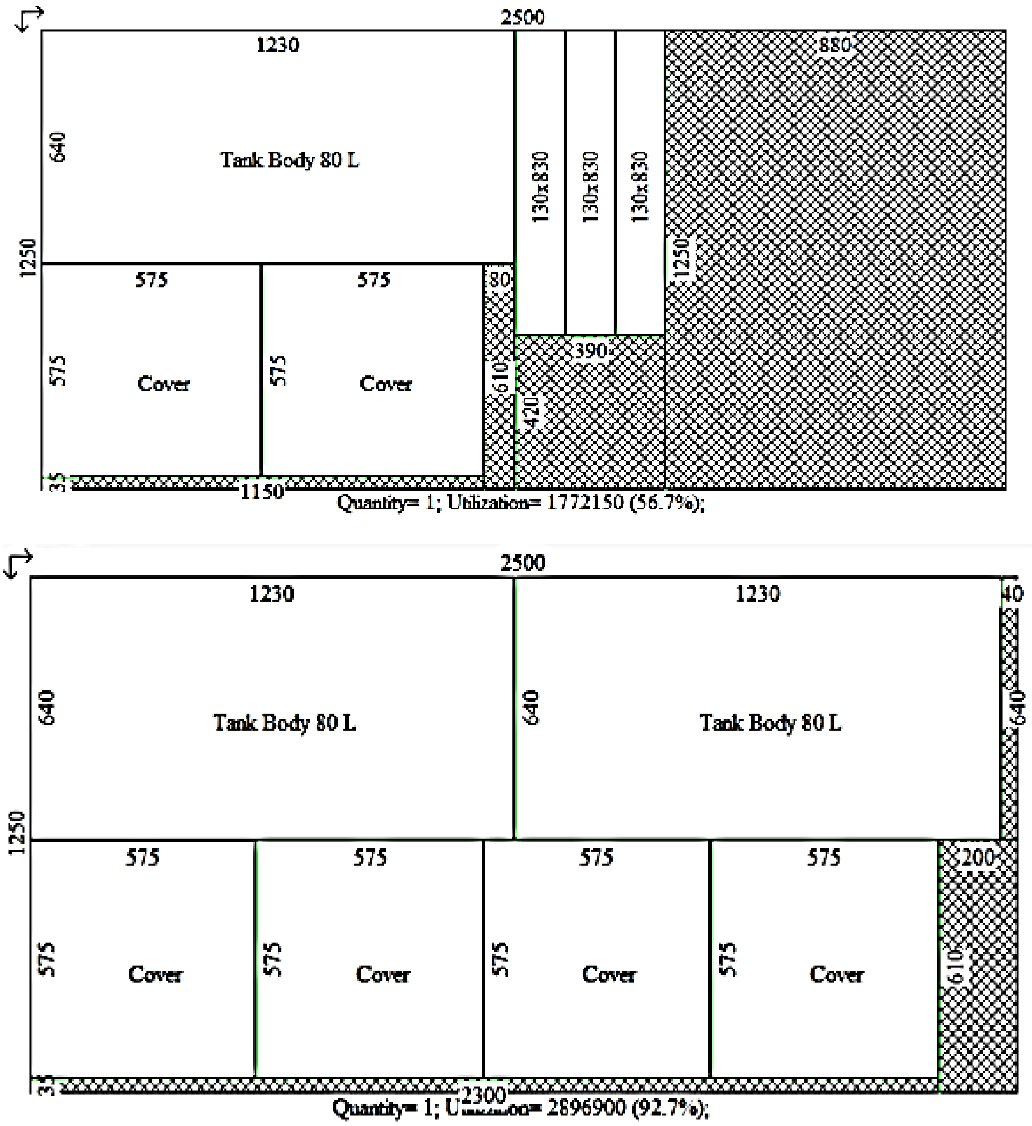
Table 4. Results for product 120 l

Results for product 120 l	Units thickness 0.7 mm		Units sheet thickness 2 mm	
	2500 mm x 1250 mm	3000 mm x 1500 mm	2500 mm x 1250 mm	3000 mm x 1500 mm
Cost sheet	17300 ID	26000 ID	70000 ID	90000 ID
Count of sheets	1	3	1	3
Total cost of sheets	17300 ID	78000 ID	70000 ID	270000 ID
Count of units	1	5	1	5
Cutting area	2299750 mm^2	11498750 mm^2	1974550	9872750
Total area	3125000 mm^2	13500000 mm^2	3125000 mm^2	13500000 mm^2
Cost for one group	17300 ID	15600 ID	70000 ID	54000 ID
Cost for one mm^2	0.005536 ID/mm^2	0.005778 ID/mm^2	0.0224 ID/mm^2	0.02 ID/ mm^2
Total cost for groups	12731.416 ID	66439.775 ID	44229.92 ID	197455 ID
Area waste	825250 mm^2	2001250 mm^2	1150450 mm^2	3627250 mm^2
Present waste for one sheet	26.41%	14.82 %	36.81%	26.87 %
Amount of Dec. % waste	-	11.59 %	-	9.94%
Rate decrease waste	-	**43.9≈44%**	-	**36.993 %**
Total waste	4569 ID	≈ 11563.2225 ID	25770.08 ID	72545 ID
Savings cost per group	-	**1700 ID**	-	**16000 ID**
Ratio discount on the cost of the used sheet	-	9.83%		22.86 %

Figures 3-4 show data on 80-l product below.

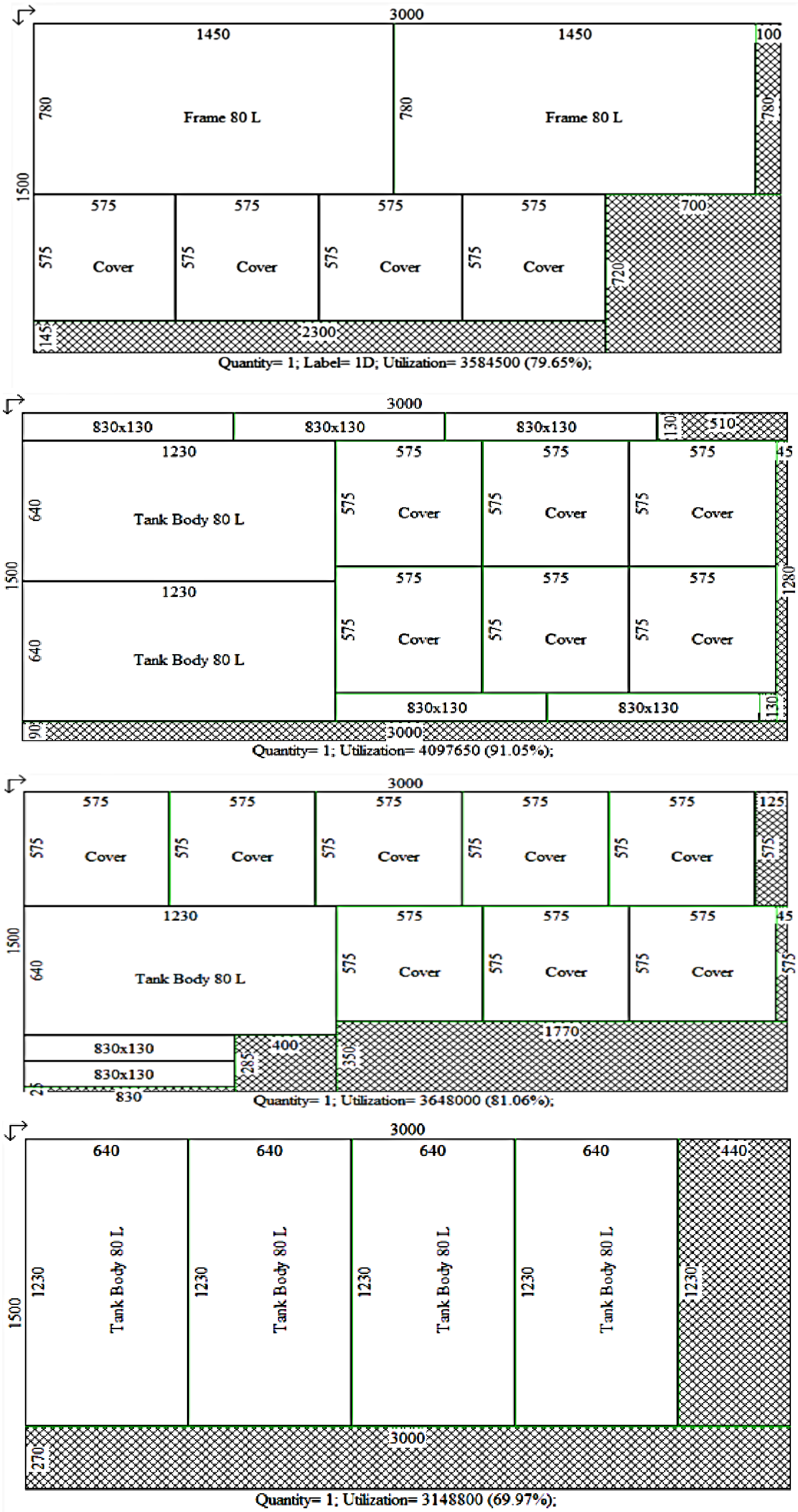


(a)



(b)

Figure 3. Used sheet for [frame, two covers]; (b) [three tank bodies, three bases, six covers] for product 80 l



(a)

(b)

Figure 4. Suggested sheet for (a) [two frames, four covers] (b) [seven tank bodies, seven bases, fourteen covers] product 80 l

The results of the cutting program statistics are presented in Table 5 for the galvanized iron sheet used and proposed.

Table 5. Results of the statistical program's Cutting Optimization Pro5 for product 80 l

	Galvanized iron sheet used		Galvanized iron sheet proposed	
Parameter	Value outer set	Value indoor set and base	Value outer set	Value indoor set and base
No. of sheets	1	2	1	3
No. of parts of set	1	3	2	7
Total used area	1792250	4669050	3584500	10894450
Total used area %	57.35	74.7	79.65	80.69
Number of utilized parts	3	12	6	28
Area of utilized sheets	3125000	6250000	4500000	13500000
All reused waste	1332750	1580950	915500	2605550
All reused waste %	42.65	25.30	20.34	19.3
Price	9921.896	104586.72	20710.44	217889
Price (Sheet)	17300	140000	26000	270000
Length of cuts	5105	16530	9305	37580
Running time (s)	0.031	0.094	0.047	0.203

The test results showed that the proposed board gives two sets cut for the outer part with a damage rate of 20.34% and 7 sets for the tank and base from three boards with a damage rate of 19.3% compared to the board used which gives one set for the outer part with a damage rate of 42.65% and 3 sets for the inner part and a base from two boards with a damage rate of 25.30%, as the percentage of waste decreased to almost half the damage rate for the outer part and 6% for the inner part and base, so the optimal decision is to choose the board with larger dimensions. The data results in the model generated from the parts and area extracted in the Win QSB2 software for the Optimal Solution Report table show the following areas of damaged sections: For a 0.7 mm sheet (1332750 mm² resulting from a cut from the used board), (915,500 mm² resulting from a cut from two sheets of the proposed type). And for a 2 mm sheet (1,580,950 mm² from two sheets of the used billet), (3627250 mm² from three sheets of the proposed type). These results are like those obtained from the cutting program, and Table 6 shows the area and cost results for both sheets.

Table 6. Results for product 80 l for both sheets

Results for product 120 l	Units: sheet thickness 0.7 mm		Units: sheet thickness 2 mm	
	2500 mm x 1250 mm	3000 mm x 1500 mm	2500 mm x 1250 mm	3000 mm x 1500 mm
Cost sheet	17300 ID	26000 ID	70000 ID	90000 ID
Count of sheets	1	1	2	3
Total cost of sheets	17300 ID	26000 ID	140000 ID	270000 ID
Count of units	1	2	3	7

Results for product 120 l	Units: sheet thickness 0.7 mm		Units: sheet thickness 2 mm	
	2500 mm x 1250 mm	3000 mm x 1500 mm	2500 mm x 1250 mm	3000 mm x 1500 mm
Cutting area	1792250 mm^2	3584500 mm^2	4669050 mm^2	10894450 mm^2
Total area	3125000 mm^2	4500000 mm2	6250000 mm^2	13500000 mm^2
Cost for one group	17300 ID	13000 ID	46666.667 ID	38571.42857 ID
Cost for one mm^2	0.05536 ID/mm^2	0.005778 ID/ mm^2	0.0224 ID/mm^2	0.02 ID/ mm^2
Total cost for groups	9921.896 ID	20711.41 ID	104586.72 ID	217889 ID
Area waste	1332750 mm^2	915500 mm^2	1580950 mm^2	2605550 mm^2
Present waste for one sheet	42.65%	20.34 %	25.30%≈	19.3%
Amount Dec. % waste	-	22.31%	-	6%
Rate decrease waste	-	**52.3094959 %**	-	**23.71541502 %**
Total waste	73781.04 ID	528.9759 ID	3541328 ID	52111 ID
Savings per group	-	**4300ID**	-	**8095 ID**
Ratio discount on the cost of the used sheet	-	50%	-	17.45%≈

According to the results, the total reduction in the cost of the complete set of the 80-l product is 12395 ID, and therefore the product price for 2024 and 2025 decreases from 110000 ID to 97000 ID; that is, the price decreases by 0.121772727% from 2024 to 2025. Based on the price of similar products in the local market in 2025 (120000 ID), the proposed board is cheaper, so the optimal decision is to choose the proposed board.

The basic idea: We have two products, each with a specific production quantity based on demand over ten years. We need to determine the production quantity after adjusting the prices of both products (a 120-liter water heater and an 80-liter water heater). This production is determined by the product cost before and after the price reduction, while holding the final price of both products' constant for 2024-2025. This means the relationship between prices and sales changed in the latter part of the data, with the cost of the first product ranging between 125,000 and 140,000 dinars and the cost of the second product ranging between 95,000 and 116,000 dinars. Figures 5-6 show the corresponding quantities.

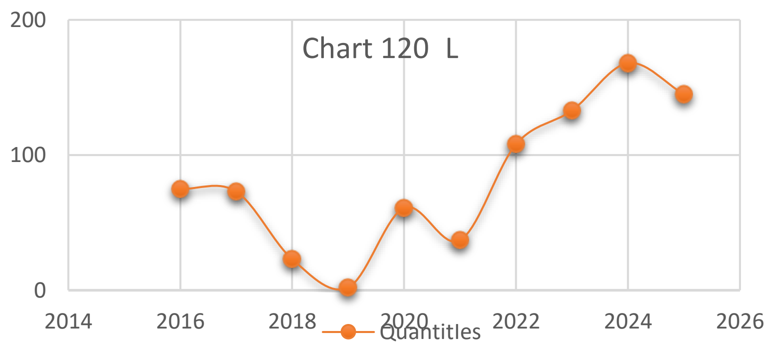


Figure 5. Production quantities for capacity

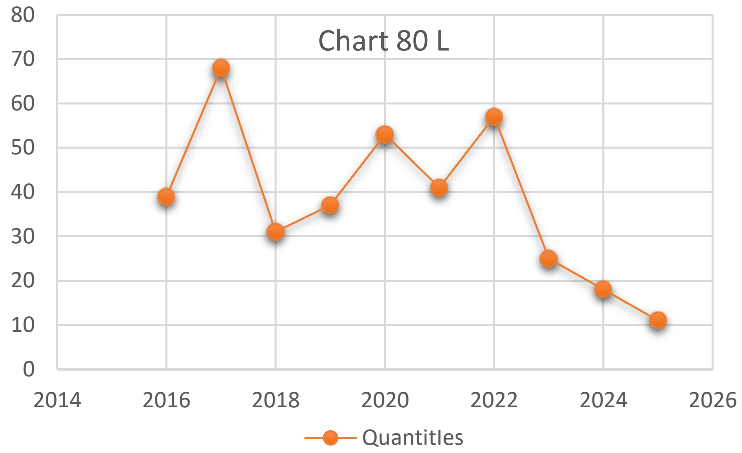


Figure 6. Production quantities for capacity

The Pearson correlation analysis, done on the small dataset (N = 12) between 2014 and 2025, showed a weak correlation between product prices and quantities produced. For the 120-l water heater, the correlation coefficient fell from r = 0.307 before implementing the price reduction to r = 0.018 after the measure was adopted, indicating almost no Positive relationship. For the 80-L water heater, the correlation coefficient changed from r = -0.292 to r = -0.097, indicating an extremely weak negative relationship that moved even closer to zero after the price reduction. These results suggest that prices have not been a key factor in determining production quantity in this period. One reason for such weak correlations is that prices remained relatively stable, while production quantity changed significantly.

The results suggest that before the price reduction strategy began, price and production volume were not statistically associated. After implementing the price reduction, however, a positive and statistically significant connection emerged for both products, indicating that the price policy successfully raised production levels. The results also show that price changes had a stronger effect on demand for the 120-liter water heater, which was more responsive to price changes than the 80-liter model.

Using the recommended pricing approach, possible production levels were forecast using the Enhanced N-BEATS Neural Network (N-BEATS*). The forecasting was performed in Python using the PyTorch deep learning framework. The forecasting model's input variables are based on historical data on production levels and goods prices. In addition, the analysis was based on splitting the data sample into training and testing sets.

To ensure stable input variables, the forecasting model's inputs were transformed into a normalized range of [0,1] to speed up neural network convergence. The Enhanced N-BEATS architecture combines multiple fully connected layers with ReLU as the core activation function, enabling it to recognize complex non-linear combinations in the production data. Each block provides dual output: one output backcasts past data, and the second forecasts future production levels. This combination of blocks is called dual-block architecture, which improves forecasting accuracy because the model can learn the residuals. Table 7 shows that the predictive data for 80 l and 120 l heaters offer low estimation quality

Table 7. Final test N-BEATS

Test N-BEATS*		Product 120 L	Product 80 L
pMAPE		0.040	0.091
nMSE		0.016	0.007
Loss fun		0.048	0.095
Forecasted year	2024	163	17
	2025	163	17

The transformed data was then returned to the original scale using the mean and standard deviation of the training data. Residual learning was done through a block-by-block adjustment process. The goal of the work is to test the model's predictability based on historical MAPE and MSE values. The research shows that pricing and cost-decrease strategies have no significant impact on production levels. Both forecasts are approximately 163 and 17 units for two years, respectively.

To determine the better forecasting method, Enhanced N-BEATS was compared with two well-known forecasting methods: Simple Linear Regression (SLR), implemented in the Scikit-learn library, and Seasonal AutoRegressive Integrated Moving Average with eXogenous variables (SARIMAX), implemented in the Statsmodels library. The comparison used the same training and test datasets.

Because of the limited sample size and the disturbance in production volumes under unchanged prices, model performance was evaluated using pMAPE, nMSE, and forecast accuracy. Table 8 presents the comparison results and clearly shows that Enhanced N-BEATS has the lowest forecasting errors and is the best among all forecasting methods. Therefore, Enhanced N-BEATS was chosen as the main forecasting method for production volumes for the period 2024-2025.

Table 8. Final test and comparison for product 120 l

Test product 120 l		N-BEATS*	Simple linear regression	SARIMAX
pMAPE		0.040	0.317	0.16
nMSE		0.016	37.24	9.456
Loss fun		0.048	18.937	4.888
Forecasted year	2024	≈163	92	117
	2025	≈163	27	97

Thus, the comThe comparisons show that the N-BEATS* model achieved the best performance in terms of accuracy, with the lowest pMAPE (0.040), loss function (0.048), and nMSE (0.016). This indicates that this model performed best over time, meaning that it was able to effectively learn the data patterns. SARIMAX is the second model that has the second-best error metrics with pMAPE = 0.160, nMSE = 9.456, and loss function = 4.888. SARIMAX did a relatively good job, but not as well as N-BEATS*, which has less capacity in exploiting time-series features for forecasting. A simple linear regression had the largest values of pMAPE (0.317), nMSE (37.240), and loss function (18.937), which are indicators of the worst model. This suggests that the model does not precisely represent the relationship between the variables and shows a low correlation between the price and quantity, in this case indicated by the correlation coefficient.

As far as predictions are concerned, it is found that the N-BEATS* model predicted the level of production in 2024 and 2025 around ≈163 units, the SARIMAX model predicted the level of production in 2024 and 2025 around 117 units and finally simple linear regression model predicted the level of production in 2024 and 2025 as 92 units and 27 units respectively, which explains the difference in the ability of each model in working with the historical data, and at the same time, the predictions are confirmed by the data and the following conclusions: N-BEATS* is the best model, followed by SARIMAX and simple linear regression is the worst.

For 2024 and 2025, N-BEATS* predicted about ≈17 units. At the same time, SARIMAX predicted 25 units for 2024 and 9 units for 2025, and simple linear regression predicted 50 units and 57 units, respectively. Thus, based on performance, the N-BEATS* model performed best, followed by SARIMAX and then simple linear regression, in forecasting production volumes for the 80-liter product, as shown in Table 9.

Table 9. Final test and comparison for product 80 l

Test product 80 l	N-BEATS*	Simple linear regression	SARIMAX
pMAPE	0.091	1.49	0.143
nMSE	0.007	64.082	1.082

Test product 80 l		N-BEATS*	Simple linear regression	SARIMAX
Loss fun		0.095	33.531	0.684
Forecasted Year	2024	≈17	50	25
	2025	≈17	57	9

The study showed the accuracy of the N-BEATS* model among three competing models, with the lowest mean percentage absolute error (0.091), normalized mean squared error (0.007), and loss function value (0.095), demonstrating its ability to forecast the actual data values closely. SARIMAX performed better than simple linear regression, but its output was not comparable to N-BEATS* based on the metrics used.

In conclusion, the research showed N-BEATS*'s deep learning capabilities in surpassing traditional statistical and regression models by learning complex patterns in production data and serving as the best predictor for forecasting production volumes for both 80-liter and 120-liter products.

The findings show that integrating cutting optimization and deep learning forecasting creates an efficient method that enhances manufacturing productivity and supports strategic production planning; implementing Cutting Optimization Pro5 reduced raw material waste. Consequently, production costs were minimized because the required cutting plans were created. Therefore, improving resource usage remains one of the most effective ways to make the production process more efficient in sheet metal producing industries.

The forecasting findings also suggest that the Enhanced N-BEATS model was more productive than forecasting benchmark models such as SARIMAX and Simple Linear Regression. The low prediction error achieved by the suggested model indicates that its ability to capture nonlinear trends and time-dependent features of industrial production improves forecasting accuracy. Therefore, the findings can be used in the production planning process to improve it for the manufacturers.

The main contribution of the study is to make a link between optimization and forecasting as two important parts of the production decision support framework. The proposed method integrates optimization of cutting method and forecasting the production process into one and establishes a direct relationship between optimization of the use of resources, reduction of production costs, pricing policies and planning the next production process.

The results of the study can be used for management. Specifically, optimized cutting can lead to more competitive pricing policies because of the reduction in production costs. Moreover, production forecasting helps to make informed decisions about resource allocation, production scheduling, procurement planning and inventory management.

4. Conclusions

The research outlines a synchronized method to manufacture decision-making that incorporates Cutting Optimization Pro5, Linear Programming, and enhanced N-BEATS deep learning. The method, which was optimized using the actual production data of the Akad Factory, would minimize cutting waste and accurately predict production quantity for the future, based on the actual production data of the Akad Factory.

The results indicated that the Enhanced N-BEATS was able to make better forecasts than conventional manufacturing forecasting techniques like SARIMAX and simple linear regression. Furthermore, the cutting optimization process eliminated raw material shortages and cost of production, thus making it possible to offer more competitive pricing policies and higher production efficiency.

The main contribution of this research is a single approach to production optimization and forecasting deep learning. The present research differs from the previous research on this topic in that it investigates the links among material system optimization, cost reduction, and production planning while relying on actual manufacturing data. The study, therefore, is valuable on scientific and practical fronts for the manufacturing industry.

Although the results were very good with the proposed method, some limitations should be considered. Firstly, the study was based on information for only a single facility and selected goods. The framework should be tested in the future with other industrial data to verify and evaluate its validity and efficiency.

Declaration of competing interests

The authors declare that they have no known financial or non-financial competing interests in any material discussed in this paper.

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Author contribution

Abeer Salim Alwan Alnajjar, Omar Mohammed Naser Alashari: conceptualization, methodology design, architectural analysis, data collection, and drafting of the manuscript. Faris M. Alwan, Marwan Abdul Hameed Ashour: theoretical framework development, heritage identity analysis, data interpretation, and critical revision of the manuscript. All authors contributed equally to the discussion of results, refinement of arguments, and final approval of the version to be published.

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