Proceedings of the 11th North American International Conference on Industrial Engineering and Operations Management, Milwaukee, Wisconsin, USA, June 9-11, 2026

Proceedings of the International Conference on Industrial Engineering and Operations Management

Publisher: IEOM Society International, USA DOI: 10.46254/NA11.20260054
Published: June 9, 2026

Resilient Manufacturing: Mitigating Input Cost Spikes and Tariff Impact with AI/ML-Powered Integrated Business Planning

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Abstract

US manufacturing sector faces constant cost volatility due to fluctuating commodity prices and reliance on imported materials. Several major events have occurred in the recent past, such as Panama Canal draught in 2023-34, Suez crises in 2024-25, Russia Ukraine war and 2025 Tariffs, that have drastically increased import costs. (Gopinath and Neiman 2026) As per market research blog, U.S. tariffs imposed in early 2025 resulted into estimated $328.2 billion annual additional cost on the manufacturing sector (marketresearch.com 2025). This paper proposes a structured analytical framework to help manufacturing companies assess these impacts objectively and enable rapid decision-making via the use of advanced technologies like Integrated Business Planning (IBP) software with AI&ML capabilities. The core of this methodology is a "What-If" analysis tool, which leverages master data and various costs maintained in an Enterprise Resource Planning (ERP) System. Manufacturing companies should utilize this analysis tool not as a one-time report but as a living dashboard.

Keywords
What-If Analysis, Import Costs, Manufacturing, Supply Chain, AI&ML

1. Introduction
The cost of commodities is inherently dynamic, creating significant uncertainty for the U.S. manufacturing industry, which heavily depends on the import of raw or semi-finished materials (Kleindorfer P. and Saad G 2005). Tariffs add immediate volatility to this segment and could result in overall supply chain uncertainty. As this tariff shock constitutes

the most significant disruption to global supply chains since the onset of the COVID-19 pandemic (Craighead, C. et al. 2020), this episode will serve as a key event (Morgeson, F et al.) that influences supply chain management (SCM) research for many years. Firms must counterbalance these costs when evaluating decisions. For example, China's rare earth export controls pushed US automakers to consider shifting some component assembly to China despite tariffs (McLain, S., and Felton R. 2025).

To maintain competitive advantage and safeguard profitability, manufacturing enterprises require robust analytical tools and techniques capable of quickly assessing the financial impact of these external variables and supporting objective, rapid strategic responses.

One powerful technique for navigating this uncertainty is "What-If" Analysis by modeling the financial outcomes resulting from varying percentages of imported material cost increases. The successful execution of this analysis requires the integration of four key elements: accurate cost baseline, multi-layer material tracking, matured demand forecasting, and sourcing flexibility.

1.1 Objectives

This paper presents a structured cost-impact modelling framework that integrates HTS Codes, COO, multi-level Bill of material costing, Sourcing strategies and Demand planning for performing "what if" analysis to help with objective strategic decision making.

2. Literature Review

This literature review examines the evolution of strategic planning from traditional Supply chain planning models to the AI/ML-powered Integrated Business Planning (IBP) frameworks proposed in this research.

2.1 Global Volatility

Recent scholarship identifies the "tariff shock" as a defining disruption for global supply chains, comparable in impact to the COVID-19 pandemic (Handfield et al. 2020). Literature suggests that firms often struggle with objective decision making because they lack granularity of data in their planning systems. This paper addresses this gap by integrating HTS, Country of Origin and Costing Bill of material data directly into the financial simulation layer.

2.2 Evolution of IBP

Traditional Sales and Operations Planning (S&OP) has historically been criticized for being siloed and reactive. The transition to Integrated Business Planning (IBP) represents a paradigm shift where financial outcomes are synchronized with operational constraints in real-time (Palmatier, G. E. & Crum, C. 2020).

2.3 AI&ML in Forecasting

Studies show that Deep Learning models, such as Long Short-Term Memory (LSTM) networks, outperform traditional ARIMA models by capturing non-linear patterns in volatile markets. Modern forecasting literature emphasizes the inclusion of "exogenous variables"—weather, social sentiment, and economic indicators—which AI/ML can ingest at scale. This paper's emphasis on Simple Exponential Smoothing (SES) optimized via ML-driven Alpha values aligns with the "Hybrid Modeling" trend, which combines the interpretability of classical statistics with the power of neural networks.

2.4 Digital Twin

According to Ivanov (2020), a Digital Twin allows for "stress-testing" the supply chain against specific disruptions like a 25% tariff hike (Ivanov, D. & Dolgui, A. 2020). This "What-If" framework acts as a digital twin of the associated data.

2.5 Research Gap

While existing literature covers AI in forecasting and the theory of IBP, there is a lack of practical frameworks that explicitly link HTS-level tariff data to Standard Cost Component Splits for real-time margin protection. This paper bridges that gap by providing a structured, data-driven methodology for manufacturers to move from reactive crisis management to proactive, objective mitigation.

3. Methods and Data Collection

This method of performing What-If analysis utilizes several master data and transactional data objects received from ERP and the Demand Planning module of IBP.

3.1 Standard Cost Estimate and Costing Bill of Material Data

The baseline for any profit or impact analysis is the Standard Cost Estimate, which is utilized to calculate the Cost of Materials. This estimation is applicable for all products including raw materials, semi-finished assemblies, and finished products. Enterprise Resource Planning (ERP) systems have matured methods to perform standard cost estimates. Standard cost estimates are performed periodically.

For raw materials, the standard cost is typically derived from vendor quotes or prices agreed upon by both the parties via contracts inclusive of any associated additional duties and overheads.

For in-house manufactured or semi-finished or finished products, the cost is calculated using a quantity structure, such as a Bill of Materials (BOM), in conjunction with production routing. The routing details different operations needed in the manufacturing process along with various capacities at each such station. Capacities are broadly categorized into Labor and Machine time. In addition, there could be additional times such as Set up time, Interoperation time, Wait time etc.

Machine, Labor and Set up rates are maintained as a standalone master data in the ERP system.

For example: Labor rate is $50/hr. Machine rate is $30/hr.

The costs are then calculated using following formulas

Labor cost = (Labor Rate x Operation Qty)/Base Qty

Machine cost = (Machine rate x operation Qty)/Base Qty

A standard cost estimate run is performed and saved in the ERP system along with its cost component split showing costs at different layers of the multi-level bill of materials. This data is integrated with IBP system.

3.2 Product and Supplier Master Data

Master data is very important for effective what if analysis. This data is maintained in ERP system and integrated with IBP system.

3.3 Country of Origin (COO)

The Country of Origin (COO) must be maintained as master data, either at the product level or derived from the Product Supplier Info Record (PSIR). If a product is sourced from multiple countries, then the COO is maintained at the PSIR level.

3.4 Harmonized Tariff Schedule (HTS) code

For companies and governments to efficiently and accurately process and monitor goods as they cross international borders the HTS code system is essential. A smoother trade flow and increased efficiency of the world economy are made possible by properly classifying goods using HTS codes which also lowers the risk of customs delays and guarantees compliance with trade regulations (Navasardyan, Z. 2024).

Precisely allocating the appropriate HTS code to a wide range of products while identifying the small variations that set one product category apart from another is crucial to the system's operation. For companies involved in international trade, achieving high accuracy is essential because any misclassification could cause logistical problems and financial ramifications (Navasardyan, Z. 2024).

Every imported component, raw material, and finished goods must be assigned the correct Harmonized Tariff Schedule (HTS) code. This is done in ERP, and this data is integrated with IBP system.

3.5 Sourcing Strategy
The chosen sourcing model—single-sourcing or multi-sourcing—fundamentally influences risk and flexibility (Iyer A. et al. 2005). Multi-sourcing is a favored strategy in volatile markets. It reduces risk, increases leverage and drives competition. It also gives flexibility in volatile situations. Sourcing master data is integrated with IBP system.

3.6 Quota Rules
Quota management is a master data object in ERP that automatically distributes a material's total requirement among multiple sources (like vendors or plants) based on defined percentages (quotas) for a specific period, ensuring fair allocation and strategic sourcing. Quota management master data is integrated with IBP system.

3.7 Lead Times and NPI Costs
Lead times are captured in the master data and reviewed and updated periodically. In case of multi-sourcing, it is maintained at eh Material Supplier Info record level. NPI costs are usually captured as overheads. These overheads can be incorporated into the standard cost estimate as part of the configuration needed for that process. Lead times and NPI costs are integrated with IBP as part of the Product and Standard cost master data.

3.8 Demand Planning
Demand planning is a critical process that uses predictive analysis to estimate future customer demand over a specified period (typically 1–2 years). This guides production, inventory, resource allocation, and profitability analysis (by comparing COGS and pricing).

Techniques are broadly categorized into Quantitative (data-driven) and Qualitative (judgment-based) methods (S. F. P. A. van der Heijden 2003). Following is some of the primarily used techniques. There are many other techniques available in modern planning systems.

3.1.1 Quantitative Models
These models rely on historical sales data and stable market conditions.

Time Series Models: Analyze demand patterns over time.
- Moving Averages (MA): Simple method for smoothing random fluctuations.
- Exponential Smoothing (ES): Gives greater weight to recent data, effective for non-seasonal, stable demand.
- Trend Projection: Mathematically extends a long-term growth or decline trend.
- Decomposition Methods (e.g., ARIMA/SARIMA): Breaks down demand into Trend, Seasonality, and Random Variation.

Causal Models: Establish cause-and-effect relationships between demand and influencing variables.
- Regression Analysis: Models the relationship between demand (dependent variable) and independent variables (e.g., price, advertising, economic indicators).
- Econometric Models: Complex systems of equations describing the relationship between broad economic factors (GDP, interest rates) and industry demand.

3.1.2 Qualitative Models
These models are essential when historical data is scarce or volatile (e.g., New Product Introductions or Marketing campaign).
- Delphi Method: Iterative, anonymous consensus-building among a panel of external experts.
- Sales Force Composite: Aggregates bottom-up forecasts from individual sales personnel.
- Market Research/Surveys: Directly assesses customer purchase intentions.
- Executive Opinion: Panel of cross-functional executives generates a forecast based on collective experience and intuition.

3.1.3 Modern Approaches
Modern industrial manufacturing utilizes Integrated Business Planning software which in turn uses **Predictive Analytics & Machine Learning (AI/ML)** algorithms. These algorithms play a transformative role in forecasting,

significantly improving accuracy and efficiency compared to standard approaches. They work by moving beyond static, historical data analysis to create predictive models that continuously learn from complex, real-time information.

3.1.4 Core Functions of AI and ML in Forecasting

Traditional methods use simpler statistical models that only use historical data. ML algorithms (like Linear Regression, Random Forests, Neural Networks, and LSTM networks) can analyze vast, multi-dimensional datasets and uncover non-linear relationships and complex patterns that are not identified by human eyes or simple tools. AI models can integrate a much wider variety of data sources than traditional methods. This includes internal data (sales history at various levels, pipeline status, inventory levels, promotions) and external data (economic indicators, social media sentiment, competitor activity, weather patterns, and website traffic). By incorporating this diverse data, the forecast provides a more comprehensive and robust picture of market drivers.

ML models are dynamic and not static. They automatically ingest new data and refine their predictions as market conditions change. This real-time capability allows the software to quickly adapt to market volatility, new product launches (where historical data is absent), and sudden disruptions, enabling businesses to make proactive decisions instead of reactive ones. AI automates time-consuming, manual tasks like data collection, cleaning, normalization, and model selection. This frees up financial and planning professionals to focus on strategic analysis and decision-making, rather than data management. For instance, a deep learning regression model in a study demonstrated an impressive R squared (R2) of 0.93 and a mean absolute percentage error (MAPE) of 2.9%, outperforming other models like AdaBoost (Ibrahim B. et al. 2022). This exemplifies the effectiveness of AI in enhancing the precision of demand predictions.

In summary, AI and Machine Learning transform forecasting software from a retrospective tool into a proactive, continuously improving, and highly accurate predictive engine.

3.1.5 AI/ML Implementation Framework

The AI/ML component is implemented as a hybrid forecasting layer within the IBP system. A baseline Simple Exponential Smoothing (SES) model is enhanced using machine learning techniques to optimize the smoothing parameter (α) by minimizing forecasting error (MSE). The model ingests historical demand data along with external variables such as commodity prices and tariff rates.

The optimized forecast is integrated into the IBP planning layer to drive consensus demand and subsequent "What-If" simulations. This enables dynamic adjustment of demand and cost projections under changing external conditions, ensuring that scenario analysis reflects both internal data and exogenous market signals.

4. Results and Discussion

4.1 What-If Analysis

One of the reasons it is recommended to perform what if analysis in IBP system is that, if the organization is using an IBP system for supply chain planning, then most of the data is likely already integrated with this system. The sales demand forecast created in the Demand planning module of IBP is used as a starting point in this What-If analysis.

4.2 Demand Forecasting

Demand forecasting is the starting point of the what if analysis. IBP planning system uses sales history and any other data received from ERP system for performing demand forecasting.

4.2.1 Example of demand forecast

Table 1 below shows sample sales history data for one product "100 KW Industrial Generator G1001" in USA-Michigan sales zone for the past 12 periods (period = month).

Table 1. This is a sample sales history data for one product and one region for 13 months

Product	**Dec 23**	**Jan 24**	**Feb 24**	**Mar 24**	**Apr 24**	**May 24**	**Jun 24**	**Jul 24**	**Aug 24**	**Sep 24**	**Oct 24**	**Nov 24**	**Dec 24**
G1001	950	800	825	1025	992	1011	1050	900	877	811	800	825	860

IBP software analyzes this data and determines, for example, Simple Exponential Smoothing is the best way to create demand forecast

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The Simple Exponential Smoothing (SES) formula is $F_{t+1} = \alpha Y_t + (1-\alpha) F_t$. Where:

- F_{t+1}: The forecast for the next time period.
- F_t: The forecast for the current (most recent) period.
- Y_t: The actual observed value for the current period.
- α (Alpha): The smoothing constant ($0 \leq \alpha \leq 1$).

Alpha Optimization: Instead of guessing α, AI/ML uses techniques (like minimizing Mean squared Error or gradient descent) to find the best α for your data.

Deep Learning Integration: SES is embedded into complex neural networks (like Multi-Layer Perceptron - MLPs) to create powerful hybrid models (e.g., Structured State Space models) that handle long, complex sequences better than just SES or even some advanced models.

Table 2 below shows the demand forecast for the next 12 months calculated using hybrid model where AI/ML model suggested $\alpha = 0.3$

Table 2. Table showing Demand forecast for next 12 months calculated using hybrid model.

Period (t)	**Month**	**Sales History (Yt)**	**Previous Forecast (Ft or St−1)**	**Smoothed Value / New Forecast (Ft+1 or St)**	**Formula (Ft+1=0.3Yt +0.7Ft)**
1	12/23/2025	950	950 (F1=Y1)	950	0.3×950+0.7×950
2	1/24/2025	800	950	905	0.3×800+0.7×950.00
3	2/24/2025	825	905	881.5	0.3×825+0.7×905.00
4	3/24/2025	1025	881.5	924.55	0.3×1025+0.7×881.50
5	4/24/2025	992	924.55	944.49	0.3×992+0.7×924.55
6	5/24/2025	1011	944.49	964.84	0.3×1011+0.7×944.49
7	6/24/2025	1050	964.84	990.39	0.3×1050+0.7×964.84
8	7/24/2025	900	990.39	963.27	0.3×900+0.7×990.39
9	8/24/2025	877	963.27	938.29	0.3×877+0.7×963.27
10	9/24/2025	811	938.29	901.4	0.3×811+0.7×938.29
11	10/24/2025	800	901.4	861.98	0.3×800+0.7×901.40
12	11/24/2025	825	861.98	851.39	0.3×825+0.7×861.98
13	12/24/2025	860	851.39	854.97	0.3×860+0.7×851.39

4.3 "What if" Scenario planning tool in IBP

The "**What if**" Cost Increase Impact Analysis is a structured assessment that quantifies the effect of increased Raw Material costs on Cost of Goods Sold (COGS), profitability, and market position. This analysis uses all the integrated master data (Product Master, Standard Costs, Harmonized Tariff Schedule (HTS) codes, Demand Forecast, and Sourcing data) within supply chain or IBP software.

Demand forecasting data determined via above technique is the starting point of this "What if" analysis. It is represented by first row in Table 3. Consensus forecast (line 2 in Table 3 below) is the final agreed upon forecast by all stakeholders. Inputs from qualitative models are also considered while generating final consensus. This is usually the locked forecast for all future uses. COGS and Selling Price received from ERP system are represented in rows 3 and 4 in Table 3 below. By utilizing the COO and HTS codes, materials are bucketed into their own groups showing the percentage of total cost. Planning systems like IBP are optimized to handle big volumes of data for these types of analysis. They provide flexibility to group data in a manner that is necessary for the analysis. Following Table shows one example with a handful of COOs and HTS combinations (lines 5-8 in Table 3) used in the analysis. However, all such different combinations can be their own lines. The tool further enables simulation of multiple cost-change scenarios (e.g., supplier shifts, tariff adjustments, or sourcing alternatives) to evaluate their comparative financial and operational impact.

Table 3. Dashboard showing Price, Costs by (sample) HTS/COO combinations and profit margin.

Period	25-Jan	25-Feb	25-Mar	25-Apr	25-May	25-Jun	25-Jul	25-Aug	25-Sep	25-Oct	25-Nov	25-Dec
Forecast	905	882	925	944	965	990	963	938	901	862	851	855
Consenses forecast (Final)	905	880	925	950	960	990	970	940	900	860	850	855
COGS @ $450	407250	396000	416250	427500	432000	445500	436500	423000	405000	387000	382500	384750
Price @799.99	723991	703991	739991	759991	767990	791990	775990	751991	719991	687991	679992	683991
China HTS 1001 @20% RM cost*	81450	79200	83250	85500	86400	89100	87300	84600	81000	77400	76500	76950
China HTS 2001 @ 12% RM cost*	48870	47520	49950	51300	51840	53460	52380	50760	48600	46440	45900	46170
MX HTS 1501 @8% RM cost*	32580	31680	33300	34200	34560	35640	34920	33840	32400	30960	30600	30780
MX HTS2501 @7% RM cost*	28508	27720	29138	29925	30240	31185	30555	29610	28350	27090	26775	26933
Domesting @ 20% RM cost*	81450	79200	83250	85500	86400	89100	87300	84600	81000	77400	76500	76950
Inhouse mfg cost*	134393	130680	137363	141075	142560	147015	144045	139590	133650	127710	126225	126968
Profit Margin	43.75%	43.75%	43.75%	43.75%	43.75%	43.75%	43.75%	43.75%	43.75%	43.75%	43.75%	43.75%

Initial cost, price and profit margins are shown in following Figure 1

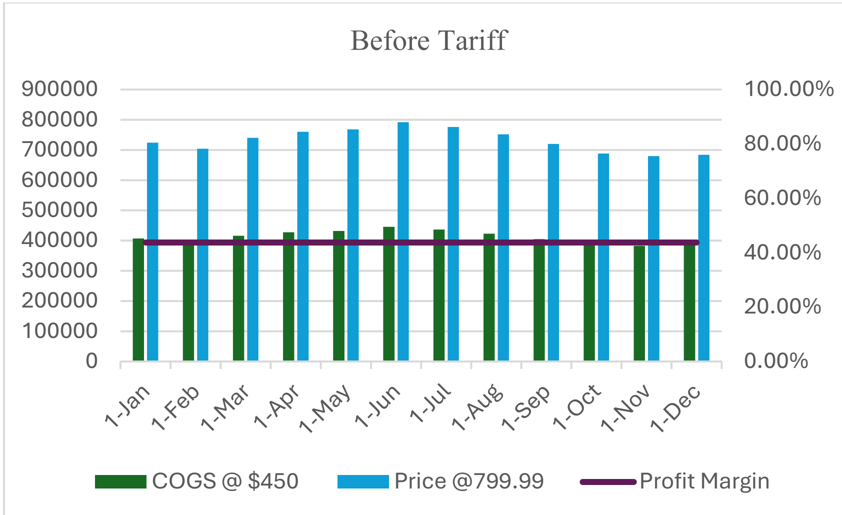

Figure 1. Chart showing Price, Costs and profits.

Different levels of aggregation or disaggregation are performed to get data for a specific level of product hierarchy. That way the models can be flexibly used for high level or low-level analysis. For example, all products in one sales zone (USA-Michigan) aggregated together could be the highest level, all products in one product category (all types of Industrial Generators) could be at a medium level, and one specific product (100 KW Industrial Generator) in that sales zone could be at the lowest level for analysis.

4.4 What If scenario 1

Once we have created a dashboard as shown above with different lines showing cost percentage by HTS codes and COO, we are now ready to apply the percentage increase in each category to assess the impact. This first What if scenario shows impact of cost increased in these specific HTS&COO combinations on the profit margin. Table 4 below reflects these changes. Figure 2 shows a profit decline because of these changes.

Table 4. Dashboard segment showing effects of first set of cost changes and its impact on profit margin.

"What if" from Mar 2025												
China HTS 1001 cost goes up by 35% &	81450	79200	112388	115425	116640	120285	117855	114210	109350	104490	103275	103883
China HTS 2001 cost going up by 30% &	48870	47520	64935	66690	67392	69498	68094	65988	63180	60372	59670	60021
MX cost going up by 25%	61088	59400	78047	80156	81000	83531	81844	79313	75938	72563	71719	72141
New COGS	407250	396000	475982	488846	493992	509429	499138	483701	463118	442535	437389	439962
New Profit Margin	43.75%	43.75%	35.68%	35.68%	35.68%	35.68%	35.68%	35.68%	35.68%	35.68%	35.68%	35.68%

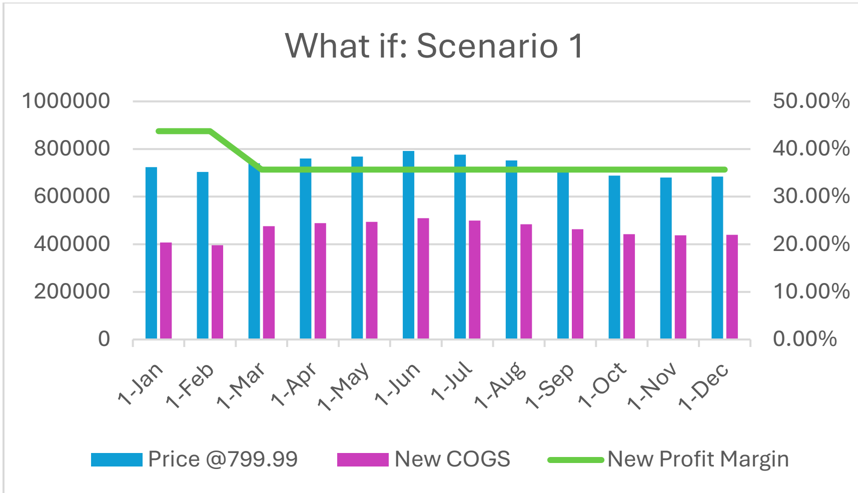

Figure 2. Chart showing effects of first set of cost changes.

This what if scenario simulation shows that the projected import cost increases indicate a non-trivial 8% drop profit margins. This is a significant drop, and it poses a substantial risk to the organization's financial stability and market share. To maintain competitive advantage in the market, company executives must utilize this iterative "What if analysis" tool further to identify and implement an optimal mitigation strategy. One of the biggest advantages of this tool is its ability to categorize the data flexibly into different buckets so that the impact analysis can be performed easily.

4.5 What If Scenario 2

This next iteration of what if analysis shows the impact of anticipated or announced tariff decreases and modified sourcing strategy from import to inhouse manufacture. This is shown in Table 5 below and Figure 3 shows associated profit margin improvements (Figure 4).

Table 5. Dashboard segment showing effects of possible action to reduce cost increase impact.

"What if" from Jun & Aug 25, we shift some sourcing												
Price @$799.99	723991	703991	739991	759991	767990	791990	775990	751991	719991	687991	679992	683991
China HTS 1001 tariffs reduced to 10% in June	81450	79200	112388	115425	116640	98010	96030	93060	89100	85140	84150	84645
China HTS 2001 moved inhouse from Aug with net increase of 10% cost	48870	47520	64935	66690	67392	69498	68094	55836	53460	51084	50490	50787
MX tariffs reduced to 15% in May	61088	59400	78047	80156	74520	76849	75296	72968	69863	66758	65981	66369
New COGS	407250	396000	475982	488846	487512	480472	470765	446054	427073	408092	403346	405719
New Profit Margin	43.75%	43.75%	35.68%	35.68%	36.52%	39.33%	39.33%	40.68%	40.68%	40.68%	40.68%	40.68%

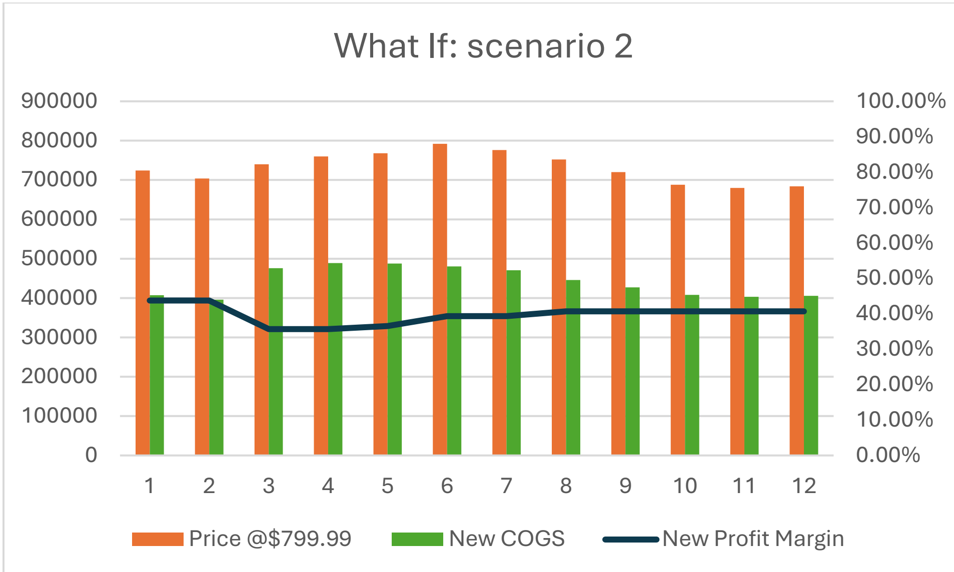

Figure 4. Chart showing profit margin improvement due to sourcing shift and reduced tariffs.

4.6 Subsequent What If Scenarios

Similarly, once the tool is available, several different scenario plannings can be performed so that the business can rapidly react to a situation. If there is anticipation of changing costs, business can also use this tool to proactively perform this analysis and be ready with strategies to respond to situations when they happen. Other variables like product lead times, time to switch supplier, cost of switch and so on could be added to this mix. IBP solutions with ML capability could also fine tune results based on Industry specific or Industry independent exogeneous variables. For example, for industries engaged in energy infrastructure, hurricane forecast for the year could be an exogenous variable that ML model could use to update the forecast and other results in this model. This scenario only shows a handful of Raw Material categories as an illustration. The beauty of today's IBP software is that it can accommodate all such necessary categories and perform all the calculations without affecting the system performance.

The model could be further evaluated to see impacts of following mitigation strategies to see which one suits well to the business.

1. Full absorption: In this case, company fully absorbs the increased costs without raising selling price. In this case, the profit margin takes a hit.
2. Full Pass-through: In this case, companies raise selling price by full amount. In this case, the margin is protected, however the demand might drop.
3. Cost Sharing: In this case, the supplier and the company share the increased cost. The profit is partially protected.
4. Sourcing Shift: A detailed analysis of alternative is performed to analyze total cost of ownership of switching suppliers, lead times etc. and supplier is switched fully or partially to mitigate the cost increase.
5. Make Vs Buy: Another approach is to determine whether manufacturing in-house is more cost-effective than sourcing externally, particularly under high-tariff conditions. Prior research shows that make-or-buy decisions are driven by cost structures, profitability, flexibility, and risk considerations, and that tariffs can significantly impact firm performance, often prompting firms to reconsider sourcing strategies and vertical integration (Arora & Kumar, 2022) (Fan et al., 2021).
6. Reshoring: Bringing production to the United States may be a strategic move for tariff reduction that also capitalizes on local incentives and market proximity. If your long-term business goals include United States expansion, accelerating these plans could mitigate short-term tariff impositions and supply chain instability (Karatzas et al. (2022))

It is critical that the Sourcing Shift scenario factor in the significant time and cost required to onboard a new supplier, which involves a full NPI sourcing and qualification process.

5. Conclusion

The integration of ERP data with AI/ML-powered Integrated Business Planning (IBP) for performing What-If analysis represents a paradigm shift in how manufacturing enterprises navigate the complexities of geopolitical instability, tariff volatility and input cost variation impacts. As demonstrated throughout this paper, the transition from reactive, legacy analysis, to a dynamic, data-driven "What-If" analytical framework is no longer a luxury but a strategic necessity for maintaining profitability and supply chain resilience.

5.1 Summary of Research Findings

Our analysis confirms that the effectiveness of geopolitical risk mitigation is predicated on the seamless integration of ERP data—specifically HTS codes, Country of Origin, Multi Level Standard Costing and sales history — with advanced algorithms of IBP. IBP leverages existing master data to group information dynamically. This allows users to organize and view their data in ways that align with specific business needs rather than being stuck in a rigid structure. The system is built to handle massive datasets with high efficiency. The transition from traditional statistical forecasting to AI-driven models (such as LSTM and Neural Networks) has proven to reduce forecast error significantly, providing optimized demand signal for accurate financial simulations.

5.2 Strategic Implications for Leadership

The two iterative scenario analysis presented in this study indicates that the tool provides easy ways to modify input data and analyze impact quickly so that the leadership can take objective decision on financial actions. Whether the organization chooses Full Absorption, Full Pass-Through, or a Sourcing Shift, the decision is now supported by objective, quantified data rather than intuition. By anticipating tariff impacts, firms can hedge their sourcing strategies quickly. The IBP dashboard serves as a "single source of truth," aligning Finance, Supply Chain, and Sales on the projected impacts of external shocks. To be truly effective, the analytical tools described herein must be utilized as a living dashboard, continuously updated with ERP data and real-time market inputs. In an era where geopolitical shifts can alter cost structures overnight, the speed of analysis is the ultimate competitive advantage. Future studies should explore the integration of Natural Language Processing (NLP) to ingest geopolitical news feeds, Government Harmonized Tariff Schedules data and other sources of data that affect input costs, into IBP systems, allowing for automated "What-If" triggers based on various input factors.

References

Gopinath G. and Neiman B., The Incidence of Tariffs: Rates and Reality, *NBER Working Paper* 34620, 2026, https://doi.org/10.3386/w34620. marketresearch.com, Tariff Shockwaves: The $328 Billion Impact Reshaping US Manufacturing.

Kleindorfer P. R. and Saad G. H., Managing disruption risks in supply chains, *Production and Operations Management*, vol. 14, no. 1, pp. 53–68, 2005.

Craighead, C. W., Ketchen Jr. D. K., and Darby J. L. Pandemics and Supply Chain Management Research: Toward a Theoretical Toolbox. *Decision Sciences* 51, no. 4: 838–866, 2020

Morgeson, F. P., T. R. Mitchell, and D. Liu. Event System Theory: An Event-Oriented Approach to the Organizational Sciences. *Academy of Management Review* 40, no. 4: 515–537. 2015.

McLain, S., and R. Felton. Automakers Race to Find Workaround to China's Stranglehold on Rare-Earth Magnets. *The Wall Street Journal* 2025.

Handfield, Graham & Burns, Coronavirus, Tariffs, Trade Wars and Supply Chain Evolutionary Design, *International Journal of Operations & Production Management*, 40(10), pp. 1649–1660, 2020.

Palmatier, G. E. & Crum, C., Transitioning From Sales and Operations Planning to Integrated Business Planning, *Dog Ear Publishing*, 2020

Ivanov, D. & Dolgui, A., A Digital Supply Chain Twin for Managing the Disruption Risks and Resilience in the Era of Industry 4.0, *Production Planning & Control*, 32, pp. 775–788, 2020.

Navasardyan, Z., "Interpretable and Generalizable HTS Code Classification Framework," *Economics, Finance and Accounting*, vol. 1, no. 13, p. 140, 2024.

Iyer A. V., Lee H. J., and Sethi A. B., Capacity management in supply chain planning and contracting for volatile demand, *European Journal of Operational Research*, vol. 161, no. 1, pp. 248–267, 2005.

S. F. P. A. van der Heijden, Forecasting methods in supply chain management, *International Journal of Production Economics*, vol. 86, no. 2, pp. 119–131, 2003.

Ibrahim, B., Rabelo, L., Gutierrez-Franco, E., & Clavijo-Buritica, N. Machine learning for short-term load forecasting in smart grids. Energies, 15(21), 8079. DOI: 10.3390/en15218079, 2022.

Arora M. and Kumar A., An Empirical Study on Make-or-buy Decision Making, *International Journal of Education and Management Engineering (IJEME)*, vol. 12, no. 1, pp. 19–28, 2022

Karatzas A., Ancarani A., Fratocchi L., Di Stefano C., and Godsell J., "When does the manufacturing reshoring strategy create value?," *Journal of Purchasing and Supply Management*, vol. 28, no. 3, p. 100771, 2022.

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