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RESEARCH PAPER

A Carbon-Constrained Production Planning Model for Sustainable Manufacturing

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ABSTRACT
While traditional production planning focused on optimizing supply-demand balance through make-to-stock/make-to-order strategies and capacity management, the new imperative of carbon neutrality introduces critical complexities. Regulatory emission caps now require manufacturers to strategically trade carbon allowances, fundamentally transforming the challenges of production optimization. This study developed an aggregate production planning model that incorporates carbon trading constraints into operational decision-making, providing industries with a systematic approach to address both economic and environmental objectives. The model optimized multi-period production plans across alternative technologies, each with distinct cost-emission profiles, while incorporating subcontracting options. It simultaneously considered government-allocated emission permits, dynamic carbon market prices, technology-specific costs and emissions, and subcontracting expenses. Through mathematical optimization of production quantities, subcontracting levels, and carbon credit transactions, the model minimized total costs while ensuring compliance. Computational experiments with nonlinear programming solved via LINGO demonstrated the model's effectiveness in identifying optimal technology deployment strategies that achieve significant cost reductions while meeting environmental targets, offering manufacturers a powerful tool for sustainable operations in carbon-constrained markets.

KEYWORDS: *Aggregate production planning; Carbon trading; Emission allowance; Emission price.*

1. Introduction

Traditional production planning has long focused on optimizing resource use to balance supply and demand, often through strategies such as make-to-stock versus make-to-order, inventory management, and capacity planning [1, 2]. These approaches aimed to reduce operational costs and improve service levels, assuming relatively stable environmental and regulatory contexts. However, this paradigm is now being disrupted by the global urgency to mitigate climate change. As nations commit to net-zero emissions, carbon regulations, most notably carbon pricing and emissions trading schemes, have emerged as critical mechanisms for enforcing climate targets [3, 4]. For industries, especially those that are energy-or emission-intensive, these developments introduce profound new challenges. Beyond fulfilling demand, firms are now expected to internalize environmental costs, track their carbon footprint, and actively participate in carbon markets. This fundamentally transforms the way production decisions are made, turning sustainability from a peripheral concern into a central, strategic requirement for long-term business viability [2, 5, 6].

In carbon-constrained environments, firms face increasingly complex and often competing objectives. While minimizing production and inventory costs remains essential, there is now an added imperative to reduce carbon emissions or incur financial penalties through carbon taxes or the purchase of emission allowances. This tension is especially pronounced in high-emission industries, such as steel, cement, and pulp and paper, where production technologies differ significantly in their environmental impact, particularly between coal-fired and gas-based systems. In such contexts, sustainability is no longer a peripheral concern but a core element of operational strategy. Technology choices, production scheduling, capacity utilization, and subcontracting decisions must now be evaluated not only through a cost-efficiency lens but also with regard to carbon intensity, regulatory limits, and carbon market dynamics. Traditional planning approaches fall short in this setting, as firms must consider real-time carbon prices, unit-level emission factors, and even the potential for

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generating revenue through emissions trading. This shift underscores the need for integrated, sustainability-aware decision models that can guide firms in balancing economic performance with environmental responsibility [7].

Production planning's significance is well-documented across industries, including automotive [8, 9], semiconductors [10, 11], pharmaceutical [12, 13], hardwood flooring [14], concrete [15, 16], TFT-LCD manufacturing [17, 18], textiles [19, 20], and PVC pipe production [21]. Studies like Panet al. [22] and Chenet al. [23] explored carbon trading's role in production, while cap-and-trade policies has been confirmed to be able to reduce pollution [24-26]. Research by Huaet al. [27] and Hovelaque and Bironneau [28] examined carbon trading's impact on inventory, and Chaabaneet al. [29] showed how better emission trading enhances supply chain sustainability. While several studies addressed carbon trading and inventory, few incorporated both production planning and emission market dynamics in a multi-period context.

Despite growing pressure for sustainable operations, most existing production planning approaches still treat environmental and economic objectives separately. This disconnect creates a critical research and practice gap, as firms are forced to make trade-offs without a unified decision-making framework. Current models often fail to capture the complexities introduced by carbon regulations—such as emission caps, allowances, and trading mechanisms—leading to decisions that may either compromise environmental compliance or erode financial performance. Addressing this gap, the present study develops a novel carbon-constrained production planning model that integrates emission-related parameters directly into the planning process. By accounting for factors such as unit emissions per technology, government-allocated carbon allowances, and emission trading prices, the model offers a cohesive approach to balancing economic efficiency with environmental responsibility. This integrated framework enables firms not only to comply with carbon regulations, but also to strategically optimize their production mix, technology choices, and carbon trading decisions—bridging a vital divide in current industrial practice. This research presents a robust decision-support model aimed at helping industries transition toward low-carbon manufacturing while maintaining operational and cost competitiveness. By bridging conventional operations management with emerging sustainability imperatives, the study addresses a timely and high-impact challenge faced by modern manufacturing systems. Its key contribution lies in offering actionable insights for balancing production efficiency, subcontracting, and environmental constraints—thereby supporting informed decision-making for policymakers, industrial planners, and sustainability officers. Ultimately, the model promotes greener industrial practices, enhances the effectiveness of carbon markets, and aligns operational strategies with global climate goals, contributing to long-term resilience and strategic leadership in an evolving regulatory environment. Symbols used in this paper are shown in the following Nomenclature.

Nomenclature

r	number of periods in planning
i	index of period = 1, …, r
j	index of technology = (1, 2) for standard and green technology, respectively
k	index of production shift = (1, 2) for regular time and overtime, respectively
n_i	demand at period i (units)
w	capacity of regular time at any period and technology (units per period)
h	unit holding cost ($/unit/period)
b	unit backorder cost per period ($/unit/period)
c_{jk}	unit production cost of technology j at shift k ($/unit)
s	subcontract cost ($/unit)
m_{jk}	unit emission of technology j at shift k (tCO_2/unit)
p_i	unit emission price at period i ($/$tCO_2$)
g	emission allowance from government per period (tCO_2/period)
Z	total cost ($)
Q_{ijk}	number of units produced using technology j at period i, shift k (units)
V_i	number of units subcontracted at period i (units)
K_i	inventory level at period i (units)
I_i	number of inventory held at the end of period i (units)
B_i	number of backorders at the end of period i (units)
Y_i	number of emissions bought at period i (tCO_2)
L_i	number of emissions sold at period i (tCO_2).

2. Problem Formulation

Let there be an industry involved in manufacturing

a product over r periods using two alternative technologies, each with distinct cost and emission profiles. Technology j incurs a production cost of c_{jk} and emits m_{jk} of CO_2 per unit when operating in shift k. While the green technology typically has higher costs, it commonly (but not always) generates fewer emissions. Demand in period i was denoted as n_i, and regular-time production capacity was limited to w units per period. Inventory holding cost h and backorder cost b are applied per unit per period. Before production begins, the government grants the manufacturer an emission allowance of g tons of CO_2 per period. The firm can trade additional permits on the carbon market at a price of p_i per ton, where Y_i represents purchased permits and L_i denotes sold permits. The manufacturer must determine the optimal production quantity Q_{ijk} for each technology, shift, and period, as well as the subcontracting volume V_i, to minimize total costs Z. We assumed that no initial or ending inventory is carried across the planning horizon, and that standard and green technologies can be employed together in a period.

The mathematical model developed for the problem is shown in Expressions (1) to (9).

$$\min Z = \frac{\sum_{i=1}^{r}\left(\sum_{j=1}^{t}\sum_{k=1}^{2} c_{jk}Q_{ijk} + s\cdot V_i + h\cdot I_i + b\cdot B_i + p_i(Y_i - L_i)\right)}{\sum_{i=1}^{r} n_i} \quad (1)$$

subject to:

$$K_i = \sum_{y=1}^{i}\left(\sum_{j=1}^{t}\sum_{k=1}^{2} Q_{yjk} + V_y - n_y\right), \quad i= 1, \ldots, r \quad (2)$$

$$K_r = 0 \quad (3)$$

$$I_i = \max(0,K_i), \quad i= 1, \ldots, r \quad (4)$$

$$B_i = \max(0,-K_i), \quad i= 1, \ldots, r \quad (5)$$

$$Y_i = \max\left(0, \sum_{j=1}^{t}\sum_{k=1}^{2} m_{jk}Q_{ijk} - g\right), \quad i= 1, \ldots, r \quad (6)$$

$$L_i = \max\left(0, g - \sum_{j=1}^{t}\sum_{k=1}^{2} m_{jk}Q_{ijk}\right), \quad i= 1, \ldots, r \quad (7)$$

$$0 \le Q_{ijk} \le w, \quad i= 1, \ldots, r, \quad j= 1, \ldots, t, \quad k= 1; \quad (8)$$

$$0 \le Q_{ijk} \le 0.25w, \quad i= 1, \ldots, r, \quad j= 1, \ldots, t, \quad k= 2; \quad (9)$$

The objective function (1) minimizes total unit costs, representing the average combined expenses from production, inventory holding, backorders, subcontracting, and emission trading. Constraint (2) calculates ending inventory for each period as the net difference between cumulative production and demand up to that period. To align with our modelling assumptions, constraint (3) enforces zero terminal inventory at the planning horizon's end. The model distinguishes between inventory and backorders through complementary constraints (4) and (5), which mutually exclude positive inventory and backorder quantities in the same period. Constraints (6) and (7), which show the carbon trading constraints in the model, determine the company's carbon market activity, calculating required emission allowance purchases or potential sales each period based on production emissions versus allocated permits. Production quantities face two capacity restrictions: constraint (8) bounds regular-time production between zero and the regular time capacity, while constraint (9) imposes an upper limit for overtime production quantities.

3. Solution Method

The mathematical model developed in this study was categorized as a nonlinear programming (NLP) problem because of the inclusion of "max" functions in certain constraints. However, it is crucial to emphasize that both the objective function and all constraint expressions, including those within the "max" functions, maintained linearity. This linear characteristic enabled efficient problem-solving using standard optimization software.

For our computational analysis, we selected LINGO 12, a sophisticated optimization package recognized for its effectiveness in solving both linear and nonlinear models [30]. This choice was motivated by LINGO's intuitive interface and its robust algorithmic capabilities, which significantly simplified the solution process. Despite the model's NLP classification, LINGO's advanced computational features allowed us to successfully navigate and resolve the optimization challenges presented by our formulation.

4. Results and Discussion

Using the proposed model and solution approach, we conducted a series of experiments across six scenarios that simultaneously function as sensitivity analyses. In each scenario, a single emission-related or operational parameter was varied while all others were held constant. Each scenario was carefully grounded in real industrial and policy contexts, allowing us to isolate the specific impacts of each parameter on cost structure and

production strategy under carbon constraints. The six scenarios are as follows:

- Emission cap scenario: The first scenario examined the effect of tightening emission regulations by varying the emission cap from 13,200 to 5,200 tCO_2. This reflects global policy trends toward stricter carbon limits. The goal was to observe how reduced emission allowances influence the trade-offs between conventional and green technologies, and whether firms are driven to increase sub-contracting to remain compliant.
- Subcontracting cost scenario: In the second scenario, we tested sensitivity to sub-contracting costs, ranging from $110 to $102 per unit. This scenario simulates real-world supplier market dynamics, exploring how small changes in subcontractor pricing affect the preference between outsourcing and in-house production, especially under environmental constraints.
- Capacity constraint scenario: The third scenario introduced changes to regular time production capacity, from 17,500 down to 1,500 units. This model operational disruptions such as labour shortages or equipment breakdowns. We evaluated how firms adapt to these limitations, including shifts toward overtime, subcontracting, or less carbon-intensive technologies.
- Green technology cost scenario: The fourth scenario focused on green technology pricing, using five distinct cost combinations (e.g., regular/overtime from $65/$80 to $45/$60 per unit). This scenario represents potential innovation-driven cost reductions in clean technologies, assessing their impact on cost competitiveness and adoption rates within constrained emission environments.
- Green emission efficiency scenario: In the fifth scenario, we reduced the unit emissions from green technologies, specifically from 0.712 to 0.512 tCO_2 per unit. This change simulates advancements in technology that improve carbon efficiency. The objective was to analyze how such gains influence the attractiveness of green technologies in production planning.
- Emission price volatility scenario: The sixth and final scenario captured the effects of carbon market fluctuations by adjusting emission prices across three bands: $68–$74, $78–$84, and $88–$94 per tCO_2. This scenario reflects the evolving nature of climate policy and carbon trading schemes, enabling an assessment of how firms react to increased costs of carbon and the resulting impact on production and trading decisions.

The results of the experiments in the six scenarios are presented in Figs 1 and 2. Figure 1 collectively illustrates how variations in key operational and environmental parameters influence overall cost structures and decision variables such as total cost, production cost, subcontract cost, emission cost, and unit cost. As these input parameters change—ranging from emission regulations to production capacities and cost structures—distinct patterns emerge that reflect the trade-offs between sustainability and economic efficiency. In all experiments, the computation time for each did not exceed 2 seconds, suggesting that the underlying model behaves similarly to a linear model in terms of computational efficiency. This fast processing time supports the practical applicability of the approach for real-time or near-real-time decision-making scenarios.

A common trend observed is the sensitivity of total cost and unit cost to environmental constraints such as emission caps, emission prices, and green unit emissions. For instance, tightening the emission cap (lower allowable CO_2 output) or increasing emission prices tends to raise emission-related costs significantly. This, in turn, elevates total and unit costs, highlighting the financial burden of stricter environmental policies. However, scenarios where emission costs eventually become negative (as in higher emission price settings) may indicate participation in carbon credit trading, where reducing emissions not only avoids penalties but also generates revenue, resulting in a surprising drop in total and unit costs.

Operational efficiency also plays a critical role. When regular time capacity is increased, the dependency on subcontracting and emissions is reduced, which leads to lower total and unit costs. This suggests that investing in internal capacity can be a cost-effective strategy, mitigating the need for more expensive or less sustainable external resources. Similarly, lowering the unit subcontract cost leads to a clear decrease in both subcontracting and overall costs, especially when outsourcing becomes economically more attractive. Another important dimension is the structure of green production costs. Adjusting the cost ratio between regular and overtime green production in

favor of cheaper green overtime options results in notable cost reductions. This implies that flexible, greener production strategies can help lower emissions while maintaining or even reducing total expenditures. Furthermore, reducing green unit emissions per production unit significantly cuts emission costs and subsequently decreases total and unit costs, reinforcing the long-term benefit of investing in clean technologies.

Overall, the integrated findings across all scenarios reveal that while environmental regulations often come with higher immediate costs, strategic operational adjustments, such as increasing regular time capacity, optimizing subcontracting decisions, and adopting cleaner technologies, can mitigate or even reverse these costs. In some cases, sustainability initiatives not only support environmental goals but also enhance economic performance, especially under mechanisms like emission trading or green production incentives. This holistic perspective underscores the importance of aligning production strategies with evolving environmental and market conditions.

Meanwhile, the diagrams in Figure 2 illustrate how changes in key parameters influence the composition of demand fulfilment across three decision variables: the use of standard technology, green technology, and subcontracting. Each horizontal axis represents a scenario where a different parameter is altered, ranging from emission regulations and production capacities to cost structures, and the vertical axis shows the percentage distribution of how total demand is met by each alternative.

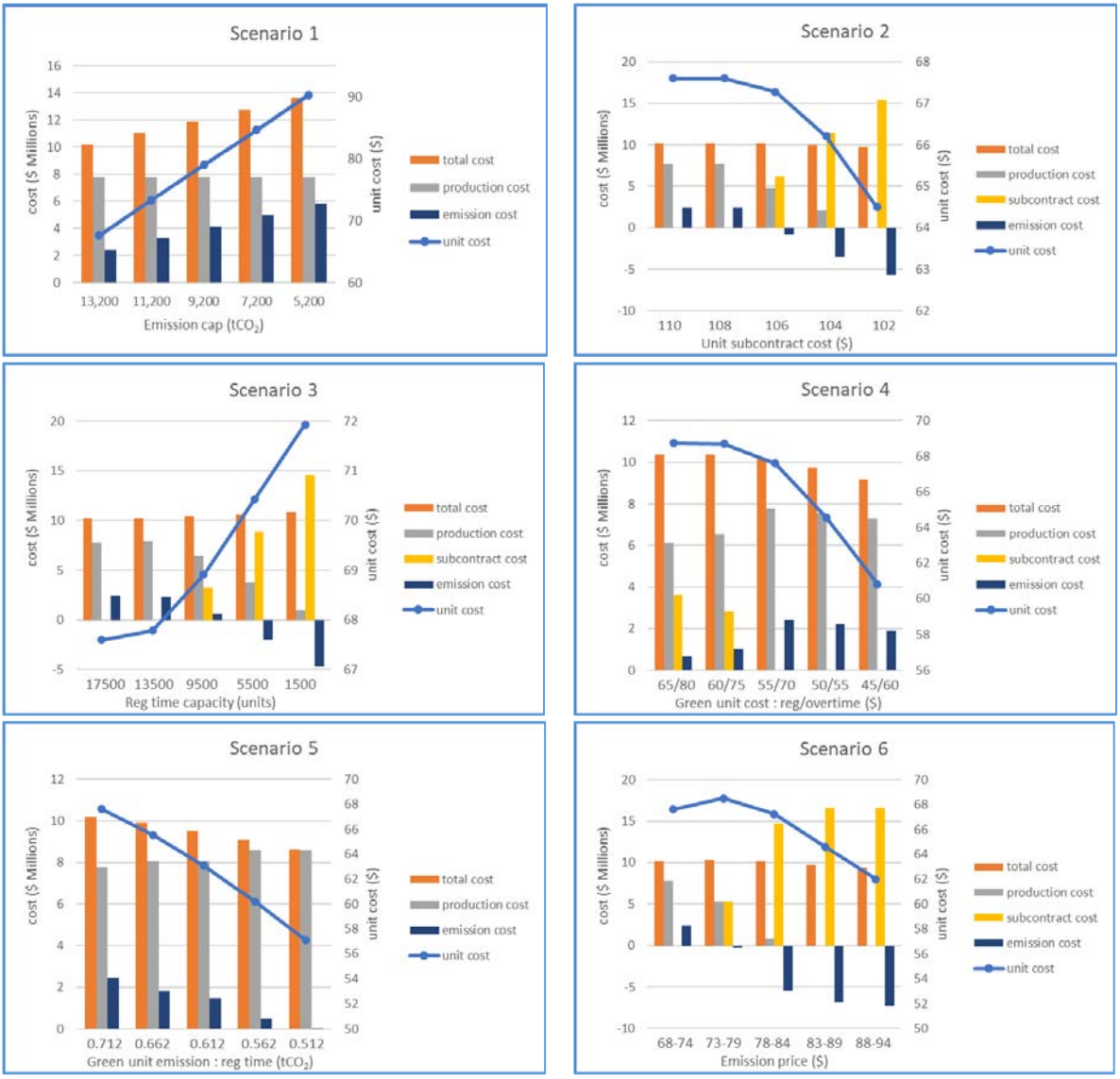

Fig.1. The results of the experiment in Scenario 1

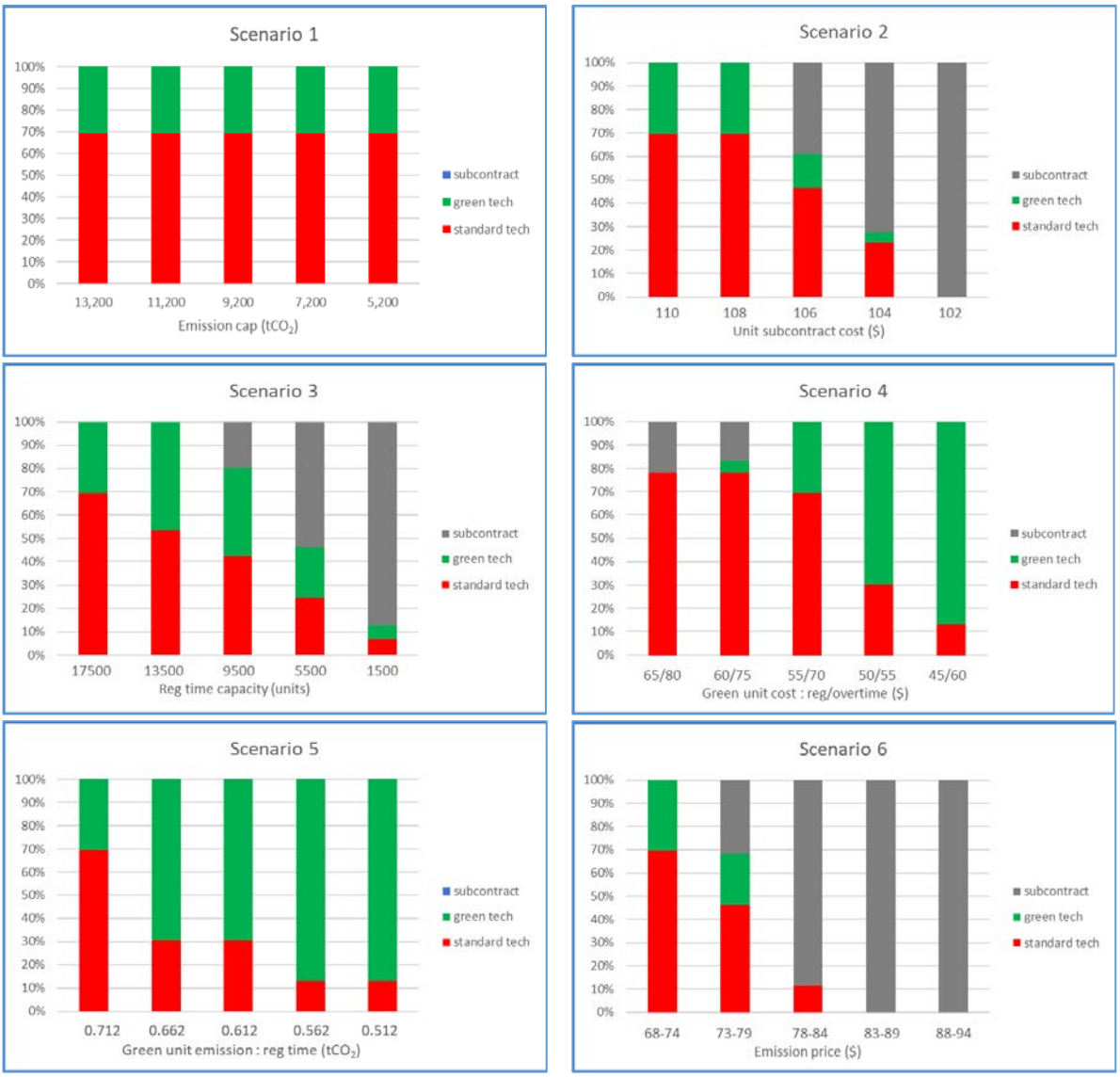

Fig.2. The results of scenarios to demand fulfilment

Across all scenarios, one consistent pattern emerges: stricter environmental constraints or higher incentives for cleaner production tend to increase the share of green technology, while reducing reliance on standard technology. For example, as the emission cap becomes tighter, the proportion of demand met through green tech rises, while standard tech usage declines. This indicates a shift in production strategy toward more sustainable options when environmental regulations become more stringent.

When unit subcontract cost is reduced, firms tend to increase their use of subcontracting, often at the expense of both standard and green technologies. This shift suggests a cost-sensitive response, where outsourcing becomes more attractive as it grows cheaper, even if it may not align with environmental goals. Similarly, as regular time capacity decreases, the limited internal capacity forces firms to rely more heavily on subcontracting. At the lowest capacity level, subcontracting fulfils nearly all demand, underscoring its role as a fallback when internal resources are constrained.

The relationship between green technology costs and technology adoption is particularly evident. When the cost of green production (especially in overtime) becomes more competitive compared to standard production, the share of green tech sharply increases. As green options become more economically viable, firms transition away from both standard technology and subcontracting, favoring a more sustainable internal solution. Conversely, when green costs are high, standard technology dominates.

A similar trend appears with green unit emissions: as emissions per green unit decrease (indicating cleaner production), green technology becomes more prominent in fulfilling demand. This shift underscores the effectiveness of cleaner technologies not only in reducing emissions but also in becoming integral to operational planning. It reflects a dual benefit, regulatory compliance and cost efficiency, achieved through cleaner operations. Finally, as emission prices increase, the use of green technology is encouraged, and standard technology is phased out. However, if emission prices become prohibitively high without corresponding capacity or cost adjustments, firms may resort to subcontracting to avoid high internal emission costs, highlighting the interplay between environmental penalties and operational flexibility. Overall, the integrated view of all scenarios emphasizes that the mix of demand fulfillment is highly responsive to environmental policy, cost structures, and capacity availability. Green technology adoption rises under tighter environmental constraints or when made cost-competitive, while subcontracting serves as a strategic alternative when internal limitations exist or when outsourcing becomes more economical. Standard technology, meanwhile, is gradually displaced as sustainability and cost efficiency gain priority. Figure 3 presents the results of the experiments from Scenarios 1 to 6 within a relational framework. The diagram illustrates the relationship between key input parameters, decision variables, and resulting costs in a sustainable production planning model under carbon regulation. Several parameters, including emission allowance, emission price, unit costs and emissions of green technology, unit cost of subcontracting, and production capacity, directly influence the primary decision variables: the amount of emission trading (buying), the extent of green technology usage, and the number of subcontracted units. These decision variables subsequently determine the three main cost components: emission cost, production cost, and subcontract cost. These individual cost elements collectively contribute to the total cost, expressed as unit cost. The diagram highlights how variations in policy or market parameters (such as stricter emission caps or higher green tech costs) can affect strategic decisions and overall cost efficiency in production planning.

The model demonstrates strong potential for scalability, particularly in handling additional periods or a greater variety of production technologies. Its structure, based on modular cost components (production, emission, subcontracting) and flexible decision variables (standard tech, green tech, subcontract), is well-suited for extension. Introducing more periods would allow for more dynamic decision-making, such as inventory balancing, emission credit banking, or temporal shifts in technology adoption. Similarly, the inclusion of more technologies, each with distinct cost, capacity, and emission profiles, would enrich the model's realism and enable a broader range of strategic trade-offs. While computational complexity may increase with added variables and constraints, the model can still be efficiently solved using optimization techniques like mixed-integer linear programming (MILP), especially if supported by decomposition methods or scenario-based heuristics. Thus, the model remains robust and adaptable for larger-scale industrial planning problems.

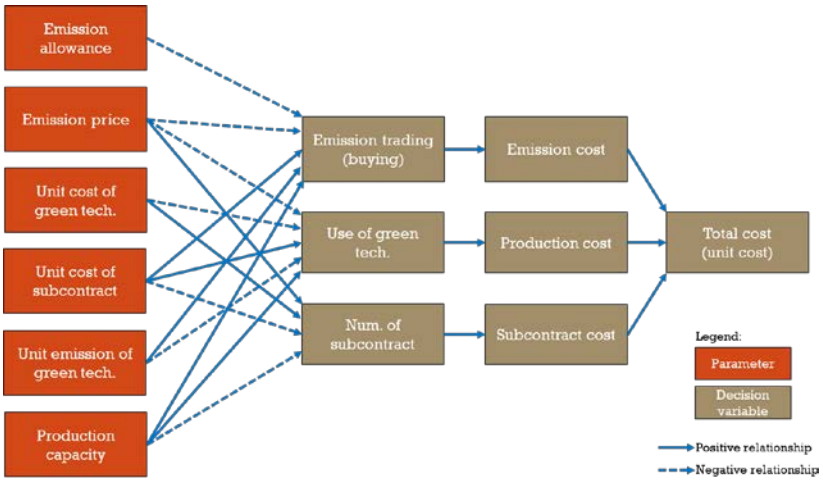

Fig.3. A relational framework among emission parameters and decision variables

5. Managerial Implications

The findings from the study suggested several important managerial implications for decision-makers aiming to balance cost efficiency, production flexibility, and environmental sustainability. First, managers should view green technology not merely as a compliance tool but as a strategic asset. The scenarios show that under tighter environmental regulations or increased emission costs, green technologies become more favourable both in terms of cost and demand fulfilment. Investing early in green capabilities can future-proof operations against regulatory changes and improve competitiveness. Second, environmental constraints such as emission caps or carbon pricing, when well-anticipated and managed, can lead to lower unit and total costs through cleaner production choices. Managers should stay ahead of regulatory trends and explore opportunities like carbon trading to turn what is often perceived as a cost burden into a potential source of operational savings. Third, subcontracting can offer flexibility under tight internal capacity, but overreliance, especially when done purely on cost grounds, may increase overall costs and reduce control over environmental impacts. Managers should evaluate subcontracting not only on price but also on service quality, emission performance, and alignment with sustainability goals.

Fourth, the analysis highlights the critical role of regular time capacity in maintaining cost-effective and environmentally sustainable operations. Managers should plan capacity investments thoughtfully to avoid excessive subcontracting, which can drive up costs and emissions. Scenario planning and capacity stress-testing can help identify optimal investment levels. Fifth, achieving a balance between environmental performance and cost control requires close collaboration between operations, finance, and sustainability teams. For instance, decisions about green technology investment or subcontracting strategies should be informed by emissions data, regulatory trends, and lifecycle cost analysis. Sixth, the model demonstrates the value of scenario-based modelling in revealing trade-offs and sensitivities in production planning. Managers should institutionalize such analysis to support more informed, resilient decision-making under uncertainty, particularly about fluctuating emission costs, changing subcontracting markets, or evolving environmental standards. Last, while the findings suggest clear benefits from adopting green technologies and emission-conscious strategies, managers must be prepared for real-world challenges in implementation. Resistance to change, such as hesitation from staff to adopt new production methods or skepticism from upper management about upfront costs, can delay or derail transitions. Additionally, external factors like market volatility in carbon prices or uncertainty in environmental regulations can make planning difficult. To address these issues, managers should invest in change management, provide training and education, and establish risk mitigation strategies (e.g., flexible contracts, scenario-based financial planning). Building a culture that values sustainability and innovation is essential for long-term success.

6. Concluding Remarks

This study offered a focused analysis of how operational and environmental parameters jointly impact production costs and demand fulfilment strategies. Three key insights emerged. First, environmental regulations, such as emission caps, carbon pricing, and green technology standards, strongly influence cost structures and production choices. Although strict policies may raise short-term costs, they drive low-emission technology adoption, ultimately reducing expenses via efficiency gains and emission trading. Second, firms embrace green technologies not just for their environmental value but also when they become cost-competitive, showing that sustainability aligns with profitability under favourable conditions. Third, operational constraints, especially production capacity and subcontracting costs, significantly affect outsourcing. Limited in-house capacity or cheap subcontracting pushes firms toward external solutions, often increasing both cost and emissions. In contrast, strong internal capacity enables more sustainable, cost-effective operations. These findings highlighted the interconnected roles of policy, economics, and operations. Firms should constantly balance internal production, subcontracting, and emissions management under varying cost, capacity, and regulatory pressures. A well-calibrated strategy, backed by affordable clean technologies and coherent policies, can promote both sustainability and financial performance, demonstrating that ecological and economic goals can reinforce each other. It is important to note that the model has limitations

that it assumes deterministic demand, which may not reflect uncertainties in real world, it operates under a single-product framework, which limits its applicability to more complex multi-product environments, and the absence of stochastic elements may oversimplify decision-making dynamics. To enhance real-world applicability, the model can be effectively integrated with existing ERP (Enterprise Resource Planning) or MRP (Material Requirements Planning) systems by linking the model's parameters (e.g., emission caps, green tech cost, subcontracting rates) to real-time data from ERP modules, such as inventory levels, supplier pricing, machine availability, and carbon reporting tools, which are then run in the background or as part of scenario planning tools to recommend cost-effective and environmentally friendly production mixes.

Future research may extend this study by considering dynamic conditions, such as changing demand, fluctuating carbon prices, and technology learning effects, to explore how decisions evolve. Incorporating multi-objective optimization could better capture trade-offs between cost, emissions, and service levels, enriching the model's decision-making relevance. Expanding to multi-tier supply chains would add practical depth, revealing the broader impacts of sustainability strategies across networks. Moreover, including behavioural factors, like stakeholder preferences or organizational inertia, could uncover barriers to implementation. Finally, validating the model with real-world data across industries would enhance its applicability and support more effective, sustainable operations for both practitioners and policymakers.

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