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Research Paper:

A Discrete-Event Simulation Study of Multi-Objective Sales and Operation Planning Under Demand Uncertainty: A Case of the Ethiopian Automotive Industry

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Sales and operation planning is one of the major categories of supply chain planning that enables the balancing of demand with supply through the integration of internal functions as well as external supply chain members. The major issues are its large scale, dynamic, multi-objective nature and presence of uncertain parameters. Handling uncertainty, extending the level of integration, enhancing collaboration, and contextualization of the models already developed in different industrial situations are the gaps identified in the literature. This research aims to develop a discrete-event simulation model from the literature in the context of the Ethiopian automotive industry and extend the level of collaboration to suppliers and customers. The industry's sales and operation planning process is surveyed to develop the model as a decision support system that can be utilized for understanding the system behavior, evaluation of manufacturing flexibility, and inventory control policies. The research findings demonstrate that the customer service level and total profit can be significantly improved through the proposed joint primary and negotiated backup supply policy with price revision. Managerial implications that are expected to improve the technical capability of Ethiopian automotive industries are also highlighted.

Keywords: sales and operation planning, supply chain planning, multi-objective, discrete-event simulation, Ethiopian automotive industry

1. Introduction

Globalization has enabled manufacturing industries to conduct business operations across distant international borders. However, this benefit did not come without disadvantages such as competitive environment and complexity arising from external interactions, uncertainties, and risks associated with several types of disruptions. Thus, collaboration among supply chain (SC) members has become necessary to overcome these challenges and remain competitive in the dynamic global market environment. Collaboration of SC members is mainly achieved through SC planning (SCP), which integrates the tactical and strategic decision-making processes related to business planning, SC design, and market-driven product innovation [1, 2].

Sales and operation planning (S&OP), one of the major categories of SCP, addresses the most fundamental issue in SC management (SCM): matching demand with supply [2–4]. It evolved from aggregate production planning (APP) papers integrating sales, operations, and finance functions [5]. Integration is made at an aggregated volume level, and optimum production quantity, inventory levels, and capacity requirements are determined. At its highest level of maturity, S&OP can enable SCP not only to fulfill sales targets, but also to improve product life cycles and SC network design through integrated demand, supply and financial planning [2]. S&OP shapes demand and modifies supply through a five-step process: statistical sales forecast, demand planning, supply planning, pre-S&OP meeting, and executive S&OP meeting in a monthly-based implementation cycle [6, 7].

The major challenges in S&OP are its large scale, complex nature, and presence of uncertain parameters. It is required to extend the integration, enhance collaboration, and validate previous model-based studies with different industrial contexts [8]. This research is a simulation study on S&OP of an Ethiopian automotive enterprise named Bishoftu Automotive Industry (BAI) based on an innovative model reported in [9]. The Ethiopian automotive industry has a highly constrained parts supply characterized by long procurement time under demand uncertainty. The study contextualizes and extends the previous study's model by introducing a joint primary and customer-negotiated emergency backup supply policy with price revision. The remainder of the manuscript is organized as follows. Sections 2 and 3 present the literature review and industrial case study, respectively. Section 4 presents details of the model development. Section 5 discusses the simulation experiment design, result analysis and managerial implications. Finally, Section 6 provides concluding remarks and discusses some future research work.

2. Literature Review

Integration in SCM enables streamlined material flow and information exchange, which enhances process efficiency and creation of value for the end customer in a coordinated manner [10]. S&OP integration should not only be about communicating and coordinating functional plans, but also about revising those plans to optimize profits [3]. The automotive sector has specifically benefited from programs that had formal S&OP organizations and strong performance management. Strategic alignment and information processing in S&OP have had a significant impact not only in the automotive industry, but also in other industries [11]. Studies based on real industrial cases showed that the benefits of SC with fully integrated S&OP model are significantly greater when compared to the decoupled model, while those of the partially integrated S&OP models offer only moderate benefits [12, 13].

The complexity in SC production planning usually requires simulation and artificial intelligence methods whenever more than one type of uncertain parameter is present [14]. Demand-driven S&OP approach enables a flexible and well-orchestrated supply network that synchronizes the rate of production with the rate of uncertain demand [15]. The first step in handling uncertainty in production planning is real-time measurement of uncertain parameters. The second step is explicit consideration of tactical decisions such as setting delivery times, handling plan revisions and stability, utilizing inventory buffers and flexible capacity, and applying planned lead time to absorb variability [16]. Simulation was preferred rather than simple analytical models since data generate a strong understanding of customer values and sustain competitive advantage [2, 15]. Such simulation studies, however, should be supported and grounded in practice with pilot studies and conceptual system models [2]. The large-scale and dynamic nature of SCP required the availability of data and high computational capacity methods such as hybrid simulation-optimization approaches [17].

Higher firm performance requires superior flexibility capabilities, particularly at the SC level (including customers and suppliers), which is usually underestimated by industries [18]. A simulation study of S&OP conducted on a real automobile manufacturer demonstrated that applying a higher degree of flexibility without a safety stock ratio reduced delayed orders and lost sales, while the logistics cost increased due to higher emergency backup supply [9]. Lim et al. [9] devised and compared several safety stock ratio and flexibility degree policies such as pure make-to-order (zero safety sock with unlimited flexibility), lock (some safety stock with zero flexibility), and threshold policy (conditional policy based on the ratio of expected demand to the historical average). Their results showed that the logistic cost and customer service level improved with higher forecast quality and utilization of the threshold policy. In their subsequent study, a simulation-optimization technique was devised and a linear policy (generalization of threshold policy) with variable safety stock ratio and flexibility degree at every period provided better results compared to the static policy [19]. A similar S&OP problem in the automotive industry was solved with the simulation-optimization technique and proved that linear policy still provides optimal results even when emergency backup supply cost is higher and uncertain [20].

Model-based S&OP studies are limited in number and extending the level of integration in the SC, introducing new inventory management techniques and validating the models in different industrial contexts were recommended [8]. Thus, the objective of this study is to develop the S&OP simulation model in the context of the Ethiopian automotive industry as a decision support system. In addition, the study extends the range of integration to customers and suppliers through negotiated emergency backup supply and upgrades the logistics cost objective function to total profit optimization with price revision.

The Ethiopian automotive industry is in its early development stage. Most of the country's motor vehicles are imported, and the local production is limited to assembly and fabrication of vehicle bodies. Market uncertainty, lack of customer focus, fact-based decision-making, and cross-functional integration are some of the problems the sector is currently facing [21]. Moreover, government regulation, tax inconsistency, and shortage of foreign currency for parts purchase are the major hindrances to its development. Despite these problems, the sector's growth prospect is increasing and thus, attention should be paid to improving the operation of the industries to enhance their contribution to the national economy [22]. This study aims to introduce the use of simulation model-based S&OP in the Ethiopian automotive industry based on the global practice found in the literature.

3. Industrial Case Study

BAI purchases parts from the international market primarily from Chinese suppliers and sells its assembled light pickup trucks, buses, and heavy-duty trucks locally. The double cabin light pickup truck product family was selected for the model development due to its diversified customers and small number of orders. The planning process starts with the marketing and sales department, which prepares an annual demand plan by conducting qualitative actual sales trend analysis and market research. The logistics department conducts international bids to select prospective suppliers and to procure the parts after securing foreign currency exchange for the purchase. Subsequently, the ordered completely knocked down (CKD) pickup truck parts are manufactured and delivered to the assembly plant. The overall process of sourcing and procuring the CKDs takes ten months on average. This is currently done at most twice a year. In the meantime, customer orders are registered, but delivery time is set only after the procured parts supply arrives. Next, a delivery time and price contract are signed and the manufacturing department assembles the trucks within two weeks. If there are not enough customer orders, the extra inventory of finished vehicles is stored in the plant until it is sold.

Table 1. S&OP system parameters, variables, and KPIs.

Parameters	Symbols	System variables	Symbols
Simulation length	H	Demand prediction at period t	d_t^p
Prediction accuracy	A_t	Actual demand arrival at period t	D_t^a
Procurement time	L	Actual order that arrived at period t and placed for period j	O_{tj}
Frozen horizon length	F	Actual order placed at period t	d_t^a
Order placing factors	x_k	Demand prediction remaining at period t	d_t^{pr}
Demand prediction moving average length	M	Sales constraint for period t	$d_t^{\max}$
Lost sales threshold	Z	Delayed order at period t	do_t
Probability of customer agreement	p	Sales loss at period t	ls_t
Initial inventory level	I_0	Anticipated inventory level at the end of period t	IP_t
Reference price	P_r	Normal supply ordered at period $t-L$ that arrives at period t	n_t
Normal supply cost per unit	C_n	Negotiated backup supply ordered at period $t-F$ that arrives at period t	b_t^n
Holding cost per unit per period	C_h	Primary backup supply ordered and arrives at period t	b_t^p
Primary backup supply cost per unit	C_{pb}	Total backup supply which arrives at period t	b_t
Negotiated backup supply cost per unit	C_{nb}	Actual inventory level at the end of period t	IL_t
Normal time manufacturing cost per unit	C_m	Orders that can be produced at period t	N_t
Normal time production capacity	N	Price factor at period t	f_t
Over-to-normal time cost per unit ratio	OTC_m	Total manufacturing cost at period t	MC_t
Normal supply interval	NSI	***Key performance indicators***	
Decision making variables		Average delayed orders percentage per period	DOP
Flexibility degree at period t	FR_t	Average lost sales percentage per period	LSP
Safety stock ratio at period t	SS_t	Average total profit per period	TP

The major issues are high forecast errors, long procurement lead time, and absence of long-term supplier contracts. The long procurement lead time is primarily due to international bids and delays in securing foreign currency exchange. The inventory percentage of finished pickup trucks at the end of the planning year out of the total sales amount for the last two consecutive years was 25.8% and 30.2%. The customer order-placing mechanism is not forward-looking, and customers sometimes cancel their requests due to inventory shortages, long procurement lead times, and price fluctuations. Qualitative customer feedback is collected monthly while quantitative customer service level measurement is absent. This may lead to unknown lower customer service levels and sales and financial losses. S&OP decision support system addresses these issues since it drives the SC collaboration, provides a top-down risk mitigation mechanism, and enhances responsiveness to internal and external environmental uncertainties.

Moreover, the survey results reveal that the Ethiopian automotive industry is characterized by distant sourcing, long lead time in procurement and unreliable demand prediction. The delays due to foreign currency exchange shortages and frequent international bids can be resolved through strong collaboration with suppliers and customers. This requires the introduction of additional decisions such as customer negotiation for emergency backup supply and price revision in the already developed S&OP models. The introduction of such additional parameters expands horizontal integration and enhances the practical applicability of the already developed models in different contexts [8].

4. Problem Definition and Model Development

This section presents details of the problem, assumptions made, and the analytical formulation based on [9] with some extensions considering the distinctive conditions of the Ethiopian automotive industry. The sales, logistics, and manufacturing functions are integrated into the S&OP system. The specifications and notations of system parameters, variables, and key performance indicators (KPIs) are presented in **Table 1**.

4.1. Demand Prediction and Order Placement

The sales data from the past 30 months shows that there is no significant trend or seasonality in the customer demand. The frequency distribution of actual sales is also almost rectangular; thus, we consider the demand to be uniformly distributed. Forecasting errors are common with long procurement time and their consideration is important to address the inherent uncertainty from demand forecasts and their effect on the S&OP [9, 16].

Hence, the demand prediction is modeled using actual demand distribution adjusted with uniformly distributed forecasting errors as shown in Eq. (1). The long procurement lead time requires a wider planning horizon, which compels the S&OP system to work under such unreliable demand predictions.

$$d_t^p = D_t^a + A_t. \quad (1)$$

The demand uncertainty and these unreliable predictions typically lead to manufacturing and logistics operation planning nervousness. This problem requires stabilizing the plan by putting time fences and freezing some portion of the planning horizon, as shown in **Fig. 1** [16].

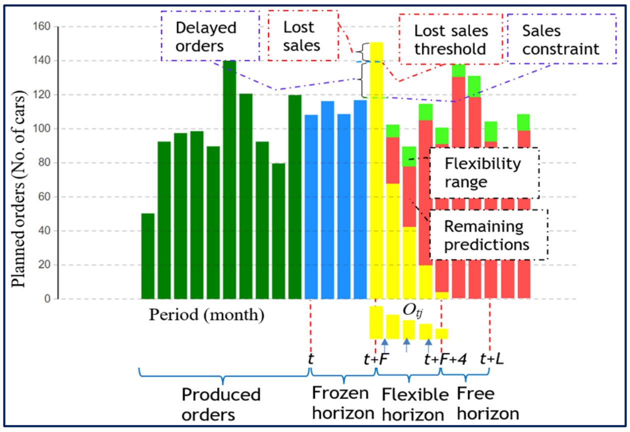


Fig. 1. Order placement against predicted demand.

There are two types of freezing methods. Period-based freezing method fixes any amount of orders placed in a specified number of planning periods. In order-based freezing, a specific order quantity is first fixed and placed irrespective of the number of planning periods required. In this study, the planning horizon is subdivided into frozen, flexible, and free horizons. The frozen horizon (blue bars) covers planning periods from t to $t + F - 1$, in which the period-based freezing method is applied. The periods from $t+F$ to $t+F+4$ represent the flexible horizon, where the amount of orders in each period changes as incoming customers' requests are placed. In the free horizon (starting from $t+F+5$), no orders are placed, and thus we only have demand predictions (red bars).

The arriving actual customer request (D_t^a) at period t is allocated gradually into period j in the flexible horizon using order placing factors x_k (**Table 2**), as shown in Eqs. (2)–(4). Order placing factors are measures of demand arrival rate estimated based on industrial data [9]. The orders placing factors decrease as we go from $t + F$ to $t + F + 4$. This decrease is attributed to the probability of orders being placed nearer to the frozen horizon is higher than at the end of the flexible horizon. We used similar order-placing factors as in [20] (see **Table 2**) since our case industry does not have a similar order-placing mechanism, and the freezing of the production plan has not been implemented. As shown in **Fig. 1**, every time the planning is rolled to the next period (month), fractions of new customer request arrivals O_{tj} (yellow bars) are aggregated and become actual orders (d_t^a) in each period. For instance, if we take the actual order placed at $t + F$, that is d_{t+4}^a, it is an aggregation of $0.03 \times D_{t-4}^a$, $0.12 \times D_{t-3}^a$, $0.17 \times D_{t-2}^a$, $0.31 \times D_{t-1}^a$, and $0.37 \times D_t^a$. As the actual orders are placed in this way, they replace the predicted demand and what remains is the remaining predicted demand, that is d_t^{pr}, indicated by the red bars in **Fig. 1**. The remaining predicted demand in the frozen horizon, if any, is eliminated from the system. Finally, the actual orders are produced (dark green) and delivered to the customers at the end of period t.

$$O_{tj} = D_t^a \times x_{j-t}, \quad \ldots \ldots \ldots \ldots (2)$$

Table 2. Order placing factors [20].

$k = j - t$	x_k
$j - t < F$	0
$j - t = F$	0.37
$j - t = F + 1$	0.31
$j - t = F + 2$	0.17
$j - t = F + 3$	0.12
$j - t = F + 4$	0.03
$j - t > F + 4$	$< 0.1 \approx 0$

$$x_{j-t} = x_k, \quad (0 \le x_k \le 1), \quad \ldots \ldots \ldots (3)$$

$$\sum_{t<j}^{H-F} \sum_{j=F}^{H} x_{j-t} = 1. \quad \ldots \ldots \ldots (4)$$

4.2. Flexibility and Inventory Control

The S&OP system's decision-making variables are the degree of flexibility and safety stock ratio, which determine the maximum orders that can be accepted and the safety stock margin required to procure normal parts supply. These variables are positive integer percentages. Two policies that determine these variables have been designed and tested in the previous study [19]. The first is the static policy that uses constant decision-making variables at every period. However, this policy suffers from a "base effect" phenomenon, which is the proportionality of the maximum number of orders that can be accepted and the safety stock margin to the quantity of predicted demand. To avoid this undesirable effect, the linear policy that utilizes different decision-making variables at each period was devised using absolute and relative coefficient values FR^α, FR^β, SS^α, and SS^β for flexibility degree safety stock ratio, as shown in Eqs. (6) and (7). In these equations, Φ_t, as in Eq. (5), is the ratio of expected demand and the historical moving average of the predicted demand.

If we have an overestimated forecast, Φ_t becomes greater than one, and thus, a lower degree of flexibility and safety stock margin are applied to avoid unused capacity and excess inventory. Conversely, if the forecast is underestimated, Φ_t becomes less than one and a higher flexibility degree and safety stock margin are applied to prevent delay of orders and stock out. We may consider the absolute values FR^α and SS^α as a representation of the static policy when the relative coefficients (FR^β and SS^β) are zero. For instance, a higher value for FR^β implies a greater adjustment is applied to the absolute value (FR^α), leading to a lower flexibility degree and thereby lower sales constraint. Thus, the relative coefficients in combination with Φ_t help to control the maximum number of orders that can be accepted and the safety stock amount required to procure parts supply. Due to the utilization of relative coefficients, the linear policy is less intuitive for industry managers but its advantage over the static policy makes it more preferable.

$$\Phi_t = \frac{d_t^a + d_t^{pr}}{\sum_{k=t-M+1}^{t} \left(\frac{d_k^p}{M} \right)}, \ \forall t \in \{M, \ldots, H\}, \quad (5)$$

$$FR_t = \max \left\{ 0;\ FR^{\alpha} - FR^{\beta} \times \Phi_t \right\}, \ \forall t \geq M, \quad (6)$$

$$SS_{t+L} = \max \left\{ 0;\ SS^{\alpha} - SS^{\beta} \times \Phi_{t+L} \right\}, \ \forall t \geq M. \quad (7)$$

The sales constraint is the maximum number of orders that can be accepted at each period (Eq. (8)). It determines the flexibility range (light green in **Fig. 1**) and serves as a constraint to restrict the arrival of customer demand in the planning system [19]. If the actual order at $t + F$ is over the sales constraint, the extra orders are delayed to the next period. If the outstanding delayed order amount is still more than the lost sales threshold (marked with the blue line at $t + F$), those extra orders are subjected to sales loss and are eliminated from the system. The customer impatience level to back ordering is modeled by the lost sales threshold parameter [20]. **Fig. 1** shows this scenario at $t + F$, where the actual order placed has overpassed the sales constraint limit (represented by the green line), leading to both delayed orders and lost sales.

$$d_t^{\max} = (1 + FR_t) \left(d_t^p \right), \ \forall t \in \{0, \ldots, H\}. \quad (8)$$

In the case industry, procurement of the parts is made in CKDs. The procurement time L is long and is assumed to be deterministic to simplify the model in this study. The anticipated inventory level for the $t+L$ period is calculated as shown in Eq. (9). Deducting the anticipated inventory level at $t + L - 1$ from the sum of expected demand at $t + L$ and the total of expected demand from $t + F + 1$ to $t + L$ multiplied by the safety stock ratio, gives the normal supply that needs to be placed L periods ahead as shown in Eq. (10). The expected change in actual orders in the flexible horizon is compensated by the safety stock ratio since these periods have not been frozen yet [9].

$$IP_{t+L} = IL_{t-1} + \sum_{k=t}^{t+L} \left\{ (n_k + b_k) - \left(d_k^a + d_k^{pr} \right) \right\}, \quad (9)$$

$$n_{t+L} = \max \left\{ 0;\ d_{t+L}^a + d_{t+L}^{pr} + SS_{t+L} \times \sum_{k=t+F+1}^{t+L} \left(d_k^a + d_k^{pr} \right) - IP_{t+L-1} \right\}. \quad (10)$$

4.3. Negotiated and Primary Backup Supply

The normal parts supply (n_t) placed at $t - L$ may not be sufficient for the actual orders to be produced at period t. In this case, an emergency backup supply with a higher cost is ordered to cover the shortage amount and arrives within the same period [9]. Utilizing such an emergency supply policy is a common practice and has proven to be beneficial in terms of improving customer service levels. In this study, we refer to this policy as the "primary backup supply."

Currently, the case industry does not have an emergency backup supply policy in case a shortage occurs. Utilization of emergency backup supply is currently not feasible in the Ethiopian situation due to the delay from foreign currency shortage. Thus, any opportunities from collaboration with suppliers and actual customer behavior need to be accounted for to alleviate this problem through supplier relationships and negotiations with customers. If long-term contract-based parts sourcing is arranged and a good relationship with suppliers is developed, it is possible to apply the primary backup supply policy whenever a shortage occurs. Supply credit can be arranged by the supplier to avoid waiting for foreign currency exchange and get expedited parts supply with extra cost. Since orders in the frozen horizon cannot be delayed, the extra cost from the primary backup supply should be covered by the industry.

In addition, customers can be stratified into any of the following three categories according to their impatience level: (1) patient customers who accept back-ordering, (2) impatient customers who agree on price revision to prevent their orders from being delayed, and (3) impatient customers who will cancel their orders. Here, we introduce a negotiated emergency backup supply ordered F periods ahead that arrives at the current period t. This policy gives impatient customers in Category 2 an opportunity to cover the extra backup supply cost to prevent their orders from being delayed to the next period or canceled on their terms. When these customers are about to cancel their orders at $t+F$, they are checked if they are willing to cover the extra backup supply cost. The extra cost is included in the total profit through the price revision factor. The amount of negotiated backup supply depends on the number of sales to be lost and the probability of customer agreement. This probability of agreement represents the percentage of customers' orders in Category 2 in relation to the total number of orders from all impatient customers. This negotiated backup supply policy is devised for Ethiopian automotive industries to improve the customer service level and reduce the amount of order canceling. Eqs. (11)–(13) show how the negotiated, primary, and total backup supply are calculated, respectively.

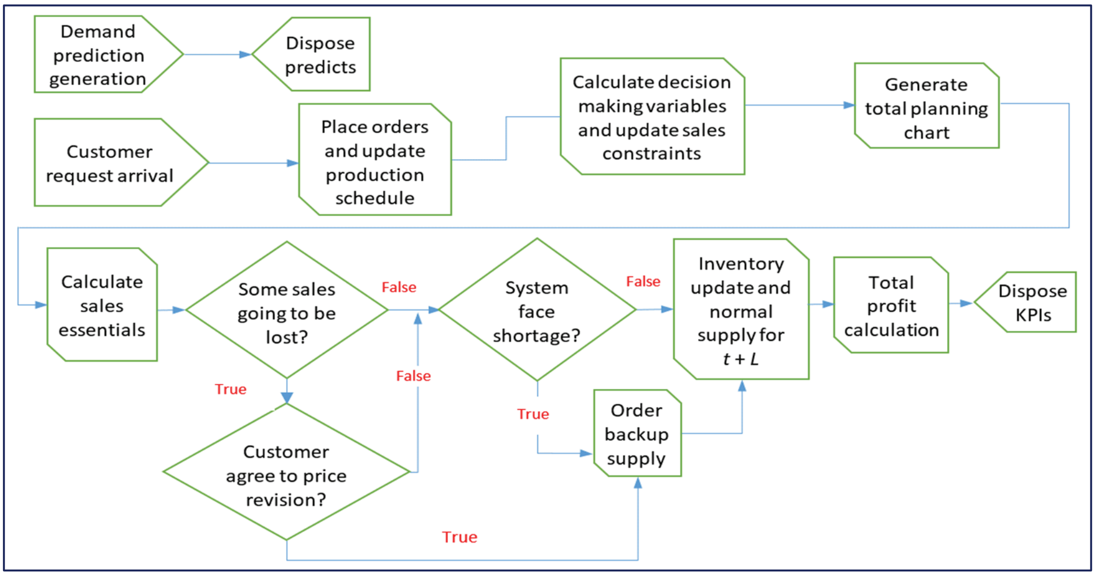
$$b_{t+F}^n = ls_{t+F} \times p, \quad t \in \{0, \ldots, H - F\}, \quad (11)$$

$$b_t^p = \max \left\{ 0;\ N_t - \left(IL_{t-1} + n_t + b_t^n \right) \right\}, \quad (12)$$

$$b_t = b_t^p + b_t^n. \quad (13)$$

4.4. Key Performance Indicators

The number of orders that can be produced and the net inventory level at the end of period t are calculated using Eqs. (14) and (15) considering the negotiated backup supply. Subsequently, the price revision factor is calculated using the number of negotiated backup supplies, the extra backup supply cost per unit added to the normal supply, and the reference price as outlined in Eq. (16). Manufacturing cost includes the overtime cost if the number of orders to be produced exceeds the normal time production capacity as shown in Eq. (17). The average total profit is determined as shown in Eq. (18). Finally, the customer service level KPIs are calculated as a percentage of the sum of delayed and lost sales at each period to the total



Source: [20] – Modified version.

Fig. 2. Conceptual flow chart of the simulation model.

number of actual orders placed throughout the simulation length (Eqs. (19) and (20)).

$$N_t = \min\left\{d_t^a, d_t^{\max} + b_t^n\right\}, \quad (14)$$

$$IL_t = IL_{t-1} + n_t + b_t - N_t, \quad (15)$$

$$f_t = 1 + \frac{b_t^n \times (c_{nb} - c_n)}{P_r}, \quad (16)$$

$$MC_t = C_m \times \Big(\min\{N;\ N_t\} + \max\{0;\ OT_{cr} \times (N_t - N)\}\Big), \quad (17)$$

$$TP = \frac{1}{H}\sum_{t=0}^{H}\Big\{P_r \times f_t \times N_t - \big(c_n \times n_t + c_h \times IL_t + c_{pb} \times b_t^p + c_{nb} \times b_t^n + MC_t\big)\Big\}, \quad (18)$$

$$DOP = \frac{\sum_{t=0}^{H} do_t}{\sum_{i<j} O_{tj}} \times 100, \quad (19)$$

$$LSP = \frac{\sum_{t=0}^{H} ls_t}{\sum_{i<j} O_{tj}} \times 100. \quad (20)$$

4.5. Simulation Model

The model, as shown in **Fig. 2**, begins with the demand prediction for the entire simulation length. Customer requests are accepted and placed in the flexible planning horizon. Subsequently, it calculates the decision-making variables, plots the total planning chart, and calculates sales essentials (delayed orders and lost sales). If some sales are about to be lost at the $t + F$ period, a negotiated backup supply is calculated and placed. If there is a shortage at the current period, a primary backup supply is ordered and utilized to fulfill the orders. Next, normal parts supply is placed for the $t + L$ period considering the net inventory level at the end of the current period. Finally, the total profit is calculated and the plan is rolled over to the next month, repeating the same process. Finally, all the KPIs are calculated at the end of the simulation length. The model is a discrete-event simulation model and utilizes AnyLogic simulation software unlike the previous studies, which used Java programming language and ARENA [9, 20]. AnyLogic is a visual and library-based multi-purpose simulation software with a three-phase and job-driven approach that enables detailed and complex process modeling [23].

5. Results and Managerial Implications

5.1. Experimental Design

For the experimental purpose, we assume that the industry is working with average customer demand equivalent to its full capacity of two eight-hour shifts per day throughout the month. This assumption is made considering the current low capacity utilization of the industry due to the shortage of parts supply. After conducting several tests, the simulation length and number of replications are set to 500 periods and 2000 runs, respectively, to keep the error level of the results under 1%. The default simulation input parameters are shown in **Table 3**. The values of order placing factors are taken from the previous study as mentioned in Section 4. The demand prediction moving average length, lost sales threshold, initial inventory level, probability of customer agreement, emergency backup supply cost per unit, flexibility degree, and safety

Table 3. Default simulation input parameters.

Parameter	Value	Parameter	Value
H	500	FR^{α}	0.3
L	10	FR^{β}	0.1
A_t	$[-15, 15]$	SS^{α}	0.2
M	6	SS^{β}	0.1
Z	20	p	10%
NSI	6	No. of simulation replications	2000
I_0	0		

stock ratio parameters are assumptions made for the simulation purpose. The values of prediction error, procurement time, normal supply interval, normal supply cost per unit, inventory holding cost per unit per period, normal time production capacity, normal time production cost per unit, over-to-normal time production cost per unit ratio, and reference price are data collected from the case industry. Due to the confidentiality concerns of the case industry, only some of these input parameters are presented in **Table 3**.

Four computational experiments are designed as follows: (1) *frozen horizon length variation*, (2) *normal supply interval variation*, (3) *introduction of emergency backup supply policies*, and (4) *flexibility and safety stock policies*. In Experiment 1, different frozen horizon lengths (F) were tested to see their impact on the KPIs. The frozen potion is typically expressed as the ratio of the rolling planning horizon length, which is the total of frozen and flexible horizon periods in this study. The rolling horizon covers periods in which the actual orders are determined and placed in each planning cycle. As the ratio of the frozen portion to the rolling planning horizon length increases, cost increment and customer service level deterioration are recorded, while its advantage is a reduction of plan instability [24]. This experiment aims to select an appropriate length that does not have a significant impact on customer service level and total profit. Experiment 2 varies the parts replenishment interval to see the effect of the case industry's practice on the KPIs and to propose a better but feasible interval. In Experiment 3, no backup supply, negotiated backup supply only, primary backup supply only, and joint primary and negotiated backup supply policies are tested and compared. In Experiment 4, first, sample flexibility degrees are tested without safety stock ratio and then vice versa to observe their impact on KPIs. Finally, from these sub-experiments, six joint flexibility degree and safety stock ratio policies are designed to select a better one that improves the total profit without violating the customer service level constraints set by the industry.

In addition, the effect of prediction accuracy on the KPIs of each emergency backup supply policy are analyzed at the end. These experiments were conducted sequentially taking the best or feasible scenario from the current experiment and applying it to the next one to demonstrate the cumulative improvement of KPIs at each step.

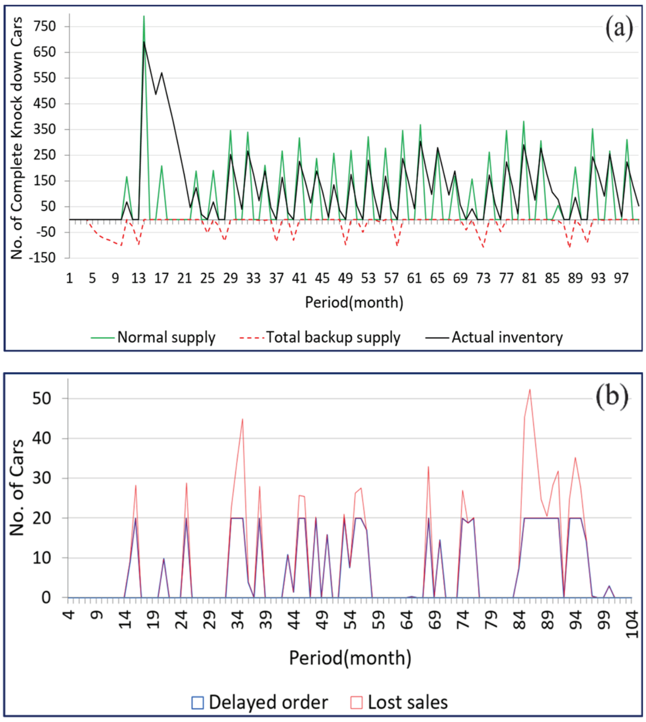


Fig. 3. Inventory and sales essential variables.

5.2. Simulation Results

The model accepts the input parameters and plots the inventory control and sales essential variables, as shown in **Fig. 3**. This figure is presented to demonstrate the dynamics of the S&OP system. In **Fig. 3(a)**, the system relies on an emergency backup supply whenever there is a shortage (shown as negative inventory). Some warmup time is required initially until the first batch of normal parts supply arrives and then the inventory level becomes stable. **Fig. 3(b)** shows the delayed orders and the lost sales, which are calculated using the sales constraint and lost sales threshold values. The maximum outstanding delayed order amount is determined by the constant lost sales threshold value used while any actual order more than that threshold is lost.

The first experiment result in **Table 4** shows that in the no-frozen horizon scenario orders do not have enough time to accumulate, leading to a lower total sales amount with a higher customer service level. Other than that, the customer service level and financial gain decrease as the frozen horizon increases from one to six months. This is due to the high frequency of shortages with longer frozen horizons in the absence of an emergency backup supply. Current practices show that once the frozen horizon length is selected through negotiation between the sales and SC departments for a specific car model, it remains unchanged thereafter [9]. This sets the average delivery time to fall between $t + F$ and $t + F + 4$. In our case industry, delivery times are not set unless parts are available in the plant, which often makes the customers wait for long periods. Thus, we fixed the frozen horizon length at 3 months to improve and standardize the current delivery time set-

Table 4. Frozen horizon variation.

	No-frozen horizon	1 month	2 months	3 months	4 months	5 months	6 months
Delayed orders [%]	0.63	10.33	10.40	10.53	10.61	10.71	10.83
Lost sales [%]	1.48	24.68	25.15	25.64	26.10	26.49	26.91
Total profit (ETB)	18,480,046	28,658,306	28,420,254	28,195,195	27,960,064	27,773,510	27,641,690

Table 5. Normal supply interval variation.

	1 month	2 months	3 months	4 months	5 months	6 months
Delayed orders [%]	4.95	7.64	8.44	9.21	10.38	10.53
Lost sales [%]	3.49	7.85	12.26	17.04	23.66	25.64
Total profit (ETB)	36,334,095	37,278,839	34,284,457	32,131,685	29,905,287	28,195,195

Table 6. Emergency backup supply introduction.

	No backup supply	Negotiated backup supply only			Primary backup supply only	Joint primary and negotiated backup supply			Improv. % of joint policy at p=10% relative to no backup supply policy
p	0%	5%	10%	15%	0%	5%	10%	15%	
Delayed orders [%]	7.64	7.60	7.59	7.60	4.41	4.40	4.41	4.41	42.3
Lost sales [%]	7.85	7.69	7.59	7.48	2.23	2.10	2.01	1.90	74.4
Total profit (ETB)	37,278,839	38,009,813	38,783,212	39,564,472	38,725,862	39,521,034	40,295,645	41,141,003	8.1

Table 7. Flexibility and safety stock policies.

$FR^\alpha, FR^\beta, SS^\alpha, SS^\beta$	Policy 1 (0.3, 0.1, 0.2, 0.1)	Policy 2 (0.3, 0.1, 0.2, 0.3)	Policy 3 (0.3, 0.2, 0.1, 0.2)	Policy 4 (0.3, 0.3, 0.1, 0.2)	Policy 5 (0.2, 0.1, 0.1, 0.2)	Policy 6 (0.2, 0.2, 0.1, 0.2)
Delayed orders [%]	4.41	4.40	7.25	9.31	6.82	9.36
Lost sales [%]	2.01	2.00	4.71	6.33	3.99	6.32
Total profit (ETB)	40,295,645	40,352,885	41,432,332	40,965,379	41,146,655	41,963,008

ting. The increment of cost and reduction in instability is significant when the ratio of the frozen horizon to the planning horizon length (frozen and flexible horizon) is more than 50% [24]. Setting the frozen horizon length to three months, which is 43% of the 7-month planning horizon, provides sufficient plan stability without compromising the total profit and customer service level. In the normal supply interval variation experiment (shown in **Table 5**), a higher customer service level is recorded in the 1-month interval, while the 2-month interval provides the highest profit. This is due to higher inventory holding costs when we have frequent parts supply. As the interval increases, such as to a 6-month interval in our case industry, the customer service level and financial gain decrease. Thus, a 2-month normal supply interval is utilized for the rest of the experiments.

In Experiment 3, the negotiated and primary backup supply cost per unit is estimated based on discussion with management. Similarly, the probability of customer agreement is estimated to be 10%, but we included 5% and 15% cases to evaluate any significant variation in the results. As can be seen from **Table 6**, the effect of negotiated backup supply only is primarily focused on reducing the percentage of lost sales and enhancing the total profit. The introduction of primary backup supply only has reduced both the delayed orders and lost sales percentages tremendously compared to that observed in the negotiated backup supply only scenario.

The total profit increment in the negotiated and primary backup supply only policies are nearly equal and significant compared to that of the no backup supply policy. The joint primary and negotiated backup supply policy at a 15% probability of customer agreement recorded the highest customer service level and total profit.

In Experiment 4, flexibility degree variation without safety stock and safety stock ratio variation without flexibility were conducted separately taking 0.1, 0.2, and 0.3 as instances of absolute and relative coefficients of flexibility degree and safety stock ratios. From these separate experiments, six joint flexibility and safety stock policies are developed as shown in **Table 7**. Policies 1 and 2 recorded the highest customer service level with lower total profit while policies 4 and 6 recorded relatively higher total profit with the lowest customer service level. Policies 3 and 5 are viable options due to their comparative optimality in both conflicting objectives, contingent on the constraints associated with the maximum customer service level.

Finally, the effect of demand prediction quality on total

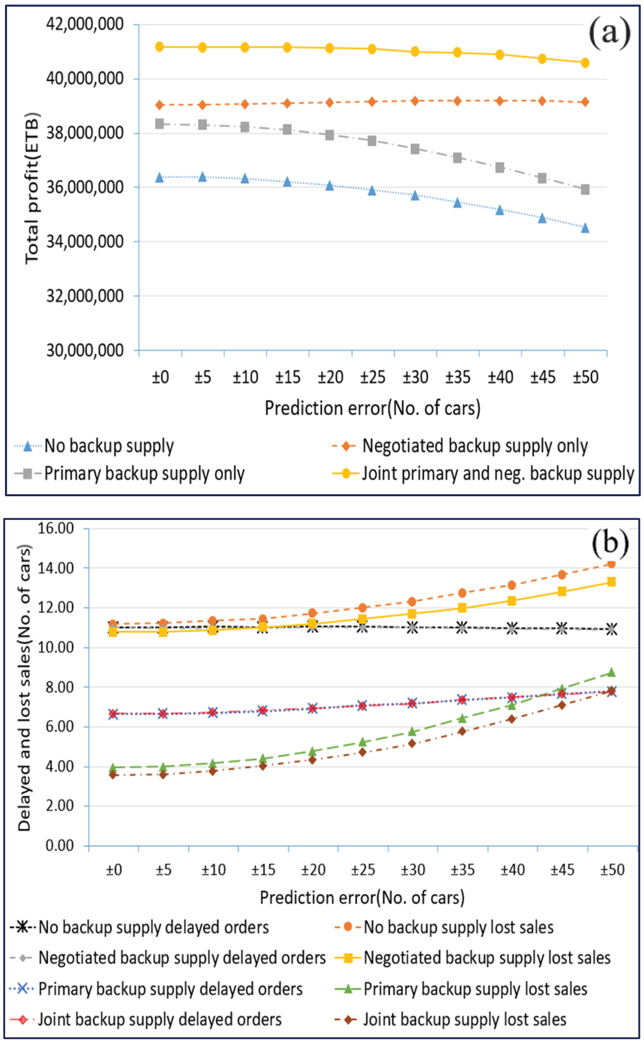


Fig. 4. Effect of prediction errors on KPIs.

profit and customer service level is plotted in **Figs. 4(a)** and **(b)**. Generally, the total profit decreases with lower prediction accuracy, while the percentages of delayed orders and lost sales increase. This result is similar to the one mentioned in [9] excluding the total profit in the case of the negotiated backup supply only policy. As the prediction error increases, the number of sales from the negotiation with impatient customers also increases due to the constant probability of agreement utilized. This leads to a slight increment of the total profit in the negotiated backup supply only policy. This effect is also reflected in the joint primary and negotiated backup supply policy, which has a lower rate of total profit reduction with higher prediction errors.

In **Fig. 4(b)**, the rate of increment of the lost sales percentages of the negotiated only and joint primary and negotiated backup supply policies is lower than that of the no backup supply and primary backup supply policies. The delayed order plots of the no backup supply policy overlap with the negotiated backup supply only policy since negotiation with the customers affects the lost sales amount only. The same is true for the primary backup supply only and joint primary and negotiated backup supply policies. The amount of delayed orders percentages remains more or less constant in the no backup supply and negotiated backup supply only policies, while it shows a slight increment before it becomes stable in the case of the primary backup supply only and joint primary and negotiated backup supply policies. The policies with primary backup supply have lower percentages of delayed orders initially when the prediction errors are lower (see the values in **Table 6**). As the prediction error increases, the delayed order amount (do_t) at each period increases until the maximum amount of orders that can be delayed, that is the constant lost sales threshold (Z), is reached. After this, the increment in prediction errors increases the sales loss (ls_t) only. This outcome creates a similar trend in **Fig. 4(b)** in which the average lost sales percentage (LSP) increases while the average delayed order percentage (DOP) remains constant as the prediction error increases.

5.3. Managerial Implications

The objective of this study was to develop a S&OP decision support system for the Ethiopian automotive industry. These industries, in addition to the demand uncertainty, operate under a supply of highly constrained parts due to the shortage of foreign currency. The study is significant since it introduces simulation model-based customer order placement in separate planning horizons, and procurement of parts supply based on hybridized real and forecasted demand. The following three distinctions from previous studies were made in this study: (1) *the S&OP model is developed in the context of the Ethiopian automotive industries*; (2) *a negotiated backup supply policy that extends the collaboration to the customers and suppliers is proposed*; and (3) *the logistics cost objective function is extended to total profit with price revision*.

Introduction of joint primary and negotiated backup supply policy with a 10% probability of customer agreement (shown in **Table 6**) alone, maximizes the total profit and minimizes the delayed order and lost sales percentages by 8.1%, 42.3%, and 74.4%, respectively, compared to the no backup supply policy. The effect of the negotiated backup supply policy is primarily in reducing lost sales thereby increasing the total profit. Its impact on the reduction of lost sales is pronounced when it is implemented with the primary backup supply policy jointly. Its advantage is that it enhances the flexibility of the S&OP system further through forward and backward integration with customers and suppliers. Thus, the result in this study contributes to the practice of S&OP since previous research indicates that the focus of integration is backward with suppliers while the forward integration with customers is less frequent [10]. This collaboration through negotiation enables the SC to thrive under unreliable demand prediction by lowering the rate of total profit reduction and customer service level deterioration with high prediction errors as demonstrated in **Figs. 4(a)** and **(b)**. However, this requires enhancing the actual supplier relationship and understanding customer behavior toward back ordering before implementation. It is also important to note that these results depend on the estimated negotiated and primary backup supply cost per unit and probability of customer agreement parameters.

Concerning the decision-making variables, appropriate policy should be selected considering the optimization of all the KPIs at once. In the result of Experiment 4 for instance, if the constraints of the maximum delayed and lost sales percentage set by the industry are 5% and 3%, respectively, Policy 2 can be selected as shown in **Table 7**. If these constraints are relaxed, to 7% and 4%, Policy 5 becomes the best policy possible in terms of total profit, as the delayed order and lost sales percentages (6.82% and 3.99%, respectively) remain lower than the maximum constraints. The simulation model does not give global optimum decision-making variables and thus, understanding the absolute and relative flexibility degree and safety stock ratio parameters is crucial. The demand uncertainty, manufacturing, and parts supply capacity need to be considered when selecting these parameters. Ethiopian automotive industry managers are recommended to understand the dynamics of the parameters involved and to enhance their organizational IT capability to utilize the model as a decision support system in their S&OP.

6. Conclusion and Future Research Work

In this research, a discrete-event simulation model from the literature was developed and extended considering the context of the Ethiopian automotive industry. In addition to the primary one, customer-negotiated backup supply policy was introduced, and the objective function was extended to total profit with price revision. The computational experiments demonstrated that the customer service level and financial gain can be significantly improved. The developed simulation model and managerial implications derived from the study are expected to support the contextualization of S&OP implementation in the Ethiopian automotive industry.

The introduction of uncertainty in the procurement time as a future research work is crucial since the parts supply of the Ethiopian automotive industry is highly constrained. The uncertainty from procurement time also increases the realism of the S&OP and introduces complexity to the simulation model. Making the frozen horizon length variable in each planning cycle is another future research work that is currently being considered with the introduction of uncertainty in procurement time. Frozen horizon length can be another decision variable due to its potential benefits such as optimizing visibility on future demands and delivery time [9]. However, it also affects plan stability, which requires the incorporation of planning instability and nervousness measures in addition to the KPIs mentioned in the current study. Extending the solution of the contextualized model to a simulation-optimization technique is also another promising future research direction. Finally, validation of the simulation model and the experimental results through implementation are also required.

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