ERP DECISION SUPPORT SYSTEM USING MULTI OBJECTIVE OPTIMIZATION– AN EXPLORATORY STUDY

[1]GHALEB Y. ABBASI, [2]ISRAA H. ABU RUMMAN

[1]Professor, Industrial Engineering Department, University of Jordan, Amman, Jordan
[2]Industrial Engineering Department, University of Jordan, Amman, Jordan
E-mail: abbasi@ju.edu.jo, israaburomman@gmail.com

Abstract- Enterprise Resource Planning (ERP) system is the main focus in this research, the actual performance criteria retrieved from different departments within ERP database for twelve product portfolios emphasised the need for a systematic approach for a Decision Support System (DSS). The proposed DSS helps the decision maker (DM) purchase the right products, in the right quantities and at minimal inventory carrying cost and at the same time meets the highest customer service by minimizing the probability of stock out instances. Multi-objective optimization of Profit-Service Level-Cash liquidity trade-off objectives supported the DM in finding the most preferred Pareto optimal solution and introduced a posteriori method in consonance with the generate-first-choose later approach in dealing with multi-objective optimization using Weighted Metric Method (Lp method) to find the Pareto Optimal set.

Keywords- ERP, Decision Support System, Pareto Optimization, Multi-objective decision making, weighted metric method, Lingo, Product Mix multi objectives optimization.

I. INTRODUCTION AND RESEARCH MOTIVATION

Supply chain performance impacts the financial performance (Arshad and Akbar, 2014). One of the biggest challenges in supply chain optimizations is maintaining accurate records for the inventory transactions for a long- time horizon strategic planning.

The needed data is always captured in the standard traditional accounting systems. Enterprise Resource Planning (ERP) is a popular supply chain control system used in the retailer enterprises to provide management with functions that can be effective to manage all links on the supply chain; these links include orders, procurement, inventory, planning, financial management, transportation, distribution, personnel management, and others (Changhui, 2015).

This paper developed an optimization module to enable the decision makers (DM's) to maximize returns on their invested money by determining the best set of targeted quantities across various product portfolio's under a financial budget constraint. The DM have to trade-off between different criteria to maximize total profit gross margin, maximize cash flow liquidity and maximize predefined service level by minimize stock out instance.

The basic objectives of the current situation analysis for the inventory is to create systematic inventory ranking procedure using three classification criteria;(1) which Items have the highest sales demand, (2) which one is most profitable (3) how much is the average inventory carrying cost to earn this profit, Figure 1 shows the main criteria for the optimization approach to trade-off between multiple Product portfolios

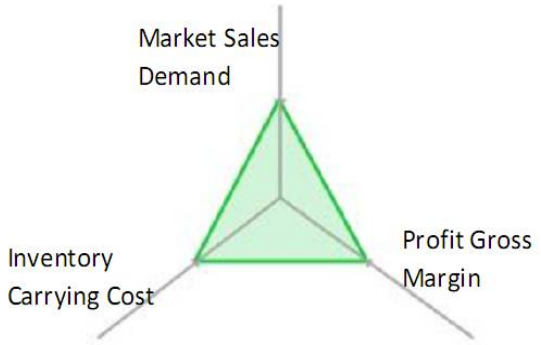


Figure 1: Multi Objective Optimization criteria

In this research case study, a well- structured ERP systems provided the management with functions that effectively integrate key business and operational activities and inherits a huge numbers of valuable shortcomings data of the supply chain process in its database, more than hundreds of thousands transactions recorded in the system since the date of go live at year 2012 related to 2500 Stock keeping units (SKU) under 12 product portfolios.

While the structured ERP system inherits a huge numbers of valuable shortcomings data in key business scenarios and priorities associated with financial budget, cash flow forecast, history of purchases, history for sales, all related inventory records. Iterative approach of simulation modeling and optimization techniques integrated with ERP can accurately represent Decision Support System (DSS) for continuous improvement and innovation for decision makers.

A computer-based procedures to create access to all relevant data source elements within ERP will minimize the complexity of decision making process comparing with other experimental studies framework in supply chains field, Figure (2) illustrate the information flow of the parameterize input to the optimization problem.

As seen in Figure (2), many short comings data from financial management, sales, procurement and warehouses modules within ERP will be a parameterized inputs to the optimization module in the proposed DSS, on the other hand sales/cash forecast and the replenishment plan will be the output of this DSS, The incoming section will discuss the nature of these inputs.

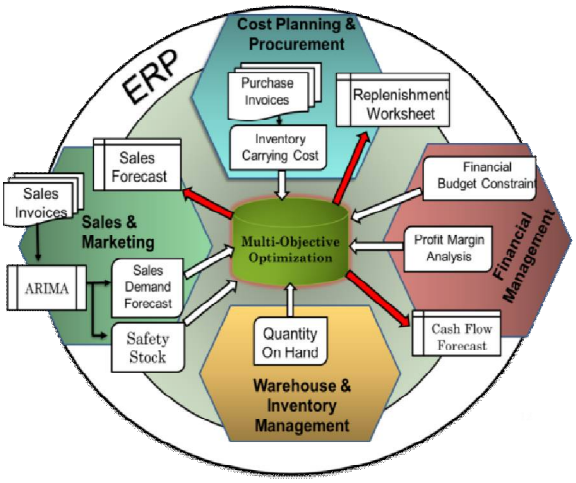


Figure 2: Information flow of the parameterize input to the optimization problem.

Cost Planning and Procurement Department: A distributor does not earn profits when they buy shares of stock in their company until purchased material is resold to a customer with a higher price than its cost (Schreibfeder, 2003); so it is crucial that every distributor need to closely monitor all costs associated with acquisitioning and holding inventory prior to their use by the business to achieve a reasonable trade-off between profit and the amount of cash invested in overall inventory which called inventory carrying cost. By reviewing all cost factors and elements that are relevant in the research case study, Figure (3) illustrates the inventory carrying costs breakdown associated with the money value invested in the stock.

In this case mainly ERP purchase module will carry direct cost of purchases price (acquisition capital cost) via purchase invoices and credit memos, in addition to that, this module gives the option to include additional costs of item charge such as freight, replacement fees, duties and customs, handling charges or/and any service cost such as insurance cost and then inherit them in the SKU unit cost so the ERP keeps accurate value of Cost of Goods Sold (COGS) for profit calculations.

On the other hand, inventory risk cost is maintained in the inventory stock functionality which as a periodic activity to check if the quantity registered in the system is the same as the physical quantity in stock and then adjust any inventory shrinkage, obsolescence or damage cost.

It's worth mentioning that the storage space cost is eliminated in this research scope because the warehouse is company-owned with significant space and with no warehouse rent, insurance or maintenance expenses. And in regards warehouse labour expense, warehouse equipment acquisition and annual depreciation, those elements are excluded too because the warehouse space is shared with all products and there will be no competitive advantage to make it as an input to the optimization module trade-off criteria.Sales and Marketing Department: To maximize the opportunity to gain profit without any un-needed surplus investment in inventory, a time series analysis statistical technique called Auto Regressive Integrated Moving Average (ARIMA) model is employed to successfully detect trends, seasonality, and cyclical in a together in comprehensive way and extract consistent patterns in sales demand history from ERP. ARIMA can be used to predict future forecasting and to maintain service level constraint; safety stock can be calculated from standard deviation of the forecasted error.

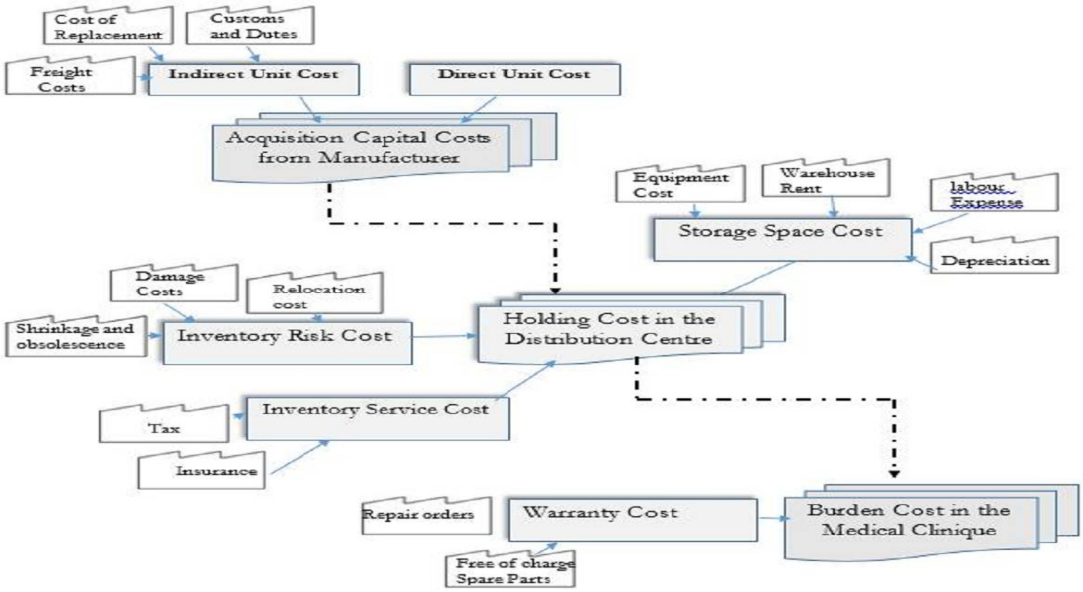


Figure 3: Inventory Carrying Cost Element Breakdown

II. CURRENT PERFORMANCE EVALUATION

Performing Multi-Criteria Inventory Ranking Classification for all product portfolio according to actual performance criteria retrieved from ERP emphasis the exiting of the trade-off criteria in the case study of interest. Performing the classification procedure involves the following steps:

1. Obtain the total inventory carrying cost for each part in a given period.
2. Calculate the total company inventory carrying cost invested in their stock in the same given period and calculate percentage shares for each product portfolio.
3. Arrange the Product Groups in ascending order based on total inventory carrying cost shares % and assign the appropriate rank correspondingly.

After repeating step 1 through step 3 for gross margin and sales demand criteria the result in Table (1) is obtained, there are interesting findings that re-assured the trade of criteria , for example SO-I product portfolio is the heaviest inventory carrying cost and ranked as the 8th, 12th , 8th and 11th profitable product portfolio among the four years, while GT product portfolio is one of the most profitable product portfolio ranked as 1st, 4th, 3rd and 4th during the four years even it has lower inventory carrying cost. This analysis is highly valuable in a situations that have a limited cash flow and the DM have to trade-off selection between different what- if scenarios .

Table (1) contains the results of the inventory carrying cost ranking for all product even the dead products and non-stock product portfolios, but only 12 portfolios with replenishment policy of buy to stock is to be considers as input to the optimization problem in the proposed DSS.

Table 1: Multi-Criteria Inventory Ranking Classification Result

	2012						2013						2014						2015					
	Inventory Carrying Cost		Gross Margin		Sales Demand		Inventory Carrying Cost		Gross Margin		Sales Demand		Inventory Carrying Cost		Gross Margin		Sales Demand		Inventory Carrying Cost		Gross Margin		Sales Demand	
Code	Rank	Shares %	Rank	Shares %	Rank	Shares %	Rank	Shares %	Rank	Shares %	Rank	Shares %	Rank	Shares %	Rank	Shares %	Rank	Shares %	Rank	Shares %	Rank	Shares %	Rank	Shares %
AC	4	7.54	2	14.39	6	8.43	5	6.66	1	17.27	6	8.25	10	4.57	6	7.33	7	4.04	14	0.67	13	0.78	12	0.20
AG	9	5.48	6	8.58	7	2.47	10	2.42	7	5.43	9	1.21	16	0.45	14	1.14	18	0.11	13	0.71	14	0.62	13	0.20
AL	22	-	-	-	-	-	9	3.18	5	8.09	8	1.41	8	5.08	5	8.52	10	1.65	5	5.76	3	12.35	7	2.53
BC-I	19	-	-	-	-	-	16	0.31	27	-0.38	19	0.02	11	2.68	27	-0.55	16	0.15	12	1.58	17	0.17	17	0.05
BT	13	0.18	14	0.16	14	0.30	18	0.22	16	0.14	17	0.17	17	0.35	18	0.16	15	0.18	15	0.60	15	0.41	11	0.40
CH	10	2.37	10	3.55	8	2.20	11	2.17	10	4.09	7	2.60	12	2.42	10	3.24	9	1.97	9	2.99	7	3.03	8	2.43
CN-I	2	14.32	11	3.01	13	0.34	2	23.91	9	4.89	13	0.63	9	4.86	13	1.16	17	0.12	17	0.33	9	1.50	15	0.05
DU	16	0.03	15	0.07	16	0.05	24	-	-	-	-	-	-	-	-	-	27	-0.02	-	-	-	-	-	-
GO	7	5.76	1	15.49	2	19.39	6	5.04	4	10.08	1	21.40	4	9.15	3	12.52	1	25.15	6	5.40	4	12.02	3	18.61
GT	6	6.51	4	11.63	3	17.90	8	4.86	6	7.25	4	14.39	5	8.06	7	7.06	2	15.31	4	9.46	5	10.70	2	19.93
HT	3	10.99	3	13.18	1	20.09	3	8.78	3	14.29	2	17.37	13	2.07	11	2.44	8	2.79	18	0.13	18	0.10	-	-
IN	5	6.54	5	9.04	5	10.42	4	8.66	2	15.08	3	15.83	2	11.30	4	12.45	3	15.14	8	4.75	8	1.82	6	7.38
IT	11	1.55	9	5.15	10	1.07	12	1.03	11	3.64	10	0.73	18	0.35	17	0.60	14	0.20	-	-	16	0.37	27	-0.10
NE	23	-	-	-	-	-	13	0.56	13	1.26	15	0.32	6	7.46	2	13.27	6	5.83	3	12.81	2	19.75	5	10.62
PO	24	-	-	-	-	-	25	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
RI	25	-	-	-	-	-	26	-	-	-	-	-	3	11.06	1	16.23	4	13.01	2	14.97	1	27.34	1	23.07
RN	26	-	-	-	-	-	17	0.25	14	0.42	14	0.53	27	-0.04	16	0.83	13	0.32	16	0.38	27	-0.10	14	0.10
SL	17	0.00	-	-	-	-	21	0.00	-	-	-	-	20	0.01	-	-	-	-	20	0.01	-	-	-	-
SN	15	0.07	13	0.31	12	0.43	14	0.44	15	0.31	16	0.19	14	0.90	12	1.37	11	0.66	11	1.71	10	1.43	9	1.26
SO	27	-	-	-	-	-	27	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
SO-I	1	32.43	8	6.54	11	0.91	1	26.06	12	3.07	11	0.68	1	22.02	8	6.41	12	0.54	1	30.31	11	1.02	10	0.61
SR	18	-	-	-	-	-	22	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
SU	8	5.65	7	8.42	4	14.59	7	4.90	8	4.91	5	13.57	7	6.36	9	4.97	5	12.78	7	5.07	6	5.71	4	12.59
SW	12	0.48	12	0.43	9	1.35	19	0.19	17	0.10	12	0.66	-	-	-	-	-	-	-	-	-	-	-	-
SY-I	20	-	-	-	-	-	23	-	-	-	-	-	15	0.89	15	0.86	19	0.03	10	2.32	12	0.98	16	0.05
VB-I	21	-	-	-	-	-	15	0.31	-	-	-	-	-	-	-	-	-	-	19	0.04	-	-	-	-
VG	14	0.10	16	0.04	15	0.07	20	0.04	18	0.05	18	0.05	19	0.01	26	-0.01	20	0.02	-	-	-	-	-	-

III. MODEL DEVELOPMENT

3.1 Multi-objective optimization

Multi-objective optimization (also known as multi-objective programming, vector optimization, multicriteria optimization, multiattribute optimization or Pareto optimization) is concerned with mathematical optimization problems involving more than one objective function to be optimized simultaneously in area of multiple criteria decision making (Wikipedia.org, 2015).

In multiobjective problems, it is very unlikely that all functions are minimized or maximized simultaneously by one optimal solution $x*$. Indeed, the multiple objectives (m) have conflicts of interest (Rocha, et el., 2015).

A Multi-objective optimization problem can be written in the general form as in the following:

$$\text{Max./Min } .F(x) = \{f_1(x), f_2(x),\ldots,f_k(x)\} \quad (1)$$

St:

$h_{i(x)} = 0$, I = 1,2,…,p

$g_i(x) \leq 0$, j = 1,2,…,m

s.t.x $\in X = \{ x \in R^{n+} | a_i x = bi, i=1,\ldots,m\}$,

Where $x = (x_1, \ldots , x_n)$ is a vector of decision variables, $F = (f_1, \ldots , f_p)$ is a vector of objective functions and X is a feasible region produced by

some constraints. R^{n+} might be restricted with $g_i(x)$ inequity constraints or/and $h_{i(x)}$ equity constraints.

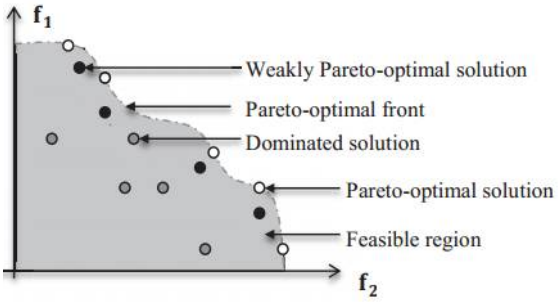


Figure 3: Illustrative example of Pareto optimality

As illustrated in Figure 4, the Nondominated solutions have the characteristic that their optimality cannot be improved further without sacrificing at least one of the other objective functions. Where x∗∈ X is an efficient solution (or nondominated solution) if and only if there does not exist another x ∈ X such that ∀j: fj(x) ⩾fj (x∗) and ∃j: fj(x) >fj(x∗), in another word change from one allocation to another that can make at least one individual better off without making any other individual worse off is called a Pareto improvement.

Pareto domination:

$$z' \succ z'' \Leftrightarrow \{z'_i \le z''_i,\ \ i = 1,2,...,m;\ \ z' \ne z''\ \} \quad (2)$$

Non-dominated (efficient, Pareto) set:

$$P(Z) = \{z \in Z : \{z' \in Z : z' \succ z\} = emptyset\} \quad (3)$$

During the process of decision making, some preference information articulation from decision makers may be required, and what type of information and when it is given play a critical role in the actual decision-making method. Under this consideration, the methods for solving Multi-objective decision making problems have been systematically classified into four classes by Hwang and Masud (1979) and Lai and Hwang (1994) as illustrated in Figure 5 (Jie Lu ,2007).

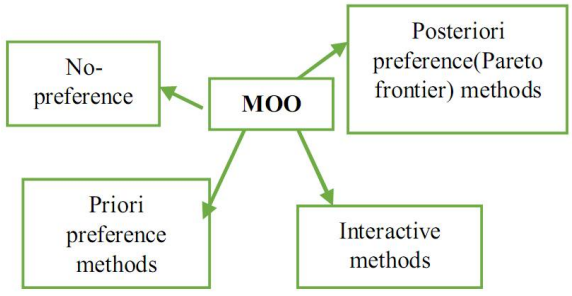


Figure 5: Classification of MOO methods according to the role of the Decision Maker

3.2Weighted Metric Method (Lp method) Theoretical Background

Weighted metric method (L_p Method) is usually discussed in Multi-Objective Decision Making (MODM) as an optimization techniques that combines multiple objectives into single objective. Combine multiple objectives using the weighted distance metric of any solution from the ideal solution for each objective optimized individually (Noorossana and Ardakani, 2009).

The weighted L_p distance measure of any solution x from the ideal solution $f_i(x^{max})$ as in equation 4:

$$\text{Min.} L_p = \left\{\sum_{i=1}^{k} w_i |f_i(x^{max}) - f_i(x)|^p\right\}^{1/p} \quad (4)$$

s.t.

$h_i(x) = 0$, I = 1,2,…,p

$g_i(x) \le 0$, j = 1,2,…,m

$X_i^{(L)} \le X_i \le X_i^{(U)}$, i = 1,2,. . , n

Where w_j is a non-negative weight assigned to each objective function by DM and p indicates the importance of each objective function deviation from its ideal value. When p = 1 is used, the resulting problem reduces to a weighted sum of the deviations. When p = 2 is used, a weighted Euclidean distance of any point in the objective space from the ideal point is minimized (Noorossana and Ardakani, 2009).

This methodology requires knowledge of minimum and maximum objective values which can be found by independently optimizing each objective functions. Therefore the first step is establishment of the payoff matrix Φ based on the calculation of the individual minimum of each objective function. The solution that minimizes the *i*th objective function (x) can be represented as $f_i^*(x_i^*)$ When it replaces the optimal individual x_i^* in the remaining objective functions, it becomes (x_i^*) in matrix notation (Rocha et al, 2015).

The payoff matrix Φ can be written as in table 2.

Table 1: Standard Formulation for payoff matrix Φ

$$\Phi = \begin{bmatrix} f_1^*(x_1^*) & \cdots & f_1(x_i^*) & \cdots & f_1(x_m^*) \\ \vdots & \ddots & & & \vdots \\ f_i(x_1^*) & \cdots & f_i^*(x_i^*) & \cdots & f_i(x_m^*) \\ \vdots & & & \ddots & \vdots \\ f_m(x_1^*) & \cdots & f_m(x_i^*) & \cdots & f_m^*(x_m^*) \end{bmatrix}$$

Once the objective functions have been defined, they are aggregated into a formulation of multiobjective optimization in single objective by a weighted metric method.

In equation 4, it is assumed that objective functions have the same scale. If fi(x_i)'s do not have the same scale then each objective function could be made scale-less using equations 5 :

$$\text{Min } Lp = \bar{f}(x) = \sum_{i=1}^{k} w_i \cdot \left[\left(\frac{f_i(x) - f_i^*(x)}{f_i^{Max} - f_i^{Min}}\right)^p\right]^{1/p} \quad (5)$$

(4)

Where $\bar{f}(x)$ is the global objective function, $f_i^*(x)$ is the ideal or the best result individually possible, and values f_i^{Max} and f_i^{Min} are obtained in the payoff matrix.

Once $\bar{f}(x)$ is formulated, an arrangement of mixtures for the weights of each objective function is defined due to the constraint $\sum_{i=1}^{k} w_i = 1$. Subsequently, the solution of the optimization problem of will be obtained for each condition defined by the arrangement of weighted mixtures.

IV. OBJECTIVE FORMULATION

Objective 1: Maximize Total profit gross margin:
Gross profit margin value comes from cost of goods sold ($C_{i,t}$) deducted from revenue earned from selling the product to the end customer. Last sales prices ($P_{i,t}$) for the current year is used as an input for the optimization model, thus this objective can be formulated as the following:

Max. Total profit gross margin =
$$\sum_t \sum_i ((P_{i,t} - C_{i,t}) \times X_{i,t}) \quad (6)$$

Objective 2: Maximize Cash Flow.
The predicted customer demand flow for a particular product can provide an indicator of how long it takes as average time for a company to convert its unit of inventory into sales revenue value and minimize Cash to Cash Cycle, here is need to include new KPI as Days Sales Of Inventory (DSI) to predict sales revenue value in the receivable balance under assumption that this company sell in cash on delivery policy.DSI will equal the average of day inventory outstanding before delivered to the end customer (Losbichler, et el., 2008). For example if the demand is one unit per month for product x that means that one unit of this product has 30 day inventory outstanding to sell one unit of product x, and if other product demand rate 120 then in average it will take 0.25 day to sell one unit of product x, In general, a lower DSI is better.
DM may prioritize a fast moving inventory products against more profitable inventory to insure more cash liquidity in the organization and this emphasis the need to develop a cash liquidity priority ranking. Priority weightage index can be obtain using the sales price multiplied by how much to buy of product i divided by DSI, Table 3 shows the result for the cash flow prioritization weightage index for the next period forecasted from ARIMA.
Thus this objective can be formulated as the following:
Max cash flow weightage index =
$$\sum_t (P_{i,t} \times X_{i,t}) / dsi \quad (7)$$

Objective 3: Maximize Service Factor by minimize stock out instant
From the customer relationship prospective the service level could be optimize by minimize the instant for unhappy customers because of inventory stock out, Service level expresses the probability that a certain level of safety stock will not lead to stock-out (Rahman, 2008). Using ARIMA forecasting point of view zero safety stocks would lead to a service level of 50%. Thus, there is a need for investigation to get optimized safety stocks with the proposed inventory forecasting model using equation number 8.
Safety Stock = σ * icdf (P) (8)
Where σ is the standard deviation retrieved from ARIMA model for each product portfolio, icdf the normalized cumulative normal distribution (zero mean and variance equal to one) and P is the targeted service level.
By revising the ARIMA estimated errors from the standard deviation, and because those errors is accumulated form 2012 DM decide to generate safety stock at 80% confidence interval to be input to the replenishment calculations. So this objective can be formulated as the following:
Min. Stock Out =
$$\sum_t [d_{i,t} + [\sigma_i \times icdf(Pi, t)] - Q_{i,t}] - x_{i,t} \quad (9)$$

The final problem formulation with decision variables, objectives, constraints, and variable bounds is as the following:

Index:

Notation	Meaning
i	index for products
t	index for time

Parameters:

Notation	Meaning
$P_{i,t}$	Sales Price in dollars for product i at time t
$C_{i,t}$	Inventory carrying unit cost in dollars for product i at time t
$d_{i,t}$	Forecasted sales demand of product i at time t predicted by ARIMA.
σ_t	Sales demand forecasting standard deviation for errors for product i
$Q_{i,t}$	Quantity on hand of product i at time t
$icdf(P_{i,t})$	Normalized cumulative normal distribution for P service level
F_t	Financial Budget Balance Available at time t
$S_{i,t}$	Safety Stock Quantity for product i at time t , predicted by ARIMA
$DSI_{i,t}$	Average inventories outstanding sales days for product i.

Variables:

Notation	Meaning
$x_{i,t}$	How much to buy of product *i at time t*

Objective 1: Maximize Total profit gross margin:
$$\sum_t \sum_i ((P_{i,t} - C_{i,t}) \times X_{i,t})$$

Objective 2: Maximize Service Factor by minimize stock out instant:

$$\sum_t (d_{i,t} + Q_{i,t} - (\sigma_i \times \text{icdf}(Pi, t))) - x_{i,t}$$

Objective 3: Maximize Cash Flow Index:

$$\sum_t \sum_i \left[\frac{(P_{i,t} \times X_{i,t}) - (C_{i,t} \times X_{i,t})}{P_{i,t} \times X_{i,t}} \right] * \text{dsi})$$

Financial Budget Balance Available Constraints

$$\sum_t \sum_i (c_{i,t} \times x_{i,t}) \leq F_t$$

Forecasted Market demand Constraints

$$\sum_t \sum_i d_{i,t} + S_{i,t} - Q_{i,t} \geq x_{i,t}$$

$$\sum_t \sum_i d_{i,t} - Q_{i,t} \leq x_{i,t}$$

V. ANALYSIS & RESULTS

Moving to the next planning period, the optimization parameters obtained in Table 3. It is obvious that the replenishment action is needed for 9 product portfolios and 3 products are still over stocked, by optimizing each objective individually and obtain the resulting Table 4, the minimum financial budget to meet ARIMA demand is 62000$ and DM decided to evaluate the performance if extra 8000$ is invested in the safety stock.

Solving the current situation using Lp method includes the following steps:

First Step: optimizing each objective individually and obtain the payoff matrix: Table 4 shows the pay-off matrix for each objective optimized individually, and it is obvious that the pay-off criteria in this scenario is significant and there is a need for multi objective optimization.

Second Step: Re-formulate the objective function using L_p method: After obtaining the pay-off table in the previous step, the objective function need to be re-formulated to fit the Weighted Metric Method (Lp method) by aggregating the three objective functions into one a multiobjective formulation, and the new objective is provided in equation number 10.

Third Step: Add new constrain for the upper and lower boundaries for each product portfolio: and new constant will be added to the optimization problem as the following:

$X_i^{(L)} \leq X_i \leq X_i^{(U)}, i = 1,2,..,n$

This condition represents the limit of the upper value and lower value for each product portfolio quantity, is obtained in Table 5.

Table 5: Upper and Lower quantity limit for each product portfolio

	CH	CNI	GO	GT	IN	NE	RI	SU
$X_i^{(U)}$	11	1	138	76	62	8	101	94
$X_i^{(L)}$	11	1	139	97	62	17	130	123

Fourth Step: weight mixtures and calculation of the new multi-objective result: The model was solved using Lingo to solve this multi-objective optimization problem, the result of weight mixtures and calculation of the new multi-objective result is obtained in Table 6.

Table 7 shows that the Weighted Metric Method multiobjective optimization discovered a trade-offs pareto optimal of objectives that was invisible when optimizing according to a single objective optimized individually in this case study of Product-Mix parameter selection problem.

Table 3: Optimization Model parameters.

Product Portfolio	Qty On Hand ($Q_{i,t}$)	Sales Price ($P_{i,t}$)	Inventory Carrying Cost ($C_{i,t}$)	Demand Forecast ($d_{i,t}$)	$DSI_{i,t}$	Safety Stock ($S_{i,t}$)	Cash Flow Priority weightage Index	Prioritization Ranking Factor		
								Profit	Demand	Cash liquidity
AC	3	824.2	247.65	1	30	8	0.004%	4th	9th	12th
AL	13	2007.4	575.46	9	3.33	3	0.866%	2nd	8th	7th
BT	9	473.4	215.87	2	15	1	0.010%	9th	11th	11th
CH	1	731.2	264.75	12	2.5	4	0.560%	6th	7th	8th
CNI	1	13352	5988.24	2	15	0	0.284%	1st	12th	9th
GO	0	240.6	70.83	101	0.3	38	12.926%	10th	2nd	4th
GT	49	249.2	107.57	125	0.24	21	20.712%	12th	1st	2nd
IN	0	434.9	170.66	62	0.48	31	8.964%	8th	5th	6th
NE	53	873.9	246.91	61	0.49	9	17.361%	3rd	6th	3rd
RI	0	502.3	164.94	100	0.3	36	26.719%	7th	3rd	1st
SN	17	703.8	197.37	5	6	2	0.094%	5th	10th	10th
SU	0	245.29	93.86	94	0.32	29	11.498%	11th	4th	5th

Table 4: Payoff matrix for the objective functions.

Objective	Total Gross margin	Total Stock Out	CH	CNI	GO	GT	IN	NE	RI	SU
S1': Maximize Profit	127973.29	103	11	1	139	76	62	17	118	94
S2': Minimize Stock Out	123960.88	79	11	1	139	97	62	8	101	123
S3': Maximize cash flow	126634.43	98	11	1	138	79	62	8	130	94

$$\text{Minimize } L_p = \left[\begin{array}{c} \sum_{x=1}^{5} W1 \times \left[\frac{((P_{i,t}-C_{i,t}) \times X_{i,t}) - ((P_{i,t}-C_{i,t}) \times X_{i,t}^{Max})}{((P_{i,t}-C_{i,t}) \times X_{i,t}^{Max}) - ((P_{i,t}-C_{i,t}) \times X_{i,t}^{Min})} \right]^2 \\ + \\ \sum_{x=1}^{5} W2 \times \left[\frac{((d_{i,t}+S_{i,t}-Q_{i,t}) - X_{i,t}) - ((d_{i,t}+S_{i,t}-Q_{i,t}) - X_{i,t}^{Min}))}{((d_{i,t}+S_{i,t}-Q_{i,t}) - X_{i,t}^{Max}) - ((d_{i,t}+S_{i,t}-Q_{i,t}) - X_{i,t}^{Min}))} \right]^2 \\ + \\ \sum_{x=1}^{5} W2 \times \left[\frac{((P_{i,t} \times X_{i,t})/Dsi) - ((P_{i,t} \times X_{i,t}^{Max})/Dsi)}{((P_{i,t} \times X_{i,t}^{Max})/Dsi) - ((P_{i,t} \times X_{i,t}^{Min})/Dsi)} \right]^2 \end{array} \right]^{1/2}$$

Table 6: Arrangement of mixtures and calculation of the new multi-objective result.

	W1	W2	W3	Total Profit	Stock Out	GO	GT	NE	RI	SU
S1'	1.00	0.00	0.00	97257.32	57	139	87	13	110	106
S2'	0.75	0.25	0.00	97257.32	57	139	87	13	110	106
S3'	0.75	0.00	0.25	97257.32	57	139	87	13	110	106
S4'	0.50	0.50	0.00	97081.05	57	139	86	13	109	108
S5'	0.50	0.25	0.25	97267.05	57	139	86	13	110	107
S6'	0.50	0.00	0.50	97257.32	57	139	87	13	110	106
S7'	0.25	0.75	0.00	91911.88	77	138	81	10	105	101
S8'	0.25	0.50	0.25	93951.46	69	138	83	11	107	104
S9*	**0.25**	**0.25**	**0.50**	**96595.72**	**57**	**139**	**87**	**12**	**109**	**108**
S10′	0.25	0.00	0.75	97257.32	57	139	87	13	110	106
S11'	0.00	1.00	0.00	87539.59	95	138	76	8	101	94
S12'	0.00	0.75	0.25	87539.59	95	138	76	8	101	94
S13'	0.00	0.50	0.50	87539.59	95	138	76	8	101	94
S14'	0.00	0.25	0.75	87539.59	95	138	76	8	101	94
S15'	0.00	0.00	1.00	87539.59	95	138	76	8	101	94
S16'	0.33	0.33	0.33	96911.2	58	138	86	13	109	108
S17'	0.67	0.17	0.17	97257.32	57	139	87	13	110	106
S18'	0.17	0.67	0.17	91281.32	80	138	80	10	104	100
S19'	0.17	0.17	0.67	96933.15	56	139	87	12	110	108

Table 7: New payoff matrix with Pareto Optimal Solution.

Objective	Total Gross margin	Total Stock Out	CH	CNI	GO	GT	IN	NE	RI	SU
S1': Maximize Profit	127973.29	103	11	1	139	76	62	17	118	94
S2': Minimize Stock Out	123960.88	79	11	1	139	97	62	8	101	123
S3': Maximize cash flow	126634.43	98	11	1	138	79	62	8	130	94
***Pareto Optimal Solution**	**126141.59**	**57**	**11**	**1**	**139**	**87**	**62**	**13**	**110**	**106**

CONCLUSIONS

To maximize ERP utilization in supply chain management optimization, DSS was successfully implemented to support the decision making process to prioritize more profitable products and to reduce focus on less profitable product combinations by determining the best set of targeted quantities across various product portfolio's criteria with a financial budget constraint.

The multi objective optimization scientific approach provided the DM with a tool to support the decision making process rather than the traditional preferences which basically relied on

tedious efforts of manually traverse the whole possible decision alternatives.

The adopted Weighted Metric Method Multiobjective Optimization on the case study for the current product mix parameter selection problem discovered Pareto optimal trade-offs of objectives which was invisible when optimizing according to a single objective optimized individually.

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