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A Comparative Study of Optimization Techniques for Aggregate Production Planning Applied in the Steel Pipes Industry

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ABSTRACT

This study introduces a new application of aggregate production planning (APP) in the manufacturing of carbon steel pipes and hot induction bends. Given the strategic importance of this type of industry, enhancing productivity through cost-effectiveness, and economic performance optimization has become crucial in such industry. The study proposes an APP optimization model that is both inspiring and realistic, aimed at increasing profitability by minimizing both production and inventory costs. The model is formulated as a deterministic, multi-product, multi-period model, and three alternative optimization techniques were applied: linear programming, genetic algorithms, and hybrid genetic algorithms, as a case study in a steel pipes manufacturing company. The results indicate that linear programming yields the same results as hybrid genetic algorithms, but in less time. Additionally, a feasibility study evaluated the effectiveness of the proposed model against the original planning system in the company, revealing a 12% decrease in overtime wages and a 9% increase in profit.

Keywords: Aggregate Production Planning (APP), Deterministic Demand, Steel Pipes Industry, Mathematical Programming, Genetic Algorithms.

1. INTRODUCTION

Aggregate production planning (APP) involves optimizing different capacities, such as production, overtime, inventory, backorder, workforce, and subcontracting, over a planned time horizon of 3 to 18 months to meet overall enterprise demand [1]. In recent years, Egypt has launched numerous mega projects in various strategic fields, including construction, such as the building of 14 new cities like the new administrative capital and the northwest coast development project [2, 3], as well as ongoing projects in the oil and gas and renewable energy sectors [4]. Additionally, Egypt has achieved significant agricultural development goals, aiming to reclaim 1.5 million feddan of desert land for creating new societies, achieving agro-industrial development, and reducing food imports [5]. Moreover, Egypt is seeking to build its first nuclear plant at the AL DABAA site on the northern coast [6]. Since carbon steel pipes and hot induction bends are essential components in all of these strategic fields, it is crucial to appropriately plan for their production to meet rising demand and prevent potential delays in delivering these strategic products. International Pipe Industry Company (IPIC) is the only Egyptian manufacturer of longitudinal submerged arc welded carbon steel pipes (LSAW) and hot induction bends. Therefore, an appropriate aggregate production planning should be established to align with the national plan time and minimize the company's production and inventory costs, leading to increased profitability.

In this research, we consider the modelling and optimization of the APP on the pipes manufacturing industry, where the demand is project-based and deterministic, and defined in terms of pipes products contracted manufacturing project. Multiple products aggregate planning were taken on, including carbon steel pipes and hot induction bends. Multiple objectives are included: Minimizing production costs and inventory costs. The ultimate objective of this research is arrive at the optimum APP solution techniques, among multiple alternative solution techniques identified, including both mathematical programming and artificial intelligence techniques, as well as hybrid techniques.

In the 1950s, the APP problem-solving approach was introduced [7], with the proposal of a linear decision rule [8] and the advancement of transportation methods to address APP [9]. Since then, the APP problem has been extensively studied due to its potential for cost control in production and inventory, which accounts for a significant portion of a manufacturer's overall costs [10]. According to jamalnia et. al. [11], conducting APP requires pre-specification of the planning horizon with pre-defined planning periods (e.g., weeks, months, or quarters), as well as the determination of relevant information and data to establish consolidated plans, such data are illustrated in the Figure 1.

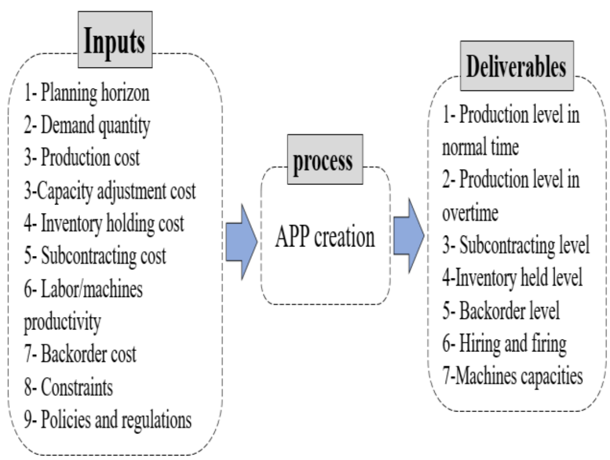

Figure 1: Creation of a generic APP model [11].

The aggregate plan is a consolidate tool in deciding the most suitable adjustment for different kinds of resources and capacities within existing constraints to meet required demand while maximize profitability.

In accordance with [12, 13], three main strategies exist for aggregate planning: level, chase, and mixed. The level strategy aims to maintain a steady production rate with a constant workforce, using surplus inventory to meet demand fluctuations. The chase strategy matches demand and production rate period by period through various methods, such as workforce size variation, subcontracting, overtime, and equipment optimization. The mixed strategy varies production rates and inventory levels to implement the most effective production plan.

Techniques for solving aggregate production planning problems can be informal, optimal, or near optimal [14–17] . Informal techniques involve creating visual aids like tables or charts to help planners utilize capacity to meet demand and develop alternative plans, but they do not always yield optimal results. Optimal techniques, such as linear programming models, transportation methods, linear decision rules, and goal programming, guarantee an optimal solution. Heuristic techniques, including search decision rules, production switching heuristics, management coefficient models, parametric coefficient planning, and simulation. Metaheuristic techniques, such as Genetic Algorithms (GA), Neural Network, Tabu Search Algorithm (TSA), Particle Swarm Optimization (PSO), Simulated Annealing (SA), Ant Colony Algorithms (ACA), and Fish Swarm Optimization (FSO) have been widely used to solve APP problems quickly and effectively, though their solutions are not always optimal.

APP optimization models can be classified depend on the uncertainty level that exist in the model into two main categories, the first is deterministic models and the second uncertain models [17]. Various industries have used different approaches to solve aggregate production planning (APP) problems. The paint industry utilized Possibilistic Linear Programming [18] and Fuzzy Goal Programming [19], while the textile industry used Genetic Algorithms [20, 21], Possibilistic Environment Based Particle Swarm Optimization, Genetic Algorithms and Fuzzy Based Genetic Algorithms [22], Hybrid Genetic Algorithm and Simulated Annealing [23], and Particle Swarm Optimization [24]. The vegetable oil industry applied Fuzzy Linear Programming [25], Simulated Annealing Algorithms, Modified Simulated Annealing Algorithms and Harmony Search Algorithms [26], simulated annealing algorithms and particle swarm optimization [27], and a combination of Fuzzy Programming, Simulated Annealing, and Simplex Downhill Algorithm [28].

The automotive industry employed Mixed Integer Linear Programming Model [29], Weighted Sum Approach [30], and Linear Programming [31]. The electro technology industry used Nonlinear Mathematical Model [14], Genetic Algorithms [32], and Transportation Model [33]. The food and drinks industry utilized Nonlinear Multi-Objective Stochastic Optimization Model [34], and Linear Programming Model [35, 36]. Lastly, the cosmetics and toiletries industry utilized Genetic Algorithms, Particle Swarm Optimization [37], and Fish Swarm Optimization [38].

Moreover, numerous applications of APP optimization have been implemented in various industries, such as home appliance [39], gardening equipment [40], machinery manufacturing [41, 42], and kitchen and bathroom cabinets [43]. However, it should be noted that some methodologies for APP optimization have only been demonstrated through hypothetical numerical examples. These include Genetic Algorithms [44, 45], Goal Programming [46–48] Fuzzy Linear programming [49] and Harmony Search Algorithm [50].

APP optimization applied in various industrial sectors over the past decade, as summarized above. However, the carbon steel pipes and hot induction bends industries are distinctive and strategic due to high capital costs, large investments, and the need for skilled workers. These industries play a critical role in supplying strategic projects in fields such as oil and gas, construction, water supply, and energy. Since IPIC is the only supplier of LSAW carbon steel pipes and hot induction bends in the Egyptian market, optimizing aggregate production planning in this unique industry is crucial to meeting rising demand and increasing profits by reducing production and inventory costs.

This study aims to compare optimization techniques for aggregate production planning (APP) of carbon steel pipes and hot induction bends. The objective is to minimize production and inventory costs that will maximize profitability in turn, and meet demand within the required time. A mathematical model will be formulated, and optimization approaches, such as genetic algorithms, hybrid genetic algorithms, and linear programming, will be applied using actual historical data from IPIC Company. The optimal approach will be selected based on a comparison of the different optimization methods. Finally, the financial feasibility of the chosen optimization approach for APP will be evaluated against the original planned results.

The subsequent sections of this paper are organized as follows: Section 2 elucidates the formulation of the mathematical model for addressing APP optimization problem. In section 3, a case study of the company is presented along with the historical data required to validate the proposed optimization model. Section 4 discusses the validation of the optimization model through various optimization approaches. The findings and results of this study are presented in section 5. Finally, section 6 summarizes the conclusions drawn from this research and delineates potential avenues for future work in this area.

2. MODEL FORMULATION

Following an extensive review of relevant literature [20, 21] [27] [32] [40], this study adopts the equations and nomenclatures deemed most appropriate for the present context. Notably, certain parameters utilized in prior literature, such as subcontracting, hiring and firing, backorder levels, related costs, and others, have been eliminated, while new parameters and equations, as detailed in this section, have been introduced. This approach is taken in light of the specific applicability of the model to the industry of carbon steel pipes and hot induction bends, and its use in the IPIC Company.

The company's range of products , consisting of carbon steel pipes of varying sizes and hot induction bends of different angles and sizes which are entirely depending on the client requirements, have been aggregated into two distinct product families: longitudinal submerged arc welded carbon steel pipes (LSAW Pipes), and hot induction bends. Standard steel plates of 12 m each are used as the raw material for pipes, while pipes are utilized for producing hot induction bends. These details are further elaborated on in section 3. As such, the company must make several adjustments, including overtime production levels, finished product inventory, and raw material inventory, in order to meet the deterministic demand for types of products over the planning periods. APP problem focuses on formulating multi-objective multi-product multi-period model for the study, which aims to minimize total production cost and minimize inventory cost through the planning horizon. The two objectives are consolidated into weighted sum single objective to make the application of Linear programming as well as Genetic Algorithms feasible. The following APP model was built upon the following assumptions, which are special for the case study.

1- All related costs are fixed during the planning horizon.
2- The demand is deterministic.
3- Backorder, subcontracting, hiring and firing policies are not applied due to the company regulations.
4- Initial inventory of raw material and finished products are equal to zero.
5- Supplement of raw material is assumed to be on hand in the beginning of each period.
6- Overtime production and inventory cannot exceed their maximum capacities.
7- Regular production is assigned to each product because each product is manufactured on a different production line so that regular production rate is known and fixed within periods.
8- Each product has an expected wastage level, and it must be covered in the level of raw material inventory.
9- The level of finished product inventory in the final period must be zero.

2.1 Problem Nomenclatures

N — Type of products, n = 1, 2... N.

T — Planning horizon number of periods, t = 1, 2... T.

D_{nt} — Demand for product n in period t (units).

QR_{nt} — Quantity of regular time production units for product n in period t (unit).

QO_{nt} — Quantity of overtime production units for product n in period t (unit).

RC_{nt}— Regular time production cost per product for product n in period t ($/unit).

OC_{nt} — Overtime production cost per product for product n in period t ($/unit).

Qr_{nt}— Quantity of raw material held in inventory for product n in period t (unit).

Cr_{nt} – Inventory carrying cost for raw material per unit for product n in period t ($/unit).

Qf_{nt} – Quantity of finished products held in inventory for product n in period t (unit).

Cf_{nt} — Inventory carrying cost for finished product per unit for product n in period t ($/unit).

$Qf_{n(t-1)}$ — Quantity of units left in finished inventory for product n in period t -1 (unit).

$Qr_{n(t-1)}$ — Quantity of units left in raw material inventory for product n in period t -1 (unit).

$minqf$ — Minimum amount of finished products inventory per product (unit).

$maxqf$ — Maximum amount of finished products inventory per product (unit).

$minqr$ — Minimum amount of raw material inventory per product (unit).

$maxqr$ — Maximum amount of raw material inventory per product (unit).

$QOmax$ — Maximum production level in overtime (unit).

$QRmax$ – Maximum production level in regular time (unit).

Wp_n – Expected wastage percentage for product n (%).

2.2 Decisions Variables

QO_{nt} — Overtime production level for product n in period t (unit).

Qr_{nt} - Inventory level of raw material per unit for product n in period t (unit).

Qf_{nt} – Inventory level of finished product for product n in period t (unit).

2.3 Objective Function

The main objective of the model is to minimize the sum of total of production cost and inventory cost. The total production cost is consisting of regular time production cost plus overtime production cost.

Regular time production cost, Equation (1), is the multiplication of the cost associated with production one unit of product in regular time and number of products produced in regular time in each period.

$$\text{Regular time production cost} = RC_{nt}QR_{nt} \tag{1}$$

Over time production cost, Equation (2), is the multiplication of the cost associated with production one unit of product in overtime and number of products produced in overtime in each period, overtime production is necessary to cover the demand in certain period, when regular time production level is insufficient to meet the demand.

$$\text{Overtime production cost} = OC_{nt}QO_{nt} \tag{2}$$

Hence, the first objective function, minimize the production cost, can be written as shown in Equation (3):

$$MinZ1=\sum_{n=1}^{N}\sum_{t=1}^{T}[RC_{nt}QR_{nt}+OC_{nt}QO_{nt}] \tag{3}$$

For the second objective function, which is minimization inventory cost, inventory cost can be separated into raw material inventory cost and finished products inventory cost. Raw material inventory cost is the related cost with inventory of raw materials that is required to satisfy the sum of production level in regular time, production level in overtime and the units that will held in raw material inventory to cover the expected wastage level for each period, it was formulated according to how the company deals with the raw material. Therefore, inventory raw material cost can be illustrated in Equation (4):

$$\text{Raw material inventory cost} =Cr_{nt}(Qr_{nt}+QR_{nt}+QO_{nt}) \tag{4}$$

Finished products inventory cost is the related cost with inventory of finished products in each period, it is consisting of inventory cost of one unit multiply by number of finished products held in finished inventory at the end of each period, represented in Equation (5).

$$\text{Finished products inventory cost} = Cf_{nt}Qf_{nt} \tag{5}$$

Therefore, the second objective function is described by the following Equation (6):

$$Min\ Z2 = \sum_{n=1}^{N}\sum_{t=1}^{T}[Cr_{nt}(Qr_{nt}+QR_{nt}+QO_{nt}+Cf_{nt}Qf_{nt}] \tag{6}$$

These two objective functions, Equation (3) and (6), can be combined into one single objective function, Equation (7), to minimize the total of production cost and inventory cost for type of products N in planning horizon number of periods T.

$$Min\ Z = \sum_{n=1}^{N}\sum_{t=1}^{T}[RC_{nt}QR_{nt}+OC_{nt}QO_{nt}] + \sum_{n=1}^{N}\sum_{t=1}^{T}[Cr_{nt}(Qr_{nt}+QR_{nt}+QO_{nt})+Cf_{nt}Qf_{nt}] \quad (7)$$

2.4 Finished Products Inventory Constraint

The first constraint indicates that the summation of regular time production level for product *n*, overtime production level for product *n*, and quantity of finished products for product *n* that kept in finished product inventory from period *t* -1 minus quantity of products *n* that are held in inventory in period *t* must be equal to the demand of product *n* in period *t*, illustrated in Equation (8).

$$Qf_{n(t-1)}+QR_{nt}+QO_{nt}-Qf_{nt}=D_{nt} \quad \forall n, \forall t \quad (8)$$

The number of finished products for product *n* must be held in inventory in period *t* must be greater than or equal to minimum quantity of inventory for product *n*, as shown in Equation (9).

$$Qf_{nt} \geq minqf \quad \forall n, \forall t \quad (9)$$

Equation (10) represents the number of finished products for product *n* in period *t* must be less than or equal to the maximum number of products that can be kept in inventory for product *n*, this constraint is according to the available inventory spaces.

$$Qf_{nt} \leq maxqf \quad \forall n, \forall t \quad (10)$$

The number of finished products for product *n* in the last period must be equal to zero as indicated in Equation (11), because this type of industry is make to order according to the requested order from client. Therefore, production only starts according to the requested order from client and there are not any products left in inventory after the order is completed.

$$Qf_{nt}=0 \quad \forall n,\ t = last\ period \quad (11)$$

2.5 Raw Material Inventory Constraint

The first constraint of raw material inventory constraints in Equation (12) demonstrates that the summation of raw material required for production of products *n* in regular time, overtime and amount of raw material that held in inventory for period *t* must be less than or equal to the maximum amount available for raw material inventory. This constraint is novel and has been specifically developed for the purposes of this case study.

$$QR_{nt}+QO_{nt}+Qr_{nt} \leq maxqr \quad \forall n, \forall t \quad (12)$$

Equation (13) features a novel formulation for the second constraint of raw material inventory. In the first period after production starts, the number or raw material that held in inventory minus the anticipated wastage level in production of product *n* in regular time and overtime must be greater than or equal to the minimum raw material inventory. Minimum raw material inventory hence represents the minimum stock must be kept in inventory of raw material according to company's policy.

$$Qr_{nt}-Wp_n\left(QR_{nt}+QO_{nt}\right) \geq minqr \quad \forall n,\ t=1 \quad (13)$$

The third constraint, which has been newly introduced in Equation (14), serves to account for any anticipated waste that may arise for product *n* during period *t* following the start period. This is accomplished by adding raw material to be held in inventory at the end of the period, while subtracting the sum of raw material inventory from the previous period *t*-1, as well as the estimated amount of waste generated during the production of the product *n* during regular and overtime production in period *t*.

$$Qr_{nt}-Qr_{n(t-1)}-Wp_n\left(QR_{nt}+QO_{nt}\right) \geq 0 \quad \forall n, \forall t>1 \quad (14)$$

The fourth and last novel constraint regarding raw material is for planning purpose, which means it is essential to have in the last period, quantity of raw material that covers any anticipated of wastage that could happens as depicted in Equation (15). In another words, the amount of wastage for the whole demand is taking under consideration and aimed to be covered through surplus raw material.

$$Qr_{nt}=Wp_n\sum_{n=1}^{N}\sum_{t=1}^{T}D_{nt} \quad \forall n,\ t=last\ period \quad (15)$$

2.6 Production Constraints

Production level of overtime for product *n* is limited by the available overtime hours in each period, as revealed in Equation (16). While, Equation (17) indicates that production level of regular time for product *n* in each period equals the maximum production level in regular time.

$$QR_{nt}=QRmax \quad \forall n, \forall t \quad (16)$$
$$QO_{nt} \leq QOmax \quad \forall n, \forall t \quad (17)$$

2.7 Non-Negativity Constraint

The last constraint, Equation (18), is to avoid negative values of decision variables.

$$QO_{nt},\ Qf_{nt},\ Qr_{nt} \geq 0 \quad \forall n, \forall t \quad (18)$$

Finally the amount of raw material to be procured from the supplier at the start of each planned period can be determined by the model's deliverables, using the novel Equation (19) developed as follows:

$$supply_{nt} = QR_{nt} + QO_{nt} + Qr_{nt} - Qr_{n(t-1)} \quad \forall n,\ \forall t \tag{19}$$

3. CASE STUDY

International Pipe Industry Company (IPIC) was incorporated in Egypt since 2001, IPIC aims to provide and support Egyptian and international oil and gas industry by LSAW pipes and hot induction bends, mainly for oil and gas, construction, infrastructure, and water Transmission projects. IPIC provides a diversification of products besides longitudinal submerged arc welded pipes there are hot induction bends, pipes accessories, Steel Structures' Fabrication & Erection, and spiral welded pipes [51]. However, the company's demand in this study considered to have been aggregated into two families of products, which are longitudinal submerged arc, welded (LSAW) carbon steel pipes and hot induction bends, having same raw material inputs for pipes that are steel plates, and for hot induction bends are pipes. The demand is deterministically, since it is based on contracted quantities and different sizes according to client requirements, as shown in the Figure 2.

The planning process in the company starts by working alongside with marketing department to meet the requirements of the clients such as delivery dates depending on projects on hand and projects on process. Planning department develops the executive budgetary with the concern departments depending on the amount of consumables, wages, raw material, resources, utilities, and the planned duration of the project. After that a production plan is made and work order is issued and distributed to production units and QC department to launch the project on the production line. Also planning department has an essential role in project's cost control according to the execution budgetary by issuing a weekly project's cost report.

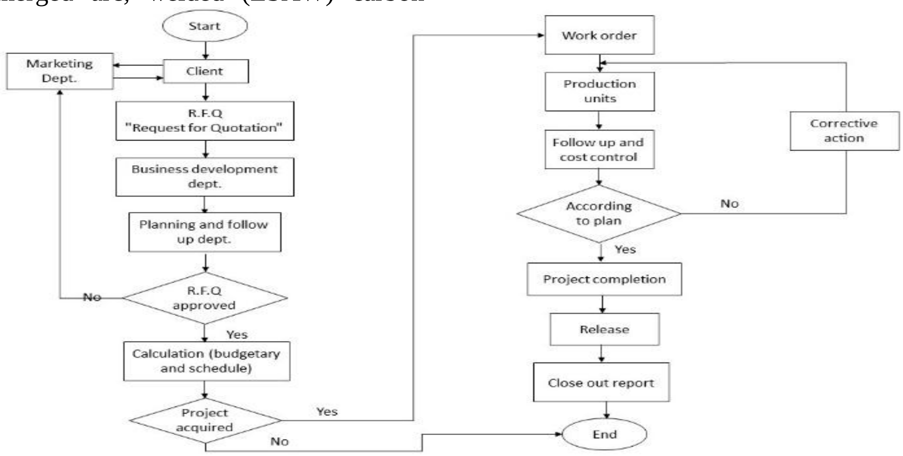

Figure 2: Contracted project-based demand and production planning at IPIC.

Original planning system in the company is obliged with the production system of finish to start, this means that a project must be finished to start with the following one, without taken into account aggregate production planning strategy. This system has many disadvantages represented in incapability of handling various projects at the same period, potential for having delay penalties imposed by customers, having of lost orders opportunities, and not achieving the optimal production and inventory costs. Therefore, it is essential to formulate APP model that is applicable for the company, and financially evaluate it against the original planning system.

The APP at IPIC can be described as multi-products, deterministic demand. The main planning objectives is multiple; including reducing production and inventory costs. According to company policies, overtime is possible, whereas backorders and subcontracting are not allowed.

Tables (1-5) presented actual historical data acquired from the company during the period from March to June 2022. The data pertains to various contracted projects regarding steel pipes of varying sizes, and hot induction bends of different angles and sizes, and was consolidated into an aggregated form. These data serve as inputs for the proposed optimization model for pipes and hot induction bends manufacturing, which will be utilized in subsequent sections to evaluate the efficacy of alternative solution techniques. Noted that pipes for hot induction bends were supplied by clients, and each pipe are producing three hot induction bends for the selected projects, while standard raw material plates for pipes were supplied by the company. In addition, the expected wastage percentage for pipes and hot bends according to the company are 1.029% and 2.2%, respectively.as mentioned in Equations (13-15)

Table 1. Total demand of *n*1 (LSAW pipes) and *n*2 (hot bends)

T (periods)	Demand	
	***n*1 (LSAW Pipes)**	***n*2 (Hot Bends)**
March	2450 pipes	200 bends
April	2350 pipes	280 bends
May	2850 pipes	300 bends
June	2850 pipes	220 bends

Table 2. Available regular time and overtime in each period

T (periods)	Working Days	Available Regular Time (hrs)	Available Over Time (hrs)
March	27	378	216
April	24	336	192
May	24	336	192
June	25	350	200

Table 3. Production capacity in regular time and overtime

Factor	Symbol		*n*1 (Pipes)	*n*2 (Hot Bends)
Productivity			5 Pipes/hr	1 Bend/2hr
Maximum Production Level in Regular Time (unit)	*QRmax*	March	1890	189
		April	1680	168
		May	1680	168
		June	1750	175
Maximum Production Level in Overtime (unit)	*QOmax*	March	1080	108
		April	960	96
		May	960	96
		June	1000	100

Table 4. All required relevant costs

Cost	Symbol	*n*1 (Pipes)	*n*2 (Hot Bends)
Regular Time Production Cost ($/unit)	RC_{nt}	$ 2,320.42	$ 624.50
Over Time Production Cost ($/unit)	OC_{nt}	$ 2,436.74	$ 799.02
Inventory Carrying Cost for Raw Material Held in Inventory ($/unit)	Cr_{nt}	$ 16.6	$ 178.8
Inventory Carrying Cost for Finished Product Held in Inventory ($/unit)	Cf_{nt}	$ 62.5	$ 119

Table 5. Inventory relevant data

Factor	Symbol	*n*1 (Pipes)	*n*2 (Hot Bends)
Minimum amount of finished product held in inventory	*minqf*	0	0
Maximum amount of finished product held in inventory	*maxqf*	1264 pipes	204 Bends
Minimum amount of raw material held in inventory	*minqr*	0	0
Maximum amount of raw material held in inventory	*maxqr*	3,360 plates	114 Pipes

Table 6 shows the original actual planned production and inventory costs for the planned period by using the original planning system.

Table 6. Original planned costs

Planned Cost	Cost
Original production cost	$ 25,558,218.76
Original inventory cost	$ 324,657.40
Original total cost	$ 25,882,876.16

4. MODEL VALIDATION

This section presents an application and validation of the proposed model based on historical data from the company, by using different optimization approaches such as Genetic Algorithms optimization, Hybrid genetic algorithms optimization, Linear programming optimization and manual method. This will be beneficial in first evaluating the feasibility of the proposed model, and then second comparing the obtained performance results of the proposed solution techniques against the results of the original plan. MATLAB 2015a software was used to solve the model by using Genetic algorithms optimization, Hybrid genetic algorithms optimization, and Linear programming optimization. For the manual method, Excel spreadsheet was used to solve it.

Next subsections presents brief description of the implemented solution techniques to optimize the proposed APP model.

4.1 Genetic Algorithms Optimization

Genetic Algorithms (GA) are used to seek for optimum or high-performance solutions by simulating Darwinian biological evolution and natural selection. Learning from how live species adapt to numerous niches in an ever-changing environment, software may emulate natural ways in assisting optimization and search issues to grow towards better solutions. Genetic Algorithms are mainly created to simulate a biological phenomenon as mentioned before, so that most of its terminologies are related to biology, but the only difference that Genetic Algorithms terminologies are simpler than their biological equivalent [52].

The fitness function is an expression for the objective function that is algorithms is trying to optimize [52] . Furthermore, the term refers to how fit each potential solution that fulfil objective function. The term chromosome is a representation of numerical value of a possible solution to the problem being optimized, which is a form of binary bit string existing in the population. During the process of Genetic Algorithms, populations are changing constantly by the replacing of current population with a new population. These chromosomes are referred to as individuals or genotypes [53].

To initiate Genetic Algorithms (GA), a set of random chromosomes is selected as the initial population or first generation. Each chromosome's fitness function is then evaluated to determine its optimization problem satisfaction. Random individuals from the current generation or population, known as parents, are selected based on their fitness value, and crossover occurs where genes from parents create a new offspring. Mutation is then applied to offspring, where bits are flipped in the new chromosomes. This process of selection, crossover, and mutation continues until the number of offspring equals the initial population, and the initial generation is replaced with a new generation consisting of entirely new offspring. This iteration continues until the best chromosome's fitness value stabilizes over generations, indicating the algorithm has reached the optimal solution [53]. GA methodology is demonstrated in Figure (3)

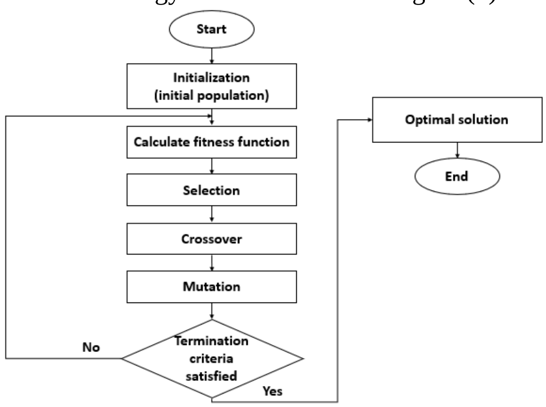

Figure 3: Genetic algorithms flowchart [53].

4.2 Hybrid Genetic Algorithms Optimization

The second approach involves the application of a hybrid genetic algorithm optimization strategy that utilizes a specialized function in MATLAB 2015a software known as the Hybrid function. This function is designed to fine-tune the results obtained from the genetic algorithms optimization process. The Hybrid function employs the Interior point algorithm as its default method for solving the optimization problem. A flowchart depicting the procedure of the hybrid genetic algorithms optimization is presented in Figure 4.

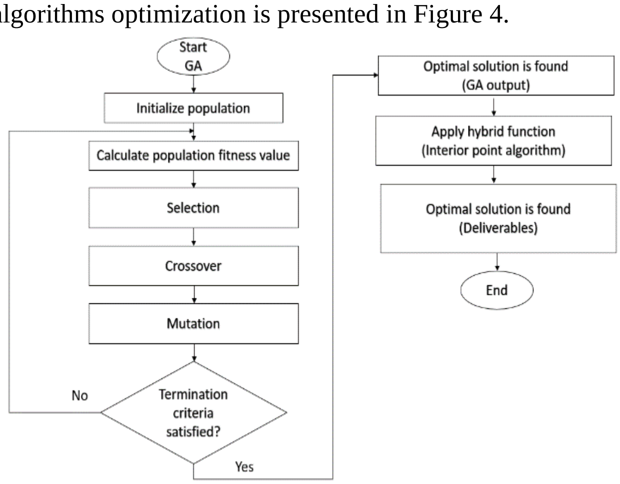

Figure 4: Hybrid genetic algorithms flowchart

4.3 Linear Programming Optimization

The proposed model can be solved using Linear Programming (LP) with MATLAB 2015a as the third approach. LP is an optimization method that involves minimizing or maximizing the objective function subject to various constraints. In LP, the objective function and constraints are both linear and consist of decision variables. The constraints are formulated into inequalities and equalities that involve the decision variables.

4.4 Manual Method

The final method involves solving the proposed model using a manual method based on a hybrid strategy [54]. This method employs an Excel spreadsheet filled manually under the proposed model constraints to represent the aggregate production planning proposed model. However, it is important to note that this method does not guarantee reaching the optimal solution.

5. RESULTS AND FINDINGS

In this section, we shall report the results and findings in applying the APP model alternative solution techniques.

5.1 Genetic Algorithms Optimization

The Genetic algorithm has been applied to optimize the APP model. Different selection and crossover options were used in order to select the most effective options that obtain the optimal value for the total of production and inventory cost, results of the total of production and inventory cost for each option are shown in Table 7 and Figure 5.

The minimum value of the total of production and inventory cost was obtained after applying of remainder selection with heuristic crossover, with a value of $ 25,738,098.20 and in a time of 94.249 seconds. The parameters selected for the genetic algorithms in MATLAB 2015a are presented in the Table 8.

Table 7. Variation of the total of production and inventory cost by using different selection and crossover options

Selection	Crossover					
	Scattered	Single point	Two point	Intermediate	Heuristic	Arithmetic
Stochastic uniform	$ 25743096.20	$ 25743955.02	$ 25743037.00	$ 25743096.20	$ 25738396.00	$ 25743096.20
Uniform	$ 25743096.20	$ 25743096.20	$ 25743096.20	$ 25743096.20	$ 25743096.20	$ 25743096.20
Roulette	$ 25743955.02	$ 25743096.20	$ 25743096.20	$ 25743096.20	$ 25739169.20	$ 25743096.20
Tournament	$ 25743096.20	$ 25743717.02	$ 25743955.02	$ 25743955.02	$ 25738455.20	$ 25743096.20
Remainder	$ 25743096.20	$ 25743955.02	$ 25743241.02	$ 25743096.20	$ 25738098.20	$ 25743096.20

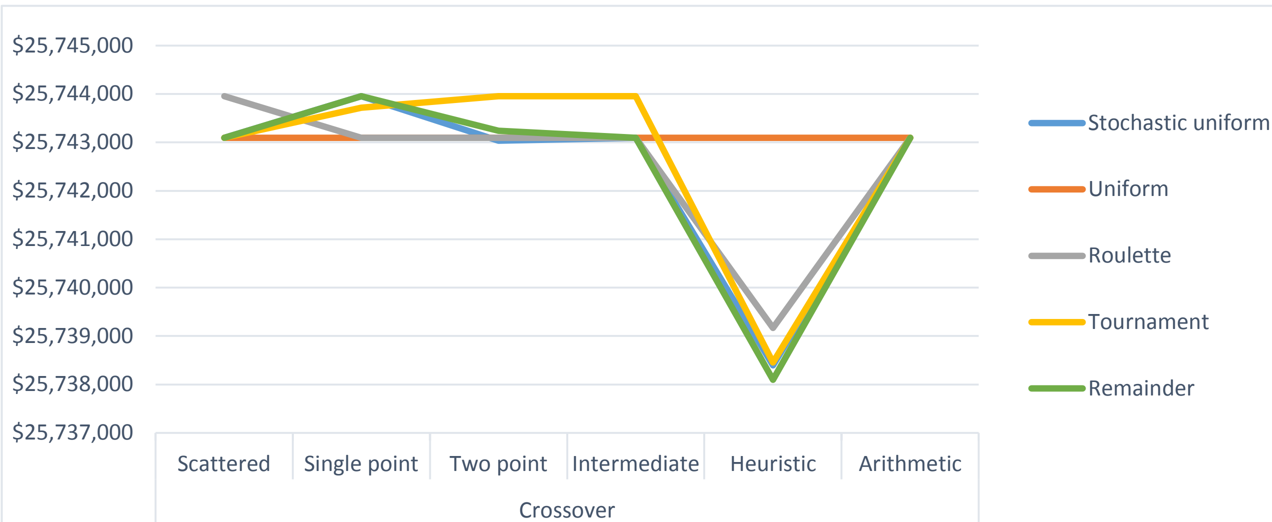

Figure 5: Genetic algorithms different options results

Table 8. Selected parameters for genetic algorithms optimization approach

Factors	Selected Option
Population Type	Double Vector (default)
Crossover	Heuristic
Function Tolerance	1e-8
Constraint Tolerance	1e-8
Crossover Fraction	0.8 (default)
Max Generations	100*number Of Variables (default)
Population size	200 (default)
Selection function	Remainder
Mutation	Mutation adapt feasible (default)

5.2 Hybrid Genetic Algorithms Optimization

The second optimization approach was applied based on the obtained optimal crossover and selection options from the first approach. Hybrid function runs after genetic algorithm optimization terminates. The result was $25,727,565.00 with a time of 91.233 seconds.

5.3 Linear Programming Optimization

Using the interior point algorithm as the default in MATLAB, the third approach was able to achieve the optimal result and overcome GA approach in accordance with [55]. It attains the same result as the previous hybrid genetic algorithms in terms of production and inventory cost, which amounted to $25,727,565.00. Furthermore, this approach took only 0.327 seconds to solve, which is significantly less time than the optimization method used in the hybrid genetic algorithms.

5.4 Manual Approach

The manual approach yielded the poorest results, with a value of $25,754,790.60. This outcome is unsurprising given the reliance on trial and error, which is the fundamental basis of this approach. It is widely acknowledged that optimal results cannot be achieved using this method.

5.5 Results Comparison

A comparison was conducted to determine the most suitable approach to be utilized for the study. The results of each approach were obtained and analyzed in the following Figure 6. The genetic algorithm optimization approach demonstrated a difference of $16,692.40 from the manual method, while the Hybrid genetic algorithms and linear programming optimization approaches achieved a reduction of $10,533.20 from the genetic algorithms optimization results, with a minimum outcome of $25,727,565.00. Despite its comparative success, the linear programming optimization method was ultimately chosen due to its superior computational speed, which resulted in a solution being obtained in just 0.327 seconds.

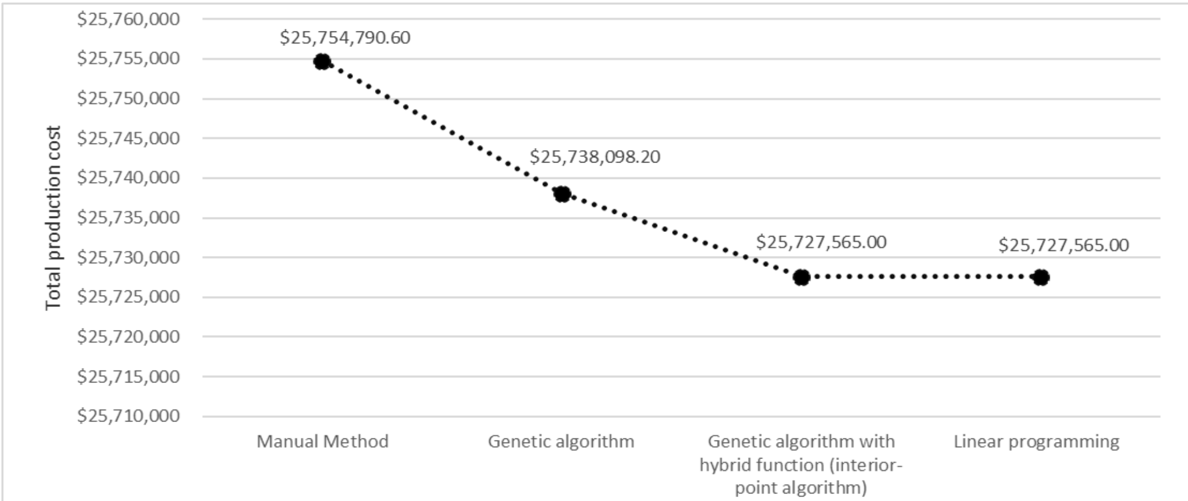

Figure 6: Comparison of results obtained from the different approaches

5.6 Model Deliverables

The optimal values of the decision variables are indicated in the Tables (9 -13), which appears after linear programming optimization has reached to the optimal of the total production and inventory cost by using MATLAB 2015a software.

Table 9. Overtime production level for two products over four periods

Product	Period 1	2	3	4
Pipes (*n*1)	580	960	960	1000
Hot bends (*n*2)	63	96	96	45

Table 10. Inventory level of raw material for two products at the end of four periods

Product	Period 1	2	3	4
Pipes (*n*1)	25	53	80	108
Hot bends (*n*2)	2	4	6	7

Table 11. Inventory level of finished products for two products over four periods

Product	Period 1	2	3	4
Pipes (*n*1)	20	310	100	0
Hot bends (*n*2)	52	36	0	0

Table 12. Inventory level of raw material for two products at the start of four periods

Product	Period 1	2	3	4
Pipes (*n*1)	2495	2693	2720	2858
Hot bends (*n*2)	86	92	94	81

Table 13. Supply of raw material for two products for four periods

Product	Period 1	2	3	4
Pipes (*n*1)	2495	2668	2667	2778
Hot bends (*n*2)	86	90	90	75

Table 9 gives the amount of overtime production that is necessary to keep with the overall contracted demand over each period. Table 10 includes the inventory level of raw materials for the two products at end of each period. The inventory level of finished products is demonstrated in Table 11. Table 12 indicates the inventory level of raw material that must be available at the start of each period, while Table 13 gives the amount of raw material for each product, which is supposed to purchase from the supplier and must be in the company's raw material store at the first of each period.

5.7 Feasibility Evaluation

After gathering all relevant financial statements and cost data for both the original and proposed plans, a feasibility analysis was conducted to evaluate the viability of the proposed model's outcomes.

The proposed APP model successfully met the delivery date requirements of each shipment by aggregating them into an overall demand, as shown in Table 1, through APP during the planning horizon. In contrast, the original planning system relied on a finish-to-start approach for each project and full utilization of overtime hours, resulting in an inability to meet the required demand of particular shipments within the specified delivery timeframe

Production costs are composed of several costs, including regular and overtime wages, raw material, production consumables, depreciation, and utilities.

Depreciation costs are calculated based on the production duration, while utilities costs encompass a variety of expenses, such as electricity, water, security, cleaning, and fuel, which also vary with the production duration.

The costs of raw materials and consumables are identical between the proposed planning approach and the original planning system, discrepancies are apparent in the wages, depreciation, and utilities costs.

The proposed model successfully optimized the utilization of overtime hours over a four-month period, resulting in a decrease from 1,536 to 1,300 overtime hours, and a difference in overtime cost of $186,364.41, demonstrating the model's ability to save on overtime wages.

The model achieved 1,400 regular hours for LSAW pipes and a corresponding amount of regular hours for hot bends, resulting in a total of 2,800 hours. In contrast, the original planning system utilized 2,688 regular hours, which is equivalent to a difference of 8 days between the two approaches. Despite this deviation, the proposed approach preferred the total wages cost over the original plan due to the optimal utilization of overtime hours, resulting in a variance of $139,132.36 or approximately 4% less than the planned cost.

The proposed planning approach resulted in a decrease in the production cost from $25,558,218.76 obtained from the original planning system, to $25,448,386.00, with a difference of $109,832.76. While the proposed model had a total wages cost difference of $139,132 in its favor, it is evident that the original planning system had lower depreciation and utilities costs, with a value of $29,299.60.This difference can be attributed to the 8-day variance between the two planning approaches, which resulted in lower utilities and depreciation costs in the original planning system.

Additionally, the proposed model achieved a 14% reduction in inventory cost, equivalent to $45,478.40, thanks to the efficient utilization of both finished products and raw materials. Once again, the proposed model and LP solution outperformed the original plan.

One of the critical features of the proposed model was its ability to eliminate the risk of delay penalties that result from inadequate planning, which had a significant impact on the outcome. The model was able to meet the required product quantities precisely on time, without any delays, thus avoiding incurring any penalty costs.

By way of contrast, the original plan incurred planned delay penalties, resulting in a total cost of $244,520.24. Despite the earlier discussed 8-day difference, the original planning system failed to meet the required delivery date of certain shipments, while the proposed model successfully met the required demand by aggregating the overall demand of each shipment according to its delivery date.

To determine the expected profit, company's profit margin percentage was applied to each of the two product types, taking into account their respective total production and inventory costs, as obtained from the model. The total projected profit can be determined to be $2,803,529.16

Finally, the differentiation between the planned and the proposed profit indicates that there is no equivalency between the original plan and the proposed plan. It shows the dominance of the proposed model, with an increasing of 9% from the planned profit with a $ 226,842.48 gab.

The previous feasibility has proofed the tremendous potential capabilities of the proposed APP optimization model against the original planning system in the company, and its direct magnificent impact in attaining maximum profitability with the minimum production and inventory costs, and at the same time to accomplish highest customer satisfaction without any needless delay.

6. CONCLUSION

Aggregate production planning has become crucial for meeting the demand of carbon steel pipes and hot induction bends, which are widely used in nowadays development projects, while optimizing associated production and inventory costs. In this study, a mathematical multi-product multi-period model was formulated to represent the aggregate production planning problem in the manufacturing of carbon steel pipes and hot induction bends, different optimization approaches, including genetic algorithms optimization, hybrid genetic algorithms, and linear programming, were applied and solved using MATLAB 2015a to select the optimal approach. The model was also applied to actual historical data to validate its feasibility against the original planning system in the company. The outcomes of this study can be summarized as follows:

- Both the linear programming and hybrid genetic algorithms optimization approaches yielded superior results compared to the genetic algorithms optimization and manual methods. However, the linear programming optimization approach outperformed in terms of computational speed
- The model has reduced overtime wages cost by 12%.

- The proposed production cost and inventory cost were significant less than the planned costs with values of $ 109,832.76 and $ 45,478.40 respectively.
- The deliverables of the model were beneficial and effective as it achieved 9% higher profit then the original planned.

Thus, the proposed model has demonstrated its practicality, functionality, efficacy, and applicability in real-world scenarios. However, for future research, certain modifications are recommended to enhance the agility and dynamism of the APP model. This would enable the model to better handle unexpected breakdowns, potential delays in raw material delivery, and fluctuations in raw material and production consumables costs throughout the planning horizon.

Credit Authorship Contribution Statement

Mostafa Ali: Generating the idea, Collecting data, Methodology, Software, and preparing original draft.
Shaban Abdou: Reviewing and supervision
Shady Aly: Reviewing, editing and supervision
Hanan Kouta: Reviewing, editing and Supervision

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper

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