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Production Scheduling using a Multi-Objective framework in an Automotive Company

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Abstract: The increased demand for highly customized products and the need for shortening lead times for competitive advantage has also affected the automotive industry. Companies that handle markets in a multi-faced network of demand, like Europe, need to be flexible, responsive, and follow a customer-focused policy. Therefore, there is an increased need for automated solutions not only in product design but also in the manufacturing section. Such solutions need to replace manual effort increasing efficiency and creating new horizons of innovation and development. In this paper, a mathematical model based on Goal Programming modeling has been introduced as a part of a more flexible and automated perspective for production scheduling. The model is applied to a production scheduling process of an automotive company headquartered in Germany to handle a multi-objective problem that manual effort cannot. The paper will explain how demand management, lead time shortening, and process efficiency can be solved through a mathematical model properly modified to its cause.

Keywords: Production Scheduling, Goal Programming, Mathematical Modelling of Decision Making Support Systems, Demand Management, Automotive Industry

1. INTRODUCTION

Production scheduling is a process that refers to allocation of resources and operations in order to provide the appropriate goods or services to the end customers. In automotive industry this process handles on monthly, weekly and even daily basis, customized orders from various countries while each of those orders have their own necessity and importance. In companies that are looking for greater market share and increased customer satisfaction this situation creates questions and difficulties. Priority issues such as which order and from which country will be produced first, especially when the capacity of the available manufacturing plants is considered limited, appear on a weekly basis. In European automotive market, various orders from every country are reaching on daily basis the headquarters of each company. Some of them are linked with customers or companies directly (crucial to be produced first, since they could lead to increase of customer satisfaction and provide direct profit) or some other are needed for dealer's stock. In a complex market network such as Europe's, companies, that are willing to strengthen their competitiveness, need to not only give the appropriate weight to each order, but also the corresponding weight in the market of each country. Therefore a multi-objective problem is being formulated, where companies need to optimize both customer satisfaction but also support each country's market in an, as much as possible, "equally distributed" manner.

2. LITERATURE REVIEW

Scheduling task in automotive industry is a customer driven time and capacity constrained-intensive task. During the last couple of decades, researchers have extensively focused on joint consideration of various operations planning in production and maintenance scheduling. In this study, we focus on schedule planning, re-planning, and rescheduling task under priority based order fulfilment strategy(Eriksen and Nielsen, (2016), Relich, (2017), Steger-Jensen et al., (2011)). We capture order delivery task priorities through the application of a goal programming (GP) technique (Calhoun et al. (2002), Lee et al. (1978), Selen and Hott (1986), Relich and Świć, (2020), Dang et al., (2012), Nedaei and Mahlooji, (2014)). However, we integrate customers needs in a periodic manner between the real manufacturing system and simulate the model in a data-exchange framework. There are many factors and constraints that decision-makers need to consider in planning and scheduling in production and service systems and it is difficult to transfer such problems entirely to modeling. However a multi-objective model will be presented, to capture all crucial parameters of a problem, aiming to assist decision maker in a more efficient manner. Therefore, goal programming can be used in such scenarios to obtain a robust scheduling[Foote et al. (1988), Gür and Eren, (2018), Frazzon et al. (2018), Moon et al., (2016)]. In the present study, we adopt a case-oriented approach to investigate the value of periodic operations planning. We refer to the recent study by [Bach et al. (2010), Bocewicz et al., (2016), Kumar et al. (2018), Mansouri et al. (2019),

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Table 1. Model's Parameters

Parameters:	
M	Market Set
E	Engine Set
i	Identity number per engine
j	Identity number per market
C	Capacity given from the plant
c_j	Capacity per engine i
a_{ij}	Monthly Allocation per engine i and per market j
b_{ij}	Estimated Production before Proposal per engine i and per market j
o_{ij}	Available back orders per engine i and per market j
p_{ij}	Priority Units per engine i and per market j
n	Index to control the level of Used Allocation each week per market $0 < n \leq 1$
Decision variables:	
x_{ij}	Amount of units proposed for scheduling per engine i and per market j
d_1^-	acceptable deviation of first objective
$d_{2_j}^-$	acceptable deviation of second objective
$d_{3_{ij}}^-$	negative deviation of third objective
$d_{3_{ij}}^+$	positive deviation of third objective

Myrelid, (2017), Sitek and Wikarek, (2011), Shuib and Kamarudin, (2019)].

3. MATHEMATICAL MODELING

In this section a mathematical model based on Goal Programming, will be introduced and used against a manual process of production scheduling proposal in a Automotive company headquartered in Germany. In order for the model to be accurate and depict the reality as much as possible, the same initial data that have been used for the actual scheduling for a specific model of the company will also be used for the Goal Programming formulation. The model will simulate the monthly production scheduling of the car model and the findings will be compared to the actual monthly production scheduling (Konstantinos (2020)).

In addition, it will be based upon 5 different datasets. These datasets correspond to any possible combination of market and engine for a specific model car. In the present case, 39 markets/countries and 4 different engines of a specific model study will be used. The 5 datasets are called Allocation, Available Back Orders, Priority orders, Production Capacity and Estimated Production before proposal and finally a specific dataset used by the company that is called **Used Allocation**. **Allocation** is the monthly production volume that is aimed to be reached for each country. **Available back orders** are the orders that are available to be scheduled. From these, the **Priority orders** are those that have been created by individual customers or companies, and is crucial to be scheduled as soon as possible. The **Production Capacity** is provided from the manufacturing plants on weekly basis. The **Estimated Production before proposal** is the sum of units that have been produced and those that have been scheduled already the current month but before the weekly production scheduling proposal. Lastly, the KPI (Key Performance Indicator) "Used Allocation" is calculated by the following equation:

$$\text{UsedAllocation\_M } (\%) = \left(\frac{\text{Weekly Proposal\_M} + \text{Est. Production\_M}}{\text{Allocation\_M}}\right) \times 100 \quad (1)$$

The model will simulate 4 different schedulings (all for November 2020 production, one per week) and therefore the data from Allocation, the weekly production capacity given, the Available back orders and the Priority orders will be the same as the actual schedulings for each week. Since the scheduling of the actual process and the simulated one will be different therefore the input of Estimated Production before proposal that will be used in the model will also be different and will correspond to the previous simulated production scheduling.

Regarding the current Multi-objective Problem that has been issued, the Lexicographic Goal Programming modelling has been chosen. The most important characteristic of Lexicographic Goal Programming is that it lets the decision maker to give an ordinal ranking of the objectives. Each of the objectives that will be chosen in the GPM belong to a different priority level. Therefore, the minimization of a deviation in a higher priority level is definitely more important than minimization of deviations in objectives that belong to lower priority levels.

3.1 Model Constraints

Initially the **soft and hard constraints** of the model need to be addressed. **Hard constraints** will be those that need to be respected in order for a feasible solution. Constraint (6), that ensures any combination of market and engine of the proposal plus the estimated production before the proposal will not exceed the corresponding combination of allocation (a_{ij}), is required. Since the production policy of the company is *make to order*, the order Constraint (7) needs to be applied to ensure that the final proposal units in any combination of i, j will not exceed the orders that are available. In that way the model will provide to the plant, only units for scheduling that are linked with a specific order. Finally, Constraint (8) will verify that the output of the proposal for all combinations i, j will be greater or equal to 0. The overall goal of LPP (Linear Programming Problem) which is part of a GPP (Goal Programming Problem) is to minimize the deviation variables in order to reach as close as possible to the ideal solution. Therefore the deviation Constraint (12) is being used to ensure that the deviation variables $d_1^-, d_{2_{ij}}^-, d_{3_{ij}}^-, d_{3_{ij}}^+$ will be greater or equal to 0.

On the other hand, **soft constraints** will be set those that they are expected not be respected fully and because the model needs to estimate the size of this deviation from their target. In that case, the model will consider the deviational variables to estimate the difference between the target and the result value in a given solution. Therefore, in order to address any of the soft constraints, a parallel definition of their deviation variables is needed to be addressed too. The lesser the deviational variables, the closer to the target the solution will be. A soft Constraint has been set (9) that will indicate the difference of units, between the production scheduling proposal and the production capacity (if there is some) using the deviation variable d_1^-. It will also prevent the model to propose for scheduling more units than the production capacity. A second soft Constraint will be set (10) to control the distribution of Used Allocation between the markets and prevent the model to schedule units focusing on few markets. Lastly a third soft Constraint (11) will be set to prevent the model of neglecting the priority orders. For (9) and (10) there is no d_1^+ and $d_{2_j}^+$ because the final proposal must not exceed the production capacity and the given monthly allocation and therefore a positive deviation from the target is not acceptable at all.

3.2 Model Formulation

As a result, the overall goal of the Goal Programming model that follows will be the minimization of the deviational variables for each of the objectives.

$$minimize\ \ Z = O_1(d_1^-), O_2(d_{2_j}^-), O_3(d_{3_{ij}}^-, d_{3_{ij}}^+) \tag{2}$$

In equation (2) the goal is to minimize all **deviation variables** $(d_1^-, d_{2_j}^-, d_{3_{ij}}^-, d_{3_{ij}}^+)$ from all objectives (O_1, O_2, O_3). This formulation will provide assistance on splitting the Goal Programming model into 3 Linear programming models and solve sequentially starting from objective in equation (3) and finishing by solving the objective's equation (5). Below are presented the objective functions of each of the 3 Linear programming problems:

- Production Capacity fulfilment:

$$\text{minimize}\ \ O_1 = d_1^- \tag{3}$$

- Used Allocation flattening

$$\text{minimize}\ \ O_2 = \sum d_{2_j}^- \tag{4}$$

- Priority Units Scheduling

$$\text{minimize}\ \ O_3 = \sum d_{3_{ij}}^- + \sum d_{3_{ij}}^+ \tag{5}$$

Since the priority levels have been determined, are being used for indication of which objective should be solved as LPP first. Therefore, the first LPP will optimize the first objective which is the "Production Capacity Fulfilment". The objective function for optimization is summarized by equation (3), with the objective to minimize the negative deviation of scheduled units from the production capacity. A formulation of the LPM (Linear Programming Model) for O_1 including the hard and soft constraints that should be respected, can be presented by the following depiction:

$$\text{minimize}\ \ O_1 = d_1^-$$

s.t

$$x_{ij} + b_{ij} \le a_{ij} \qquad \forall\ i \in E, j \in M \tag{6}$$

$$x_{ij} \le o_{ij} \qquad \forall\ i \in E, j \in M \tag{7}$$

$$x_{ij} \ge 0 \qquad \forall i \in E, j \in M \tag{8}$$

$$\sum_{i=1}^{E}\sum_{j=1}^{M} x_{ij} + d_1^- = C \tag{9}$$

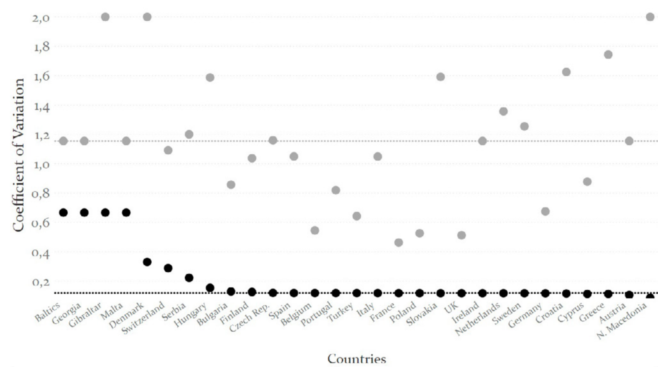

Fig. 1. The Coefficient of Variation per Market, of Used Allocation for the 4 weeks of November (GPM Version)

$$\sum_{i=1}^{E} x_{ij} + \sum_{i=1}^{E} b_{ij} + d_{2_j}^- = \sum_{i=1}^{E} a_{ij} \times n$$

$$\forall j \in M, 0 < n \le 1 \tag{10}$$

$$x_{ij} + d_{3_{ij}}^- - d_{3_{ij}}^+ = p_{ij} \qquad \forall\ i \in E, j \in M \tag{11}$$

$$d_1^-\ , d_{2_i}^-, d_{3_{ij}}^-\ , d_{3_{ij}}^+ \ge 0, \quad \forall i \in E, j \in M \tag{12}$$

The equation (9) will indicate the difference of units, between the production scheduling proposal and the production capacity (if there is some) using the deviation variable d_1^-. After solving the first LPP, then d_1^- receives a value that will be used for the next one objective function (4) and also the last objective function (5). The process is repeated for each of the objectives functions (4) and (5). More specifically, while the first LPP is being solved, equations (10) and (11) are not included in solving process. The output of the 1st LPP (the value of d_1^-) is then used for the solution of the 2nd LPP (where the equation (11) is not included) and then the output of the 1st and 2nd LPP (the values of deviation d_1^- and $d_{2_j}^-$) is used for the solution of the 3rd LPP. All objective functions need to respect the constraints that have been set ((6), (7), (8) and (12) and the values that have given to the deviation variables from the previous solved LPP (Konstantinos (2020)).

4. FINDINGS AND COMPARISON INDICATORS

The model is programmed in such a way as to try to reduce the variation of used allocation's distribution of the markets for a more "fair" production scheduling. To understand this, a comparison should be made between the coefficient of variation of the actual production scheduling and that of the simulation, per market.

In the Figure 1, it is depicted the stable scheduling the model has achieved. The CoV describes the deviation of Used Allocation each week from the current process in the case study (grey dots) compared to those that could been planned from the model proposed (black dots). All markets are located below 1 and most of them below 0.50. With these coefficient of variation values, the scheduling can be considered stable and to some markets even identical every week. Creating a uniform distribution for each of the markets every week, the model provides the characteristic of predictability to the production scheduling.

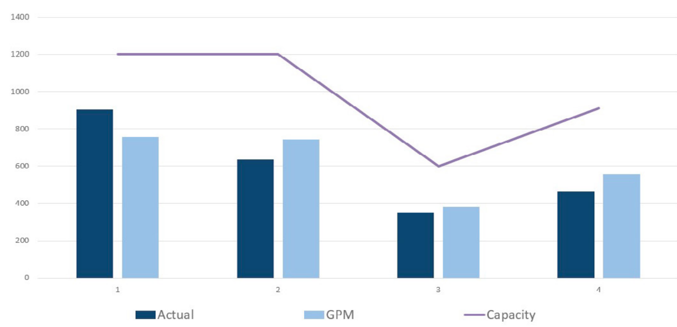

Fig. 2. Difference between Actual and Simulated Priority Units Scheduling

Therefore this scheduling can helps subsidiaries that operating in each market and collaborate with the main company to **predict** the production scheduling every week under normal circumstances. For a better understanding, the weekly variation of Used Allocation is presented below, in order to get a better picture, of the fair distribution of production that has been achieved.

	1st Week		2nd Week		3rd Week		4th Week	
	Act.	GPM	Act.	GPM	Act.	GPM	Act.	GPM
CoV	1.391	0.428	0.855	0.269	1.023	0.535	1.409	0.556

Table 2. A comparison using Coefficient of Variation, between Actual and GPM scheduling on weekly basis

The table above depicts the difference on the distribution of production using Used Allocation as indication. More specifically, the less coefficient of variation per week, the more similar are the Used Allocation values between the markets. That means, for example, that the model, scheduled similar percentage of market's allocation for production for all markets. In comparison with the actual production scheduling, this strategy can prove itself more reliable and eliminate or, at least, reduce the subsidiaries complaints for late and irregular scheduling.

As previously mentioned, priority orders also play an important role in the production scheduling. So the model was designed in this way to deepen as much as possible in this area. It is considered to be an element of reliability of the model to be able to also target these orders regardless of whether or not the final solution needs further modifications to fit the needs that have been unexpectedly raised. Therefore this goal in order to be achieved, the model should plan as many priority orders as possible every week. But since it is not possible to set a certain number of priority orders with which the model will satisfy with the providing solution, a comparison will follow the number of priority orders of the actual weekly schedulings and the simulated ones. The Figure 2 shows the performance of the model, in which it has been achieved the scheduling 84 more priority orders than the actual scheduling in November cumulatively. Moreover it managed to maintain a "fair" distribution between the markets and schedule more priority orders in three of the four weeks of November compared to the actual scheduling(Konstantinos (2020)).

5. CONCLUSION

As the findings prove, the model is capable of satisfying in two different areas. Initially the model is able to correct the aforementioned symptom of high deviation in used allocation between the countries. Lastly an additional attempt was made to further optimize the model by scheduling more priority units for production every week. To sum up, a mathematical model that is properly customized in a specific production scheduling is able to provide higher effectiveness into the process and lead to increased customer satisfaction and profitability. This kind of solutions are able to provide efficiency and responsiveness to automotive industry.

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