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IMPACT OF DYNAMIC HUMAN AND TECHNOLOGICAL RESOURCE COST ON LOT SIZE OPTIMIZATION

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Abstract. The design methods of production systems have evolved significantly in recent decades. New methods have emerged that are capable of determining the optimal parameters of production systems operating in increasingly complex environments. The two best known methods for lot sizing problems are the Wagner-Whitin algorithm and the Silver-Meal heuristics. The original versions of these two methods are only suitable for solving simple lot sizing problems, but there are several complex mutations of these methods that allow solving complex lot sizing problems. In the present research, the author presents a modified Wagner-Whitin algorithm that is suitable for solving the lot sizing problem and also for investigating the impact of dynamically changing resource costs. The proposed method is validated through case studies. The case studies demonstrate that the dynamic nature of cost of human resources and technological resources has a significant impact on the solution of lot sizing problems. **Keywords:** lot sizing; production planning and scheduling; cost minimization; modelling.

1. INTRODUCTION

Companies are making ever greater efforts to meet customer demand, but they also need to reduce costs while increasing efficiency. Cost reduction involves both resource optimisation and process improvement. Since resource availability is a dynamic phenomenon, resource costs are often a dynamic parameter to be considered when solving production planning problems. In the present research work, the author proposes an improvement of the Wagner-Whitin algorithm (WWA) in order to take into account the dynamically varying cost of resources when solving the lot sizing problem. In the second chapter of the article, a short literature review shows the importance of lot sizing problems, and highlights the importance of WWA-based solutions. In the third chapter a novel WWA-based approach is described, which makes it possible to analyse the impact of dynamic changing costs of human resources and technological resources. In chapter four a case study shows the efficiency of the developed algorithm, while in the last chapter the results are summarized and the potential future research directions are discussed.

2. LITERATURE REVIEW

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Kumar et al. [1] analysed various lot sizing strategies including lot for lot, Wagner-Whitin algorithm and Silver-Meal heuristics. Their analysis showed, that these algorithms are suitable to solve dynamic lot sizing problems also in the case when demand surpasses a predicted value. This research validated, that WWA and SMH are suitable for lot sizing problems in uncertain operation environment. Asmal et al. [2] applied WWA and SMH to solve inventory problems when inventories are influenced by dynamic safety stock and lead time due to uncertain logistics. Zhang et al. [3] developed a new extended mixed-integer programming formulation, which makes it possible to take Wagner-Whitin conditions into consideration in order to solve the static joint chance-constrained lot-sizing problem. Kuznetsov and Demidenko [4] focuses on their work on the organization of material resources supply in transport construction, and they showed, that WWA can be used for the problem solution of probabilistic nature of the construction logistics systems. Narkhede and Rajhans described in a research [5] on redesign inventory management strategies, that WWA can be integrated with other lot sizing methodologies. The proposed an integrated Wagner-Whitin & Rank Order Clustering approach (WW&ROC), which could lead to savings in amount of total cost compared to existing purchase strategies and stock-out situations can be also improved. A lot sizing model for two items with imperfect manufacturing process, time varying demand and return rates was proposed by van Zyl and Adetunji [6]. Their research focuses on constrained returns and the potential of secondary use of returns. A modified WWA was supposed to solve the lot sizing problems. Assi and Effanga [7] showed in a research focusing on human resource aspects including recruitment and promotion policies, that a WWA like dynamic programming algorithm can also solve human resource optimization problems. Oca Sánchez et al. [8] discusses in a research work the raw material problems of automotive industry, and showed, that the efficiency of WWA can be improved by the integration of forecast methodologies. Kian et al. [9] described a novel optimization approach for problems with demands exhibiting stationary, increasing and decreasing trends and seasonality. Their proposed solution is a combination and variation of the well known WWA, SMH and least Unit Cost (LUC) approaches. Production planning and facility location can be also integrated as shown by Wu et al. [10] in a research describing the relationship between pricing problems and uncapacitated lot-sizing problems with Wagner-Whitin property. The importance of forecasting and their impact on production planning and scheduling is highlighted in a research by Olesen et al. [11]. Their showed a method to support cost savings by managerial decisions. Gaol and Matsuo [12] focuses on the impact of state-of-the-art technologies on the solution of lot sizing problems. They showed the importance of sensor technologies by simulation supported analysis. Uncertainties are also modelled by Hanafizadeh et al. [13] in a research focusing on the application of WWA. In their research robustness was in the focus. Güner and Tunali [14] showed a novel approach of capacitated lot-sizing problems, which is a special extension of Wagner-Whitin

problems. Other important topics in the field of lot sizing problems were also intensively researched including improvement of existing solution methodologies [15] and they are also focusing on supply chain disruption problems [16], which can also significantly improve the complexity of dynamic lot sizing problems in production processes. This short literature review showed the importance and complexity of lot sizing problems. Following this brief literature review, the paper presents a novel methodology, which takes into consideration of the dynamic resource cost, including human resources and technological resources.

3. MATERIALS AND METHODS

Within the frame of this chapter, a novel, Wagner-Whitin algorithm-based approach will be described, which integrates the dynamic costs of human resources (operators for logistics and technological resources) and technological resources (machine tools). The novelty of the methodology is, that conventional Wagner-Whitin algorithm focuses on the initialization cost of production, on the production cost depending on the quantity and the warehousing cost (inventory), while this approach makes it possible to analyse the impact of time dependent costs of human and technological resources.

The input parameters of the model are the followings:

- C_{IP} : initialization cost of production per time frame,
- C_P : specific production cost,
- C_W : specific warehousing cost,
- L_{OP} : lot size assigned to operators (the operators are assigned to lot size L_{OP} and their specific, time dependent specific cost is defined for this L_{OP} lot size),
- L_{TR} : lot size assigned to technological resources (machine tools, assembly stations), the machines are assigned to lot size L_{TR} and their specific, time dependent specific cost is defined for this L_{TR} lot size),
- D_i : demand in time frame i,
- C_i^{OP} . operator cost per operator related lot in time frame *i*,
- C_i^{TR} : technological resource cost per production lot in time frame *i*,
- i_{max} : the total number of time frames.

The algorithm includes i_{max} computational phases. The first phase computes the local optimal production scheduling for the last time frame. The second phase computes the local optimal production schedule for the second last time frames, etc.

As a first step, we can calculate the local optimal production schedule for the last day as follows:

$$C_{imax} = C_{imax}^{imax} = C_{IP} + D_{imax}C_P + \left[\frac{D_{imax}}{L_{OP}}\right]C_{imax}^{OP} + \left[\frac{D_{imax}}{L_{TR}}\right]C_{imax}^{TR}$$
(1)

In the second phase, for the predecessor time frame, the local optimal production schedule can be defined as follows:

$$C_{imax-1} = \min\left(C_{imax-1}^{imax-1}, C_{imax-1}^{imax-1-imax}\right)$$
(2)

$$C_{imax-1}^{imax-1} = C_{IP} + D_{imax-1}C_P + \left[\frac{D_{imax-1}}{L_{OP}}\right]C_{imax-1}^{OP} + \left[\frac{D_{imax-1}}{L_{TR}}\right]C_{imax-1}^{TR} + C_{imax} \quad (3)$$

$$C_{imax-1-imax}^{imax-1-imax} - C_{in} + \sum_{imax}^{imax} D_{in}(C_{in} + (i - imax + 1)C_{in}) + C_{imax}^{imax-1-imax} + C_{imax}^{imax-1-imax}$$

$$C_{imax-1} = C_{IP} + \sum_{i=imax-1}^{i=imax-1} D_i (C_P + (i - imax + 1)C_W) + \left[\frac{\sum_{i=imax-1}^{imax} D_i}{L_{OP}}\right] C_{imax-1}^{OP} + \left[\frac{\sum_{i=imax-1}^{imax-1} D_i}{L_{TR}}\right] C_{imax-1}^{TR}$$
(4)

Eq (2) defines, that in this phase of the algorithm we can choose beteen to potential solutions:

- C_{imax-1}^{imax-1} defines a solution, where within the time frame imax 1 only the demand of time frame imax 1 is produced,
- $C_{imax-1}^{imax-1-imax}$ defines a solution, where within the time frame imax 1 the demands for both time frame imax 1 and time frame imax are produced. We can define a general computational phase for time frame *j* as follows:

$$C_{j} = min\left(C_{j}^{j}, C_{j}^{j-(j+1)}, C_{j}^{j-(j+2)}, ..., C_{j}^{j-imax}\right)$$

$$C_{j}^{j} = C_{j} + D_{j}C_{j} + \left[\frac{D_{j}}{2}\right]C^{OP} + \left[\frac{D_{j}}{2}\right]C^{TR} + C_{j}$$
(5)

$$C_{j}^{J} = C_{IP} + D_{j}C_{P} + \left|\frac{-j}{L_{OP}}\right|C_{j}^{OP} + \left|\frac{-j}{L_{TR}}\right|C_{j}^{TR} + C_{j+1}$$
(6)

$$C_{j}^{j-(j+1)} = C_{IP} + \sum_{i=j}^{j+1} D_{i}(C_{P} + (i-j)C_{W}) + \left| \frac{\sum_{i=j}^{j+1} D_{i}}{L_{OP}} \right| C_{j}^{OP} + \left| \frac{\sum_{i=j}^{j+1} D_{i}}{L_{TR}} \right| C_{j}^{TR} + C_{j+2}$$
(7)

$$C_{j}^{j-(j+2)} = C_{IP} + \sum_{i=j}^{j+2} D_{i}(C_{P} + (i-j)C_{W}) + \left|\frac{\sum_{i=j}^{j+2} D_{i}}{L_{OP}}\right| C_{j}^{OP} + \left|\frac{\sum_{i=j}^{j+2} D_{i}}{L_{TR}}\right| C_{j}^{TR} + C_{j+3}$$
(8)

$$C_{j}^{j-imax} = C_{IP} + \sum_{i=j}^{imax} D_{i}(C_{P} + (i-j)C_{W}) + \left|\frac{\sum_{i=j}^{imax} D_{i}}{L_{OP}}\right| C_{j}^{OP} + \left|\frac{\sum_{i=j}^{imax} D_{i}}{L_{TR}}\right| C_{j}^{TR}$$
(9)

Figure 1 demonstrates the flowchart of the production schedule optimization. As the flowchart shows, the local optimal solutions for each time frame can be calculated analytical, it means no heuristics or metaheuristics are required to find the optimal solution.



Figure 1 – Layout of the production plant

Within the frame of the next chapter, some numerical examples will validate the above-mentioned approach and show the suitability of the describe methodology to find the optimal production schedule and analyse the impact of dynamic human and technological resource costs.

4. RESULTS

Within the frame of this section, the main results of some numerical studies are summarized. The first scenario analysis focuses on the comparison of conventional lot sizing and the dynamic lot sizing taking the cost of human resources (machine operators) and technological resources (machine tools) into consideration. In the first case study, the results of traditional scheduling and dynamic scheduling are compared over a seven-day time horizon. The time-dependent parameters of the first case study are summarised in Table 1.

	Table 1 – Examples for the identification of production line							
Time frames	T1	T2	T3	T4	T5	T6	T7	
Demand to be produced	100	105	95	110	94	111	89	
Operator cost per operator related lot	7.8	8.2	8.9	7.8	9.7	9.1	8.2	
Technological resource cost per production lot	10.2	11.4	12.3	11.1	10.5	10.6	13.4	

Table 1 – Examples for the identification of production lines

The initialization cost of production per time frame is $C_{IP} = 500 \notin$, the specific production cost is $C_P = 3 \notin/pcs$ and the specific warehousing cost is $C_W = 2 \notin/time \ frame$. The lot size assigned to operators is $L_{OP} = 50 \ pcs$ and the lot size assigned to technological resources is $L_{TR} = 75 \ pcs$.

As the first phase of the optimization, we can compute the total cost for the last time frame as follows:

$$C_{7} = C_{7}^{7} = C_{IP} + D_{7}C_{P} + \left[\frac{D_{7}}{L_{OP}}\right]C_{7}^{OP} + \left[\frac{D_{7}}{L_{TR}}\right]C_{7}^{TR} = 1166.2 \in (10)$$

The second phase of the optimization is to calculate the total cost of the predecessor time frame based on the following equations:

$$C_6 = \min\left(C_6^6, C_6^{6-7}\right) \tag{11}$$

$$C_6^6 = C_{IP} + D_6 C_P + \left[\frac{D_6}{L_{OP}}\right] C_6^{OP} + \left[\frac{D_6}{L_{TR}}\right] C_6^{TR} + C_7$$
(12)

$$C_6^{6-7} = C_{IP} + \sum_{i=6}^{7} D_i (C_P + (i-6)C_W) + \left[\frac{\sum_{i=6}^{7} D_i}{L_{OP}}\right] C_6^{OP} + \left[\frac{\sum_{i=6}^{7} D_i}{L_{TR}}\right] C_6^{TR}$$
(13)

$$C_6 = \min \begin{cases} C_6^6 = 2491.7 \\ C_6^{6-7} = 2146.2 \\ C_6^{6-7} = 2146.2 \\ \epsilon \end{cases}$$
(14)

The third phase of the optimization is to calculate the total cost of time frame 5 based on the following equations:

$$C_5 = \min\left(C_5^5, C_5^{5-6}, C_5^{5-7}\right) \tag{15}$$

$$C_{5}^{5} = C_{IP} + D_{5}C_{P} + \left[\frac{D_{5}}{L_{OP}}\right]C_{5}^{OP} + \left[\frac{D_{5}}{L_{TR}}\right]C_{5}^{TR} + C_{6}$$
(16)

$$C_5^{5-6} = C_{IP} + \sum_{i=5}^{6} D_i (C_P + (i-5)C_W) + \left[\frac{\sum_{i=5}^{6} D_i}{L_{OP}}\right] C_5^{OP} + \left[\frac{\sum_{i=5}^{6} D_i}{L_{TR}}\right] C_5^{TR} + C_7 \quad (17)$$

$$C_5^{5-7} = C_{IP} + \sum_{i=5}^{7} D_i (C_P + (i-5)C_W) + \left[\frac{\sum_{i=5}^{7} D_i}{L_{OP}}\right] C_5^{OP} + \left[\frac{\sum_{i=5}^{7} D_i}{L_{TR}}\right] C_5^{TR}$$
(18)

$$C_5 = \min \begin{cases} C_5^5 - 3344.5 \ \ C_5^{5-6} = 3403.2 \ \ \in \ 3236.2 \ \ \in \ (19) \\ C_5^{5-7} = 3236.2 \ \ \in \ \end{cases}$$

The fourth phase of the optimization is to calculate the total cost of time frame 4 based on the following equations:

$$C_4 = \min\left(C_4^4, C_4^{4-5}, C_4^{4-6}, C_4^{4-7}\right) \tag{20}$$

$$C_{4}^{4} = C_{IP} + D_{4}C_{P} + \left[\frac{D_{4}}{L_{OP}}\right]C_{4}^{OP} + \left[\frac{D_{4}}{L_{TR}}\right]C_{4}^{TR} + C_{5}$$
(21)

$$C_4^{4-5} = C_{IP} + \sum_{i=4}^5 D_i (C_P + (i-4)C_W) + \left[\frac{\sum_{i=4}^5 D_i}{L_{OP}}\right] C_4^{OP} + \left[\frac{\sum_{i=4}^5 D_i}{L_{TR}}\right] C_4^{TR} + C_6 \quad (22)$$

$$C_{4}^{4-6} = C_{IP} + \sum_{i=4}^{6} D_i (C_P + (i-4)C_W) + \left[\frac{\sum_{i=4}^{6} D_i}{L_{OP}}\right] C_{4}^{OP} + \left[\frac{\sum_{i=4}^{6} D_i}{L_{TR}}\right] C_{4}^{TR} + C_7 \quad (23)$$

$$C_{4}^{4-7} = C_{IP} + \sum_{i=4}^{7} D_{i}(C_{P} + (i-4)C_{W}) + \left|\frac{\sum_{i=4}^{2} D_{i}}{L_{OP}}\right| C_{4}^{OP} + \left|\frac{\sum_{i=4}^{2} D_{i}}{L_{TR}}\right| C_{4}^{TR}$$
(24)
$$\left(C_{4}^{4} = 4551.8 \notin\right)$$

$$C_4 = \min \begin{cases} C_4^{4-5} = 4334.5 \notin \\ C_4^{4-6} = 4613.3 \notin \\ C_4^{4-7} = 4630.8 \notin \end{cases}$$
(25)

The fifth phase of the optimization is to calculate the total cost of time frame 3 based on the following equations:

$$C_3 = \min\left(C_3^3, C_3^{3-4}, C_3^{3-5}, C_3^{3-6}, C_3^{3-7}\right)$$
(26)

$$C_3^3 = C_{IP} + D_3 C_P + \left[\frac{D_3}{L_{OP}}\right] C_3^{OP} + \left[\frac{D_3}{L_{TR}}\right] C_3^{TR} + C_4$$
(27)

$$C_{3}^{3-4} = C_{IP} + \sum_{i=3}^{4} D_{i}(C_{P} + (i-3)C_{W}) + \left[\frac{\sum_{i=3}^{4} D_{i}}{L_{OP}}\right]C_{3}^{OP} + \left[\frac{\sum_{i=3}^{4} D_{i}}{L_{TR}}\right]C_{3}^{TR} + C_{5}$$
(28)

$$C_{3}^{3-5} = C_{IP} + \sum_{i=3}^{5} D_{i}(C_{P} + (i-3)C_{W}) + \left| \frac{\sum_{i=3}^{5} D_{i}}{L_{OP}} \right| C_{3}^{OP} + \left| \frac{\sum_{i=3}^{5} D_{i}}{L_{TR}} \right| C_{3}^{TR} + C_{6}$$
(29)

$$C_{3}^{3-6} = C_{IP} + \sum_{i=3}^{6} D_{i}(C_{P} + (i-3)C_{W}) + \left|\frac{\sum_{i=3}^{6} D_{i}}{L_{OP}}\right| C_{3}^{OP} + \left|\frac{\sum_{i=3}^{6} D_{i}}{L_{TR}}\right| C_{3}^{TR} + C_{7} \quad (30)$$

$$C_{3}^{3-7} = C_{IP} + \sum_{i=3}^{7} D_{i}(C_{P} + (i-3)C_{W}) + \left|\frac{\sum_{i=3}^{2} D_{i}}{L_{OP}}\right| C_{3}^{OP} + \left|\frac{\sum_{i=3}^{2} D_{i}}{L_{TR}}\right| C_{3}^{TR}$$
(31)
$$(C_{3}^{3} = 5541.9 \notin$$

$$C_{3} = \min \begin{cases} C_{3}^{3-4} = 5472.6 \in \\ C_{3}^{3-5} = 5437.8 \in 5437.8 \in \\ C_{3}^{3-6} = 5952.1 \in \\ C_{3}^{3-7} = 6142.1 \in \\ \end{array}$$
(32)

The sixth phase of the optimization is to calculate the total cost of time frame 2 based on the following equations:

$$C_2 = \min\left(C_2^2, C_2^{2-3}, C_2^{2-4}, C_2^{2-5}, C_2^{2-6}, C_2^{2-7}\right)$$
(33)

$$C_2^2 = C_{IP} + D_2 C_P + \left[\frac{D_2}{L_{OP}}\right] C_2^{OP} + \left[\frac{D_2}{L_{TR}}\right] C_2^{TR} + C_3$$
(34)

$$C_2^{2-3} = C_{IP} + \sum_{i=2}^{3} D_i (C_P + (i-2)C_W) + \left[\frac{\sum_{i=2}^{3} D_i}{L_{OP}}\right] C_2^{OP} + \left[\frac{\sum_{i=2}^{3} D_i}{L_{TR}}\right] C_2^{TR} + C_4 \quad (35)$$

$$C_{2}^{2-4} = C_{IP} + \sum_{i=2}^{4} D_i (C_P + (i-2)C_W) + \frac{\sum_{i=2}^{2} D_i}{L_{OP}} \left[C_{2}^{OP} + \left[\frac{\sum_{i=2}^{2} D_i}{L_{TR}} \right] C_{2}^{IR} + C_5 \right]$$
(36)

$$C_{2}^{2-6} = C_{IP} + \sum_{i=2}^{5} D_{i}(C_{P} + (i-2)C_{W}) + \left| \frac{D_{i=2}}{L_{OP}} \right| C_{2}^{OP} + \left| \frac{D_{i=2}}{L_{TR}} \right| C_{2}^{iR} + C_{6} \quad (37)$$

$$C_{2}^{2-6} = C_{e} + \sum_{i=2}^{6} D_{i}(C_{e} + (i-2)C_{e}) + \left| \sum_{i=2}^{6} D_{i} \right| C_{2}^{OP} + \left| \sum_{i=2}^{6} D_{i} \right| C_{2}^{TR} + C_{6} \quad (37)$$

$$C_{2}^{2-7} = C_{IP} + \sum_{i=2}^{7} D_{i}(C_{P} + (i-2)C_{W}) + \left| \frac{\sum_{i=2}^{7} D_{i}}{L_{OP}} \right| C_{2}^{OP} + \left| \frac{\sum_{i=2}^{7} D_{i}}{L_{TR}} \right| C_{2}^{TR}$$
(39)

$$C_{2} = \min \begin{cases} C_{2}^{2} = 6720.2 \in C_{2}^{2-3} = 6491.5 \in C_{2}^{2-3} = 6491.5 \in C_{2}^{2-4} = 6650.6 \in C_{2}^{2-5} = 6810.4 \in C_{2}^{2-5} = 6810.4 \in C_{2}^{2-6} = 7523.2 \in C_{2}^{2-7} = 7909.2 \in C_{2}^{2-7} = 7909.2 \notin C_{2}^{2-7} = 7909.2 \# C_{2}^{2-7} = 7900.2 \# C_{2}^{2-7} = 7000.2 \# C_{2}^{2-7$$

The last phase of the optimization is to calculate the total cost of the first time frame based on the following equations:

$$C_{1} = \min\left(C_{1}^{1}, C_{1}^{1-2}, C_{1}^{1-3}, C_{1}^{1-4}, C_{1}^{1-5}, C_{1}^{1-6}, C_{1}^{1-7}\right)$$
(41)

$$C_{1}^{1} = C_{IP} + D_{1}C_{P} + \left|\frac{D_{1}}{L_{OP}}\right| C_{1}^{OP} + \left|\frac{D_{1}}{L_{PR}}\right| C_{1}^{TR} + C_{1}$$
(42)

$$C_{1}^{1-2} = C_{IP} + \sum_{i=1}^{2} D_{i}(C_{P} + (i-1)C_{W}) + \left[\frac{\sum_{i=1}^{2} D_{i}}{L_{OP}}\right]C_{1}^{OP} + \left[\frac{\sum_{i=1}^{2} D_{i}}{L_{TR}}\right]C_{1}^{TR} + C_{3} \quad (43)$$

$$C_{1}^{1-3} = C_{IP} + \sum_{i=1}^{3} D_{i}(C_{P} + (i-1)C_{W}) + \left| \frac{\sum_{i=1}^{r} D_{i}}{L_{OP}} \right| C_{1}^{OP} + \left| \frac{\sum_{i=1}^{r} D_{i}}{L_{TR}} \right| C_{1}^{TR} + C_{4} \quad (44)$$

$$C_{1}^{1-4} = C_{P} + \sum_{i=1}^{4} D_{i}(C_{P} + (i-1)C_{P}) + \left| \frac{\sum_{i=1}^{r} D_{i}}{L_{OP}} \right| C_{1}^{OP} + \left| \frac{\sum_{i=1}^{4} D_{i}}{L_{TR}} \right| C_{1}^{TR} + C_{4} \quad (45)$$

$$C_{1}^{1-5} = C_{IP} + \sum_{i=1}^{5} D_{i}(C_{P} + (i-1)C_{W}) + \left[\frac{\sum_{i=1}^{5} D_{i}}{L_{OP}}\right]C_{1}^{OP} + \left[\frac{\sum_{i=1}^{5} D_{i}}{L_{TR}}\right]C_{1}^{TR} + C_{6} \quad (46)$$

$$C_{1}^{1-6} = C_{IP} + \sum_{i=1}^{6} D_{i}(C_{P} + (i-1)C_{W}) + \left[\frac{\sum_{i=1}^{6} D_{i}}{L_{OP}}\right]C_{1}^{OP} + \left[\frac{\sum_{i=1}^{6} D_{i}}{L_{TR}}\right]C_{1}^{TR} + C_{7} \quad (47)$$

$$C_{1}^{1-7} = C_{IP} + \sum_{i=1}^{7} D_{i}(C_{P} + (i-1)C_{W}) + \left|\frac{\Sigma_{i=1}D_{i}}{L_{OP}}\right| C_{1}^{OP} + \left|\frac{\Sigma_{i=1}D_{i}}{L_{TR}}\right| C_{1}^{TR}$$
(48)
$$(C_{1}^{1} = 77275 \notin$$

$$C_{1} = \min \begin{cases} C_{1}^{1-2} = 7652.4 \in \\ C_{1}^{1-2} = 7652.4 \in \\ C_{1}^{1-3} = 7612.1 \in \\ C_{1}^{1-4} = 7987.6 \in = 7612.1 \in \\ C_{1}^{1-5} = 8333.4 \in \\ C_{1}^{1-6} = 9276.4 \in \\ C_{1}^{1-7} = 9827.0 \in \end{cases}$$
(49)

The above described computation resulted, that within the first time frame the demands of three weeks must be produced, because $C_1 = C_1^{1-3}$. The $C_1 = C_1^{1-3}$ equation resulted that the next production operation must be performed on the fourth time frame, where $C_4 = C_4^{4-5}$, which means, that within the fourth time frame the demands from two weeks must be produced. The $C_4 = C_4^{4-5}$ equation resulted that the next production must be performed on the sixth time frame, where

 $C_6 = C_6^{6-7}$, which means, that within the sixth time frame the demands from two weeks must be produced.

Figure 2 shows the process of computations and the detailed results of each potential lot-size and scheduling. However, the computation goes backwards, from the last time frame to the first time frame, but after finishing all computations, the optimal lot sizing and scheduling of production can be defined forwards, from the first time frame until the last time frame, as Figure 2 shows.

	Production of demand until time frame									
	1	2	3	4	5	6	7			
Time frame 1	7727.5	7652.4	7612.1	7987.6	8333.4	9276.4	9827			
Time frame 2		6720.2	6491.5	6650.6	6810.4	7523.2	7909.2			
Time frame 3			5541.9	5472.6	5437.8	5952.1	6142.1			
Time frame 4				4551.8	4334.5	4613.3	4630.8			
Time frame 5					3344.6	3403.2	3236.2			
Time frame 6						2491.7	2146.2			
Time frame 7							1166.2			

Figure 2 - The optimization process and the detailed results of different lot size solutions

Figure 3 demonstrates the cost distribution function including the initialization cost of production, the total production cost, the warehousing cost, the cost of operators and the cost of technological resources.



Figure 3 – The cost distribution of the optimal lot sizing

To validate the above mentioned approach, the next phase is to compare the solution of this extended dynamic lot size optimization and the conventional solution of the production scheduling.

The total cost of the conventional solution can be calculated as follows:

$$C_{CONV} = \sum_{i=1}^{7} (D_i C_P + C_{IP} + \left| \frac{D_i}{L_{OP}} \right| C_i^{OP} + \left| \frac{D_i}{L_{TR}} \right| C_i^{TR}) = 8731.5$$
 (50)

Figure 4 demonstrates the cost distribution function of the conventional scheduling. As Figure 4 demonstrates, the conventional production scheduling has a

significant higher production initialization cost, because production is initialized in all time frames. The warehousing cost in the case of conventional production scheduling is zero, which means, that in this case we are talking about just-in-time production. The cost of just-in-time production are too high, because the zero inventory costs $1119.4 \in$.



Figure 4 - The cost distribution of the conventional production scheduling

Figure 5 shows the comparison of the total costs of each time frames. In the case of conventional production scheduling, the distribution of the total costs is much more uniform than in the case of optimized production scheduling.



Figure 5 - Cost comparison of conventional and optimized production scheduling

As demonstrated in the case study presented above, the calculation and analysis of dynamic batch sizes is a good way to optimize production processes, as it can lead to significant efficiency gains. The results presented above show that while just-intime production can be beneficial in terms of storage costs, it is important to consider the cost of achieving these warehousing cost savings. The analysis of the scenario shows, that the dynamic cost of human resources and technological resources can also significantly influence the optimal schedule, because depending on the fluctuation of specific operator costs and technological resource cost, different schedules can lead to the more cost efficient production schedule.

5. SUMMARY

The efficiency of production processes can be affected by many factors. In order to increase the efficiency of production processes, it is becoming increasingly important to take into account a growing number of parameters. Although the Wagner-Whitin algorithm is an excellent method for determining dynamic batch sizes, there are a number of environmental parameters that cannot be taken into account by current algorithms. In the present research work, a method based on the Wagner-Whitin algorithm is presented which allows to take into account dynamically varying resource costs focusing on both human and technological resources. The applicability of the developed method was demonstrated by means of calculations. The method has been demonstrated through a case study that, compared to conventional production scheduling. The application of the method can lead to significant cost reductions when taking into account the impact of dynamic changes in resource costs. The study confirmed the fact that, although just-in-time production can be very beneficial from an inventory point of view, as just-in-time production can lead to significant inventory cost reductions, these inventory cost reductions can lead to multiple increases for other cost components, and it is therefore important to consider as many environmental parameters as possible in the calculations. In the present research work, the model was tested using deterministic parameters, so a potential future research task could be to develop a stochastic approach.

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ВПЛИВ ДИНАМІЧНИХ ВИТРАТ НА ЛЮДСЬКІ ТА ТЕХНОЛОГІЧНІ РЕСУРСИ ПРИ ОПТИМІЗАЦІЇ РОЗМІРУ ПАРТІЇ ТОВАРІВ

Анотація. Методи проектування виробничих систем за останні десятиліття значно еволюціонували. З'явилися нові методи, здатні визначати оптимальні параметри виробничих систем, що функціонують у все більш складних середовищах. Двома найбільш відомими методами для задач на розмір лотів (партій) є алгоритм Вагнера-Вітіна та евристика Сільвера-Міла. Оригінальні версії цих двох методів підходять тільки для вирішення простих задач на розмір лота, але існує кілька складних мутацій цих методів, які дозволяють вирішувати складні задачі розміру партії. На ефективність виробничих процесів може впливати безліч факторів. Для того щоб підвищити ефективність виробничих процесів, все більш важливим стає облік зростаючого числа параметрів. Хоча алгоритм Вагнера-Вітіна є відмінним методом для визначення динамічних розмірів партії, існує ряд параметрів середовища, які не можуть бути враховані сучасними алгоритмами. У даній дослідницькій роботі представлений метод, заснований на алгоритмі Вагнера-Вітіна, який дозволяє враховувати динамічно мінливі ресурсні витрати, орієнтуючись як на людські, так і на технологічні ресурси. За допомогою розрахунків продемонстровано застосовність розробленого методу, який був продемонстрований на конкретному прикладі у порівнянні зі звичайним виробничим плануванням. Застосування методу може призвести до значного зниження витрат при врахуванні впливу динамічних змін витрат на ресурси. Дослідження підтвердило той факт, що, хоча виробництво точно в строк може бути дуже вигідним з точки зору запасів, оскільки виробництво точно в строк може призвести до значного зниження витрат на запаси, яке в свою чергу може призвести до багаторазового збільшення інших компонентів витрат, і тому важливо враховувати якомога більше параметрів навколишнього середовища в розрахунках. У даній дослідницькій роботі модель була перевірена з використанням детермінованих параметрів, тому потенційним майбутнім дослідницьким завданням може бути розробка стохастичного підходу.

Ключові слова: розмір партії; планування та складання графіків виробництва; мінімізація витрат; моделювання.