

MODELS FOR ESTIMATING PRODUCTION PHASE DURATION AS A FOUNDATION FOR EFFICIENT PRODUCTION MANAGEMENT

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ABSTRACT

In modern manufacturing systems, accurately defining and managing the duration of individual production phases is crucial for achieving high efficiency and reliable delivery timelines. This paper presents two methodologically grounded models for estimating the duration of the production phase: one based on the technological (ideal) cycle, and the other on the projected (realistic) cycle that incorporates organizational and logistical constraints. A case study is provided involving the packaging of a 20 mm round into a crate, part of the production program of the 'Sloboda' Co. - Cacak, Serbia.

By analyzing the flow coefficient, defined as the ratio between the actual and ideal/projected cycle durations, potential inefficiencies within the production process can be identified. The results suggest that predefining projected durations for each production phase significantly improves planning accuracy and coordination across the production flow. The proposed models serve as a practical decision-support tool within production management systems.

Keywords: production management, production phase, production cycle, flow coefficient.

INTRODUCTION AND PREVIOUS RESEARCH

In today's dynamic manufacturing environments, the ability to accurately plan, schedule, and control production processes is a critical determinant of operational efficiency and market competitiveness. The duration of each production phase plays a central role in determining delivery accuracy, resource utilization, and the overall responsiveness of the production system.

Theoretical and practical studies have increasingly focused on the application of diverse methods and techniques to reduce the duration of the production cycle. The complexity of production processes and the need for efficiency improvements have led to the development of various models, performance measures, and analytical approaches.

Aouam and Uzsoy (Aouam & Uzsoy, 2014) proposed zero-order production planning models that incorporate stochastic demand and workload-dependent lead times, providing a valuable framework for understanding uncertainties in production environments. Similarly, Huang and Yao (Huang & Yao, 2013) investigated optimal lot-sizing and scheduling in serial-type supply chains using time-varying policies, highlighting the role of planning dynamics in cycle time management.

Jovanović, Milanović, and Djukić (Jovanović et al., 2014) introduced two flow coefficients, the ratio of actual to planned cycle time and the ratio of actual to technological (ideal) cycle time—as indicators of production efficiency. Their work emphasized the importance of quantifying these relationships to identify inefficiencies and guide scheduling improvements.

Macchi (Macchi, 2008) examined performance trade-offs between flow time and throughput in complex manufacturing systems. His research provided context for evaluating flow coefficients within broader production performance strategies.

Material Flow Cost Accounting (MFCA) has also emerged as a significant tool for identifying and analyzing inefficiencies in production systems. Dierkes and Siepelmeyer (Dierkes & Siepelmeyer, 2025) developed an MFCA model that incorporates multiple inefficiency factors such as waste, rework, and recycling, enabling detailed cost assessments related to material losses.

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Takakuwa, Zhao, and Ichimura (Takakuwa et al., 2014) applied simulation techniques within the MFCA framework to analyze material flows and improve both environmental and economic performance.

Research has also explored more specialized aspects of cycle time estimation and material flow. Chincholkar and Herrmann (Chincholkar & Herrmann, 2008) modeled manufacturing cycle time and throughput in flow shops affected by process drift and inspections, using queuing network approximations. Dong et al. (Dong et al., 2016) investigated material flow in aluminum extrusion, emphasizing die modifications to improve flow uniformity in complex profiles.

Efficient material handling is another key concern. Ellis et al. (Ellis et al., 2010) proposed a multi-commodity network flow model for optimizing assembly facility operations, stressing the role of layout and flow path design in reducing handling costs. In a similar vein, Gould and Colwill (Gould & Colwill, 2015) developed a framework for assessing material flow in manufacturing systems, aiming to detect inefficiencies and propose targeted improvements.

Stanisavljev, Zakin, and Istrat (Stanisavljev et al., 2014) argued that production cycle time in real-world scenarios is stochastic rather than deterministic. Their study, based on data from Serbian manufacturing enterprises, supports the use of a multi-dimensional model of production scheduling and monitoring rooted in modern organizational theory. This model emphasizes interconnectivity between production elements and the benefits of integrated planning.

On a more systemic level, Müller et al. (Müller et al., 2014) reviewed dynamic material flow analysis (MFA) methods used to model metal stocks and flows. Their work categorizes modeling approaches according to the ODD protocol (Overview, Design concepts, Details), accounting for dispersion, spatial flow dimensions, and uncertainty management. This review serves as a foundation for understanding long-term material usage trends and sustainability implications.

Sendra, Gabarrell, and Vicent (Sendra et al., 2007) adapted MFA methodology to industrial areas, particularly in Catalonia, Spain. Their research integrated material, water, and energy flows to assess resource efficiency and identify opportunities for waste reduction. By demonstrating the effectiveness of MFA indicators even with limited data, the study underscored the value of localized and tailored approaches to improving industrial sustainability.

Together, these studies form a comprehensive body of knowledge that spans from theoretical modeling of production cycles and flow dynamics to applied frameworks like MFCA and MFA. This literature highlights the importance of accurate cycle time estimation, efficiency measurement through flow coefficients, and the continuous monitoring and improvement of material flows across diverse industrial contexts.

In Table 1, the reviewed studies are organized into thematic groups, with a concise summary of the research focus for each study.

This paper addresses the need for precise estimation models of production phase duration by introducing two complementary approaches: one that reflects the ideal technological cycle, and another that incorporates realistic conditions through a projected cycle model.

The aim is to demonstrate how these models can serve as analytical tools to support effective production planning and management, with particular emphasis on identifying and minimizing inefficiencies.

A real-world case study is presented from the production program of the defense industry company *Sloboda Cacak*, focusing on the packaging phase of a 20mm caliber round. Through this example, the paper illustrates how the proposed models can be applied to complex manufacturing systems and how the analysis of the flow coefficient—defined as the ratio between actual and ideal/projected cycle times—can guide decision-making in production management.

The structure of the paper comprises the following chapters:

- Models for calculating cycle duration and flow coefficient,
- Application of the proposed model: case study and results,
- Conclusion and future research, and
- Literature.

Table 1. Grouping of relevant studies by research focus.

Group	Authors and Year	Focus / Contribution
1. Production Cycle Time Modeling and Scheduling Optimization	Jovanović et al. (2014)	Introduced K_p and K_t coefficients for measuring and improving production efficiency.
	Chincholkar & Herrmann (2008)	Developed a model for estimating cycle time and throughput in flow shops with inspections.
	Stanisavljev et al. (2014)	Proposed a multidimensional model for stochastic production cycle scheduling and monitoring.
2. Flow Coefficients and Performance Trade-offs	Macchi (2008)	Analyzed trade-offs between flow time and throughput in complex systems.
	Jovanović et al. (2014)	Applied flow coefficients to real production systems for scheduling improvement.
3. Material Flow Cost Accounting (MFCA)	Dierkes & Siepelmeyer (2025)	Developed an MFCA model incorporating waste, rework, and recycling inefficiencies.
	Takakuwa et al. (2014)	Used simulation with MFCA to detect losses and improve flow efficiency.
4. Material Flow Analysis (MFA) and Resource Efficiency	Müller et al. (2014)	Reviewed dynamic MFA approaches for modeling metal stocks and material dispersion.
	Sendra et al. (2007)	Applied MFA to industrial areas to assess resource efficiency and identify inefficiencies.
5. Material Flow Optimization and Layout Design	Dong et al. (2016)	Improved material flow in aluminum extrusion via die design modifications.
	Ellis et al. (2010)	Developed a network flow model to optimize assembly facility material handling.
	Gould & Colwill (2015)	Proposed a framework for assessing and improving material flow in manufacturing.
6. Planning Models in Production and Supply Chains	Aouam & Uzsoy (2014)	Introduced zero-order planning models with stochastic demand and variable lead times.
	Huang & Yao (2013)	Studied lot-sizing and scheduling in serial supply chains with time-varying policies.

MODELS FOR CALCULATING CYCLE DURATION AND FLOW COEFFICIENT

From the perspective of theoretical considerations, industrial practice, and duration, three types of cycles can be distinguished: the technological cycle or ideal production cycle ($T_t \equiv T_{ci}$), the production (actual) cycle (T_{cs}), and the projected production cycle (T_{cp}), as shown in Figure 1.

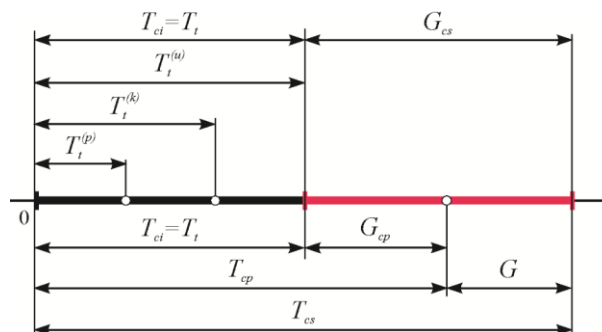


Figure 1. Types of cycles according to duration.

Technological manufacturing cycle T_t , which is also an ideal cycle T_{ci} includes the time needed for performing all n operations predicted by the technological procedure, on the products of a single lot. Production organization plays critical role in determining the technological cycle, where moves may be consecutive (Relation (1)), parallel (Relation (2)) and combined (Relation (3)), depending on the type of production consisting of a complex set of features. The combined type of work flow in manufacturing process is most often encountered in serial production. Its goal is to eliminate downtimes emerging at some workplaces (operations) at parallel type due to different duration of successive operations.

$$T_t^{(u)} = q \cdot \sum_{i=1}^n t_i, \quad (1)$$

$$T_t^{(p)} = \sum_{i=1}^n t_i + (q - 1) \cdot t_{max}, \quad (2)$$

$$T_t^{(k)} = \sum_{i=1}^n t_i + (q - 1) \cdot (\sum_k t_k - \sum_j t_j), \\ (t_{k-1} < t_k \geq t_{k+1}, k = \overline{1, n}) \wedge (t_{j-1} \geq t_j < t_{j+1}, j = \overline{2, n-1}), \quad (3)$$

Where:

t_i - total time per technological operation in norm hour/piece
 q - lot size in pieces

The projected production cycle duration T_{cp} , Relation (4), aside from productive and non-productive cycle times, predicted by technological procedures, takes into account: scheduled manufacturing capacity utilization level, real manufacturing conditions per operation and scheduled losses in a cycle. The first step in the scheduling process is calculating the manufacturing cycle time duration per operation (τ_i) using Relation (5), with respect to real manufacturing conditions: number of workplaces per technological operation (r_m), number of shifts per day (S_n), average norm-hour execution (p_n), and norm-set capacity per shift (q_s). Inventories in unfinished production and losses due to quality inadequacy are included in calculations via the formulas for planning the quantity (q) of the product to be produced. In the second step, it is needed to adopt total losses in the cycle G_{cp} , and then to determine average partial losses between technological operations $\Delta\tau$.

$$T_{cp} = \tau_1 + (n - 1) \cdot \Delta\tau + \sum_p^k (\tau_p - \tau_{p-1}), p: \tau_p > \tau_{p-1}, \quad (4)$$

$$\tau_1 = q / (q_s \cdot S_n \cdot r_m \cdot p_n), \quad (5)$$

The flow coefficient is a measure of the efficiency of the production process. It can be calculated in two ways. The first as the ratio of the actual and technological length of the production cycle, usually according to the sequential way of moving objects of work, Relation (6). And another way as the ratio of the actual and projected length of the production cycle, Relation (7).

$$K_t = T_{cs} / T_t^{(u)}, \quad (6)$$

$$K_p = T_{cs} / T_{cp}, \quad (7)$$

Viewed from the angle of the manufacturing system, flow coefficient K_p has a higher use value, because the accomplished values of the cycle are correlated with scheduled (planned) values. In this context, model design becomes a cyclic process with the aim to minimize total

Table 2. Parameters for technological and projected cycle calculations.

Order of operation	Time per operation t_i [cmh/piece]	Capacity in a shift q_{si} [piece/shift]	t_k	t_j	S_n	r_m	p_n	p
1	75	10000			1	2	1.25	
2	125	6000	+		1	2	1.18	+
3	125	6000			1	2	1.19	
4	50	15000		+	1	2	1.2	
5	63	12000			1	3	1.16	
6	220	3400	+		1	4	1.15	+
7	62	12000			1	3	1.18	
8	14	55000			1	1	1.25	
9	14	55000		+	1	1	1.25	
10	30	25000			1	3	1.24	
11	188	4000	+		1	3	1.18	+
12	62	12000			1	4	1.19	
$q = 10200$ pieces		$\Delta\tau = 0.5$ shift = 3.75 h						

Using formulas (1), (3), (4), (5), (6), and (7), along with the parameters listed in Table 2, the results were obtained and are presented through expressions (8), (9), (10), and (11).

$$T_t^{(u)} = (10200 \cdot 0.01028) / 7.5 = 14 \text{ shift}, \quad (8)$$

$$T_t^{(k)} = (0.01028 + (10200 - 1) \cdot (0.00533 - 0.00064)) / 7.5 = 7 \text{ shift}, \quad (9)$$

$$T_{cp} = 0.41 + (12 - 1) \cdot 0.5 + 1.33 = 7.24 \text{ shift}, \quad (10)$$

$$K_t = T_{cs} / 14, \quad K_p = T_{cs} / 7.24, \quad (11)$$

The length of the cycle according to the first model is 14 shifts (consecutive mode) and 7 shifts (combined mode), and according to the second model 7.24 shifts (combined mode). The projected values are close to the ideal length of the cycle, of course if the combined way of movement of the objects of work is observed, so that both can be used for planning and production management. However, in the second model, that is, the model for designing the production cycle, it is also necessary to take into account the degree of utilization of machine capacities for the corresponding operations. This can be quantitatively incorporated by introducing a machine utilization coefficient, defined as the ratio between the actual machine working time and the available scheduled time for each operation. Integrating this parameter into the model enables a more realistic estimation of the production cycle duration, particularly in environments with variable workload distribution or partial equipment utilization.

CONCLUSION AND FUTURE RESEARCH

This paper presents two models for estimating the duration of the production phase cycle, serving as a foundation for efficient production management. The first model calculates the ideal (technological) cycle, while the second focuses on the projected production cycle, accounting for real-world organizational and logistical constraints. A detailed calculation is provided for the packaging phase of a 20mm round into a crate, which is part of the production program of the 'Sloboda' Co. Cacak. The length of the cycle according to the first model is 14 shifts (consecutive mode) and 7 shifts (combined mode), and according to the second model 7.24 shifts (combined mode). The projected values are close to the ideal length of the cycle, of course if the combined way of movement of the objects of work is observed, so that both can be used for planning and production management. For the calculation of the flow coefficient K_f , it is necessary to take a technological cycle that corresponds to the type of production and not, as has been the practice until now, to always take the sequential way of movement of the objects of work.

Future research should be directed towards the identification of the causes of losses and the analysis of the degree of utilization of production capacities, which should be included in the model for designing the production cycle of each operation. In addition, it is necessary to analyze the actual length of the cycle and determine the values of the flow coefficient, which is an indicator of potential inefficiency in the production process.

DECLARATIONS OF INTEREST STATEMENT

The authors affirm that there are no conflicts of interest to declare in relation to the research presented in this paper.

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