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Modeling the Work of Multi-spindle Machining Centers with the Petri Nets

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Abstract

The article presents the results of the simulation studies concerning the impact of random production interruptions on the efficiency of multi-spindle machining centers. Four different machining center configuration models were developed using a dedicated class of stochastic Petri nets. In addition to the number of machine spindles, the number of simultaneously mounted parts, loading time of parts, their machining time, and reliability parameters regarding the frequency of machine interruptions caused by random factors were also taken into account as model parameters. A series of virtual tests was carried out for machining processes over a period of 1000 hours of operation. Analysis of the results confirmed the purpose of conducting simulation tests prior to making a decision regarding the purchase of a multi-spindle milling center. This work fills the existing research gap, as there are no examples in the technical literature of evaluating the effectiveness of multi-spindle machining centers.

Keywords

Stochastic Petri Nets; Machining centers; Process modeling; Process simulation.

Introduction

Selecting a suitable machine tool configuration is one of the most important steps in the process of designing a production system. The varied level of reliability of individual elements of the production system means that the reliability of the system as a whole largely depends on the way they are configu red (Gola et al., 2011, Kopania & Kuczmaszewska, 2021, Dahia et al. 2021). Modern requirements regarding the efficiency of mass production are increasingly prompting manufacturers to buy multi-spindle milling centers equipped with multi-position clamping devices (Chiron Werke, 2022). These types of solutions are currently perceived as a future trend in flexible, high-volume production of machine parts (Esmaeilian et al., 2016). The rationale for using multi-spindle machining centers can be summarised as follows: manufacture up to 75% faster from a smaller workshop area (Vigel, 2022). The size of the machine is a huge determiner of machine cost. Compared to four single-spindle machines, four-spindle machines tend to be smaller. It is noteworthy that other benefits include higher energy efficiency of such machine tools, which translates into a valuable contribution to environmental protection. Apart from tool costs, energy consumption is the main cost-driver in the production. For example, four-spindle machine tools reduce the cycle time per workpiece by almost two-thirds; therefore, they are able to produce more, while using less energy. Further organizational and economic benefits include the reduction of the direct service personnel per production unit. In fact, modern machining centers allow conducting work with minimal involvement of the machine tool operator (Aderobal, 1997).

On the other hand, there are the reliability factors, which compared to the single-spindle centers, remain unfavorable. Failure of a multi-spindle machine tool most often results in cessation of the entire production, while failure of a single-spindle machine tool, which performs the same process in parallel with others, means stopping only parts of the production (1/2, 1/4, etc.). The average service time for multi-spindle machine tools in the event of mechanical failures is also usually extended. This is a consequence of the greater complexity of their construction and thus more difficult access to any damaged elements. The analysis of the purpose of purchasing a multi-spindle milling center should be comprehensive, taking into account the pros and cons of such a solution

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for a specific machining process. The construction of the manufacturing process model and the implementation of the simulation tests of the overall equipment effectiveness or overall labor effectiveness indicators should enable the selection of the most suitable machine configuration (Daniewski et al. 2018, Nurprihatin et al. 2019, Nurprihatin et al. 2023, Pekarčiková et al. 2023).

The presented work proposes a stochastic Petri net model for the purpose of estimating the desirability of using selected configurations of multi-spindle machining centers. The test results of the constructed model and the conclusions resulting from the tests are presented herein.

Literature review

The modeling technique, which has been widely used since the 1960s are the Petri nets (Petri, 1960). Developed with a view to solving broadly understood communication problems, Petri nets quickly gained popularity in very distant fields of science and technology. Researchers gradually expanded the language of the Petri net, which resulted in a number of its forms such as: time, block, hierarchical, coloured, priority, stochastic, attribute, fuzzy, object-oriented or predicate Petri nets. With the help of a simulation of the model developed as a Petri net, one can identify potential conflict situations in the model, blockades in the designed system, availability and load of resources, detect unused resources, or obtain data for calculations of the potential system efficiency in its virtual form. Petri nets have proven particularly useful for modeling distributed and parallel systems that exhibit concurrency, synchronisation, mutual exclusion and conflicts. The interest in the use of Petri nets is continuously growing. Kaid et al. (2015) performed an analysis of the distribution of scientific articles in 1988-2015, regarding the issues of Petri nets in the context of modeling production systems, including deterministic timed Petri nets, stochastic timed Petri nets and fuzzy timed Petri nets. Grobelna and Karatkevich (2021) present and analyze the most relevant challenges and opportunities related to the use of Petri nets as a modeling technique of manufacturing systems. Trends for the future are also identified.

Broad interest in the Petri net methodology for system design and manufacturing processes appeared in the 1980s. The first attempts to use a Petri net in designing manufacturing processes involved linking the manufacturing process plan to the constraints arising from the production department's potential. The proposal by Srihari and Emerson (1990) to use the information from the Petri net model controlling the production process to verify the designed manufacturing process in real time is noteworthy. The prototype of the dynamic computer aided process planning system was created in this way. The work of Kiritsis et al. (1994) focused on analyzing the possibilities of scheduling operations in the production process and representing alternative production process based on the Petri net model. At the same time, Lee and Jung (1995) forecasted the use of the Petri net for two purposes: modeling the knowledge related to the selection and scheduling of procedures as well as a flexible representation of the order of procedures. The most complete approach in the 90s was presented by Rudas and Horvát (1997). It covered both the acquisition of knowledge and modeling of the process structure as well as evaluation of the generated Petri net. The goal of the authors was to build a methodology for modeling a knowledge-based production process. In the study described by Xirouchakis et al. (1999), the researchers consider the problem of estimating the upper and lower time limits and the cost of making a production series for a particular part under specific workshop conditions. The possibility of a variant course of individual processes for individual parts of the production batch is assumed. The process of estimating the time and costs is approximate. The reason for this is imprecision and incomplete knowledge regarding the actual implementation of the production at the stage of production preparation. The obtained model was more efficient in terms of the machine tool availability and production instrumentation than the traditional approach, based on the critical path determination. A broader characterisation of utilising Petri nets in modeling the process of a manufacturing operation is presented Stryczek (2018).

The possible scope of modeling of issues related to the computer integration of flexible manufacturing systems using the Petri net technique is currently very extensive. Modeling of production systems, in particular flexible machining systems for process control, management and monitoring (Pla et al. 2014), production scheduling (Tuncel and Bayha, 2007), or e.g. preventive blockade detection (Uzam 2004) remains the basic application of the Petri nets in this field. Recently, flexible, re-configurable manufacturing systems have been a popular scientific topic. In the work described by Tigane et al. (2017) the authors proposed a stochastic extension of the Petri nets called re-configurable Petri nets. In turn, Tüysüz and Kahraman (2010) presented an approach to modeling and analysis of time-critical, dynamic and complex flexible systems using stochastic, fuzzy Petri nets. Transition times are described by fuzzy numbers, and subsequently the probabilities of the fuzzy steady state are calculated. This approach therefore allows for stochastic variation and inaccuracy to be taken into account. Al-Ahmari and Li (2016) presented a generalized stochastic Petri nets model for the considered multi-machine flexible manufacturing cells.

Random factors in modeling production process

The deterministic model assigns a fixed execution time to the events included in the model. This means that the changes in the process implementation in the deterministic model are predictable in advance. The model description does not contain elements of randomness. This means that the evolution of the system in the deterministic model is a foregone conclusion. Deterministic models have significant limitations in terms of the ability to describe real world processes, subjected to the systematic interference and/or intelligent control. An example of intelligent control can be adaptive control, where the duration of machining is variable, because it depends on many random factors, such as: machining allowance, material machinability, wear of the cutting tool, etc. Therefore, effective attempts to expand them have been made to allow for the development of stochastic models. Stochastic extensions of the Petri nets are associated with the use of additional formalisms operating on random variables.

The simplest way to introduce randomness into the model is the random appearance of a specific state defined by the probability of such a case. A simple model taking this type of randomness into account is demonstrated in Fig. 1. The bipartite directed graph contains 6 vertices, of which p_1, p_2 and p_3 represent conditions (states), while t_1, t_2, t_3 represent events. Condition p_1 triggers quality control (t_1), after which one of the events occurs: the transfer of parts to the container with defective products t_2 or the transfer of parts to the transporter of good products t_3. Which of these events will be performed depends on the state of condition p_2 (the manufactured part has defects). Each time, after the end of t_1, the p_1 condition (quality control operation completed) is true. The p_2 condition is true only in some cases described by the probability of occurrence. The arc between the vertices p_2 and t_3 is an inhibitor arc that settles the conflict between t_2 and t_3. If p_2 is true then t_3 will not be executed.

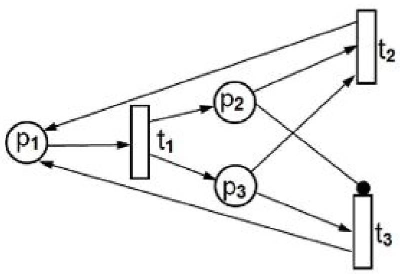

Fig. 1. Model of the function of sorting parts in the production system

Figure 2 presents the results of 100 tests carried out to control the number of defective products, assuming that the probability of a defective product appearing is 0.03. There were 5539 products made each time. The average number of defective products was 167 (rounded 166.8), which represents 3% of the production. The calculated standard deviation was 14.5.

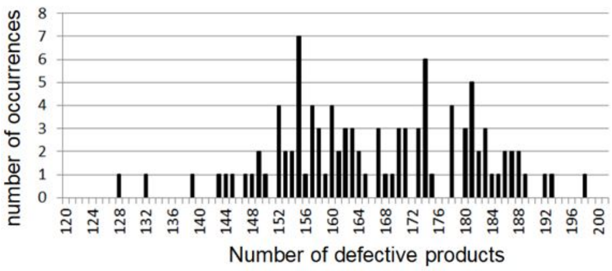

Fig. 2. Sample histogram of the number of defective products appearing

A much more complex problem is enabling the time courses of variable time events, with the possibility of delays in the start or end of the event and/or interruptions in its implementation. The model of the manufacturing process should take into account the possibility of unplanned interruptions in the operation of the machine tool, caused by random factors, such as: machine failure, catastrophic wear of the tool, lack of power supply, etc. Therefore, each event related to the execution of a manufacturing operation should correspond to: the possibility of an unplanned interruption in its execution, and the randomly selected length of such an interruption.

The probability P_b of the occurrence of an interruption during the event t, depends on the time T_t of the event t and the assumed number of events with the interruption in the assumed time period T and the assumed average duration of the interruption a, which is calculated using the following formula:

$$P_b = \frac{N_b}{N_t} = \frac{T_b/a}{(T - T_b)/T_t} \tag{1}$$

where: P_b – probability of an interruption during the event t, N_b – number of events in the considered period T during which the interruption occurred, N_t – number of completed events t in period T, a – assumed average interruption time [min], T_b – the total time of interruptions during the execution of the event t in period T [h], T_t – nominal duration of the execution of event t [min], T – available time [h].

The N_b and a parameters are set on the basis of previous data known from monitoring and/or own knowledge as well as data provided by the machine tool manufacturer. Fig. 3 illustrates the probability of an interruption occurring during event t, depending on the total interruption time and duration of event t, in accordance with formula (1).

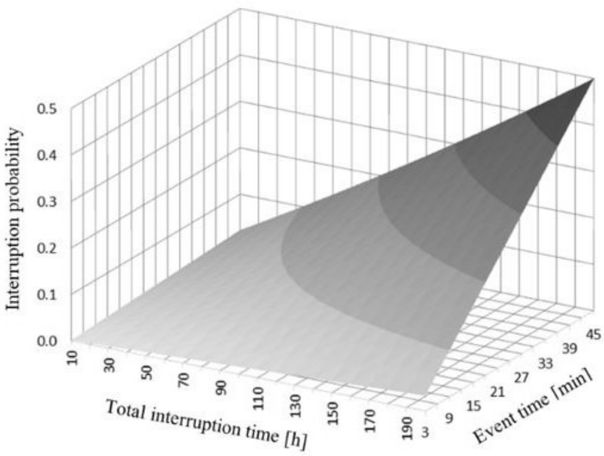

Fig. 3. The probability of an interruption in one event for $T = 2000$ h and $a = 10$ min

The duration of unplanned interruptions should be described by a continuous random variable. The course of the density of probability function of the occurrence of an interruption at a specified time was adopted in the form of exponential distribution. Such an arbitrary assumption results from the observation that in long periods of time, the number of short interruptions in the operation is much greater than the number of serious failures associated with a long interruption in the machine's operation.

The randomly generated interruption duration is proportional to the assumed average interruption time a. The random length of the tb event interruption can be calculated from formula:

$$t_b = -a \cdot \ln(r), \tag{2}$$

where: t_b – duration of the interruption, r – random number from the set $[0, 1]$.

The courses of relationship (2) are illustrated in Fig. 4. An exemplary histogram of the generated interruptions is shown in Fig. 5.

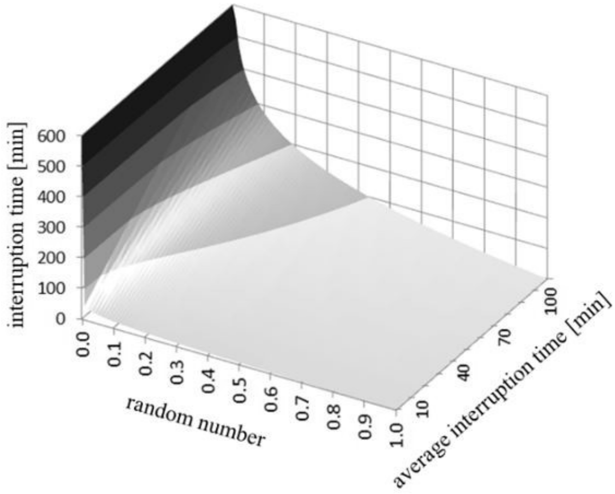

Fig. 4. Random interruption length depending on the assumed average duration of the interruption

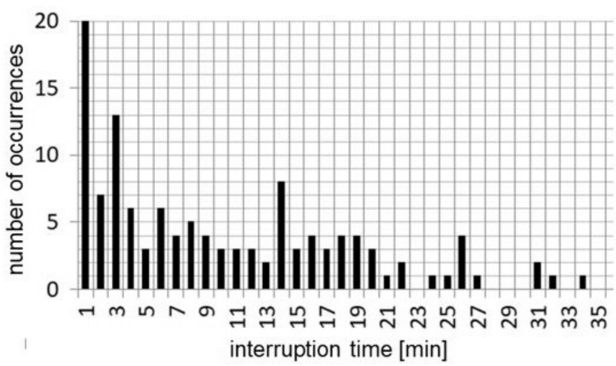

Fig. 5. Exemplary histogram of the appearance of an interruption at a specified time for $a = 10$ min, $T_t = 2$ min, $P_b = 0.022$ and simulation time 200 h

Based on the theory presented in this chapter, one can easily expand the software simulator mechanism with random functions that increase the duration of some events with the duration of interruptions. If the drawn real number r from the range [0, 1] is bigger than the calculated P_b for a given event, then the duration time of its realization will not be extended. Otherwise, the event realization time is increased by the length of the interruption calculated according to relationship (2).

The simulator arbitrarily generated 123 interruptions during 200 h of simulation, the total time of which is 21 h 7 min with the assumed interruption time of 20 h. Hence, the simulator error did not exceed 1%. The quoted test results showed the need to analyze the issue from the point of view of production practice.

Time-stochastic Petri nets

A Petri net is defined as a bipartite graph incorporating two types of nodes, identified as places and transitions, as well as directed arcs connecting these nodes. Places represent the passive system components that incorporate markers and represent individual states of the system. Transitions represent active system components that can generate, send, or absorb markers. The Petri net is hence a place/transition system; however, it also belongs to the condition/event class of calculation models. Petri nets might be useful tools for simulating dynamic and simultaneous activities. They can convey dynamic system behaviour in a simple and intuitive manner. As a visual communication tool, the Petri net can be as helpful as block diagrams or graphs. Moreover, Petri nets may be easily combined with other techniques and theories, e.g. Markov's processes. A crucial advantage is also the ease of programming Petri nets, defined on the basis of the set theory, in declarative programming languages such as Prolog.

Many researchers have proposed different ways of including time information into the timed Petri nets (TPN) models: timed places, timed tokens, timed arcs, timed transitions. Two approaches to consider time in TPN are particularly common: the time the marker is in a given place or the time of the process of transition. While interpreting Petri nets as state/event models, time is naturally connected with the activities that induce changes of state. Hence, in the later part of the current article, the time factor will be associated with each transition. In a special case it might be zero time, which means immediate transition.

Stochastic Petri nets (SPN) were implemented in 1980 as a formalism to describe discrete event dynamic systems (Balbo, 2001). In the following years, a number of researchers expanded this idea, making numerous changes or supplements to the initially proposed formalism. In the present research, a variant of the Petri net PN* (3), defined as timed, priority, stochastic Petri nets with inhibitor arcs, has been used to perform the simulation tests. Timed because the time function assigns each event a time to execute it. Priority, because each event has an assigned priority in the form of a real number from the range $[0, 1]$. This allows, among others, for conflict resolution and automatic model optimisation (Stryczek, 2009). Stochastic because of the fact that two additional elements, i.e. the probability of production interruptions and the average duration time of the interruption, allow for an automatic, random assignment of an interruption and its duration time. In addition, there is a possibility to assign probability for a marker to occur for each item. Inhibitor arcs included in this class of nets simplify the model, while at the same time making the construction and analysis simpler. It should be noted that the multiplicity of the flow through the arc is assigned to both ordinary arcs belonging to the incidence relationship E as well as to the inhibitor arcs. Attributing multiplicity to the inhibitor arcs enables withdrawal of another element, which is the function of the capacity of places. Inhibitor arcs can be used to regulate the flow of the markers, e.g. by preventing overload of inter-operative buffers.

Based on the Set theory, the PN* net can be defined as eleven-tuple:

$$PN^* = (P, T, E, P_S, W, I, S, Y, P_b, A, M_0)\,, \tag{3}$$

where:
P: nonempty, finite set of places (conditions),
T: nonempty, finite, disjoint from P set of transitions,
$E \subset (P \times T) \cup (T \times P)$: flow relation,
P_S: $P \to [0, 1]$, probability of the condition occurring,
W: $(E \cup I) \to N$, weight arc function,
I: set of inhibitor arcs,
S: $T \to N_0$, function of time,
Y: $T \to [0, 1]$, function of priorities,
P_b: $T \to [0, 1]$ the probability of an interruption,
A: $T \to N$, average random interruption time,
M_0: $P \to N_0$, initial marking vector,
N: set of natural numbers, $N_0 = N \cup 0$.

In this instance, the conditions for preparing the t transition are:

$$\begin{cases} \mathrm{M}(p) \geq W(p, t), & \forall p \in {}^{\cdot}t \\ \mathrm{M}(p) < W(p, t), & \forall (p, t) \in I \end{cases} \tag{4}$$

where ${}^{\cdot}t$: set of input places of event t.

Process models for multi-spindle milling centers

Four configurations of milling centers are presented in Fig. 6.

In addition to the elements shown in the drawing, these configurations include delivery and receiving transporters and an industrial robot for automatic loading and unloading of the machined parts. Models developed utilizing the Petri net technique corresponding to the above machine tool configurations are presented in Fig. 7–10.

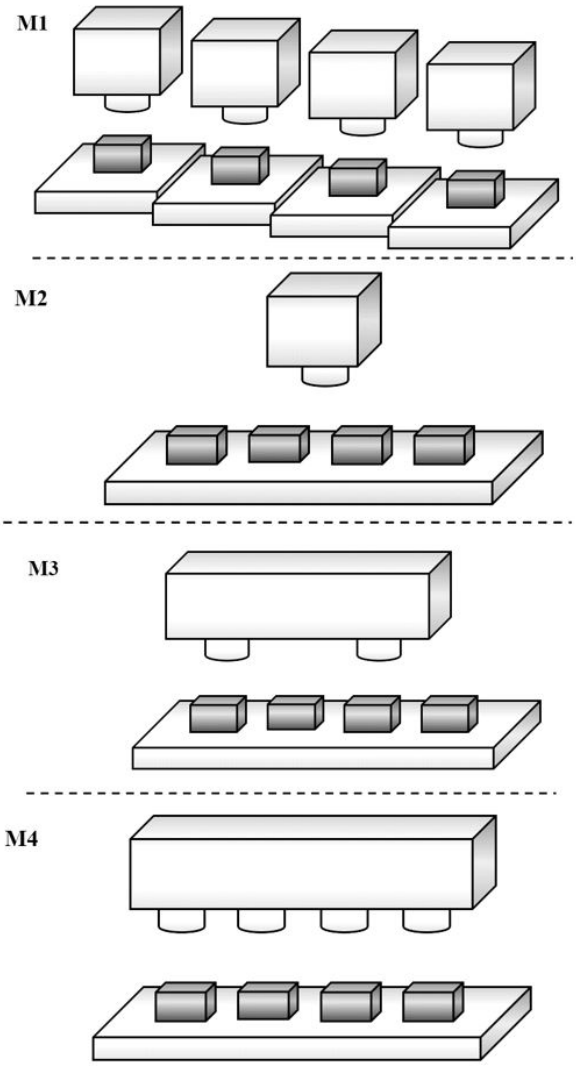

Fig. 6. Overall Machine tool configurations taken into consideration: M1 – four single-spindle milling centers equipped with a single fixture; M2 – single-spindle milling center equipped with a four fixture; M3 – a two-spindle milling center equipped with a four fixture; M4 – a four-spindle milling center equipped with a four fixture control structure

All loading/unloading activities in the above configurations are served by a single industrial robot. Hence, these production systems can work in a maintenance-free manner for long periods of time. A mass character of production was assumed; hence, the operations of setting up the individual machine tools were not modelled.

The indicators of the net nodes were unified for all models presented Table 1 and Table 2.

The models have their multiplicity marked next to the arcs only if it is different from 1. All processes

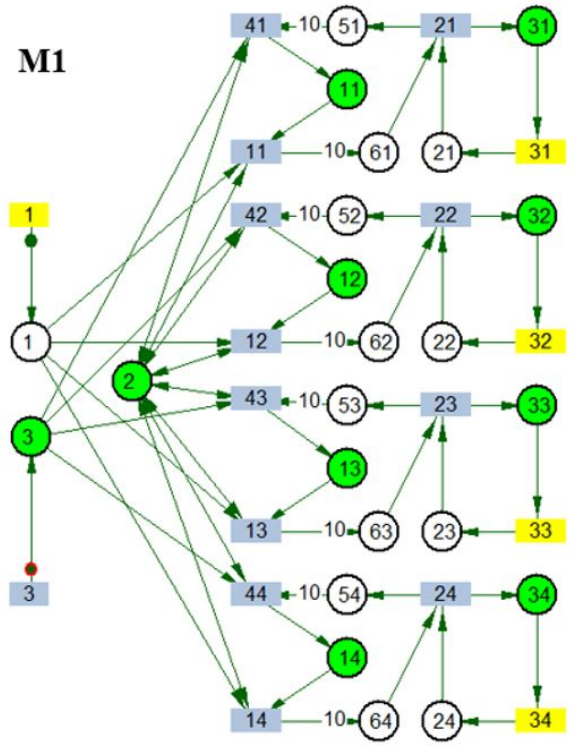

Fig. 7. Model: M1 – four single-spindle machining centers with a single fixture

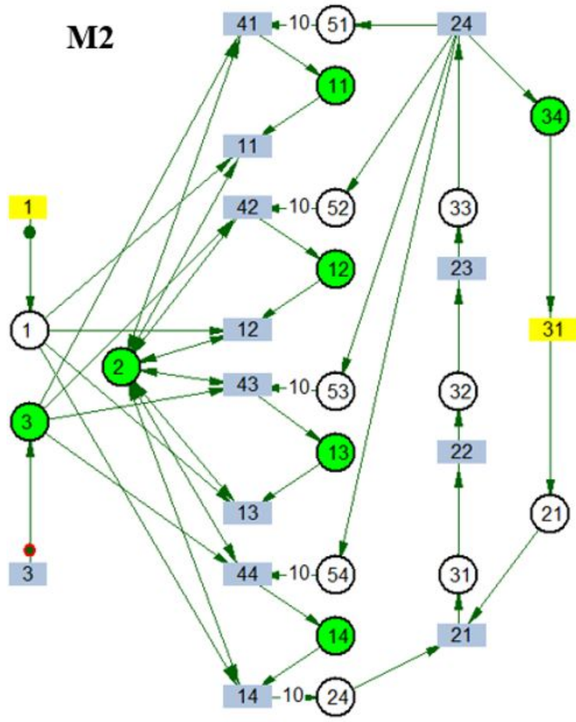

Fig. 8. Model M2 – single-spindle machining center with four fixture

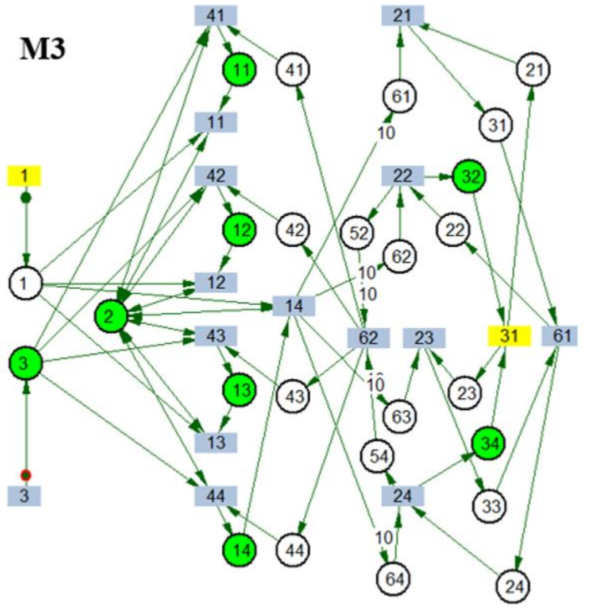

Fig. 9. Model M3 – double-spindle machining center with a four-position clamping device

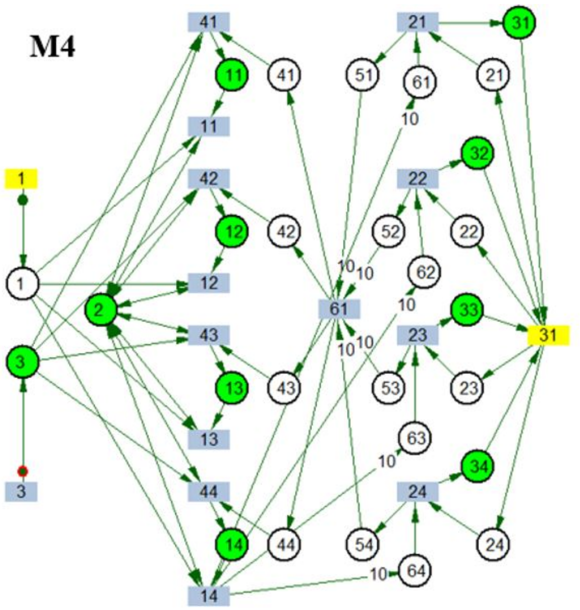

Fig. 10. Model M4 – four-spindle machining center with a four-position clamping device

presented on the models include 10 various machining operations handled with 10 different tools. Primary marking of the net was indicated by a darker (green) background of the individual items. Transitions t61 and t62 are examples of immediate transitions.

The models presented in the previous section were simulated during 1000 h. The times of the individual

Table 1
The positions specification

Node	Description
p1	Blank available
p2	Robot available
p3	Conveyor available
p1*	Device position* available
p2*	Start machining of part*
p3*	Task for part* completed
p4*	Machining of part* completed
p5*	Counter of tasks performed for the part*
p6*	Counter of tasks to be performed for part*

events are presented in Table 1. The average duration of one machining job #1 was variable and ranged from 10 s to 120 s, which with 10 tools gives a total machining time from 1 min 40 s to 20 min. A linearly variable interruption probability was assumed during the machining of part #2, 0.001 respectively for every 10 seconds of the duration of the process. The assumed probabilities of events resulted from the experience of workshop practitioners. Firstly, the performance of individual machine configurations for stochastic and deterministic models was compared (see Fig. 11) for the full tested range. The time of unforeseen production interruptions was not included in the deterministic models. The general conclusion that arises from this study is unambiguous. The omission of random interruptions in the work of machine tools in the model leads to significantly overstated performance

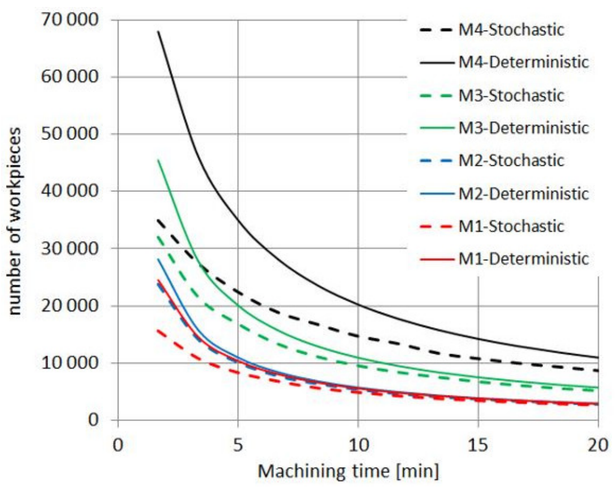

Fig. 11. The number of parts produced depending on the processing time and the type of machine tool configuration

Table 2
The transitions specification

Node	Description	Time [s]	Break probability	Average break [min]
t1	Move of the delivering transporter by 1 position	5	0.001	1
t3	Move of the receiving transporter by 1 position	5	0.001	1
t1*	Loading of a new part into position*	10	0.005	20
t2*	Performing the machining task	#[1]	#[2]	5
t3*	Change of tool	3	0.002	30
t4*	Unloading the parts from position*	10	0.005	20
t61	Continuation of the operation for the second pair	0	0	0
t62	Termination of the operation	0	0	0

Comments:
* takes values from the set {1, 2, 3, 4} and denotes the index of the workpiece;
#1 – ranged from 10 s to 120 s; #2 – 0.001 respectively for every 10 seconds of the duration of the process.

indicators. This tendency is particularly pronounced for short production cycle times.

In order to clearly illustrate the sensitivity to random failures of the machine tools configurations taken into consideration, the *FSI* sensitivity indicator was calculated according to the following relationship:

$$FSI = 100\frac{N_D - N_S}{N_D}, \tag{5}$$

where: *FSI*: the failure sensitivity indicator, N_S: number of parts produced in the stochastic model, N_D: number of parts produced in the deterministic model.

The results of calculations in the form of logarithmic trends are shown in Fig. 12. The figure unambiguously demonstrates that the M4 configuration is by far the most vulnerable to failures. This is confirmed by the fact that an interruption at the stage of machining of one of four concurrently machined parts or an interruption caused by a change of one of four simultaneously working tools causes standstill of the entire machine tool. In turn, the M2 configuration is the least sensitive, because theoretically there are four times less tool changes, which are a frequent reason for additional, random interruptions in the work of a machine tool. An interesting remark can be observed between the M1 and M3 configurations. The M1 configuration is more sensitive to failures than M3 for short machine times, while for long machine times the tendencies are reversed. Another interesting remark is illustrated in Fig. 13. It presents the trends

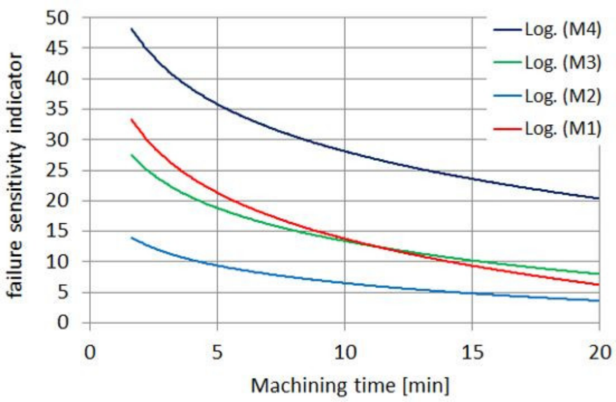

Fig. 12. Comparison of the sensitivity to random interruptions depending on machining time and the type of configuration of the machine tool

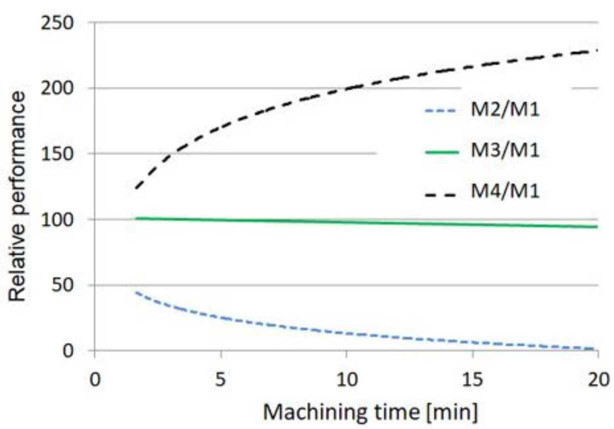

Fig. 13. The relative performance

in the relative performance of the M2, M3 and M4 configurations in relation to M1, which is the reference performance here.

The analysis applies only to stochastic models. It can be seen that the relative increase of the performance for the M3 configuration remains practically unchanged at the level of 100%. The relative performance of the M2 configuration decreases because the benefits of fewer tool changes, with longer times of a machining cycle, disappear. On the other hand, the relative performance of the M4 configuration is continuously increasing, particularly dynamically for low machining times. For the adopted parameters, the maximum increase in the performance did not exceed 230%.

The next aim of the research study was to determine how the performance of individual configurations of machine tools changes with the increase in the probability of random interruptions in production. A series of tests were carried out for 3 different machining cycle times: 2 min, 10 min and 20 min. The results are presented in Fig. 14 and Fig. 15. Fig. 14 compares the performances for previously assumed interruption probability values, according to Table 1, with the performance obtained after doubling these values. As shown in the attached diagrams, the differences in performance are significant. For the M4 configuration, the number of parts produced for the shortest cycle 2' decreased by approximately 12 000 units (33%) during the 1000 h test. To determine the sensitivity of individual configurations to the frequency of random interruptions, the percentage of the decrease of the performance was calculated (see Fig. 15).

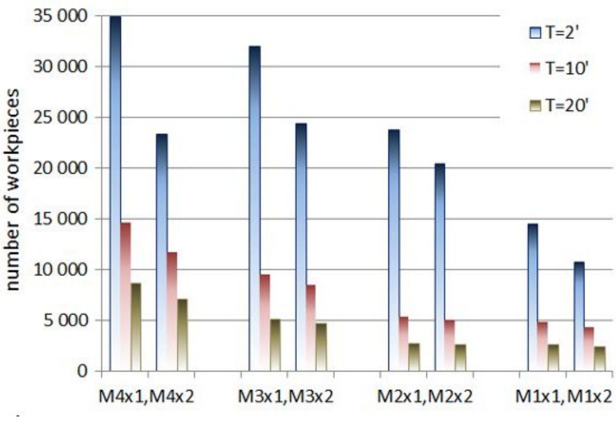

Fig. 14. Comparison of the performance at various levels of probability of interruptions during operation

Unsurprisingly, the largest reductions were noted for the short machining cycle time. The most resis-

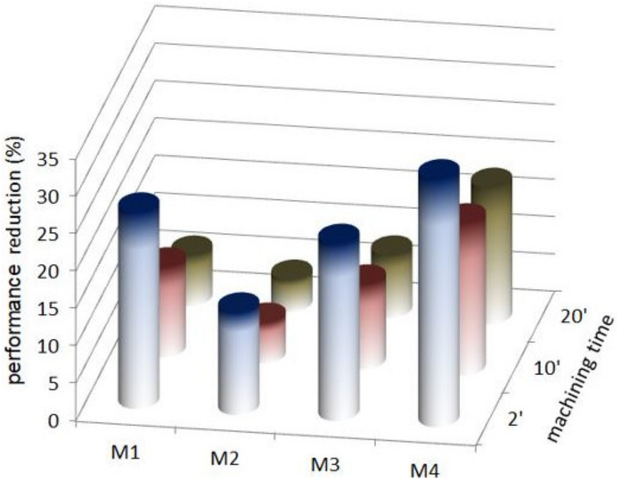

Fig. 15. The relative performance decrease with a twofold increase in the interruption probability

tant configuration proved to be M2, and the most sensitive M4. For longer machining cycle times, the relative performance reductions reach similar levels, except for the M1 configuration.

Conclusions

Petri nets have been recognized as tools for modeling the operation of production systems for years. Classic Petri nets are in this regard limited to the representation of mutual logical conditions of the elements of the production system, in particular conflict resolution in access to shared resources. Only timed, stochastic Petri nets allow for reliable reproduction of the real levels of performance of such systems, necessary for estimating the overall equipment effectiveness indicator. This work formulates the form of a temporary, stochastic class of the Petri nets, helpful in analysing the work of various machine tool configurations. The obtained results should allow making the right decisions at the design stage of the production system. This article shows that in this class of Petri nets it is possible to conveniently model the production system, taking into account random factors influencing the course of production. Due to the readability of the presented examples, such analyses were abandoned in the conducted tests. The four presented models should be considered as one of the examples of building a model of machining work center. Due to the high flexibility of the adopted modeling technique, these models can be easily specified or extended by further functions. The presented article aims to popularize this method in industrial practice. The relevant software will be made available on the nets. The continuation of the presented research should be focused on industrial trials, taking into account the analysis of production costs.

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