Hybrid Internet of Things and Petri Nets for Tool Condition Monitoring System in CNC Machines

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Abstract

Tool failure is one of the primary causes of failure in computer numerical control (CNC) machine tool machining. Such necessitates condition monitoring of CNC machine tools to improve the effectiveness of failure-free operation and decrease the probability of waste and equipment failure caused by tool failure. This paper proposes a novel method based on the Internet of Things (IoT) and Petri nets (PNs). In the first iteration of the proposed method, a PN model is designed to represent the milling machine and guarantee the model's liveness. Then, the developed model is integrated with the IoT model to monitor the tool condition based on the obtained data from the sensors. The experiment results demonstrate that the developed method can represent the tool's wear state and provide a timely reminder to replace the tool.

Keywords
Internet of things, cyber-physical systems, Petri net, tool failure, automated manufacturing systems, CNC machine.

1. Introduction
Increasing the productivity of CNC milling machines while maintaining a high level of accuracy and surface roughness is a top priority for many manufacturers. How to control frequent failures in CNC machines, including "tool wear," "noise," and "tool breakage," is a challenge (Kaid et al. 2023). Tool wear (TW) is difficult to manage because it is not a linear process; it degrades rapidly initially, then at a moderate rate for a period of time, and then accelerates until breakdown. TW is a frequent and undesirable issue in most machining operations. It introduces several challenges to the productivity and quality of "automated machining processes," thereby preventing the growth of smart and combined manufacturing enterprises (Tran et al. 2022a).

Several diagnostic and monitoring methods for the cutting operation were designed to address this issue, employing "cutting signals" for chatter recognition (Chen et al. 2019, Kuljanic et al.2008, Ghoneim et al. 2021). Most of these methods, however, are offline. Generally, the chatter monitoring procedure requires data collection, signal processing, and the use of statistical approaches and machine learning for chatter diagnosis (Liu et al. 2020, Tran et al. 2020). The study (Kious et al. 2010) addressed the use of "cutting force signals" to improve "tool condition monitoring" (TCM) in milling operations by designing a tool wear prediction method. The paper (Wang and Cui 2013) presented a "self-supervised neural network" entirely generated from data collected under typical machining conditions, eliminating the requirement for tool wear conditions during training. The work (Nouri et al. 2015) developed another approach for TCM in "end milling" and diagnosed a real-time failure by observing the force model's coefficients.

The development of an Internet of Things (IoT)-based intelligent online technique for TCM in CNC machine tools is now the solution for efficient "predictive maintenance systems," which regularly record and document the condition of the machine's tools (Civerchia et al. 2017). Recently, robust fault detection and monitoring methods based on "Cyber-Physical Systems" (CPSs), "artificial machine learning," and IoT have been developed. New IoT infrastructures have been constructed for the online monitoring of induction motor failures (Tran et al. 2021), vibration conditions (Tran et al. 2022b), and tool wear (Kaid et al. 2023) during the CNC machine center cutting operation.

As the literature states, companies apply rigorous operational techniques to minimize such failures and prevent expensive TW (Rangwala and Dornfeld 1989). However, because of the necessity to replace the tool early, machine stoppage and replacement expenses result in less productive and more expensive operations (Kaid et al., 2023). This paper aims to present a new approach based on "Petri nets" (PNs) and IoT for an online TCM system. First, PNs considering "resource failures" are designed to ensure the PN's liveness. Then, for TCM systems, an IoT and PN-integrated approach is used.

The remaining sections of this study are stated as: The development of hybrid PN and IoT is presented in Section 2. Then, section 3 shows the milling machine example, which illustrates the effectiveness of the proposed method. Finally, in Section 4, conclusions and future study directions are provided.

2. Hybrid PN and IoT

A Petri net (PN) can be defined as $N = (P, T, I, O, M)$, if

1) $P = \{p_o\} \cup P_R$, represents a set of net places, where p_o and P_R, respectively, are a load/unload station place and a set of net resource places;
2) T is a set of net transitions, $P \cup T \neq \emptyset$, and $P \cap T = \emptyset$;
3) $I(p, t)$, $O(p, t)$:$\rightarrow$ **IN** are the net's input and output functions, respectively, and **IN** $=\{0, 1, 2, ...\}$;
4) M: $P \rightarrow$ **IN** represents the net state (marking) function, which assigns a number of tokens to each place p in a net and can be denoted as $M(p)$.

The following are some formal properties of the PN:

1) The input (preset) and output (postset) transitions of place p can be respectively described as "$^{\bullet}p = \{t \in T \mid (t, p) \in F\}$" and "$p^{\bullet} = \{t \in T \mid (p, t) \in F\}$," where $F= I(p, t) \cup O(p, t)$, $\forall(p, t) \in F$.
2) The input (preset) and output (postset) places of transition t can be stated as "$^{\bullet}t = \{p \in P \mid (p, t) \in F\}$" and "$t^{\bullet} = \{p \in P \mid (t, p) \in F\}$," respectively.
3) When $\forall(p, t) \in F$ and "$I(p, t) = 1$," the net is said to be an ordinary PN.
4) When $(p, t) \in F$, $\exists p \in P$, $\exists t \in T$, and "$I(p, t)> 1$", the net is said to be a weighted PN.
5) When $\forall(p, t) \in P \cup T$, "$I(p, t) > 0$" and "$O(p, t)= 0$," the net has no self-loop.
6) When $\forall(p, t) \in P \cup T$ "$I(p, t) > 0$," and "$O(p, t)> 0$,", the net has self-loop.
7) When the $t \in T$ is enabled at marking M, it fires, and the marking modifies to M', indicated as $M[t\rangle M'$ and formulated as

$$\text{"}\forall p \in P, p \in t^{\bullet} \cap {}^{\bullet}t, M'(p) = M(p) + O(p, t) - I(p, t)."$$

"Tool failure" in CNC machines indicates an issue with temporal uncertainty. In the event of a "tool failure," one can develop a "recovery subnet" capable of fixing it. The machine can then be reused. In addition, for CNC machines to operate efficiently, "tool failure detection and treatment" should happen immediately (Kaid et al., 2021, Al-Shayea et al., 2021, Al-Ahmari et al., 2020, Kaid et al. 2020). In this study, formal definitions for constructing "recovery," "detection," and "treatment" nets for tool failures in CNC machines employing IoT are presented. Assume the system detects tool failures using sensors. The data is transmitted to the Internet by the sensors. As a result, the acquired information can be retrieved from any location on Earth. After the data is transmitted to the "Internet", the computer will retrieve and use it to identify and correct any faults. To designate how the system will manage itself, a "set point" or "threshold value" is established based on the sensor data (Kaid et al. 2023).

Let $N_{IoT} = (\{p, p_{Sk}, p_{DT}, p_{RT}, p_X, p_{PC}\}, \{t_f, t_r, t_{DT}, t_{RT}, t_X, t_{PC}\}, F_{IoT}, M_{IoTo})$ be the "recovery net" of $p \in P_R$, where

1) p, p_{Sk}, p_{DT}, p_{RT}, p_X, and p_{PC} represent a resource place, sensors of the resource p for fault diagnosis, "data capture with wireless shield," a "router," a place for sending sensor information to the "Internet", and a "PC-LabVIEW," respectively;
2) t_f, t_r, t_{DT}, t_{RT}, t_X, and t_{PC} represent the transitions of failure, recovery, "data capture," the "router," the "Xively," and the "PC-LabVIEW" for resource p, respectively;
3) "$F_{IoT} = \{(p, t_f), (t_f, p_{Sk}), (p_{Sk}, t_{DT}), (t_{DT}, p_{DT}), (p_{DT}, t_{RT}),(t_{RT}, p_{RT}), (p_{RT}, t_X), (t_X, p_X), (p_X, t_{PC}), (t_{PC}, p_{PC}), (p_{PC}, t_r), (t_r, t_f)\}$";
4) M_{IoTo} models the initial markings of the net N_{IoT}.

The combination of the PN (N, M_o) and the recovery net (N_{IoT}, M_{IoTo}) results in a PN based on the IoT model. This is shown in the formula $(N_U, M_{Uo}) = (N, M_o) \parallel (N_{IoT}, M_{IoTo})$, where $\parallel$ is the combination of (N, M_o) and (N_{IoT}, M_{IoTo}).

Using the previous notations, Algorithm 1 illustrates the PN-based IoT construction and can rapidly monitor sensor changes using the control function program of the TMC system.

Algorithm 1: *Designing a PN based on IoT.*

Input: *The milling machine parameters;*

1. ***Build*** *a PN model* (N, M_o);
2. ***Add*** "$p_{DT}, p_{RT}, p_X, p_{PC}$" *to a PN ;*
3. ***Insert*** "$t_{DT}, t_{RT}, t_X, t_{PC}$" *to a PN;*
4. ***Add*** *arcs* "$(t_{DT}, p_{DT}), (p_{DT}, t_{RT}), (t_{RT}, p_{RT}), (p_{RT}, t_X), (t_X, p_X), (p_X, t_{PC}), (t_{PC}, p_{PC})$" *to the PN;*
5. ***Insert*** *a transition* t_f *of a place p* (*milling machine*) *to the PN;*
6. ***Insert*** *a transition* t_r *of a place p to the PN;*
7. ***Insert*** *sensors* p_{sj} *for a place p,* $j=1,2,\ldots,k$*, where k is the number of sensors;*
8. ***Add*** *the arc from* t_f *to each sensor* p_{sj}*;*
9. ***Insert*** *the arc from each* p_{sj} *to the* t_{DT}*;*
10. ***Add*** *arcs* $(p_{PC}, t_r), (t_r, p)$*;*
11. ***Output****: A PN based on IoT;*
12. ***End***

3. Experimental Results

Consider the milling machine shown in Figure 1 to demonstrate the PN's IoT-based architecture. It includes one machine m_1, and a loading/unloading station. Therefore, the milling machine produces one component type A.

Figure 1. A milling machine.

Using Algorithm 1, Figure 2 illustrates the designed model of PN and IoT for the milling machine presented in Figure 1 to illustrate how to model the TMC system. The following is a description of its places and transitions0\.

p_1 represents a CNC machine m_1.
p_0 models the loading/unloading Area.
p_{s1} and p_{s2} respectively model "current sensors" that measure changes in "alternating current" and "direct current" of the "spindle motor" for machine m_1.
p_{s3} and p_{s4} respectively model "accelerometer sensors" that measure table and spindle vibrations for machine m_1.
p_{s5} and p_{s6} respectively represent the "acoustic emission sensors," which measure "acoustic stress wave" impacts at a table and the "spindle motor" for machine m_1.
p_{DT}, p_{RT}, p_X, and p_{PC} model the "data capture," the "router," a place for sending sensor information to the "Internet", and the "PC-LabVIEW," respectively.
t_1 and t_2 represent the transferring of part A from a place p_0 to a place p_1 and from the place p_1 to the place p_0, respectively.
t_f and t_r represent the failure and recovery transitions of machine m_1, respectively.
t_{DT}, t_{RT}, t_X, and t_{PC} model the transitions of "data capture," "router," a place for sending sensor information to the "Internet", and "PC-LabVIEW," respectively.

This paper studied a tool condition with the single operational state using a sample of a mill dataset, as provided in (Agogino and Goebel, 2007). The dataset was obtained from "controlled laboratory experiments" of milling machine processes with multiple parameters, including cutting depth, material type, and feed rate. At multiple locations, three different kinds of sensors ("acoustic emission sensor," "vibration sensor," and "current sensor") collect a dataset (Agogino and Goebel 2007).

As shown in Figure 2, the procedure for sending information to the Internet includes several stages. First, using t_{DT} and p_{DT}, the sensors p_{s1}–p_{s6} record the information and transmit it to a "Wi-Fi wireless shield." Using t_{DT} and p_{DT}, a shield then transmits the information to the "wireless router." Next, the "cloud-stored data" is downloaded using "PC-LabVIEW" (designated as t_{PC} and p_{PC})) for processing and sending to the PN based on an IoT. The PN based on the IoT is responsible for performing failure diagnosis and treatment monitoring.

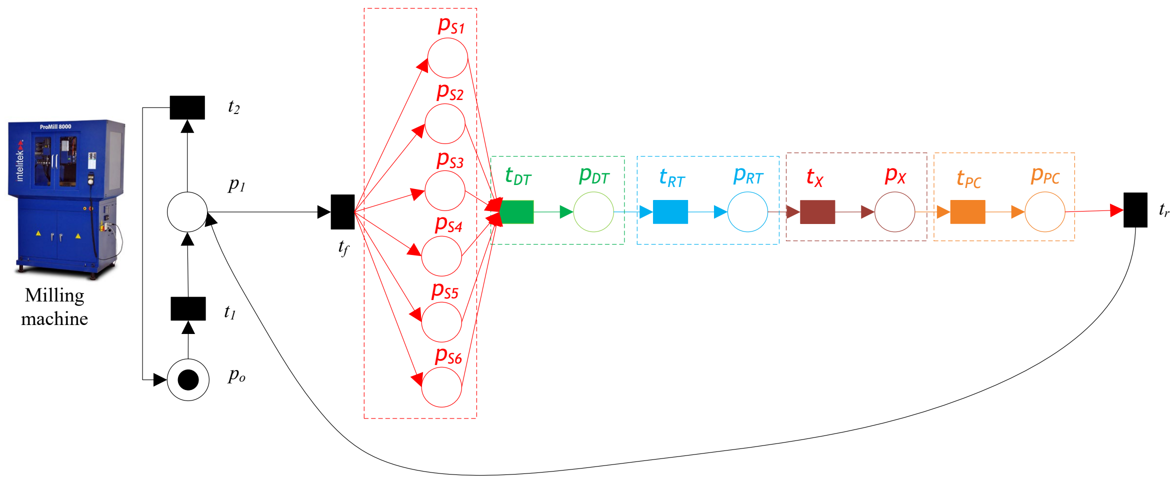

Figure 2. A PN -based IoT network for the milling machine is presented in Figure 1.

Figure 3 depicts a "graphical user interface" (GUI), which facilitates connectivity with various sensors and displays the obtained data for the tool monitoring condition system depicted in Figure 2. The GUI permits the processing and plotting of data to find possible trends or significant events. Therefore, it monitors and supervises the process and performs the system's response when sensor data reach the threshold.

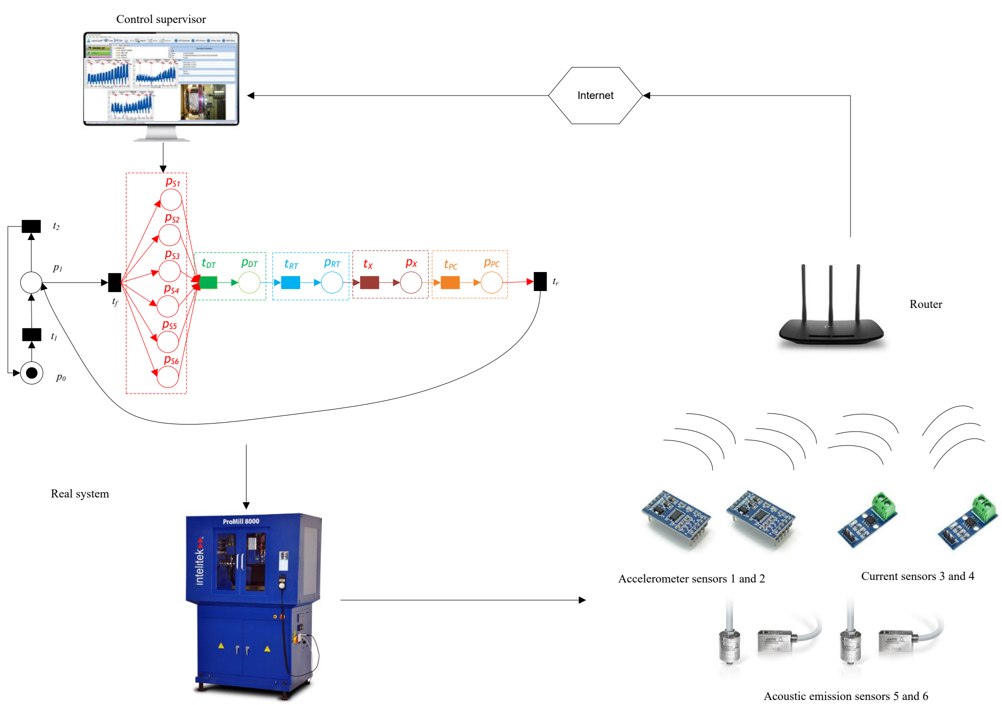

Figure 3. GUI for the PN-based IoT model is illustrated in Figure 2.

4. Conclusion

Due to the enormous growth of IoT-based "cyber-physical systems" in milling machines, in which a specific level of adaptability is essential, this study highlights the importance of methods and tools developed to assist automatic failure detection and repair. This paper introduces a novel technique based on PNs and the IoT for an online tool condition monitoring system. First, the PN model is designed to represent the milling machine and guarantee the model's liveness. Then, the developed model is integrated with the IoT model to monitor the tool condition based on the obtained data from the sensors. The results highlight that the developed technique is simpler in configuration. In addition, the proposed strategy is applicable to various intelligent systems in future studies.

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Biography

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