Development of a cloud based smart manufacturing system

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Abstract

Smart manufacturing considered as a new trend of modern manufacturing helps to satisfy objectives associated with the productivity, quality, cost and competitiveness. The smart manufacturing system is characterized by decentralized, distributed, networked compositions of autonomous systems. The model of smart manufacturing is inherited from the organization of the living systems in biology and nature such as ant colony, school of fish, bee’s foraging behaviors, and so on. In which, the resources of the manufacturing system are considered as biological organisms, which are autonomous entities so that the manufacturing system has the advanced characteristics inspired from biology such as self-adaptation, self-diagnosis, and self-healing. In this paper, a cloud based smart manufacturing system for machining transmission cases is considered as research object in which the advanced information and communication technology such as cognitive agent, swarm intelligence, and cloud computing are used to integrate, organize and allocate the machining resources.

Key words: Smart machining, Cognitive agent, Swarm intelligence, Cloud computing, Cloud machining, Networked manufacturing

1. Introduction

Manufacturing systems of the future will be characterized by the strong individualization of products under the conditions of value-added processes and high quality services. So, new technologies and methods are researched for the next stage of industrial manufacturing. Numerous researches in the manufacturing field to achieve an intelligent manufacturing have been reported in the literature. The research area can be classified as follows:

- Technologies for the advanced information systems such as cloud computing system and process planning, industrial network, inheritance of data, information and communication technology (ICT) for industry;
- Evolvable hardware/software such as integration of industrial systems, intelligent diagnosis, effective maintenance for equipment and system, hi-tech machinery industry and intelligent sensors;
- Cloud manufacturing system architecture such as international standards, design technology and model of the cloud manufacturing system.

The new trends of the manufacturing system development are to apply autonomous behaviors inspired from biology and the advanced ICT to the manufacturing systems. For these trends, the emerged technologies such as cloud computing, service-oriented technologies and high performance computing for solving the bottlenecks in the informatisation development and manufacturing applications are applied.

The paper presents a cloud based smart manufacturing system (CSMS) in which the machining system structure is a swarm of cognitive agents; and cloud system is a private cloud computing in order to improve the system adaptability to disturbances. Consequently, resources on the shop floor such as machine tools, robots, and so on are controlled by corresponding cognitive agents. The CSMS is designed with following characteristics for adapting to disturbances:

- Allowing the control system to take an action when the disturbance happens through communicating and using the power of the cloud computing system, and to continue to operate instead of stopping the manufacturing system.
completely:
- Equipping the entities in the manufacturing system with the decision-making and self-controlling abilities.

2. Literature review

The complexity and dynamic of the manufacturing environment are growing due to the changes of product types, suppliers, as well as the unexpected disturbances in the machining or assembly systems such as machine breakdown, malfunction of robot or transporter. Currently, the conventional manufacturing systems, such as the flexible manufacturing systems (FMS) are unable to adapt to the complexity and dynamic of the manufacturing environment. These systems activate the automatic operations by using the pre-instructed programs and should be stopped to re-program and re-plan in case of disturbances, which reduce the flexibility of the systems and increase the downtime. In order to cope up with the changes of the manufacturing environment, new methods and technologies have been proposed in which the distributed manufacturing control system and the biology inspired technologies for implementing this system are remarked. Self-adaptation to disturbances is a crucial issue in the development of intelligent manufacturing systems. It is the ability of a manufacturing system to respond rapidly to disturbances and recover autonomously to keep the manufacturing system running and avoid the manufacturing processes stopping completely. Many novel paradigms that are known as intelligent manufacturing systems (IMS) were proposed in the literature. The biological, holonic, and cognitive manufacturing systems are the most remarkable concepts. In the holonic manufacturing system, machines, parts, transporters, and robots of the manufacturing system are called holons, which should have autonomous and cooperative characteristics. The agent technology is used for carrying out this framework because this technology enables the implementation of a distributed manufacturing control (Leitao, 2009, Sudo, et al., 2010). In the biological manufacturing system (BMS), machine tools, transporters, robots, and so on should be seen as biological organisms, which are capable of adapting themselves to environmental changes (Ueda, et al., 2000). In order to realize BMS, agent technology was proposed for carrying out the intelligent behaviors of the system such as the self-organization, evolution and learning. The reinforcement learning method was applied for generating the appropriate rules that determine the intelligent behaviors of machines. In the cognitive manufacturing system, each machine and its process are equipped with cognitive capabilities in order to enable the factory environments to react flexibly and autonomously to the changes, which are similar to human behaviors (Zaeh, et al., 2009).

Modern manufacturing has changed significantly due to rapid development of advanced manufacturing, information, computer and management technologies. The advanced information and communication technologies have speeded up the development of manufacturing. In which, ICT infrastructure and a new service computing model such as cloud computing, have emerged and have been widely applied in various fields. A new paradigm namely cloud manufacturing has proposed with applying cloud computing (Zhang, et al., 2014, Li, et al., 2013, Wu, D., et al., 2013, Lin Zhang, et al. 2014). The idea of cloud computing is to construct the computer storage and computing service centre by specified computer and network, and virtualized resources are stored as ‘cloud’ to provide services for process planning. In technology, cloud computing is an extension of virtualization and grid computing, but the transformation of service mode brought by the idea of cloud computing is more important. Cloud computing is a model for enabling ubiquitous, convenient, on-demand network access to a shared pool of configurable computing resources that can be rapidly provisioned and released with minimal management effort or service provider interaction. The key spirit of the cloud concept can be summarized as the capability of providing distributed, fast-responding, on-demand and quantifiable services (Xu, et al., 2012, Mizuno, et al., 2012, Herrmann, et al., 2014). Therefore, these advantages of the cloud computing can be applied for the IMS to increase the efficiency of this system in the wide network application.

3. Core technologies
3.1 Cognitive agent

Cognitive agents are either biological entities including human and animals or artificial entities such as robots and software agents. The paper concerns with the software agent where the concept of the cognitive agent is derived from the conventional agent technology and the intelligent human behaviors (Park, et al., 2012). In the literature, the
The implementation of the FMS and the above-mentioned IMS use conventional agents, called reactive agents. The reactive agents use the rule-based mechanism to adapt to the changes of the manufacturing environment. In our research, a synthetic method of agent and cognitive technologies, which applies the beliefs-desires-intentions (BDI) architecture for agents, is proposed. Beliefs are the information of the current states of an agent’s environment. Desires are all the possible states of tasks that the agent could carry out. Intentions are the states of the tasks that the agent has decided to work towards (Zhao, et al., 2008). The BDI architecture is used to arm an agent with cognitive capabilities. The agents built by this architecture are called intelligent agents or cognitive agents which are smarter and more autonomous in operation scope than conventional agents. As a result, the agent performs cognitive activities that emulate the human cognitive behaviors. Cognitive activities perform a loop of three steps: perception, reasoning, and execution. The cognitive agent inherits all characteristics from the conventional agent, including the cooperation, reactivity and pro-activeness (Zhou, et al., 2007). The cooperation of agents is to get the global goal of the system. The reactivity is an ability of agents to respond to changes of the environment that is based on the relation between perception and action. The pro-activeness of agents is an ability to express the goal-directed behaviors. The different feature of cognitive agent in comparison with the conventional agent is intelligence shown by improving the pro-activeness characteristic. Intelligence is the ability of the agent to use its knowledge (intentions) and reasoning mechanisms for making a suitable decision with respect to the environmental changes.

The architecture of a cognitive agent is shown in Fig. 1. It consists of five modules: perception, decision making, knowledge, control, and communication. The perception module is responsible for data acquisition from the environment. The decision-making module is in charge of making a decision autonomously. The control module processes the plan into tasks and executes the tasks to the environment. The interactions between the cognitive agents are carried out via the communication module. The knowledge module contains intentions, plans, and behavior mechanism of the agent. The algorithm for the decision making is given as follows:

\[
\begin{align*}
B := B_{initial}; & \quad /* initial values of beliefs */ \\
I := I_{initial}; & \quad /* initial values of goals */ \\
\textbf{Loop}\ & \\
\text{s := see}; & \quad /* agent gets information from sensors */ \\
\text{If } s := \text{disturbance (type)} & \\
\quad \text{then} & \quad /* the manufacturing system cannot be operated, and the disturbance belongs to categories either long recovering time or unable recovery, so the agent requires the manufacturing execution system (MES) for rescheduling */ \\
\quad \text{send (message)} & \\
\text{Else} & \\
\quad B := \text{update}(B, s); & \quad /* agent updates its beliefs */
\end{align*}
\]
Fig. 2 Practical reasoning mechanism of the cognitive agent.

\[ D := \text{process(task)}; \]

\[ k := \text{compare}(B,D); \]

\[ \text{If } k = 0 \text{ (normal status) then} \]

\[ \text{send(message); } \]

\[ \text{Else} \]

\[ I := \text{filter}(B,D,I); \]

\[ p := \text{plan}(B,I,c); \]

\[ \text{If not empty (p) then} \]

\[ \text{execute(p); } \]

\[ \text{send (message); } \]
else
uplicates in cloud environment (agents); /*agent cooperates with the other agents using the ant colony mechanism as presented in Section 3.2*/
a := select(agent); /*agent selects another agent to do its work*/
if not empty(a) then
send(task); /*agent sends its work to the selected agent*/
else
send(message); /*agent sends a message to the MES to require rescheduling*/
end if;
End If;
End If;
End If;
End Loop.

In the present research, we applied a human reasoning process, namely, the practical reasoning mechanism for cognitive agents that would process machine events such as tool wear and machine breakdown (Fig. 2). From this reasoning mechanism, beliefs denoted by $B$ are information about the status of machine and machining processes. Intentions denoted by $I$ are the states of the tasks that the machine has decided to work towards. The $B$ value always update through sensors on the machine. Desires denoted by $D$ are all the possible states of tasks that the machine would like to accomplish. The machine gets the $D$ value from the MES. A disturbance is recognized through a comparison between the current state of the machining task and the desires of the processed task using the $k$ variable. If the $D$ and $B$ are the same value then the $k$ value is zero which means the status of the machine is normal. Otherwise, the disturbance happens on the machine. The type of disturbance is recognized through the $c$ variable. The disturbance is classified according to the criteria presented in Section 5. If the disturbance belongs to the non-negotiation type (type B), the machine has the reactive behavior to the disturbance. Reactive behavior is an autonomous control of the machine to overcome the disturbance by itself, for example, in the case of the tool wear the machine will adjust cutting conditions without affecting to the quality of product. For carrying out this behavior, the cognitive agent will reason a new plan (denoted by $p$) in consideration of the $B$, $I$ and $c$ values. In which the intentions (denoted by $I$) are updated using the filter function in consideration of the previous state. In case the solution cannot be found, or the disturbance belongs to the negotiation type (type C), for example, a broken tool, a negotiation process is carried out. In this process, a machine within the machining shop is selected that can execute the given task; it then carries out that task. If no machine can execute the task, or the disturbance belongs to the rescheduling type (type A), the MES performs a rescheduling (Vieira, et al., 2003). In negotiation, the failure machine sends information on the failed task to the remaining machines through cloud environment, specifically, the machining method, the cutting conditions and the tool type. Each machine is considered as an ant, and the mechanism for negotiation among agents is explained in Section 3.2.

3.2 Ant colony technique

In the natural environment, ant colonies show the collective intelligence as finding the shortest route from the food to their nest through the simple interactions of ants using chemical substances called pheromones (Garg, et al., 2009, Pham, et al., 2013). The ant colony adapts to the environmental changes by modifying the relationships among ants. Transferring this principle to the artificial intelligence area, the ant colony algorithm is considered under the category of swarm intelligence (Mullen, et al., 2009). In the manufacturing field, this algorithm has been applied efficiently for generation of the optimal process planning in machining (Krishna, et al., 2006) or in assembly (Wang, et al., 2005) as well as for generating the optimal solution in the resource allocation (Zhou, et al., 2008). In the biology inspired manufacturing system, the ant colony mechanism is proposed for agent negotiation. The negotiation of agents using the ant colony technique to find out the optimal solution in the case of disturbance enables the control system to overcome the weakness of the contract net protocol known as the most popularly employed cooperation mechanism of the conventional agents. The contract net protocol provides almost no guarantee of robustness and optimization of performance (Gao, et al., 2008). In agent negotiation, the machine agent managing the failure machine sends the task information to the remaining machine agents. In the consideration of the machining system, the task information consists of the machining method, the cutting conditions, and the tool type. The machine agents compare these
information to their machine ability through their database. In the database, potential factors of a machine for carrying out a task such as machine specification and capability to machine work-piece according to its functional requirements are stored. Each machine agent is considered as an ant, and the pheromone is used as a communication mediator. The function of pheromone is to indicate the ability of machine for carrying out the task roughly. In case the machine agents meet the requirements of the task, they generate the pheromone values. Otherwise, the pheromone value equals zero. The formulation for calculating the pheromone value was designed in consideration of the executing ability, processing time and machining cost (Xiang, et al., 2008). It is shown as follows:

\[
P_{\text{MA}} = \frac{q}{\alpha_t \times \frac{M_t}{M_{\text{co}}} + \alpha_c \times \frac{M_c}{M_{\text{co}}}}
\]

(1)

\(q\) is the executing ability of the machine \(MA_i\) about the task asked from the failure machine. In the executing ability, the functional requirements of work-piece such as dimension, tolerance, surface roughness and micro structural change must be fulfilled. If the task \(t\) can be carried out at the machine \(MA_i\), \(q=1\), otherwise, \(q=0\). \(M_t\) and \(M_c\) represent the processing time and machining cost of the task \(t\) at the machine \(MA_i\), respectively. \(M_{\text{co}}\) and \(M_{\text{co}}\) known by the originally planned machine are the minimum machining time and machining cost of the task \(t\), respectively. The highest pheromone value of the task requires the lowest processing time \((M_t)\) and machining cost \((M_c)\). The same task \(t\) may have the different processing time on different machines due to the different cutting parameters. These parameters are determined by the cutting conditions, machine capability and tool type.

The factors \(\alpha_t\) and \(\alpha_c\) represent the weight of the machining time and cost, respectively. The weight of these two influences is different under the different circumstances of the market. For example, in an economic boom, the machining time is critical; in a depression, the machining cost is more important.

### 3.3 ICT infrastructure

Radio frequency identification (RFID) technology and the sensor technology related to it have a great potential in changing the way of control, production automation, and special data collection in connection with the higher level such as enterprise resource planning (ERP), supply chain management (SCM), and customer relationship management (CRM) (Günther, et al., 2008). They also make a contribution for cutting down labor cost, reducing breakdown time, and improving production effectiveness. In the machining system controlled by the cognitive system, RFID technology plays the role of tracking on core components in complicated processes in real time because this technology enables to read and write data to an RFID tag at the moving parts.

Ubiquitous sensor network (USN) is a tool for collecting production data in real-time constraint. The USN plays the role of monitoring for machine operating status, actual production, and increasing the product quality (Kim, et al., 2009). A component is called intelligence if it shows advanced characteristics, such as unique identification, communication with the environment, ability to store data about itself, language to display its features or production requirements (Meyer, et al., 2009). Currently, the intelligent components use RFID tags for storing information. The tags are attached to the machine components which may be detached occasionally during the manufacturing process. As it is inspired from the biological organism of which the information exists within itself, a new approach is to store directly the production data on the component surface by merging the information and component (Denkena, et al., 2008, Schmidt, et al., 2008). For the chosen approach, it is necessary to develop the magnetic magnesium (Mg). The Mg used as a sintered material is integrated into an appropriate component (Wu, et al., 2010). The vision of “feeling” machine components is achieved by attaching multi-sensor system to these components (Denkena, et al., 2010). Intelligent components are the results of applying sensor technologies and the ICT progress that ensure the precise operations and flexibility of the manufacturing system.

Ubiquitous computing, ubiquitous networking and ambient intelligence are three representative conceptions that embody the most important aspects of the ubiquitous technology. In ubiquitous computing, the computing devices are embedded into the machine tools so that the operators can interact with the devices at the same time as they interact with the machine tool. In ubiquitous networking, computers and machines can be operated at any place, at any time. Ambient intelligence comes out from the integration of ubiquitous computing and ubiquitous networking. Normally, it represents a well defined space with a certain level of intelligence that results from embedding technology (Serrano, et
The model of ubiquitous machine (U-Machine) is shown in Fig. 3. Being ubiquitous machine, the machine status and machining data of computer numerical control (CNC) machines can be monitored with wired/wireless environments, including the environments of international mobile telecommunications-2000 (IMT2000) and wireless LAN. CNC machines are controlled and monitored in real-time, anywhere and anytime. Moreover, prompt notification from CNC machines to mobile phones is automatically realized in emergencies (Kim, et al., 2008).

The evolution of control techniques toward the intelligent machine for future is shown in Fig. 4 (Park, et al., 2014). The first innovation focuses on developing the hardware for machine tools that brings the high speed, high precision, and high productivity. In the second innovation, the software for generating automatic operations and adaptive control are focused. The machines can carry out multiple tasks, and multiple functions. The third innovation focuses on the autonomous operations with applying of artificial intelligence. In this innovation, new concepts of machine tools have been proposed such as reconfigurable machine, self-maintenance machine, and ubiquitous machines.

Cloud computing is the next step in the evolution of ICT infrastructure as shown in Fig. 5. It enables to realize collaborative design, distributed manufacturing, collective innovation, data mining, semantic web technology, and virtualization. A new paradigm namely cloud manufacturing has proposed with applying cloud computing (Zhang, et al., 2014). In smart manufacturing, cloud computing enables to develop products quickly with minimum costs through a social networking. Model of the cloud computing system is parallel and distribution which consists of a collection of
inter-connected physical and virtualized service pools of design and manufacturing resources. The manufacturing cloud service can offer capabilities for design and manufacturing solutions at certain levels, such as manufacturing cells, general purpose machine tools, and standardized machine components (Wu, et al., 2012, Herrmann, et al., 2014).

Fig. 5 Concept of cloud computing.

4. Development of a cloud based smart machining system

The architecture of a machining system based on cognitive agents for adapting to disturbances is shown in Fig. 6. A multi-agent system was developed to keep the manufacturing process running when disturbances appear. In this application, resources of the machining shop are controlled by cognitive agents in the case of disturbances. Cognitive agents are divided into functional agents including work-piece agent, transporter agent, machine agent, and robot agent. This division is based on functions which agents undertake in the machining shop. Work-piece agent manages the processing state of a work-piece. Each work-piece is assigned by an identification number stored in the RFID tag that was attached on the work-piece. Every machine on the shop floor is represented by a machine agent. The machine
agent has knowledge about its machine’s physical, process capabilities, probable tooling and schedule. The machine agent receives the sensor information from the machine about the machine status and processes. This enables the machine agent to inform the work-piece agent when the processing starts and in particular, when the processing ends and the work-piece leaves the machine. The transporter agent contains routings of the transporter, consequently, interacting with the work-piece agent to transfer the work-piece to the corresponding machine tool for processes. The robot agent contains the information of the robot, about the operations, availability, and interactions with the machine agent to put or take the work-piece to the machine tool. In the smart manufacturing, the cloud computing are proposed for integrating and reallocating the machining resources. Communication among machines or machine to machine (M2M) in cloud environment is established using wireless technology.

In order to accomplish the activities of a smart machining system, the information and their flow were modelled as shown in Fig. 7. The manufacturing execution system (MES) information for scheduling and planning, dispatching, and process manage, is supported to generate the process and operation plan as well as to monitor the process and schedule.
The information of the machine agent includes the information of its own machine’s physical and process capabilities, as well as the information for reasoning and decision making. This information is used for carrying out the composed machining process and the cooperation with other agents. The information of work-piece, transporter, and robot agent delivers their own data to support the decisions of other agents and to communicate for deciding where to go (Park, et al., 2012).

Fig. 8 Mechanism of the machining system for adapting to disturbances.

The mechanism of system for adapting to disturbances is shown in Fig. 8, the MES first sends a task command to both the controllers and the machine agent (denoted by 1). The cognitive processor identifies the goals and transforms them into desires. The state of the machining shop is updated by the monitoring module. In case disturbances occur, depending on the types of high- or low-frequency signal, fuzzy logic is used for diagnosis with low frequencies, and a neural network is used for high frequencies (Wang, et al., 1999). Diagnosis results report states of the machining shop: either disturbed or normal status (denoted by 2). The planner compares the data from the output of the diagnosis
module with the desired goals. If the data match the desired goals, a message is sent to the MES to report the normal state of the machine (denoted by 3), and the shop floor continues running. Otherwise the decision maker generates a new plan based on the data, desires and intentions (denoted by 4). This plan is carried out directly by the machine in which the disturbance happens (denoted by 5) when the disturbance is easy to recover from. This case is illustrated by a disturbance such as tool wear, for which the machine agent adjusts cutting conditions without affecting the quality of the product. In case the disturbance is difficult to recover or needs operator intervention, such as in the case of a machine breakdown, this plan is carried out by another machine. The machine implements a negotiation with other machines, sending a request for help to all machines. Then, the work of the machine in which the disturbance happens is performed at another machine in order to keep the manufacturing system running (denoted by 6). The selected machine sends a message to the work-piece and the transporter (denoted by 7) to report that it is performing the work of the machine in which there was a disturbance. The machining system returns to the previous plan when the disturbed machine is restored. This solution is applied for disturbances that require only a short recovery time. In case the disturbances require a long time to recover, or the negotiation between machines does not have any solution, the request is sent to the MES for rescheduling (denoted by 8).

For realizing a cloud based machining system, the private cloud was chosen as shown in Fig. 9. In this model, the server system of the enterprise is used for developing as a private cloud, and clients are the machining machines which are managed by the computer. The communication between clients and private cloud is executed through LAN network. All of the computing function modules, which are necessary for managing the machining machines in the CSMS, are developed and stored in the server system. Through the control interfaces and communication special protocols, the clients enable to query the cloud for using the suitable function module that they need to analysis data, and get the necessary results. The advantage of the private cloud model comparing to the two remain model (public cloud and hybrid cloud) is the lower investment cost for developing and maintaining system, and the data are safety also.

![Fig. 9 Deployment models of cloud computing system.](image)

Based on the smart machining system (SMS) concept and cloud computing technique, Fig. 10 shows the concept of private cloud based SMS. In this concept, a server system with high computing power and large data memory is used for developing to a cloud module, and clients are the cognitive agents. The cognitive agents of the SMS are developed to the clients in the cloud based SMS. The LAN network is used for communicating between the cloud module and the clients. In the cloud based SMS system, all of the function modules which are necessary for performing the characteristics of an autonomous system such as database function module, knowledge based function module, communication function module and agent functional modules are developed and embedded into the cloud module. A
main interface is also developed in the server system for communicating to clients and managing the sub function modules. The main function of the cloud module in this system is to receive the computing requests from clients, process that requests by using its high computing power, and response results to the clients.

![Diagram](image)

Fig. 10 Concept of private cloud based SMS.

5. Case study

To develop the cloud based smart machining system, the manufacturing system for machining the transmission cases is considered as the research object. The machining system consists of 12 machines for 17 processing operations. There were 685 disturbances happened during three years. These disturbances were classified into groups as shown in Table 1.

Table 1. Disturbance group

| Disturbance group               | Type of disturbance                                      |
|---------------------------------|----------------------------------------------------------|
| Related to resources            | Machine breakdown                                        |
|                                 | Maintenance of machine                                   |
|                                 | Tool broken                                              |
|                                 | Tool-wear                                                |
|                                 | Operator absenteeism                                     |
| Related to orders               | Unavailability of raw material                           |
|                                 | Cancellation order                                       |
|                                 | Rework                                                   |
|                                 | Arrival of a new job order                               |
|                                 | Urgent job                                               |
|                                 | Delay in transport using the material handling system     |
| Related to measurement of data  | Processing time variation                                |
|                                 | Variation of set-up time                                 |
|                                 | Change of priority                                       |
| Control software and Communication networks | Malfunction                                      |

The disturbances happening in the conventional machining shop were analyzed to classify and to derive out of the measures as shown in Fig. 11. From the analysis of happened disturbances, there are three types of disturbances, which are rescheduling, non-negotiation and negotiation type. In the consideration of taking measures, the rescheduling type
means that the assigned machining task should be rescheduled due to the long recovery time, e.g. more than one hour while stopping the whole system. This given time is based on the effect of disturbance to the planned schedule of the considered machining shop. Over this time, it is very hard to keep the planned schedule within the limited tolerance. Rescheduling policies specified during the rescheduling process were proposed in the literature. The rescheduling is done when disturbances belong to external factors of manufacturing systems such as job cancellation, due date change, urgent job arrival, and arrival delay or shortage of materials. The machine breakdown and other kinds of internal disturbances are considered for rescheduling if they take long recovering time or inability to recover, which affects the current planned schedule. The non-negotiation type belongs to the disturbances of which the recovering time is less than 30 minutes, and the methods for recovery are known from the previous experience. The given time for classifying non-negotiation or negotiation types is based on the statistics of disturbances when machining the transmission case. The disturbances requiring less than 30 minutes for recovering them are mostly fixed by an operator with his own knowledge. So these disturbances were classified into the non-negotiation type. The remainder of disturbances was grouped to the negotiation problem. Those disturbances can be solved with the knowledge collected when operating the conventional machining shop through the agent negotiation process within the machining shop. The disturbance analysis points out the 685 disturbances (100%) collected in the machining shop which can be distributed into: the non-negotiation with 11.4%, negotiation with 40.9% and rescheduling with 47.7%.

![Disturbance classification and management methods.](image)

In the conventional machining system as shown in Fig. 12, due to manual recovery when the disturbances happen, the system utilization is too low. Currently, in the case of the disturbance such as the tool wear, the cutting conditions are not changed. In case the disturbance belongs to the negotiation group such as the tool broken, the machining system must be stopped.

Based on the hierarchy structure of the real machining system, the test-bed of a cloud based smart machining system (CSMS) was build and developed as shown in Fig. 13. The CSMS hardware is classified to three layers such as control, monitoring and LAN layer. At the lowest level, the control layer consists of the actuators, robots and switches. For a cognitive agent, these components are controlled by a programmable logic controller (PLC). The PLC is also using for collecting the agent status and send to the computer (PC) managing agent. Profibus or TCP/IP protocol is used for connecting and communicating between PLCs with PC. The middle level is the controlling and monitoring layer. All of
the computers which manage agents belong to this layer. In the CSMS, all of working situations of a machining machine are monitored and managed by a computer. The computers in this layer are also the bridge to connect from control layer to cloud layer. Cloud layer, the highest level, includes all the equipments which are used for configuring cloud system. Cloud system is considered as the brain of the CSMS where all the database and knowledge base of the CSMS are stored. This layer also provides the high computing power to the cognitive agents for analysing disturbance and making decision to overcome the problem during working time.

![Fig. 12 Conventional machining system.](image12)

![Fig. 13 Hardware architecture of a private CSMS.](image13)
Fig. 14 shows the proposed system software architecture for a CSMS based on the system hardware structure. This system operates on Microsoft Windows OS. The .NET platform with Microsoft Visual Studio tool is used for developing the functional modules of virtual private cloud and also the cognitive agents. MySQL server tool is used for managing the system data in the cloud. In the client, Kepware OPC tool is used for communicating between client management computer and outside hardware. TCP/IP protocol with wireless technique is used for communicating between cloud and clients.

Fig. 15 System behavior of the cloud based SMS in the case of negotiation.
When any disturbance occurs in the system at current working time, for solving this problem, the client is enabled to connect to cloud and the others for getting the best solution. The communicating framework of this system in the case of negotiation disturbance for agents is presented in Fig. 15. The strategy for developing communication protocol between cloud and clients in the cloud based SMS is shown in Fig. 16. The LAN wireless network with the TCP/IP protocol is used for exchanging data between cloud and clients. The messages with appropriate encodes are used for sending and getting the data in the cloud and clients. The communication message structure is also presented in this figure. The message is classified into the bytes with the rule: the first three bytes show the sender address; the next three bytes show that message is the request or response; and remaining bytes show the request or response contents. Following these rules, the communication between cloud and clients is performed easily.

Fig. 16 Message structure for communicating between cloud and the agents.

Fig. 17 presents the strategy for developing the cloud module of the cloud based SMS system. C# tool was used for developing the cloud module. The MySQL server is used for developing the database and knowledge modules for the
system, where store all the necessary data and knowledge for the working time of the system. In this strategy, the main interface will manage all the operation of the cloud modules. It enables to query to all the function modules of cloud including the database and knowledge function. After receiving the request from clients, main interface module will analyze the message and make the decision, then send the result to the appropriate function modules embedded in the cloud.

![Diagram of CSMS client development](image)

Fig. 18 Development of the CSMS client.

All of the sub function modules of the cloud such as database, knowledge, communication function module and agent’s function modules are developed for performing the characteristic of the SMS. The C# was used for developing the interface of the clients as shown in Fig. 18. After programming, these interface modules are built to .exe format and embed into the clients. The data of the machining time are collected by the programmable logic controller (PLC) and connected to the computer through TCP/IP protocol. For getting the data from PLC, Kepware OPC tool was used. The OPC Automation reference tool is used for programming to link from the client interface to the Kepware OPC tool. In the processing time, through the Kepware OPC tool, the clients are enabled to get the process information from the machine and sensors.

With the proposed technologies, the functionality of the SMS was tested successfully on the test-bed. In comparison with other system, the cloud computing based machining system shows the more advantages such as the short time to response to the changes of manufacturing environment. Fig. 19 shows the machine’s self-adjustment mechanism in the case of tool wear. The MES dispatches the process plan of each machine according to the identification information of the machine tools (which are called machine tool ID numbers). During the machining process, the amount of current tool wear is predicted using an artificial neural network (ANN). The neural network configuration is 6-10-1 as shown in Fig. 20. The network consists of 6 input neurons corresponding to 6 input parameters: cutting force, feed rate, depth of cut, processing time, cutting speed and initial tool wear. Assume that the initial tool wear is zero for the fresh tool. The value of cutting force is got from the force sensor on the machine. The values of cutting conditions (feed rate, depth of cut and cutting speed) and the processing time are from the process planning for machining the product. There is one hidden layer with 10 neurons. The offline training was stopped after 2000 training iterations and the minimum error achieved was 0.025. The formula for calculating the surface roughness of the machined part in consideration of the predicted tool wear is given by Pal, et al. (2011). The $R_s$ must stay within an allowed range. The value of the surface roughness in the case of the turning operation, for example, is as follows:
where $r_e$ is the tool nose radius (mm), $f$ is the feed rate (mm/rev), and $T_w$ is the amount of tool wear (mm). Example of ANN input data for predicting the tool wear and comparison of the result with the experimental data is shown in Table 2.

$$R_u = \frac{0.125 \times f^2}{r_e} \times (1 + 1.6103 \times T_w)^{0.7315}$$  \hspace{1cm} (2)
Table 2. Example of ANN input data for predicting the tool wear and comparison of the result with the experimental data

| Test | Cutting force (N) | Feed rate (mm/rev) | Depth of cut (mm) | Processing time (mm) | Cutting speed (m/min) | Initial tool wear (mm) | Actual tool wear (mm) | Predicted tool wear (mm) | Error (mm) |
|------|-------------------|--------------------|------------------|---------------------|----------------------|------------------------|----------------------|-------------------------|-------------|
| 1    | 609               | 0.1449             | 1.5              | 5                   | 160                  | 0                      | 0.140                | 0.133                   | 0.007       |
| 2    | 608               | 0.1398             | 1.5              | 10                  | 160                  | 0                      | 0.174                | 0.173                   | 0.001       |
| 3    | 607               | 0.1347             | 1.5              | 20                  | 160                  | 0                      | 0.208                | 0.205                   | 0.003       |
| 4    | 609               | 0.1449             | 1.5              | 30                  | 160                  | 0                      | 0.292                | 0.279                   | 0.013       |
| 5    | 619               | 0.1680             | 2.0              | 5                   | 160                  | 0                      | 0.165                | 0.147                   | 0.015       |
| 6    | 610               | 0.1500             | 2.0              | 20                  | 160                  | 0                      | 0.195                | 0.216                   | -0.021      |

High quality. In order to achieve this goal, the determination of optimal machining parameters such as cutting speed ($v_c$), feed rate ($f$) and depth of cut ($a_p$) plays an important role (Fig. 21). The generation of optimal cutting parameters ($v_c$, $f$, $a_p$) includes consideration of objective functions such as cutting quality (represented by the surface quality $R_a$), production rate and operation cost. The production rate and operation cost are determined via the metal removal rate ($MRR$) and tool life ($T$) functions.

To maintain consistent quality in the machined products, the new cutting parameters are determined using another ANN, using as its inputs the depth of cut, the cutting speed and the amount of tool wear, and giving the optimal feed rate as its output; the neural network configuration is 3-9-9-1 (Fig. 22). There are two hidden layers of 9 neurons each. The offline training was stopped after 2000 training iterations and the minimum error achieved was 0.28. Table 3 shows some examples of ANN input data for generating the feed rate and comparison of the result with the experimental data. Two ANN models were tested, showing reasonable results in comparison with the experimental data (Fig. 20, Fig. 22). The smart machining system with cognitive agents was tested successfully in the case of tool wear as well as the case of a broken tool. The self-optimizing turning process at machining center #1 allows the quality of the machined products to be maintained despite tool wear, as shown in Table 3. Allowable average range of surface roughness in turning is from $Ra = 0.4 \mu m$ to $Ra = 6.3 \mu m$ (Oberg, et al., 2004). In the case of the fresh tool with the optimal cutting
condition, the surface roughness of the machined part is $Ra = 2.628 \mu m$. In case the amount of tool wear is 0.133 mm, the surface roughness calculated by the equation (2) with the new generated optimal feed rate is $Ra = 2.625 \mu m$ as shown in Table 4. After machining on the real machine, the Mitutoyo SJ-201 equipment for measuring the surface roughness was used. The surface roughness of the machined part measured by the equipment is $Ra = 2.60 \mu m$. The measured value of the surface roughness is a reasonable result in comparison with the target surface roughness ($Ra = 2.625 \mu m$).

Fig. 22 Generation of the optimal feed rate using ANN

Table 3. Example of ANN input data for generating the feed rate and comparison of the result with the experimental data

| Test | Cutting speed (m/min) | Amount of tool wear (mm) | Depth of cut (mm) | Expected feed rate (mm/rev) | Generated feed rate (mm/rev) | Error |
|------|-----------------------|--------------------------|------------------|-----------------------------|-------------------------------|-------|
| 1    | 160                   | 0.158                    | 1.635            | 0.29                        | 0.270                         | 0.020 |
| 2    | 160                   | 0.174                    | 1.755            | 0.45                        | 0.423                         | 0.027 |
| 3    | 160                   | 0.180                    | 1.800            | 0.55                        | 0.500                         | 0.050 |
| 4    | 160                   | 0.230                    | 2.175            | 1.11                        | 1.010                         | 0.100 |
| 5    | 160                   | 0.290                    | 2.626            | 1.61                        | 1.580                         | 0.030 |
| 6    | 160                   | 0.248                    | 2.310            | 1.19                        | 1.170                         | 0.020 |

Table 4. The generated optimal feed rate in consideration of tool wear

| Feed rate (mm/rev) | Depth of cut (mm) | Processing time (min) | Cutting speed (m/min) | Amount of tool wear (mm) | Surface roughness $Ra$ (µm) |
|--------------------|-------------------|-----------------------|-----------------------|--------------------------|----------------------------|
| 0.135              | 1.5               | 5                     | 160                   | 0.133                    | 2.625                      |

Assume that the disturbance happens in machine #1, and that the machine agent diagnosis assigns it to the negotiation group, for example when the tool breaks. Immediately, the machines begin negotiation as shown in Fig. 23. Machine agent #1 sends a message for help to the remaining machines. The machines negotiate to discover another route. This negotiation is based on the evaluation of the pheromone values of machines, the precedence relationship between the operations and current status of the machines. Each machine has a pheromone value for a specific operation, with the highest pheromone value belonging to the machine with the shortest processing time and the lowest machining cost for that operation. Table 5 shows the pheromone values of machine agent #2 and machine agent #3 for task #1.
Fig. 23 Agent negotiation process.

Table 5. The pheromone value of remaining machine agents to task #1

| Machine | Process       | $M_t$ | $M_o$ | $M_c$ | $M_{co}$ | $\alpha_t$ | $\alpha_c$ | Pheromone value |
|---------|---------------|-------|-------|-------|----------|-------------|-------------|-----------------|
| MA2     | Turning (T1)  | 2     | 2     | 30    | 30       | 1           | 1           | p(t2)=0.5       |
| MA3     | Turning (T1)  | 3     | 2     | 30    | 30       | 1           | 1           | p(t3)=0.4       |

The machine has the highest pheromone value that is chosen for carrying out the jobs of machine #1. After negotiating, the machine agent #2 is chosen for machining the task #1 of the machine #1 based on its own pheromone value, current status, and work-piece information. The machine agent #2 requests the scheduling information from the MES system, and then cooperates with the transporter and work-piece agent to carry out the accepted job. As the result, the green light at the machine #2 on the test-bed is “ON”.

The screen shot of the developed system in the case of the tool broken is shown in Fig. 24. The machine agent gets the disturbance signal from the PLC through KEPServerEx™ software (denoted by 1). Then, the disturbance is diagnosed (denoted by 2). If the disturbance belongs to the negotiation type such as the tool broken (denoted by 3). The network of server/clients is established for agent negotiation (denoted by 4). Then, the negotiation of machine agents is activated using the ant colony based mechanism (denoted by 5). After negotiating, the machine agent with the highest pheromone value is chosen for carrying out the task #1 of the machine #1.
Fig. 24 The screen shot of the system in the case of tool broken.

6. Conclusion

Globalization, unpredictable markets, increased products customization and frequent changes in products, production technologies and manufacturing systems has become a complexity in today’s manufacturing environment. One key strategy for coping with the evolution of this situation is to develop or apply an enable technology such as cloud computing based smart manufacturing. In this article, a new trend related to manufacturing technology is presented. The cognitive agents as well as advanced ICT such as cloud computing increase the system robustness by avoiding centralized control and show the potential of implementing autonomous behaviors by flexible ability in decision making. The cloud based manufacturing system has the enough ability to adapt autonomously to disturbances without upper-level aids or a total planning modification. On the other hand, the manufacturing control system equipped with the artificial cognitive capabilities meets the requirements of flexibility, adaptability and reliability. This technology enables the applicability of cognitive behaviors of human to overcome the disturbances within the machining system. It supports the fast response to disturbances without rescheduling. In the existing manufacturing systems, the dynamic rescheduling is done when the disturbances, such as the machine breakdown or malfunction of the robot, happen. Through the applications of the smart manufacturing in practice, the productivity of the machining system and the machining quality of products will be increased by using the self-adapting and self-optimizing processes, respectively.
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