Closed-loop design evolution of engineering system using condition monitoring through internet of things and cloud computing

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Cloud computing

A B S T R A C T

Flexibility of a manufacturing system is quite important and advantageous in modern industry, which function in a competitive environment where market diversity and the need for customized product are growing. Key machinery in a manufacturing system should be reliable, flexible, intelligent, less complex, and cost effective. To achieve these goals, the design methodologies for engineering systems should be revisited and improved. In particular, continuous or on-demand design improvements have to be incorporated rapidly and effectively in order to address new design requirements or resolve potential weaknesses of the original design. Design of an engineering system, which is typically a multi-domain system, can become complicated due to its complex structure and possible dynamic coupling between domains. An integrated and concurrent approach should be considered in the design process, in particular in the conceptual and detailed design phases. In the context of multi-domain design, attention has been given recently to such subjects as multi-criteria decision making, multi-domain modeling, evolutionary computing, and genetic programing. More recently, machine condition monitoring has been considered for integration into a scheme of design evolution even though many challenges exist for this to become a reality such as lack of systematic approaches and the existence of technical barriers in massive condition data acquisition, transmission, storage and mining. Recently, the internet of things (IoT) and cloud computing (CC) are being developed quickly and they offer new opportunities for evolutionary design for such tasks as data acquisition, storage and processing. In this paper, a framework for the closed-loop design evolution of engineering systems is proposed in order to achieve continuous design improvement for an engineering system through the use of a machine condition monitoring system assisted by IoT and CC. New design requirements or the detection of design weaknesses of an existing engineering system can be addressed through the proposed framework. A design knowledge base that is constructed by integrating design expertise from domain experts, on-line process information from condition monitoring and other design information from various sources is proposed to realize and supervise the design process so as to achieve increased efficiency, design speed, and effectiveness. The framework developed in this paper is illustrated by using a case study of design evolution of an industrial manufacturing system.

1. Introduction

Globalization has intensely changed the engineering manufacturing sector as is the case in many other areas.

The growing demand for novel, high quality and highly customized products at low cost with rapid adaptation to market diversity is fundamentally changing the way production systems are designed and implemented [1]. With the development of information, communication, management, sensing and other technologies and theories, various advanced manufacturing system methodologies have been proposed such as lean manufacturing, agile manufacturing, flexible manufacturing, concurrent manufacturing, sustainable manufacturing, global manufacturing, and so on, in order to accommodate the current extremely dynamic operating environment of manufacturing companies such as market variations, changes to time and quantity of product demand and manufacturing system failure [2]. Most of this new research and development has contributed to advanced manufacturing system at the level of manufacturing and planning. However, one fundamental and significant element in forming a competitive manufacturing system that can adapt to rapid market changes is the capability of automated and evolutionary reconfiguration and design improvement of the system.

In modern production processes, most engineering systems are in fact multi-domain mechatronic systems [3,4], which consist of different domains such as mechanical, electrical, hydraulic, pneumatic, thermal, control, and so on, examples of which are automated packaging lines [5] and car assembly lines with industrial robots [6]. The reconfiguration or design improvement of a multi-domain multi-component system will require simultaneous consideration of all its components and characteristics [7]. This particularly means that dynamic interactions between domains should be considered concurrently throughout the design process. Concurrent, multi-criteria and optimal design are the current main challenges in the design of mechatronic systems [8]. Research on the design methodologies of mechatronic systems is becoming active, which aims to achieve a design with increased reliability and flexibility, greater intelligence, and reduced complexity and cost. The design process of a multi-domain engineering system can be complicated due to its complex structure and dynamic coupling (interaction) between domains. Ideally, designing a multi-domain system should be done in an integrated and concurrent manner, where dynamic interactions between domains in the entire system have to be considered simultaneously, throughout the design process [4,9]. In recent years, researchers have made some progress in the integrated and optimal design of multi-domain systems. Dynamic modeling tools such as Bond Graphs (BG) [4,10] and Linear Graphs (LG) [4,9] have been considered for modeling multi-domain systems, which can facilitate the design process. Design optimization can then be achieved by using methods of evolutionary computing, genetic programing in particular. Koza et al. [11] employed GP for the automated design of electrical circuits. The solution space represented in a tree-like structure is explored by GP. Inspired by the work of Koza et al., Seo et al. [12] combined bond graph modeling with GP to explore the design space of a mechatronic system in achieving an optimal design. Wang et al. [13] utilized a similar framework for the automated design of a controller. Design knowledge was also acquired from their framework to supervise the search of the design space. Behbahani [14] and de Silva [15] extended the combined BG–GP approach for nonlinear mechatronic systems. More recently, machine condition monitoring has been integrated into the framework of evolutionary design optimization [16,17]. It can provide the information of locations of a possible design weakness which may lead to system malfunctions or unsatisfactory system performance. It shows promising potential for precise and continuous design improvement of complex engineering system. However, the progress of implementing machine condition monitoring to engineering system design improvement is still at the beginning as there are still many issues to be solved. Monitoring of a complex engineering system with a large amount of components brings technical challenges and unaffordable cost in sensing, massive data transmission, storage and processing. For instance, acoustic emission sensors are widely used in detecting early stage failure of rotating machine such as bearings and gearboxes. However, use of one acoustic emission sensor at sampling frequency of 1 MHz will create 200– 300 GB raw data per hour which is unaffordable by traditional data storage and processing approaches.

The internet of things (IoT) [18] and cloud computing (CC) [19] have brought about new opportunities for sensing, storage and mining of data, online computing, ubiquitous accessibility and affordable cost. Technologies of IoT and CC have been developed and applied at a rapid rate, which have provided new opportunities to address the challenges in achieving more efficient and effective machine condition monitoring for reconfiguration and design improvement of manufacturing systems. In the field of engineering, evolution of an industrial system from its original creative solution to a modern system progresses gradually, with specific contributions from design experts [20]. However, this process takes a comparatively long time and heavily relies on reliable domain expertise. In this paper, a framework for the design evolution of an engineering system with the assistance of IoT and CC is proposed. Through the process of closed loop design evolution, the engineering system can be improved continuously, efficiently, and cost-effectively. The remaining of the paper is organized as follows. Section 2 introduces the related work on engineering system design, machine condition monitoring and IoT and CC. The framework of the closed loop design evolution of an engineering system is described in Section 3. A comprehensive case study is performed in Section 4 to demonstrate the application of the proposed framework for design evolution. Section 5 concludes the paper and indicates possible future work.

2. Related work

2.1. Engineering system design

The design of an engineering system is carried out broadly at two levels: the conceptual design where the type and function of the subsystems are identified and some high-level decisions about the operation of the system are made [21], and the detailed design where the

In the conceptual phase, high-level decisions of the system structure and feasible conceptual choices are made according to the design expectation. Conceptual design is rather important in a design process. The design space can be huge as there can be a variety of possible configurations, and it is not feasible to achieve the best design in one step. In conceptual design, the designer divides the complex design space into several subspaces and evaluates all these subspaces properly and narrows the design down to one or two subspaces. This offers a less complex searching space for the subsequent phase of detailed design. Moulianitis et al. [22] proposed a model to evaluate the conceptual design of a mechatronic system. However, the possible interactions between criteria were not considered in criteria aggregation. A rather challenging task in design optimization is to concurrently satisfy multiple design objectives. Behbahani and de Silva [23] presented a systematic approach for concurrent and integrated design of a mechatronic system by using the concepts of mechatronic design quotient (MDQ). Their approach used MDQ in the evaluation model to facilitate decision making to achieve an optimal conceptual design of a 2-D manipulator. MDQ is an effective tool in multi-criteria design evaluation for mechatronic systems. It can be utilized to evaluate the possible conceptual alternatives in the conceptual design phase. In a design problem of n design criteria and r constrains, MDQ can be written in the following form:

$$\mathrm{MDQ}(a) = M[x_1^a, x_2^a, \ldots, x_n^a] \prod_{i=1}^{r} g_i(a) \tag{1}$$

where a represents a design alternative, M is an aggregation operator, x_i^a is the partial score that shows the degree of satisfaction of the ith criterion, and $g_i(a)$ is a function indicating whether a constraint has been met. In particular, $g_i(a)$ is equal to one if the ith constraint is met. Otherwise, it equals to zero.

The evolution criteria in the MDQ formulation may include "Meeting task requirement," "Complexity," "Reliability," "Matching," "Flexibility," "Control friendliness," "Efficiency," and "Cost" [15]. In practice, the designer may decide to utilize other criteria if they are important for the design problem, or drop some of the above criteria if they are not important to the particular design problem. Some of the criteria may take an analytical form while some others may be qualitative and fuzzy and may involve human perception [7]. A key step is the aggregation of criteria. Interactions can exist between criteria. The traditional aggregation method, weighted average, cannot deal with the interaction between criteria and it is only suitable when the criteria are independent. Fuzzy measure is effective in modeling interactions between criteria. Fuzzy measures are used to model the interactions between criteria in many situations [24]. In the discrete case, a fuzzy measure on N is a set function $\nu : 2^N \to [0,1]$ satisfying

$$\nu(\phi) = 0 \tag{2}$$

$$\nu(N) = 1 \tag{3}$$

$$S \subseteq T \Rightarrow \nu(S) \le \nu(T) \tag{4}$$

For any $S \subseteq N$, $\nu(S)$ can be interpreted as the weight of the degree of importance of the combination S of criteria [25]. Several fuzzy integrals have been developed in aggregating the criteria in multi-criteria decision making [26]. The Choquet integral has been developed and utilized in many applications of multi-criteria evaluation [27,28]. A Choquet integral can be used for the aggregation of criteria in MDQ.

A Choquet integral can then be utilized to aggregate the criteria to compute the global score of each alternative using the following equation

$$C_\nu(x) := \sum_{i=1}^{n} x_{(i)}[\nu(A_{(i)}) - \nu(A_{(i+1)})] \tag{5}$$

where $(\cdot)$ indicates a permutation of N such that $x_{(1)} \le \cdots \le x_{(n)}$, $A_{(i)} = \{(i), \ldots, (n)\}$ and $A_{(n+1)} = \phi$ [24]. The Choquet integral can be written in another form

$$C_\nu(x) = \sum_{T \subseteq N} a(T) \bigwedge_{i \in T} x_i \tag{6}$$

where $\wedge$ denotes the minimum operator and the set function $a : 2^N \to \mathrm{R}$ is the Mobius transform of fuzzy measure ν as given by

$$a(S) = \sum_{T \subseteq S} (-1)^{s-t} \nu(T) \tag{7}$$

where $s = |S|$ and $t = |T|$.

The key problem in using the Choquet integral is that 2^n coefficients in $[0,1]$ need to be specified to define the fuzzy measure on every subset of n criteria. This is challenging for designer and is not practical in real application. Grabisch [29] suggested to consider the 2nd order Choquet integral that seems to be more practical in real applications. It allows to model interaction among criteria while remaining very simple and operational. The 2nd order Choquet integral is given by

$$C_\nu(x) = \sum_{i \in N} a(i) x_i + \sum_{\{i,j\} \in N} a(ij)(x_i \wedge x_j) \tag{8}$$

where $a(i) = \nu(i)$ and $a(ij) = \nu(ij) - \nu(i) - \nu(j)$ by Eq. (7).

After the specification of $\nu(i)$ and $\nu(ij)$, all $a(i)$ and $a(ij)$ can be calculated. Therefore, instead of 2^n coefficients, only $n + C_n^2 = n(n+1)/2$ coefficients are required.

In the phase of detailed design, first the best topology is determined, for example, system components and their interconnection. Then component details are specified to achieve a best satisfaction of the design requirement. Methods of evolutionary computing, genetic programing (GP) in particular, have received much attention in recent years for autonomous topology generation. Evolutionary algorithms are proved to be effective in assisting designers to search the detailed design space and achieve an optimal design. The loop of GP operation is iterated until a termination condition is reached or predefined number of iterations is carried out. The design outcome is then further evaluated for practical implementation.

However, many issues are still to be addressed before this approach can be applied in practice for complex mechatronic systems. For example, arbitrary evolution of a design model of complex system can result in vast computation [12] as well as infeasible outcomes that cannot be

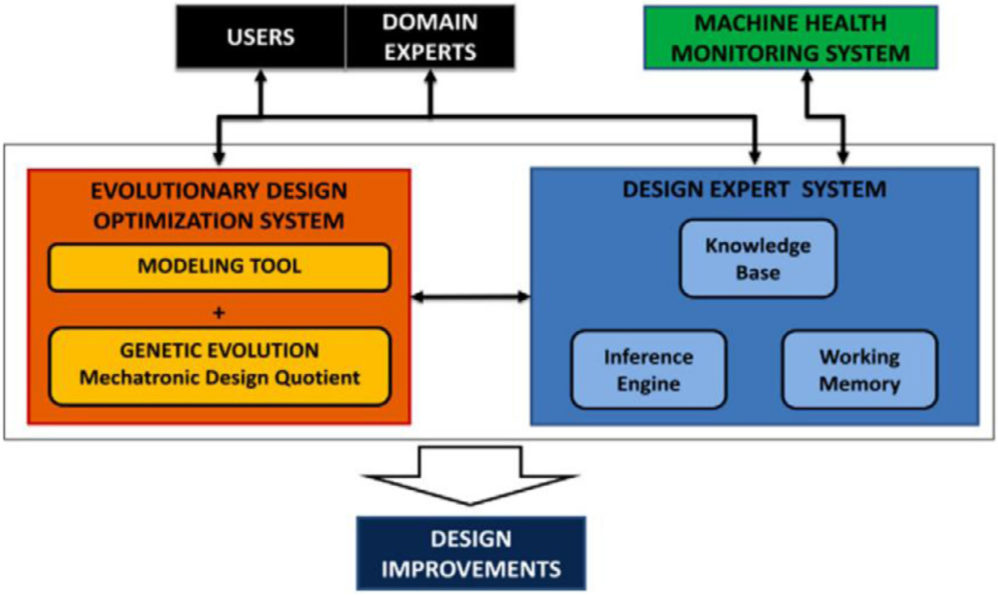

Fig. 1. System framework of design evolution with machine health monitoring system [16].

implemented in reality [16]. Therefore, it is important to narrow down the search space by detecting the potential weaknesses where redesign or design improvement should be conducted.

2.2. Machine condition monitoring

With the growing capabilities of condition data acquisition and data mining of a running system, machine condition monitoring has shown much potential in identifying weaknesses in engineering systems that can be related to inappropriate design. De Silva [4] and then Gamage et al. [16] proposed a framework that can specifically integrate a machine health monitoring system and an expert system to carry out design evolution of a multi-domain dynamic system, as shown in Fig. 1. The utilization of information from condition monitoring of the engineering system was proved to be useful in design improvement of the system by detecting a malfunction of the system.

Machine condition monitoring (or, machine health monitoring) has been traditionally used to detect, diagnose and correct system faults [30]. In the past several decades, much research has been conducted in the area of condition monitoring and fault diagnosis of industrial engineering systems [31–34]. Another significant application area of machine condition monitoring is prognostics and condition-based maintenance. Through the information from condition monitoring of a dynamic system, the remaining useful life (RUL) of the system can be predicted and an appropriate maintenance plan can be established to achieve good performance of the system at a minimum maintenance cost [35–39]. Besides fault detection, more valuable information such as system performance and remaining useful life can be evaluated from the condition monitoring data to detect potential for design weakness detection of an engineering system through machine health monitoring. Using the sensed condition data, system performance evaluation, fault diagnosis and remaining useful life estimation are performed to identify the weaknesses of the current design.

Still, there are many important and unresolved issues of integrating machine condition monitoring and engineering system design. For instance: (1) The traditional monitoring systems face many challenges related to communication of sensed data and storage of huge amounts of data.
(2) Computing capability of a local computer to analyze and interpret large quantities of data. (3) How to collect sufficient condition data. (4) How to monitor the same or similar modules at different locations. (5) How to analyze the data and translate the results into knowledge. (6) How to manage and share the knowledge for assisting the design process, especially collaborative design. (7) How to keep it cost effective due to the large amount of sensors and data acquisition devices needed.

2.3. IoT and CC

In order to address the issues mentioned above, the present work utilizes a machine condition monitoring system based on IoT and CC to assist the design improvement of an engineering system. As an emerging technology, IoT has seen considerable development. It is expected to offer promising solutions to improve the operation and the role of many systems such as manufacturing, healthcare and transportation [41–43]. The application of IoT in modern manufacturing is an active topic. Tao et al. [44] proposed a cloud manufacturing service system that uses CC and IoT, addressing the bottlenecks experienced by the current manufacturing system. Their system consisted of four layers: IoT layer, service layer, application layer, and bottom supporting layer. Wang et al. [45] discussed a framework

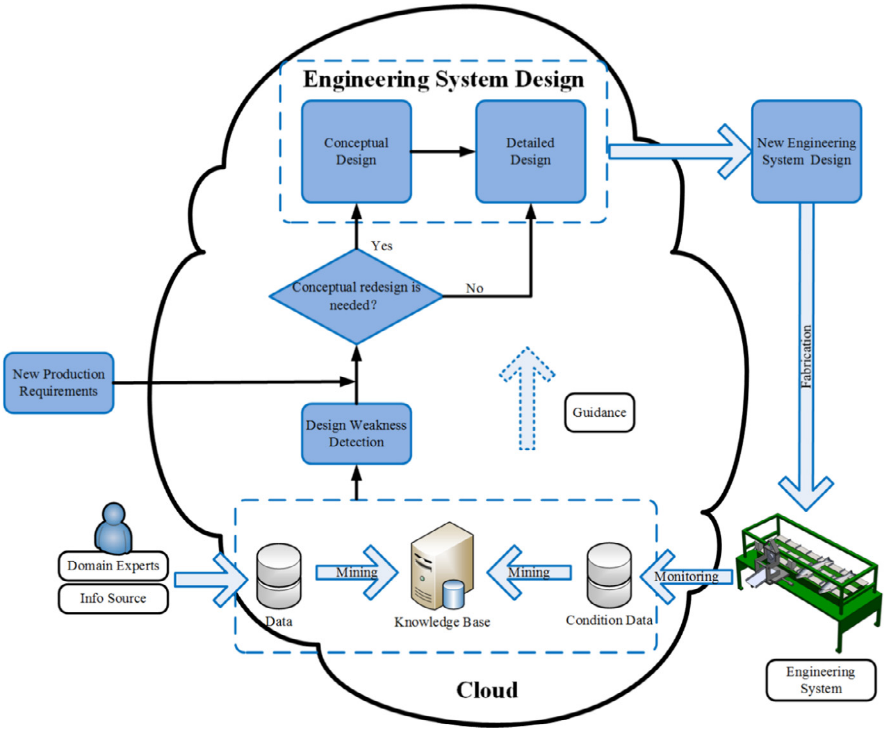

Fig. 2. Framework for closed-loop design evolution of an engineering system.

for implementing a smart factory based on IoT, industrial wireless networks, and cloud and mobile terminals. IoT has shown a great potential in collecting information from production resources, manufacturing devices, supply chain, and so on to assist decision-making at various levels of manufacturing enterprises. One fundamental technology of IoT is wireless sensor network (WSN) that interconnects intelligent sensors to sense, communicate, and monitor [46]. WSN has been successfully applied in various monitoring scenarios such as environmental, health and wellness, power, inventory location, seismic, structural, factory, and process automation [47]. Due to its advantages of smaller size, easier connection and communication and lower cost compared with wired systems, WSN has been widely used in industrial monitoring application [48]. Lee et al. [49] designed an autonomous networked wireless sensing system for monitoring mechanical wear-out of the parts in a CNC machine. WSN has been utilized for industrial machine condition monitoring and fault diagnosis [50,51], and industrial automation [52,53]. In the present work, a condition monitoring system under the framework of IoT is utilized to collect system operational data (production speed, capacity, precision, energy consumption, etc.), machine condition monitoring data, and database of available resources such as different engineering models, modules or components for representation, reconfiguration or design improvement of an engineering system, as well as any other useful data that is related to the system performance, which will be considered in the design process. Furthermore, with IoT support, data collected not only from the manufacturing system at one site, but also from the same or a similar manufacturing system at different sites can be utilized to generate a more precise estimation of the system status.

At present, CC is rapidly developing as a promising paradigm for the usage of resources in the form of a service over the network [54]. It offers more flexible, more accessible and on-demand computing and data storage services. With decreasing cost of implementation and maintenance, and improving reliability and capacity of CC, more and more enterprises have begun to embrace this paradigm by moving their data-base and applications into the cloud [55]. Valilai and Houshmand [56] proposed an integrated and collaborative platform for distributed manufacturing agents based on CC. Bahga and Madisetti [57] presented a novel framework with CC for storage, processing and analysis of massive machine maintenance data, collected from a large number of sensors embedded in industrial machines. With the advantages of CC, the problem of massive data storage and analysis can be dealt with in a more rapid, efficient and effective way. Thus, CC is used in the architecture that is proposed in the present paper to address the issues of the traditional condition monitoring system in data transmission, data storage, sharing and computing of data (and information) to assist the decision making.

3. System architecture

Fig. 2 shows the overall framework of design evolution of engineering system through condition monitoring using IoT and CC. With the support of IoT, condition

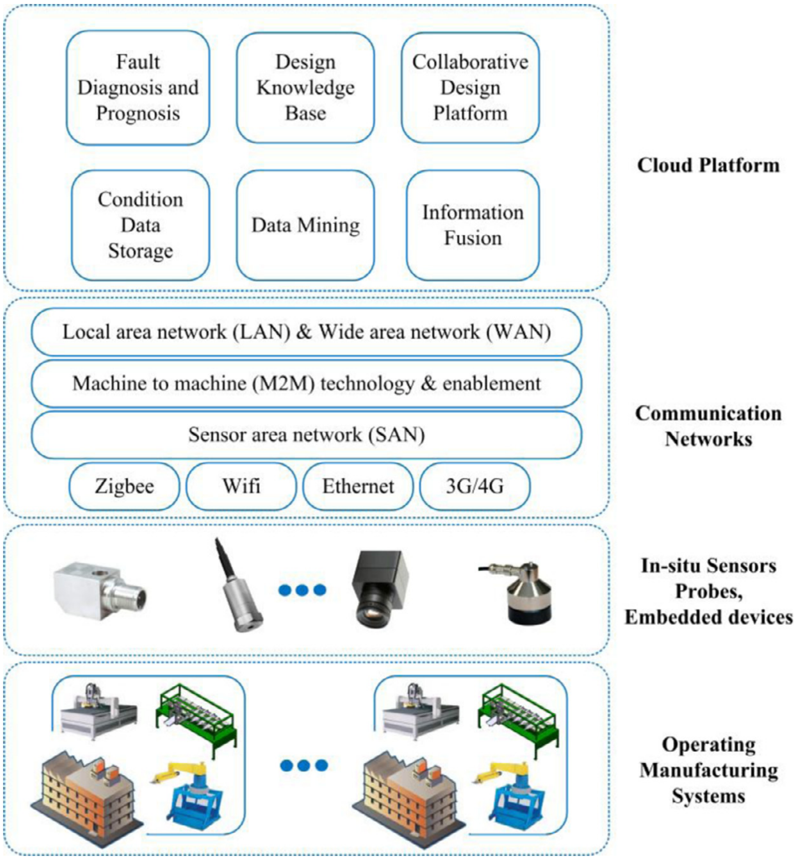

Fig. 3. Proposed scheme of condition monitoring through the IoT and CC.

data are collected at different sites of the engineering system. The status of the operational system and of the subsystem modules are analyzed through data mining technologies by evaluation of the system performance, diagnosis of faults, and estimation of the remaining useful life. Then design weaknesses are detected for the monitored system and provided for consideration in a future stage of design improvement. New design methodologies, available technologies, developed functional modules and their parameters can be collected from domain experts, handbooks, Internet and other information sources. This information, together with the information from condition monitoring, can be utilized in forming a design knowledge base. The design knowledge base is continuously updated in this manner. It can assist the designers in generating a more innovative and efficient design solution both in the conceptual design stage and the detailed design stage. In this manner, a closed-loop design improvement process is achieved to accommodate new design requirements or to correct any system design weakness.

3.1. Condition monitoring through IoT and CC

The main task of condition monitoring is to acquire put, capacity, speed, torque, power consumption, size, weight, vibration, current, voltage, and other response variables and parameters that can be valuable for evaluating the current status of the system. The proposed scheme of condition monitoring through IoT and CC is shown in Fig. 3. With the support of IoT, the condition data from various modules of an engineering system, not just at one site but at different and geographically separated sites can be collected. When a system consists of multiple sites (or sensor nodes), fusion of the condition data from different sites can provide a more reliable estimation of the system performance. This process includes three main steps: data acquisition and preprocessing, data transmission, and data analysis.

3.1.1. Data transmission

A network layer is utilized to transmit the sensed data. Short-range wireless networks such as WiFi, Bluetooth, Zigbee and Sensor Area Network (SAN) are common technologies to support the connection of sensors, devices and users, for data transmission. Internet Protocol version 4/Internet Protocol version 6 (IPv4/IPv6) are common standards for the transport networks. Data on the system condition (condition data), after preprocessing, are transmitted through the network layer to the cloud database.

3.1.2. Data mining

From the condition data, three main types of analysis are conducted: system performance evaluation, machine fault detection, and prediction of the remaining useful life.

Desirable system performance and low cost are two key objectives in mechatronic system design. Factors related to performance of a mechatronic system include: capacity, efficiency, reliability, stability, accuracy, and so on. Requirements of system performance can be extended to integrate other requirements such as controllability and low cost. Here, performance variables are defined by the designers according to the design specifications.

Machine fault detection may be treated as a procedure of mapping the information obtained in the measurement space and/or features in the feature space to machine faults in the fault space [30]. This mapping process may be considered as a procedure of pattern recognition. It is achieved by automatic classification of the signals based on the features extracted from them. Artificial Intelligence (AI) techniques have been increasingly applied to machine diagnosis and have shown improved performance over conventional approaches. Some common AI techniques include expert systems, fuzzy logic, artificial neural networks, genetic algorithms and support vector machines. The efficiency of AI techniques has been found to be satisfactory in many case studies.

Prediction of the remaining useful life implies the prediction of the time left before a failure would occur given the current and past profile of the machine condition. To perform prognosis, we must have a knowledge (or information) on the failure mechanism as well as knowledge (or information) on the fault propagation process. Similar to fault diagnosis, there are three main approaches of prognosis: statistical approaches, artifi-cial intelligence approaches, and model-based approaches. In particular, statistical approaches such as the Hidden Markov Model and Particle Filter are widely used in RUL prediction.

3.1.3. Design knowledge base through CC

In the proposed framework, the design knowledge base is constructed on a cloud computing platform using the design expertise of domain experts (design methodologies, regularized design, etc.), technical solutions, available function modules with their specifications, design handbooks, data tables, catalogs, the Internet, information from condition monitoring system (system performance, detected fault, maintenance history, remaining useful life), and so on. The knowledge base is updated in an evolutionary manner through mining of the continuous condition monitoring data, experts input, new technology approaches, newly developed modules, etc. with the support of IoT. Collaborative design can be promoted by sharing the knowledge base between the designers from different sites through ubiquitous access to the knowledge base. Through an inference engine, the design knowledge base is utilized to supervise the searching of design space both in the conceptual and detailed phases by reducing

3.2. Closed-loop design improvement

As shown in Fig. 2, closed-loop design improvement of an engineering system is achieved through design weakness detection using condition monitoring and subsequent conceptual design, detailed design, and implementation of the design improvements. The process of design improvement is carried out under the guidance of a design knowledge base that is continuously updated.

In the stage of conceptual design, innovative ideas and multi-criteria evaluation are crucial. With a cloud-based design knowledge base and a collaborative design scheme, creative design ideas can be investigated among the design team more easily and efficiently. With the assistance of the design knowledge base, the design space for conceptual design can be structured to form possible conceptual alternatives.

In the detailed design stage, after establishing a dynamic model of a multi-domain system, an algorithm that can explore the design space should be applied to achieve the detailed design leading to a desired optimal behavior of the system. Specifically, the model will be modified in some manner so that the behavior approaches the desired behavior, in an optimal manner, as represented by a cost function. In the area of detailed design optimization, genetic programing has been employed to realize an optimal design in an evolutionary manner, so as to satisfy a set of specified design objectives.

Using the outcome of detailed design, production of the engineering system will be carried out. Then, this new generation of the engineering system will be implemented in manufacturing to achieve the required production task. Condition monitoring will be conducted once the designed system starts running. Fig. 4 shows the procedure of detecting a potential design weakness in the current design.

From the monitored condition data, system performance evaluation, fault diagnosis, and prognosis are carried out. Design weakness candidates can be identified using the Design Weakness Candidate Index, which is defined as

$$\mathrm{DWCI} = W \begin{bmatrix} S(\vec{P}) \\ E(\vec{T}) \end{bmatrix} \prod_{i=1}^{f} g_i(\vec{F}) \tag{9}$$

where W is an $r+k$ element row vector, and $\sum_{i=1}^{r+k} w_i = 1$. $S(\vec{P})$ is an r element column vector. Each element $s_i(p_i)$ is a function that shows the degree of satisfaction of the ith performance aspect. $\vec{P} = [p_1, p_2, \ldots, p_r]^T$ is a vector consisting of all performance aspects, $E(\vec{T})$ is a k element column vector. Each element $e_i(t_i)$ is a function that indicates whether the estimated RUL of the ith component is close to its designed life time. $\vec{T} = [t_1, t_2, \ldots, t_r]^T$ is a vector consisting of all estimated RUL values of the components. $g_i(\vec{F})$ is a function indicating whether a fault has occurred. It is equal to 0 if a fault occurs and 1 otherwise. Both $S(\vec{P})$ and $E(\vec{T})$ should take into consideration the situation of over performance and under performance. This means if the performance or RUL of the system considerably exceeds the designed specification, it

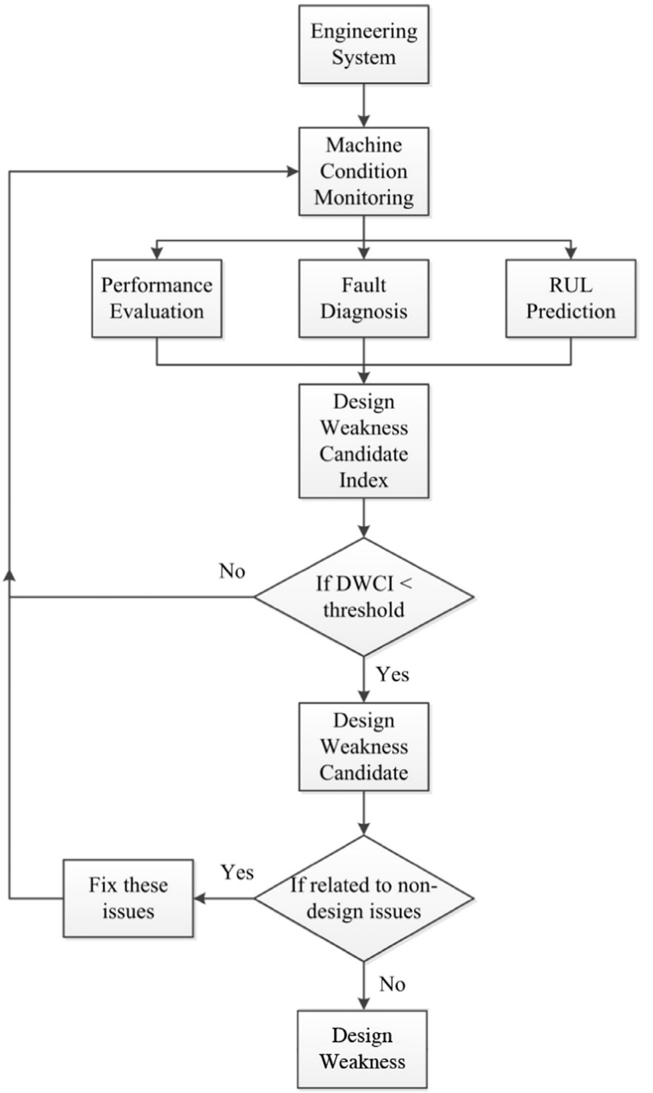

Fig. 4. Procedure of design weakness detection.

is a wasteful situation, and those functions should be able to add a punishment into the DWCI.

According to the definition of DWCI, once a failure is detected, its value will drop to zero. If a fault does not occur and the system is running smoothly, DWCI should also be as smooth as $S(\overrightarrow{P})$ and $E(\overrightarrow{T})$ would change slightly. If a significant decrease is observed in a comparatively short time period, there must be some problem in the running system. Therefore, once DWCI drops to zero or decreases significantly, the design weakness candidates will be isolated by checking the components of the index. Then the design weakness candidates will be evaluated first to see if the issues are related to non-design issues such as inappropriate installation, non-standard operation or poor maintenance. If so, these issues will be corrected and condition monitoring of the system will be continued. Otherwise, the design weakness will be imported to the design process for design improvement. After the design improvement is made, the redesigned engineering system will be fabricated and put into production. Condition monitoring is continued to detect further design weakness. The process of design evolution is in a closed form and it can offer a continuous design improvement.

4. Case study

Reconfiguration and design evolution of an automated industrial fish cutting system is investigated as a case study. This automated fish cutting system is designed by the Industrial Automation Laboratory at University of British Columbia and is used in industry to cut the fish head automatically with minimized wastage of fish meat [4,9]. The conventional machines used in the industry cause about 10–15% wastage of useful meat, each unit percentage of wastage costing about $5 million annually in the province of British Columbia, Canada [16]. The

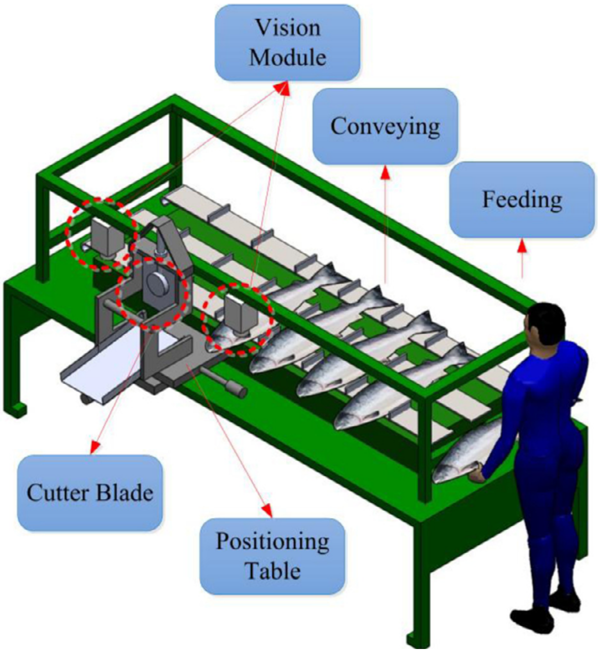

Fig. 5. Schematic diagram of the automated fish cutting system.

automated fish cutting system is a multi-domain manufacturing system that consists of mechanical, electrical, hydraulic and pneumatic subsystems [58]. A schematic diagram of the system is shown in Fig. 5. The present case study employs the proposed closed loop design improvement architecture for the reconfiguration and design evolution of this engineering system, based on a new set of production requirements.

4.1. Machine condition monitoring

Within the framework proposed in Section 3, both real-time condition data of the system (production speed, capacity, power consumption, size, weight, waste percentage, malfunction record, etc.) and condition data from similar machines at other fish-processing plants can be acquired by a variety of sensors and then be transmitted to the cloud database through the network layer. The sensed condition data provides a rather precise and up to date status of the current manufacturing system. Also, the system model, information of available subsystem alternatives (technologies, devices, parameters, cost, etc.) and design expertise are acquired and transmitted to the cloud platform. Then the design knowledge base is formed with this information to assist the design process.

Two key production requirements of the automated fish cutting system are production speed and percent wastage. The performance limit of the original system is 1.5 fish per second with 3.5% wastage of fish meat according to the sensed condition data. In the present case study, new production requirements are given (2.0 fish per second production requirements, as the current system is not capable for achieving these requirements, the performance of the system is unsatisfactory. Consideration of a conceptual redesign is needed as the new technical solutions for the subsystems are available (e.g. robotic arms are more capable and cost-effective that may replace the human operator).

4.2. Conceptual design stage

First the conceptual design improvement is carried out. Then the outcome of the improved conceptual design is presented to the detailed design process for exploration of the topologies and parameters of each component. This case study will illustrate the closed-loop design improvement framework, with a focus on detailed steps of the multi-criteria decision making of the conceptual design phase. MDQ is utilized here for the multi-criteria evaluation of the design alternatives.

The current automated fish cutting system contains five main subsystems as listed in Table 1.

Given the new production requirements, the following steps are taken to achieve a conceptual design of the automated fish cutting system that satisfies the production requirements as well as other constrains.

Step 1: Review the design specifications.

The new production requirements are 2.0 fish per second and 2% wastage of fish meat.

Step 2: Determine the system configuration. According to the design expertise in the design knowl edge base, the current configuration (feeding, conveying, vision, positioning table and cutter blade) can achieve the task of removing the fish head.

Step 3: Design specification estimation.

Condition monitoring data shows the current system specifications. Based on the current values, designer can estimate the requirements for each subsystem according to the new production requirements. Table 2 lists the specifications of the current subsystems and the estimated required specifications for the new design requirements.

Step 4: Construct in the conceptual design space.

For each subsystem, search the knowledge base for available and feasible design alternatives. Table 3 lists the available technology choices for each subsystem to achieve its function.

Step 5: Determine the criteria for evaluation.

The criteria of “meeting task requirements,” “reliability,” “matching,” “efficiency,” “intelligence” and “cost” are chosen as MDQ attributes for this problem.

Step 6: Reduce the design search space by veto effect criteria.

Among these six criteria, “meeting task requirements” has veto effect. Use this criterion to eliminate any design alternative that cannot meet the task requirements. From Table 3, for feeding and cutter blade, both their two alternatives can meet the requirements. For the conveying module, output speed of AC Motor #0002 is below the required value. For the positioning table, only the electrical solution can achieve the requirement of motion accuracy. Camera kit type C can fulfill the image processing within the time limit. The cropped tree structure of conceptual

Table 1
Subsystems of the automated fish cutting system.

Subsystems	Description
Feeding	A human operator will place raw fish in the feeding area of the conveyer, ideally at the same pace of movement of the conveyer to achieve maximum productivity.
Conveying	An electromechanical conveying subsystem delivers the raw fish from the feeding area to the cutting area and then off the fish cutting system after removing the head. The conveying subsystem is driven by an AC induction motor.
Vision	There are two primary tasks for the vision subsystem: identifying the optimal cutting location and evaluating cutting quality, particularly related to the wastage of fish meat and the smoothness of the cut. One image is taken for each fish before it enters the cutting area. Image processing is then performed at a local computer to identify the best reference location for the cut. The corresponding coordinates are sent to the controller of the positioning table control system. After the cut, another image is taken to check the quality of the cut and the percent wastage.
Positioning table	This subsystem moves the positioning table that carries the cutting blade accurately and rapidly to the desired cutting location as identified by the vision subsystem. Motion in the horizontal plane, perpendicular to the cutter blade, is controlled to achieve this task. The positioning table is powered by two hydraulic actuators.
Cutter blade	This subsystem is assembled on the positioning table. The cutter blade is pushed down by a pneumatic cylinder to cut the fish head when a raw fish is brought to the cutting area by the conveyor and the positioning table with the cutter is moved to the correct location.

Table 2
Specifications of the current subsystems and estimated design requirements.

Subsystem	Parameter	Current	Performance limit	Required
Feeding Human operator	Feed speed (Fish/s/person)	1.50	1.50	2.00
Conveying AC Motor #0001	Output speed with desired output torque (rpm)	2400	6000	4000
Positioning table Hydraulic solution	Motion time (s)	0.48	0.45	This plus cutting time should be less than 0.50
	Motion accuracy (mm)	5.00	5.00	3.00
Cutter blade Pneumatic solution	Cutting time (s)	0.10	0.10	This plus motion time should be less than 0.50
Vision Camera kit type A	Processing time (s)	0.55	0.55	0.50

Table 3
Available choices for each subsystem.

Subsystem	Available choices	Estimated cost ($)	Parameter	Performance limit
Feeding	Two operators	85,000	Feed speed	3.0 (Fish/s)
	Robotic arm	120,000		2.5 (Fish/s)
Conveying	AC Motor #0001	8000	Output speed with desired output torque	6000 (rpm)
	AC Motor #0002	5000		3800 (rpm)
	AC Motor #0003	6000		5000 (rpm)
Positioning table	Hydraulic solution	15,000	Motion time	0.45 (s)
			Motion accuracy	5.0 (mm)
	Electrical solution	18,000	Motion time	0.30 (s)
			Motion accuracy	2.0 (mm)
Cutter blade	Hydraulic solution	9000	Cutting time	0.15 (s)
	Pneumatic solution	7000		0.11 (s)
Vision	Camera kit type A	5000	Processing time	0.65 (s)
	Camera kit type B	3000		0.80 (s)
	Camera kit type C	7500		0.35 (s)

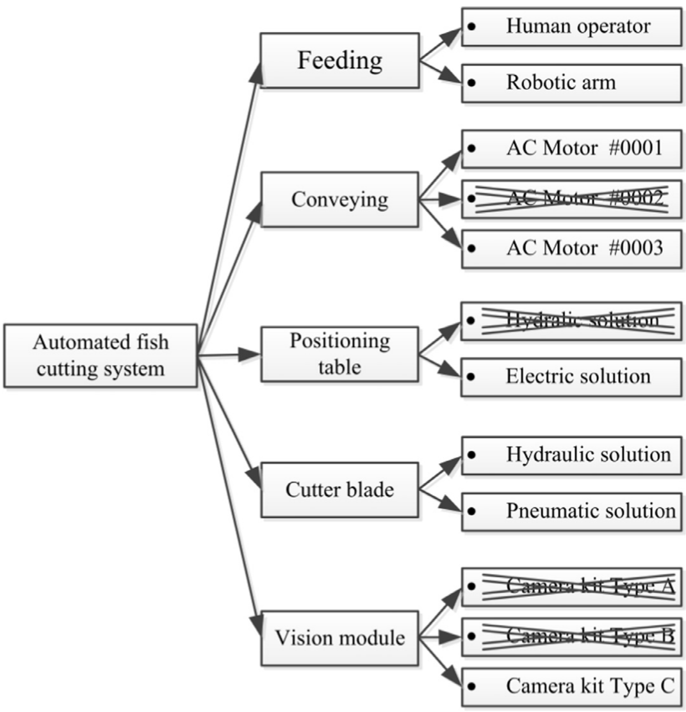

Fig. 6. Reduced conceptual design space.

Table 4
Typical interactions between criteria.

Interaction type	Explanation	Relation
Positive correlation	High score in criterion i implies a high score in criterion j, and vice versa.	$v(ij) < v(i) + v(j)$
Negative correlation	High score in criterion i implies a low score in criterion j, and vice versa.	$v(ij) > v(i) + v(j)$
Substitutiveness	Satisfaction of only one criterion produces almost the same effect than the satisfaction of both.	$v(T) < \left\{\begin{matrix} v(T\cup i) \\ v(T\cup j) \end{matrix}\right\} \approx v(T\cup ij),\ T \subseteq N\backslash ij$
Complementarity	Satisfaction of only one criterion produces a very weak effect compared with the satisfaction of both.	$v(T) \approx \left\{\begin{matrix} v(T\cup i) \\ v(T\cup j) \end{matrix}\right\} < v(T\cup ij),\ T \subseteq N\backslash ij$

design space is shown in Fig. 6. Eight design alternatives need to be evaluated through the multi-criteria evaluation.

Step 7: Assign a fuzzy measure to each subset of the criteria.

The remaining five criteria, “reliability,” “matching,” “efficiency,” “intelligence,” and “cost” form a number of $2^5 = 32$ subsets of criteria. It needs 32 fuzzy measures using the ordinary Choquet integral (two of them are self-evident: $v(\phi) = 0$ and $v(N) = 1$). Here, the 2-additive Choquet integral is adopted [25]. Thus, only $n(n+1)/2 = 15$ fuzzy measures need to be specified. The common type of interactions and their fuzzy measure representation are summarized in Table 4.

The fuzzy measures are typically assigned by expert designers and the fuzzy measures used in this case study are derived from [23] since the engineering system is the same and the criteria are similar. The fuzzy measures are listed as follows. $v_1 = 0.25$, $v_2 = 0.35$, $v_3 = 0.22$, $v_4 = 0.18$, $v_5 = 0.15$, $v_{12} = 0.52$, $v_{13} = 0.45$, $v_{14} = 0.50$, $v_{15} = 0.52$, $v_{23} = 0.50$, $v_{24} = 0.48$, $v_{25} = 0.60$, $v_{34} = 0.45$, $v_{35} = 0.50$ and $v_{45} = 0.42$. These values reflect a negative correlation between cost and the other criteria and a small positive correlation between any two criteria except cost.

Step 8: Multi-criteria evaluation of each design alternative.

Evaluate each design alternative according to the chosen criteria except the ones of veto effect and assign a score for each of the design alternatives. Evaluation guideline can be found in [23]. Aggregate the partial scores by using 2-additive Choquet integral to determine the global score of each design alternative. Choose the design alternative with the highest global score. The results are shown in Table 5.

The best conceptual design of the automated fish cutting system is the No. 8 design alternative which corresponds to a conceptual design solution of Robotic arm

Table 5
MDQ evaluation of design alternatives.

	#1	#2	#3	#4	#5	#6	#7	#8
Feeding module	Human operator	Human operator	Human operator	Human operator	Robotic arm	Robotic arm	Robotic arm	Robotic arm
Conveying	Motor #0001	Motor #0001	Motor #0003	Motor #0003	Motor #0001	Motor #0001	Motor #0003	Motor #0003
Positioning table	Electrical solution	Electrical solution	Electrical solution	Electrical solution	Electrical solution	Electrical solution	Electrical solution	Electrical solution
Cutter blade	Hydraulic solution	Pneumatic solution	Hydraulic solution	Pneumatic solution	Hydraulic solution	Pneumatic solution	Hydraulic solution	Pneumatic solution
Vision	Type C	Type C	Type C	Type C	Type C	Type C	Type C	Type C
Matching	0.70	0.60	0.70	0.60	0.80	0.70	0.80	0.70
Reliability	0.50	0.40	0.50	0.40	0.50	0.60	0.50	0.60
Intelligence	0.70	0.60	0.70	0.60	0.90	0.80	0.90	0.80
Efficiency	0.50	0.60	0.60	0.70	0.60	0.70	0.70	0.80
Cost	0.85	0.90	0.90	0.95	0.70	0.75	0.75	0.80
Global score	0.621	0.589	0.651	0.624	0.657	0.694	0.693	0.729

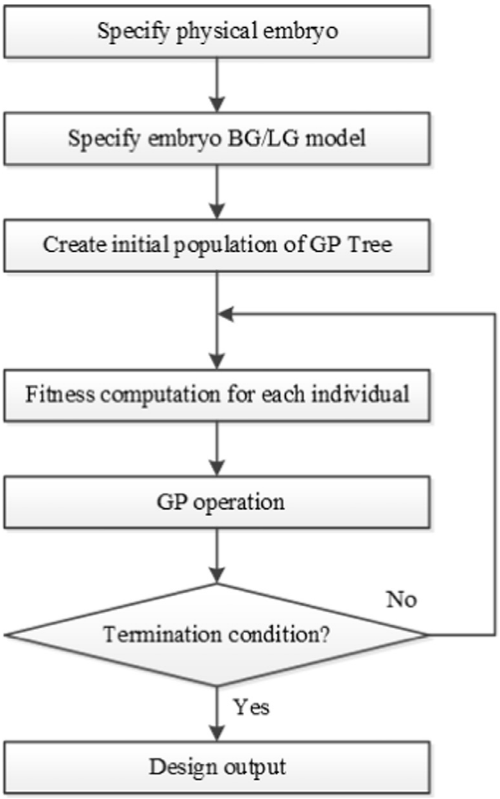

Fig. 7. Procedure of evolutionary design with GP.

(feeding module), Motor #003 (conveying), Electrical solution (positioning table), Hydraulic solution (cutter blade), Type C camera kit (vision module).

4.3. Detailed design stage

After the conceptual design process, detailed design will be conducted to specify the topology and tune the parameters to achieve the desired design requirements. Genetic algorithms and genetic programing can be utilized to explore the detailed design space to find the optimal sign in the design space. The procedure of evolutionary design with GP is shown in Fig. 7.

GP evolution for complex engineering system with a large amount of subsystems and components can be computationally expansive. The CC platform is utilized here as well to executive the GP computation to find the optimal detailed design with the specific topologies and parameters for each subsystem of the fish cutting machine. The design solution is further evaluated and then realized physically. The redesigned fish cutting machine will be put into production.

4.4. Continuous design improvement

The IoT and CC assisted condition monitoring system will continue to collect real-time condition data of the system (production speed, capacity, power consumption, size, weight, waste percentage, malfunction record, etc.) and condition data from similar machines at other fish-processing plants once the redesigned engineering system becomes operational. The condition data will continuously update the knowledge base by evaluating the system performance, detecting system mismatch or failure, estimating remaining useful life, and so on. Design weakness candidate index is monitored to detect further design weakness. The knowledge base will be further updated by new technical solutions, components with higher capacity, devices with higher reliability and lower maintenance cost and so on, guided by design experts, design handbooks, data tables, catalogs, the Internet and other information sources. Also, with any new production requirement, current engineering system will be evaluated to see if a redesign is needed and which stage it should go, conceptual redesign or detailed redesign. The evaluation of the current design can be carried out continuously and throughout the lifetime of the system for making design improvements.

5. Conclusion

A novel closed-loop design evolution framework for engineering systems is presented in this paper. Compared with other design evolution methodologies, firstly, it can systems through conceptual design, detailed design, implementation, condition monitoring and design weakness detection. New design requirements or potential design weaknesses can be addressed by the proposed framework. Secondly, IoT and CC are introduced to address the limitation of traditional machine condition monitoring approach in sensing, data transmission, data storage and data processing. A condition monitoring scheme based on IoT and CC is proposed to employ condition monitoring in the design improvement process by evaluating system performance, detecting system failure and estimating system heath status. Thirdly, A systematic evaluation approach is developed to detect potential design weaknesses that will guild the redesign by narrowing down the search space. A cloud-based design knowledge base is proposed using information on design expertise from domain experts, and data and information from condition monitoring and other sources to assist the design process by reducing the design search space and offering design guidelines. Multi-criteria evaluation and evolutionary algorithms are utilized in conceptual and detailed design for a more effective and efficient design process. A case study on industrial production is conducted to demonstrate the procedure of the proposed framework. The proposed approach shows great potential in real application for complex engineering system design evolution, especially with the advance of IoT and CC technologies.

Future work will focus on the investigation of a systematic approach to specify the type of condition data that needs to be collected for typical industry engineering configurations as well as the related features that need to be extracted for detecting potential design weaknesses. A comprehensive scheme for constructing a design knowledge base and the knowledge-based system for real application needs to be developed as well.