Application of Artificial Intelligence Technology in Product Design

● Naoyuki Nozaki ● Eiichi Konno ● Mitsuru Sato ● Makoto Sakairi
● Toshiyuki Shibuya ● Yuuji Kanazawa ● Serban Georgescu

Artificial intelligence (AI) technology applied to product design in Monozukuri (Japanese way of manufacturing) aims to provide computerized support to various tasks in developing products that currently rely on human experience. As the conventional approach, in which knowledge and rules are explicitly given, has its limit, new technologies based on machine learning have been recognized as important in research and development of AI. Applying machine learning that predicts data to be acquired in the future with a certain accuracy, we can obtain efficient and less-variable judgment and eliminate conventional work depended on personal knowledge or experience. In order to apply AI technology to a product development environment, MONOZUKURI AI framework was developed on the cloud as a system to facilitate efficient collection of product development data, and, at the same time, for managing and leveraging learning models extracted from such data. By connecting this framework with Flexible Technical Computing Platform (FTCP), Fujitsu's integrated development platform, this new design development environment will provide various design tools on a platform with new, enhanced design-assisting features. This paper describes various cases in which machine learning is applied to designing, and presents our plan to introduce it into an integrated development platform.

1. Introduction

The traditional approach to solving a given problem with software has been to clearly formulate a procedure, i.e., an algorithm. However, there are many problems that do not lend themselves to the clear formulation of an algorithm. In the case of estimating the number of layers in a printed circuit board (PCB), described later on in this paper, a skilled designer is able to judge the number of layers based on past experience rather than consciousness of a set of clearly defined rules. Product development involves many such tasks that require designers to make judgments based on experience. There are many such problems where the clear formulation of an algorithm is difficult and where the incorporation of all the factors that need to be considered requires complex calculations, which is also difficult.

Meanwhile, the importance of machine learning, an artificial intelligence (AI) technology for the utilization of the big data generated by the Internet of Things (IoT), has been drawing attention. Fujitsu has been promoting AI systematization through its concept, Human Centric AI Zinrai.[1] Through the automatic acquisition of knowledge and rules from data, AI technology has the potential to overcome the limits of the conventional approach based on the presentation of explicit knowledge and rules. Fujitsu has accumulated an enormous body of product design data from its Monozukuri (Japanese way of manufacturing) activities to date, and the successful modeling for learning of the knowledge data included in all this product design data would allow the application of this knowledge and these rules to new designs. To this end, the authors are evaluating the effectiveness of machine learning in product design, and are working on applying machine learning to the product design environment.

This paper presents cases of the application of machine learning to product development. Next, it introduces Fujitsu's MONOZUKURI AI framework as an example of the incorporation of machine learning in the Flexible Technical Computing Platform (FTCP), an integrated development platform.[2] Finally, it describes

Fujitsu's aims for its Human Centric AI Zinrai system for the systematization of AI in the design and development environment.

2. Examples of application to electrical/ structural design

As examples of the application of machine learning technology in the design field, this section describes the development of a function to estimate the number of layers in PCBs in the electrical design environment, and the development of an automatic detection function of 3D model components using shape recognition in the structural design environment.

2.1 Application example in the electrical design environment

This section introduces the case of the application of machine learning to the development of a function to estimate the number of layers in PCBs.

1) Importance of estimating the number of PCB layers

The design process of PCBs consists mainly of the circuit design stage and the board design stage. In the circuit design stage, appropriate components are selected and logical connections between the various components and their mounting conditions (signal line lengths, etc.) are specified. In the board design stage, components and logical connections are physically arranged and wired on the board according to the mounting conditions specified in the circuit design.

An important design decision to be made when transitioning from the circuit design stage to the board design stage is the number of layers in the PCB. The task of estimating this number requires taking into consideration a number of factors such as the placement location of the various components, the wiring route, and the allowable size of the PCB, which is restricted by the target apparatus size. This is because the number of layers in the PCB affects the number of components and the number of wiring paths, which directly affects the manufacturing cost, making this an important decision for eliminating design rework.

For this reason, highly skilled designers often proceed while considering the requirements of products, the circuit configuration, and so on, and trade off the various elements involved, comprehensively judging their relative priority levels. Especially when one wants to optimize the number of layers, it is common to route key signals (such as high-speed signals) temporarily and estimate the number of layers in a process that can take several hundred hours.

Thus, the task of estimating the number of layers in PCBs is an important part of the PCB design process, and it is a difficult and time-consuming task even for skilled designers.

2) Utilization of machine learning technology for the estimation of the number of layers

As described above, one method for estimating the number of layers in a PCB is to provisionally arrange the main components and perform provisional routing of the signals and the like to which particularly severe mounting conditions apply. However, this requires manual work and sophisticated judgment, making the automation of such work an inadvisable proposition. Therefore, the authors hypothesized that it might be possible to create a model to predict the number of layers in a PCB through machine learning from past product design data.

Generally, the PCB of a server or a network device consists of signal layers, a power supply layer, and a ground (GND) layer. In the case of manual design, often the number of signal layers is first estimated empirically by the designer. As in the case of manual design, the signal layers were first targeted for the estimation of the number of layers through machine learning.

In the machine learning method, support vector regression,[3] which is a regression analysis method used in supervised learning, was employed. Normally, because the number of layers has to be estimated before starting board design, the feature vectors (numerical data) that are input as training data for the creation of the learning model are those obtained at the circuit design stage only.

Next, we introduce the initiatives that led to improvement of the accuracy of the estimation of the number of layers during the learning model creation process.

The first one was to select only items close to the estimation target product from the design data as training data. The target learning data was narrowed down by sorting past design data by product type and PCB type. This sorting made it possible to improve the accuracy of estimation of the number of layers for specific product categories.

The second initiative was to review the feature vectors to be input as training data. During the learning model creation process, we surveyed PCB designers about the items that they emphasize for layer number estimation, and we conducted a review of the feature vectors accordingly.

The third initiative was algorithm optimization during learning model creation. For example, we were able to improve estimation accuracy by changing the kernel function for support vector regression from linear to nonlinear, and by changing the parameters supplied to the kernel function.

Figure 1 shows the results of estimation of the number of signal layers based on cross validation for a given product type. The x axis shows the actual number of signal layers and the y axis shows the estimated number of signal layers obtained from the developed learning model. Each plot corresponds to one design data. All data are plotted along the $y = x$ line, indicating that the number of signal layers can be estimated with high accuracy.

Based on these results, we plan to also estimate the number of layers other than signal layers, and determine the layer configuration.

2.2 Application example in the structural design environment

This section introduces the case of the application of machine learning to the development of a function for the automatic detection of 3D model components using shape recognition.

1) Design verification during structural design

Structural design work and design reviews are usually carried out by referring to check lists that have been compiled from the accumulated experience and know-how of highly experienced designers designing similar products. However, as the accumulated experience and know-how increase, so does the verification work time and the load on the designers. Moreover, in structural design, shapes are modeled to reflect the intentions of the designer (e.g.: adding a rib for greater strength). However, the generated 3D models are merely shape information, and computers cannot judge the intentions of designers. Therefore, the only way to verify whether a design intent works correctly was for a human to visually judge the location to be verified. As a result, as well as long verification times, there is also the issue of verification omissions due to human factors.

2) Utilization of machine learning for automatic detection of 3D model components

We investigated whether it is possible to achieve machine learning based on past design data for the automatic detection of similarly shaped components (such as screws). In doing so, based on the hypothesis that similarity of 3D shapes means also similarity of 2D shapes, we tested whether image recognition using 2D images can be applied to the detection of 3D shapes. The automatic detection procedure is outlined below.

(i) Twenty 2D images are generated for each component from past design data (as shown in **Figure 2**, the vertex of a 20-sided polygon relative to the center of the component is taken as the camera viewpoint).

(ii) The feature vectors of each component are extracted from the 2D images.

(iii) Twenty 2D images are generated in the same way for components for which similar shaped components are to be detected.

(iv) The feature vectors of (iii) are extracted, their similarity with the feature vectors stored in the created database is calculated, and similarly shaped components are detected in the database.

This time, we created a learning model based on approximately 8,000 components for which we had past design data, and we verified whether automatic

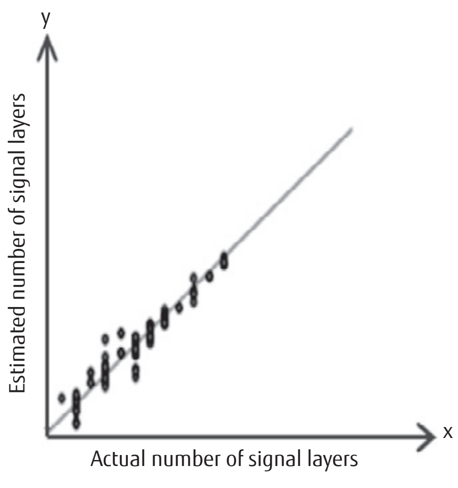

Figure 1
Evaluation of estimation accuracy of the number of signal layers.

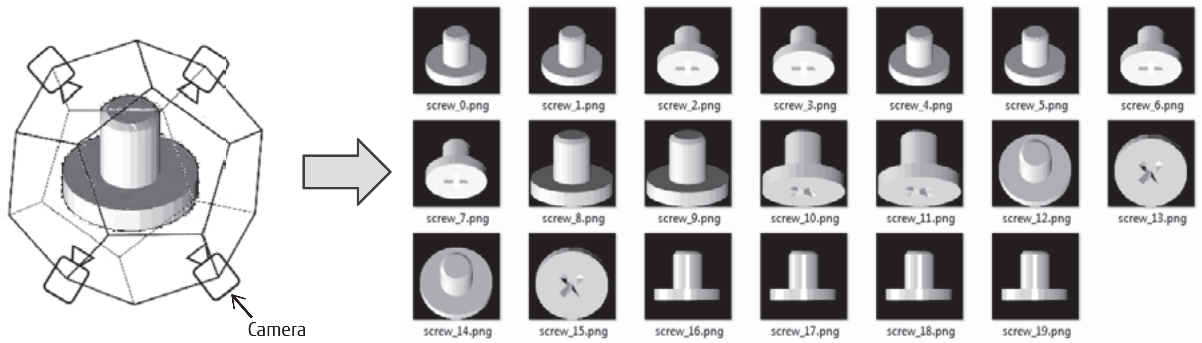

Figure 2
2D image representation.

detection of screws was possible.

Figure 3 shows the results of initial verification in descending order of similarity. Approximately half of the 60 components recognized as most similar consisted of components other than screws. This was due to the fact that, in the case of symmetrical components such as screws, a number of the 2D images generated for the extraction of feature vectors in Step (i) above are actually identical, which seems in turn to reduce shape recognition accuracy. We solved this problem, generating 2D images by changing the angle of view, so as to prevent the duplication of 2D images. In addition, we incorporated also component size and surface area information. As a result, as shown in **Figure 4**, the detection accuracy of similar shapes was greatly improved compared with the initial verification results.

Thus, through the above-described initiatives, we were able to verify the feasibility of automatic detection of components based on a 3D model. In the future, we plan to further improve the detection accuracy and achieve automation of the verification of components. Further, since there are many other items to be verified besides components, including the specific shapes of parts of components such as ribs and bosses, we would like to also apply the obtained findings to the detection of the shapes of parts of components.

3. MONOZUKURI AI framework

In applying machine learning technology to the field of product design, there are processes common to various design fields and application themes. As the basis for standardizing common processes related to machine learning, we are working on a framework for utilization and development in the form of the MONOZUKURI AI framework introduced in this section.

3.1 Learning model development framework

The utilization of machine learning technology allows us to predict what will occur next from new data and classify such new data based on its characteristics. However, building a highly accurate learning model applicable to design requires optimization of the learning model by various means. To this end, as regards the work required to develop practical learning models, we are currently developing guidelines and tools and building a learning model development framework that will support service development using machine learning technology. As an example, **Figure 5** shows the development flow of a learning model based on the supervised learning method for machine learning.

In order to use the supervised learning method, it is necessary to first collect training data. To improve the accuracy of the learning model, it is effective to remove training data that will just be noise (for example, incomplete design data) and classify the retained training data by applicable theme. To make the selection of training data more efficient, we have developed and utilized tools to visualize the characteristics of design data in the form of graphs. After the training data has been collected, it is necessary to extract feature vectors (numerical data) from the training data for use as input data for the learning model.

An effective way to make feature-vector extraction more efficient is to expand the types of numerical data that can be extracted from design data. The kinds of numerical data that are appropriate to use as feature vectors differ according to the theme to which machine

Figure 3
Initial verification results of screw component detection.

Figure 4
Improvement results of screw component detection.

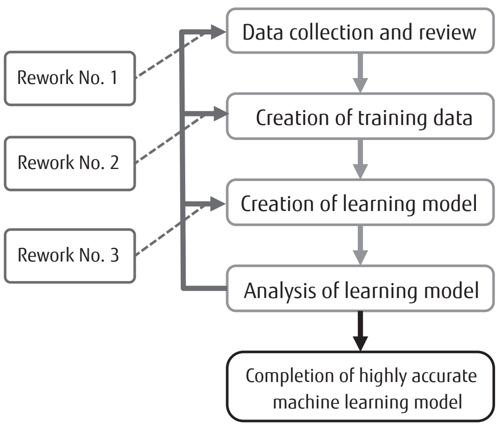

Figure 5
Machine learning flow.

learning technology is applied. However, there are also commonly used feature vectors, so increasing the types of numerical data that can be extracted from the design data is effective for developing a large number of learning models.

The final step of the supervised learning method consists in analyzing the learning model created from the training data and improving its accuracy. To this end, we apply methods for improving the accuracy of general learning models, such as comparison of prediction results by multiple algorithms and cross validation, as tools for supporting work.

In this way, by preparing a series of environments necessary for learning model development, it is possible to minimize rework shown in Figure 5 (rework No. 1, 2, 3) to make learning model development more efficient. Going forward, we plan to deal not only with supervised learning but also methods such as unsupervised learning and deep learning.

3.2 Learning model utilization framework

To improve the accuracy of prediction and classification by machine learning technology, it is effective to create learning models according to specific purposes. In other words, the aim is to develop a learning model specific to the purpose for each applicable design field and further for each applicable theme within each field.

Further, design support services utilizing machine learning technology are expected to be utilized from various usage environments including design tools such as computer-aided design (CAD) tools and computer-aided engineering (CAE) tools, and web browsers. For this reason, we are working to construct a learning model utilization framework that makes it easy to use multiple learning models from various environments.

Figure 6 shows the system configuration of the learning model utilization framework. The utilization framework system is a web service on the Engineering Cloud. The Engineering Cloud is a cloud environment offered by Fujitsu for the engineering field.[4] Websites and CAD/CAE tools that offer services utilizing machine learning technology access the utilization framework on the cloud.

A web application programming interface (API) using Web technology is used as the access API. The functions provided by the utilization framework through the web API consist mainly of the following two.

1) Access control to learning models (for users)

This is a mechanism that allows users to select an appropriate learning model according to the usage purpose. Access control to learning models is implemented through a set of APIs that appropriately select learning models and execute prediction and classification processing, selecting for example a learning model for electrical design support in response to a user request from an electrical CAD, or a learning model for structural design support in response to a user request from a structural system verification tool. The information required for using the learning model is stored in a database in the cloud, and by linking the APIs and the database, it becomes possible to use learning models according to the purpose.

2) Registration/updating of learning models (for service providers)

This is a mechanism for service providers using machine learning. The design support service provider registers learning models in a database for managing the learning models on the cloud using APIs for learning model registration. As technology and design processes applied to product design always progress, there is concern that deviation from actual product design will occur if the learning model, once made, is used as is.

To prevent this, it is necessary to have a

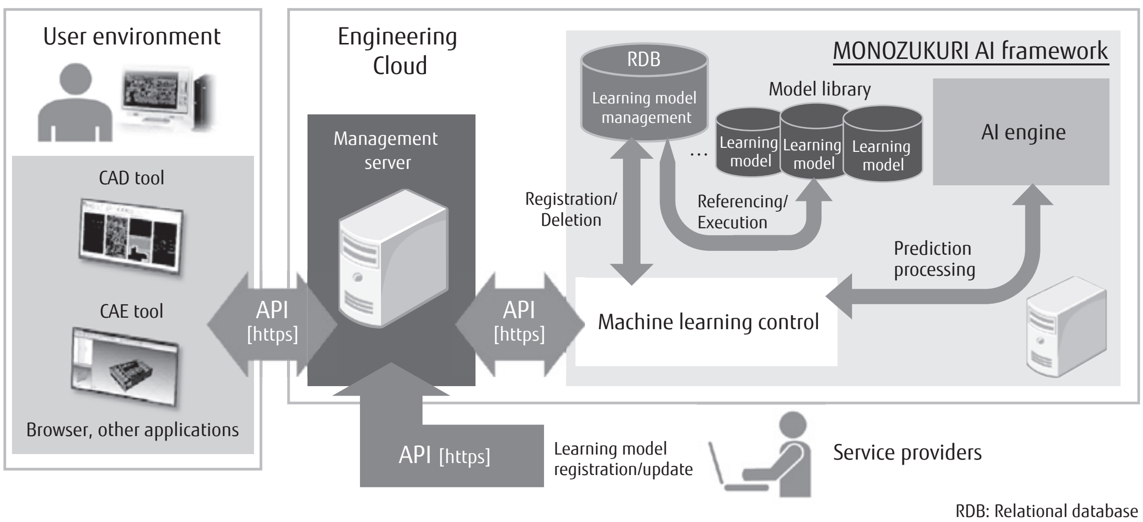

Figure 6
Learning model utilization framework.

mechanism to periodically update the learning model according to the development of new design technology and processes. In the utilization framework, the processing necessary for such learning model updating is also implemented with APIs. Service providers can update the learning model on the Engineering Cloud by using the APIs for updating learning models.

By constructing an operation environment for services using machine learning as the common foundation, we are aiming for a design environment that is beneficial to both users and developers of services.

4. Goals

So far, we have described the application of machine learning technology to the design field and its effects, and the MONOZUKURI AI framework as an application of AI to the FTCP integrated development framework. We are currently working on the development of FTCP 3.0 based on the concept of One Platform, and the MONOZUKURI AI framework is an important component of that. For details about One Platform, please refer to the paper "Cloud-based Development Platform for Next-Generation Monozukuri" also published in this issue.[5] The configuration of FTCP 3.0 is shown in **Figure 7**. The learning models on the MONOZUKURI AI framework will be constructed as design support services through the cloud in the future. We will also strengthen the following initiatives to automate design and verification using CAD/CAE and design assets.

The first initiative is to increase the number of cases in which machine learning technology is applied in the design field, and to accumulate know-how that so far has been dependent on people through the use of information and communications technology (ICT). We will address the various issues in product design using the solutions to problems encountered in product development, such as in the development of machine learning methods and in determining the value of features. More such solutions will provide us with the means to create an ever greater number of machine learning models that can make available heretofore people-based know-how.

The second initiative is to develop data standards that utilize design assets as learning data. Design data so far was not intended to be used for machine learning technology, but manpower is often required to extract feature vectors and analyze correlations among data. In this regard, we will establish methods to efficiently associate various kinds of data accumulated in the past and to shape data.

Finally, on the topic of design that uses the latest technology, of design scale and design constraints, measures need to be looked into by which to deal with

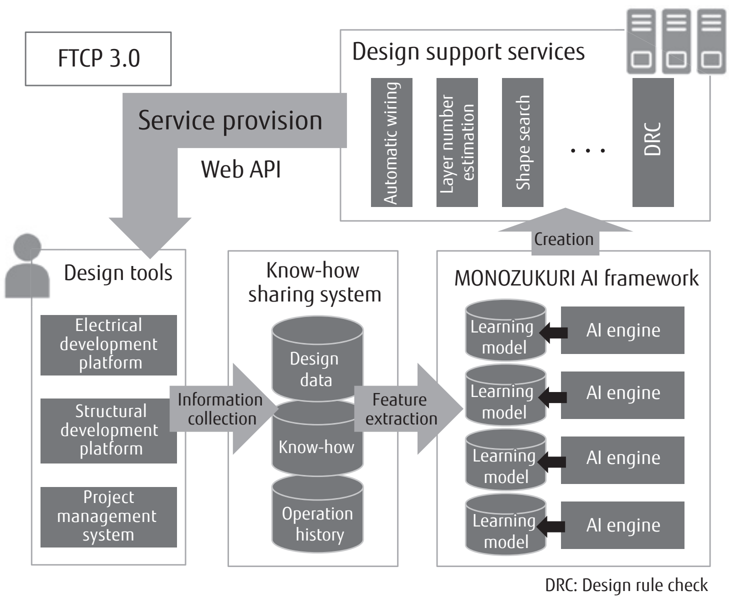

Figure 7
Configuration of FTCP 3.0.

designs that deviate from existing designs. In the case of a technical breakthrough, sufficient consideration such as how to utilize the design assets before and after the breakthrough will be necessary. In the future, we will establish indicators that can quantitatively make such judgments.

Machine learning is good at "prediction/classification" and "clustering." Rather than solving everything with machine learning technology, we will work on differentiated design and automated verification for "rule-based automation," "automation by machine learning," and "hybrid automation combining rule-based and machine learning automation" depending on the design issue at hand.

5. Conclusion

In the IoT era, AI is expected to play a role in many different situations. On the other hand, AI technology at the present time is not necessarily universal, and application areas will have to be identified within the scope of answers obtained from probability and statistics. By mechanically calculating the correlation of a plurality of feature vectors that people did not notice, AI can be used as a tool for deriving responses that approximate human experience and know-how. Using AI to gather the experience and know-how that to date has been considered the preserve of humans and put it to work in ICT opens the way to the use of AI in product design. The FTCP supports product design, and we intend to contribute to the further strengthening of Fujitsu's, and Japan's, Monozukuri by adding to the FTCP AI options developed in collaboration with various product design departments.

References

1) Fujitsu: Fujitsu Takes Systematic Approach to Artificial Intelligence with "Human Centric AI Zinrai." *http://www.fujitsu.com/global/about/resources/news/press-releases/2015/1102-01.html*
2) A. Miyazawa et al.: Construction of Integrated Design Development Environment and Its Deployment on Cloud. FUJITSU Sci. Tech. J., Vol.48, No.4, pp.394–403 (2012). *http://www.fujitsu.com/global/documents/about/resources/publications/fstj/archives/vol48-4/paper02.pdf*
3) T. Kaniwa et al.: The Challenge of Developing Design Automation using Design Resources. The 2015 IEICE Engineering Science/NOLTA Conference. 2015 (in Japanese).
4) M. Yasuda: Fujitsu's Engineering Cloud. FUJITSU Sci. Tech. J., Vol.48, No.4, pp.404–412 (2012). *http://www.fujitsu.com/global/documents/about/resources/publications/fstj/archives/vol48-4/paper03.pdf*
5) E. Konno: Cloud-based Development Platform for Next-Generation Monozukuri. FUJITSU Sci. Tech. J., Vol. 53, No. 4, pp.22–29 (2017). *http://www.fujitsu.com/global/documents/about/resources/publications/fstj/archives/vol53-4/paper03.pdf*

Naoyuki Nozaki
Fujitsu Advanced Technologies Limited

Mr. Nozaki is currently engaged in the creation of development platform environments for product design.

Eiichi Konno
Fujitsu Advanced Technologies Limited

Mr. Nozaki is currently engaged in the creation of development platform environments for product design.

Mitsuru Sato
Fujitsu Advanced Technologies Limited

Mr. Nozaki is currently engaged in the creation of development platform environments for product design.

Makoto Sakairi
Fujitsu Advanced Technologies Limited

Mr. Sakairi is currently engaged in the creation of structural platform environments.

Toshiyuki Shibuya
Fujitsu Laboratories Ltd.
Mr. Shibuya is currently engaged in research on product design automation.

Yuuji Kanazawa
Fujitsu Laboratories Ltd.
Mr. Shibuya is currently engaged in research on product design automation.

Serban Georgescu
Fujitsu Laboratories of Europe Ltd.
Mr. Georgescu is currently engaged in the development of applied machine learning technology.