Case Study of Product Development through Generative Design according to Anemometer Replacement Cycles

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ABSTRACT

Product Lifecycle Management (PLM) systems are commonly used to manage various product data generated throughout the product lifecycle. This paper explains the results obtained by multiple participants using commercial software within the PLM environment to perform structural and vibration analyses of an Anemometer. Generative design techniques were employed for 3D CAD modeling of the Anemometer, and the commercial analysis software NASTRAN was used for simulation analyses. The open-source PLM system ARAS Innovator's project and workflow management modules were utilized to manage the generated design data, allocate tasks among participants, and control schedules. Through this approach, we propose a method to predict and manage the replacement cycle of Anemometer.

Key Words: Generative Design, PLM, Nastran, ARAS Innovator

1. INTRODUCTION

Currently, the technology for generative AI is very active and progressing at a very fast pace. [1] This direction is also being applied to industrial companies to reflect generative design [2], and this research is being conducted through a research project as described later.

This study is still a work in process, and the model applied in this study evaluated the structural stability of an anemometer, one of the products of the client company, and presented a case of applying it to ARAS Innovator, an OPEN PLM solution, as a management method for a large number of design plans generated through generative design. He is currently conducting research by expanding its application to assembly design in the aero/defense field.

2. DISCUSSION

2.1. Structural Analysis

Fig. 1 shows an anemometer that was damaged during operation. To analyze it, we performed a structural analysis as shown in Fig. 2, a structural analysis was performed.

Fig. 1 Breakage of the Anemometer cup

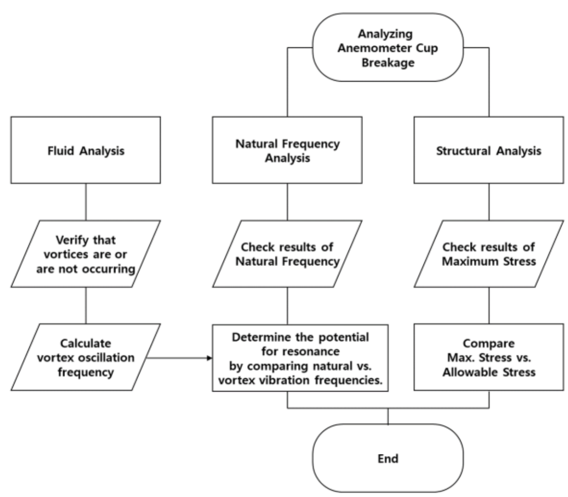

Fig. 2 Analysis process flow chart

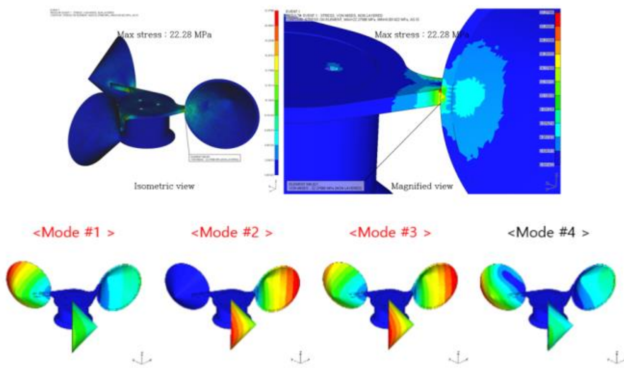

Fig. 3 Structural & Natural Frequency Analysis

The analysis showed that the natural frequency analysis of the structure should be designed to avoid the vortex-induced vibration frequencies around the anemometer cup, and a generative design was derived to satisfy these design criteria.

2.2. Generative Design Draft

Fig. 4 shows a schematic of the design generation process. It shows the process of generating a large number of designs using generative design methods and then optimizing them to find the optimal design. This detailed study is in progress through joint research [3].

Fig. 4 at the bottom, Generative Adversarial Networks with Boundary Constraints (GAN-BC), a deep learning-based model for reverse engineering, is shown. The samples generated from the model and their prediction performance were considered, and supervised learning was performed using the data extracted for prediction and used as a surrogate model. This improved the engineering performance and additive manufacturing suitability of the design created by learning in a direction that minimizes the predicted performance value.

1,000 samples were generated by learning GAN-BC, and compared to existing randomly generated samples, the average weight decreased by about 35.6% from 2.16 kg to 1.39 kg, the average amount of support also decreased by about 21.6%, and the defined It was noticed that the evaluation criteria had improved.

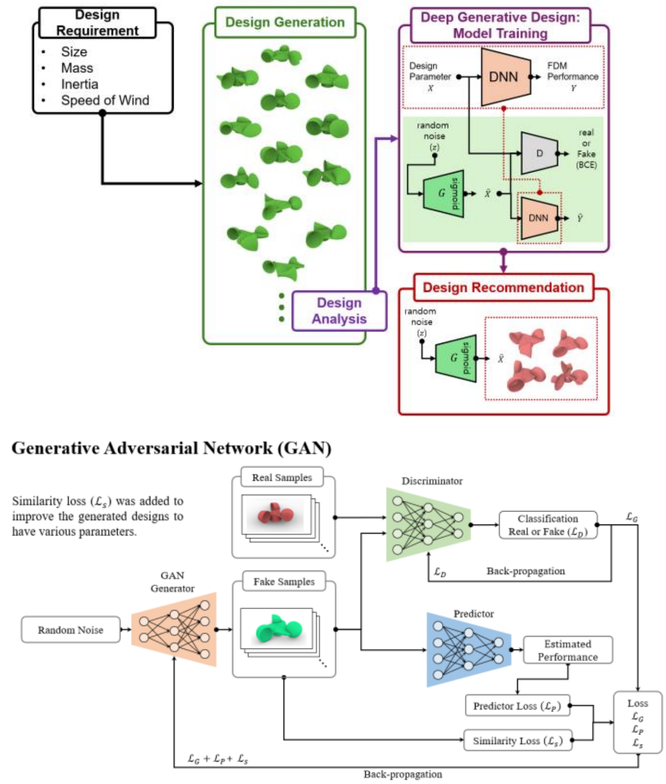

Fig. 4 Generative Design Framework

2.3. Adapting to an open PLM system

The massive number of design alternatives generated through generative design techniques necessitates the establishment and management of a database containing the characteristics of each design alternative. Additionally, procedures such as history management for items reviewed at each step of the workflow will be required.

To implement these elements, we applied the open-source PLM system ARAS INNOVATOR to our research. In Fig. 5, we created a Workflow Manager environment for the design process using the Workflow Map module. Fig. 6 demonstrates an example of establishing a database for the design alternatives.

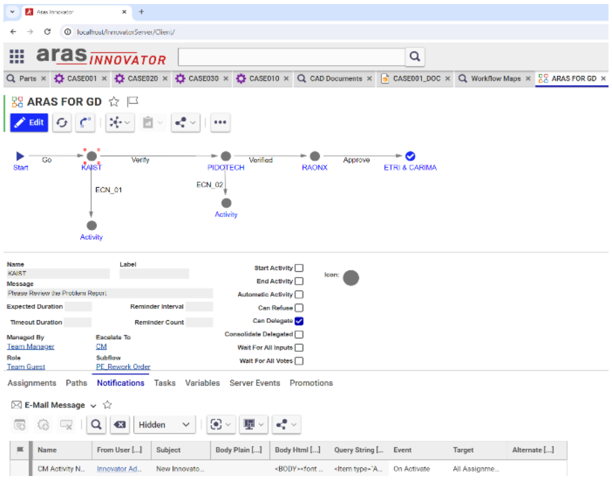

Fig. 5 Workflow Manager for Generative Design

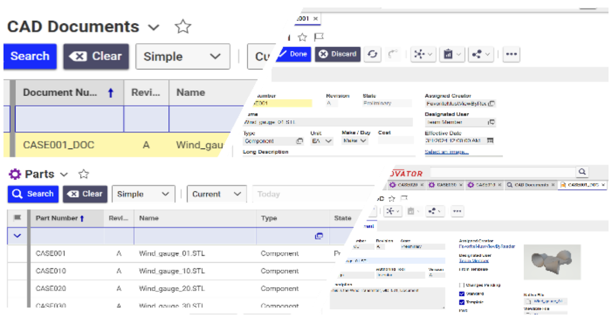

Fig. 6 Open PLM System Application Cases

In the case of workflow manager development, the first year was conducted in an environment where the outputs from each joint organization were integrated, and the second year was conducted to apply it to the PLM system. Currently, research on embedding it in the CAD system is in progress through the third year.

3. CONCLUSION

So far, we have introduced the analytical evaluation and generative design of anemometer, as well as the management plan for multiple design alternatives. Although there were limitations in terms of functionality due to its open-source nature, it is believed that systematic management data for the generated designs will play an important role. Subsequent research is ongoing to apply the final design selected through optimization to production via 3D printing [4]. Based on the technologies developed through such application cases, we are currently conducting generative design for wearable devices in the aerospace and defense industries. Additionally, we are actively promoting our work to secure demand from companies in the electrical and electronics sectors.

4. ACKNOWLEDGMENTS

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