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INTELLIGENT SUPPORTING SYSTEM FOR NEW PRODUCT DEVELOPMENT

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ABSTRACT

The success and growth of any business is directly proportional to the innovative product development strategies adopted by it and is a renowned fact in the industry. Development of the product lasts from the first idea about the product till the end of production. In that time a lot of activities take place in order to achieve the success on the market. New product development is also a very risky process due to the high uncertainty degree encountered at every development stage and the inevitable dependence on how previous steps are successfully accomplished.

In this paper we propose an integrated decision-making framework based on neural networks (NN) helping the developers of beverage appliances. The NN model is used to build a design decision support database, which enables product designers to obtain the optimal design alternatives that best meet market's preferences for a new product design. The data were collected from various beverage appliances. With neural networks the acquired data were set as a base for creating supporting neural networks. Testing results show that the method is suitable for new appliance development. System itself predicted expected solutions well enough to confirm usability for development purposes.

Keywords: new product development, potential solutions, intelligent system support, neural network

1. INTRODUCTION

Shorter product life cycles, rapidly changing customer needs and expectations in highly competitive global business environment have heightened the corresponding need for efficient product engineering, both the improvement of current products and the design and development of new products. In fact, new products and intelligent new product development are mandatory to remain competitive. Another major concern is the time pressure to launch a significant number of new products to preserve and increase the competitive power of the company.

Companies tend to realize more and more that development itself is the key factor that impacts the success or fiasco of the product. Based on the competition it would be unrealistically to expect customer loyalty in a case of bad experience with a certain product. Therefore it is necessary to target the key factors that have currently the biggest impact on the development. Too much resources applied in the development phase mean high product's price. If there is too less resources assigned, it could happen the product is qualitatively not sufficient and therefore market rejects it. Optimum development requires minimal resources necessary with preserving quality of the end product. So, it is absolutely crucial for the existing knowledge to be used as much as possible. For that reason a system that would help developers during different stages would be a very good option.

2. BRIEF LITERATURE REVIEW OF UP-TO-DATE PUBLICATIONS

Intelligent product configurators are very useful in product development process [1]. Fields in which neural networks (NN) have been used in product development are quite many. One of the optimization approaches is being talked about in the paper that takes on optimization of the costs during lifecycle with the hybrid method and the use of NN [2]. In the field of product manufacturing some methods were introduced which with the help of NN foresee the manufacturing processes and help to improve surface properties [3,4]. Also it was developed a method for setting processing parameters and predicting the correlations of mechanical properties of the part [5] or predicting the cut quality of part edges [6]. Similar method with the aim of improving the properties of the end product was also introduced in [7]. For the support on design oriented decisions a model was introduced based on the Hebb's learning rule of NN. Therefore NN support is introduced even as early as in the design stage [8]. In the area of product optimization (case study of shaft for compressors) the process was introduced which evaluated different properties of the product with the help of NN. The developer was able to choose the appropriate solution based on the data and in the meantime also decrease the development time and costs [9]. For the decision of the product itself, a model has been introduced, which combines functions of design, development and marketing as early as in the concept phase for the purpose of optimal end product. Study has been carried out on the case study of the iron [10]. In [11] the optimization process using advanced methods has been introduced. For the evolution of design some models have been developed which predict adequacy in regards to potential customer response [12,13]. Companies tend to use different requirements checklists to achieve appropriate needs and demands. NN method was introduced also into QFD methodology [14].

3. SUPPORTING SYSTEM AND NEURAL MODULES

To define the supporting system, we first need to divide product or, in our case, beverage appliance in the smaller groups. Methodology that is often used here is to divide the appliance in sub-assemblies. In the recent times also dividing based on functionality and purpose is being done. For the development purposes the base dividing was done with 6 sub-assemblies. Therefore those sub-assemblies are housing, user interface, carrying parts, vital parts, electronics and interactive parts. In those 6 main areas parts and different assemblies are being placed. Also needed is the further sub-division in the area of each part. Therefore in the part level the system was divided into 7 categories. Those categories consist of function, operating field, type of load, classification (part/assembly), material, manufacturing process and type of bond. Because of the module concept the list can be expanded but for the development purposes the following concept is adequate.

Modules were developed with the methodology of neural networks and backpropagation learning algorithm. With the backpropagation learning method a learning sample is introduced into the neural network which later checks the output. Output sample is then introduced to the expected sample and based on the deviation an error is calculated. Weights are adjusted based on the error calculated. Algorithm adjusts the weights based on the *RMS* error of the output sample. Samples are then over and over introduced to the network until the error is sufficiently small.

With the help of before fixed database of data from the selection of 24 appliances and other different databases there were implemented 7 modulus systems for helping during development. Systems were divided into 2 separate fields depending on the functionality. Under the quantitative NN systems, the systems for selection of material, production process and type of bond were placed. Those systems suggest a selection of possible solutions based on the desired parameters. Under the qualitative systems the systems for evaluating the appliance price, size of the injection machine, number of required of gate points and checking of adequacy of the snap fit are placed. This systems propose qualitative results for orientation during development. Schematic presentation of the system with implemented modules is shown in Fig. 1.

Implementation and training of neural networks were done with the software framework Multiple backpropagation (MBP). This software framework allows easy and fast implementation of the network topology itself and learning. After the implementation it is possible to test the network with the patterns that were initially not introduced during training. So it is possible to evaluate the robustness in regards of usage. Support modules were executed with various configurations. Since each module's purpose is different also data about each NN varies. With that in mind Root Mean Square (*RMS*) of one network can on paper be better but the network with bigger *RMS* works better on real examples. Training of networks was taking place in series and endured till the networks fit the learning configuration at least 90 %. When this threshold was achieved the fine tuning process took place. Table 1 shows the end configurations regarding the number of input data, hidden neurons, output data, needed iterations to achieve end network, RMS of the network and the number of learning patterns.

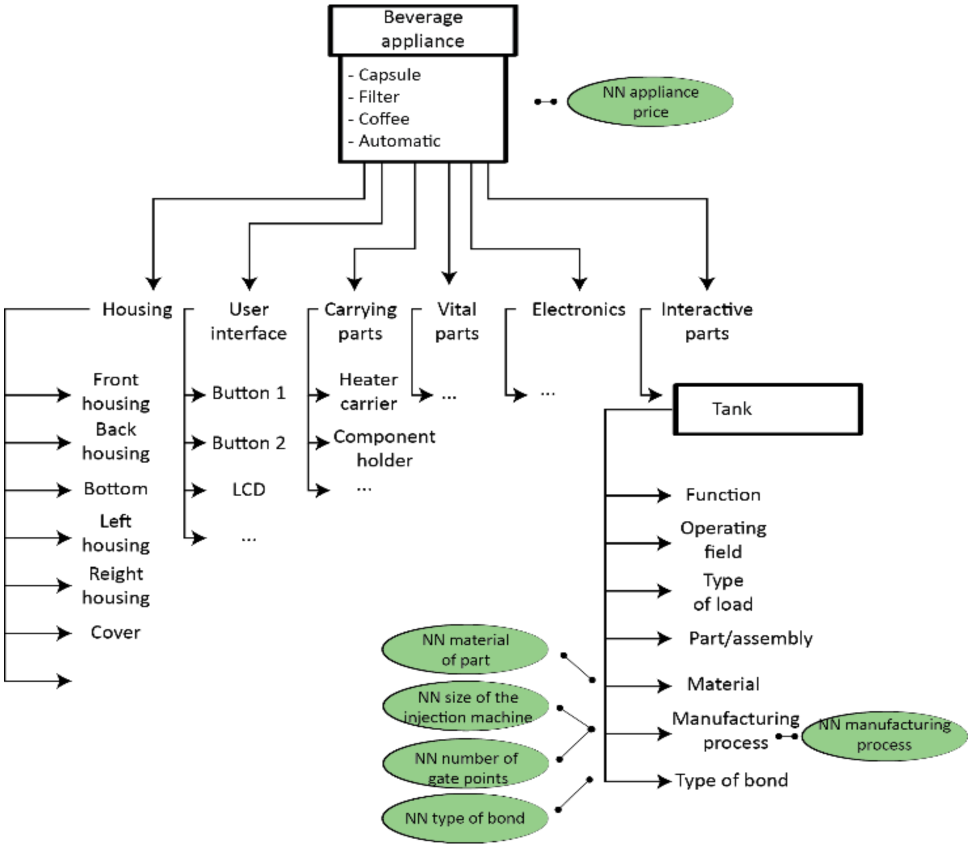

Figure 1. Supporting system with implemented NN modules.

Table 1. Neural network module configurations.

Module	Number of inputs	Number of hidden neurons	Number of outputs	Iterations	*RMS* of learning	Number of learning patterns
Price of the appliance	28	42	1	45864	0.0017	24
Material	24	86	43	468000	0.0606	43
Manufacturing process	13	34	17	16665	0.125	17
Type of bond	16	36	13	73528	0.043	13
Injection machine size	12	24	1	98276	0.00389	25
Number of gate points	13	26	2	75311	0.0099	25
Adequacy of snap fit	15	28	3	4944	0.013	26

3.1. Testing of the system

Testing of the system was carried out on the patterns that were initially not presented to the network as the learning inputs for NN training. Therefore it was assured the independent testing of the system that showed actual response of the system in real practice. The difference in the types of modules lead to the differences between results in range of an error. But it has to be said that for evaluating the suitability of NN not only *RMS* needs to be evaluated but also the deviation of the results in regard to expected data. An example is shown for the "price of the appliance", where 6 previously unknown appliances were presented to the system. Expected end result was approximate price of the appliance in regards to the input data (see Table 2).

Table 2. Results of the testing module Price of the appliance.

Sample	1	2	3	4	5	6
Expected price	135.33	172.70	566.39	661.52	586.41	52.15
Real price	140	150	550	650	750	70

4. CONCLUSION

Implementation of the system based on neural networks is bringing significant improvements in the product design phase. The concept is easy to use, it is also taking into account the existing knowledge for its work, which is in most companies shared verbally or through other channels. The later concept almost never transfers the knowledge to the right place. The information mostly gets lost.

With the case study of supporting system it was shown that the system itself is efficient enough to provide useful information during different development phases. The biggest error provided by the module for estimation of appliance price was 24 % in regards to expected price. Other modules were from the error perspective even more successful. With the constant knowledge database expansion it is possible to upgrade and improve the accuracy of the system constantly. We can conclude that the proposed system represents an effective way of development process optimization in the future.

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