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Concept of intelligent supporting information system for development of new appliances

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A B S T R A C T

There is increasing momentum in industrial practice to improve the development process itself. One of the key factors to do so is the desire for the profit made per appliance. The second reason is increase of the development oriented companies and with this also fierce competition in the global market. Development of the appliance lasts from the first idea about the product till the end of production. In between that time a lot of activities take place in order to achieve the success on the market. But because, as we know from the other fields, of more competition, the terms for success get stricter. This means that equally progressing companies can't make a significant competitive advantage on the market. If there is too much resources applied in the development phase it later shows on the price of the product itself. If there is too less resources assigned to it could happen the product is qualitatively not sufficient and therefore market rejects it. Therefore optimum development would be to minimize resources to the minimum necessary quantity with preserving quality of the end product. In this article there is suggested a method for helping the appliance developers, which based on existing knowledge foresees potential solutions with new challenges. To implement the system there were data collected from various beverage appliances. The main methods within the system were neural networks so the acquired data were set as a base for creating supporting neural networks. System was tested with the data that were previously not included into learning patterns. Results show the method to be suitable during new appliance development. System itself predicted expected solutions well enough to confirm usability for development purposes.

A R T I C L E I N F O

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1. Introduction

Companies around the world face fiercer competition every year. Borders of the market had erased in the last couple of years in a manner that virtually everyone in the world could compete in a global market nowadays. This means greater choice for the customer. On the other hand it means that a company has to push even harder for the market share. Since the companies work on the global market this means that they compete with multinationals as well as new companies formed just a while ago.

Because of ever stricter market situation which is delegated by the competition as well as more demanding customers, the companies itself need to examine even more in detail how to gain competitive edge. For the company which main business is development of the end products one of the focuses if not the main focus is set on development. Development is a broad term which contains many different areas. It contains different motivations, goals and methods for achieving them [1-3]. The thing that matters the most is the end product. So we can say that developing the appliances is goal oriented project or activity for achieving that goal with minimum required effort.

During the last couple of years development changed itself on many different fields. Even though the main factors remain, their importance share changes constantly. Main factor for this situation is the increase in development companies. Companies tend to realize more and more that development itself is the key factor that impacts the success or failure of the product. Based on the competition it would be unrealistically to expect customer loyalty in case bad experience with certain product. Therefore it is necessary to target the key factors that have currently the biggest impact on the development. After that we can set the guidelines and activities to gain maximum output. Identification and optimising key factors can with relative small input bring significant outputs [4]. As an example we can have a product that is by specification and usability very good but was 4 month delayed into the market. This brings consequences either way. It can mean company lost its market share, it can mean the sales are not as good as predicted or it could happen that the product doesn't sell at all. Either way there was a loss. On this occasion we didn't put brand reputation on the line or the global brand meaning into perspective in regards to delay.

Based on the before mentioned reasons it is absolutely crucial for the existing knowledge to be used as much as possible. Since there is a lot of knowledge present there is a need to put it in order and offer this knowledge to the developers. But to offer knowledge in a way that wouldn't consume a lot of time and thinking. For that reason a system that would help developers during different stages would be a very good option.

2. Literature review

Fields in which neural networks (NN) have been used are quite many. Also there are good enough data and examination being done in the field of product lifecycle. Also the optimisation approaches are shown. One of the optimisation approaches is being talked about in the paper that takes on optimisation of the costs during lifecycle with the hybrid method and the use of NN [5] and very similar in the paper about project time and costs [6]. When we talk about the product development it mostly means quite a vast and diverse fields which needs to be addressed. Therefore there are many fields that fit into the product development term. In the field product manufacturing method FDM (fused deposition modelling) there was a method introduced which with the help of NN foresees the product manufacturing and helps to improve the end surface roughness [7, 8]. Also it was developed a method that in regards to set processing parameters predicts the correlations of mechanical properties of the part [9, 10] or predicts the cut quality of part edges [11]. Similar method with the aim of improving the properties of the end product was also introduced in 2014 [12]. In 2016 there was a study being carried out which searched through usage of NN in processing technologies [13]. On the topic of innovation in segment of production processes a method was introduced that upgraded the knowledge through innovation process [14]. For the support on design oriented decisions there was a model introduced that is based on the Hebb's learning rule of NN. Therefore NN support is introduced even as early as in the design stage [15]. For managing complexity during production, there was on the production model of dishwashers, a model introduced for managing complexity of inventory and production which provides optimal decisions during phases of production [16]. For helping companies during customer data collecting and adjustment to these needs there was a model introduced in 2016, which with the help of advanced techniques acquires the data and segments it for later usage. Therefore the company response time for adjustment is decreased [17]. In the area of product optimisation (case study of shaft in high performance compressor) the process was introduced which evaluated different properties of the product with the help of NN. Therefore the developer was able to choose based on the data the appropriate solution and in the meantime also decrease the development time and costs [18]. 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 [19]. In 2011 and 2015 two articles have been published in which optimisation process with the help of advanced methods has been introduced [20, 21]. Interesting work has been shown in the area of quality improvement. NN method has been introduced into existing Taguchi method. On the study case a 7.8 % gain has been shown [22]. In 2014 there was a NN model introduced for the purposes of predicting turbine blades [23]. For the evolution of design a model has been developed which predicts adequacy in regards to potential customer response [24]. Similar model has also been investigated in 2013 [25]. In the case study of solar panels an approach has been introduced which evaluates technical and non-technical attributes during development for the optimal end product [26] and similarly for other products [27, 28]. Companies tend to use different requirements checklist to help achieve different needs and demands. NN method was introduced also into QFD methodology [29]. In the field of evaluation of mechanical properties where mostly numerical methods are being used there was a method based on NN introduced in 2015. Case study has been done on bending model of concrete rods with reinforced with polymer [30]. Also NN methodology was used in the ballistic field. For the prediction of penetration during high speeds the method was proven to be adequate [31]. The usage of NN in other fields is quite big. But the fact remains that the fields are covered quite narrow. System that would actively support during development hasn't yet been shown.

3. Support system

To define the support 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 being done with 6 sub-assemblies. Therefore those sub-assemblies are housing, user interface, carrying parts, vital parts, electronics and interactive parts (Fig. 1). In those 6 main areas parts and different assemblies are being placed.

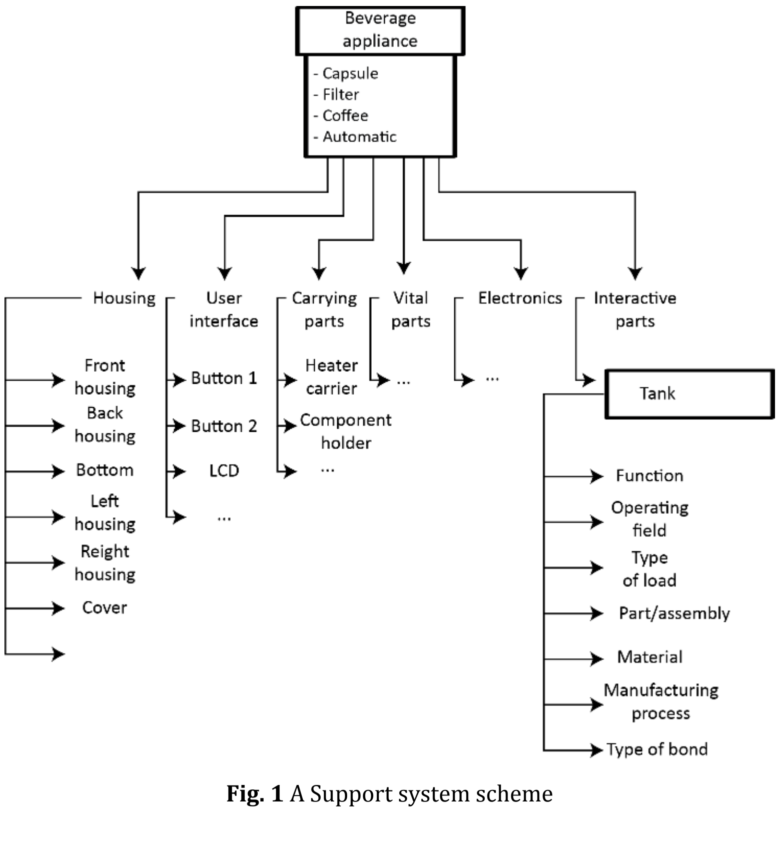

Fig. 1 A Support system scheme

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.

4. Support system and neural modules

4.1 Methodology and framework

To the basic support system NN modules were being added to support the developers during different phases of the product development. Modules were being 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 into the network until the error is not sufficiently small. Schematic mathematical model of the neuron is shown in Fig. 2.

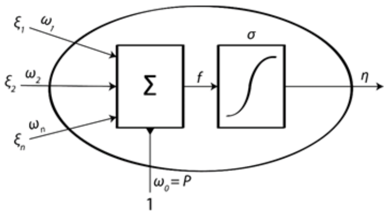

Fig. 2 Mathematical model of neuron

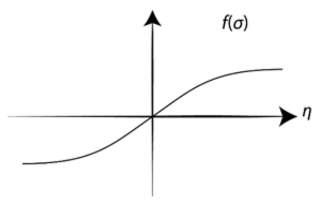

Fig. 3 Sigmoid activation function

On the model shown in Fig. 2 are the following variables:

η – neuron output, based on output function
σ – output function or activation function
ξ_j – primary variables, which can contain digital or analogue values (j = 1, 2, …, n)
ω_j – weights of input variables (j = 1, 2, …, n)
P – threshold value or threshold of element
$\sum$ – sum
f – function

Function of the model of the neuron can be described with the below shown equation:

$$\eta = \sigma\,(f) = \sigma\left(\sum_{j=1}^{n} \omega_j\,\xi_j - P\right) \tag{1}$$

There is more than one activation function available for activating the neuron in the model. Because of the usability of the function itself a sigmoid activation function has been chosen (Fig. 3). This function has whole range of continuous values from 0 to 1 available.

With the help of before fixed database of data from the selection of 24 appliances and other different databases there was 7 modulus systems for helping during development implemented. Systems were divided into 2 separate fields depends on the functionality. Under the quantitative NN systems, the system for selection of material, production process and type of bond were placed. Those systems under possible solutions suggest based on the desired parameters propose selection of solutions. Under the qualitative systems the system 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 system proposes qualitative results for orientation during development. Schematic picture of the system with implemented modules is shown in Fig. 4.

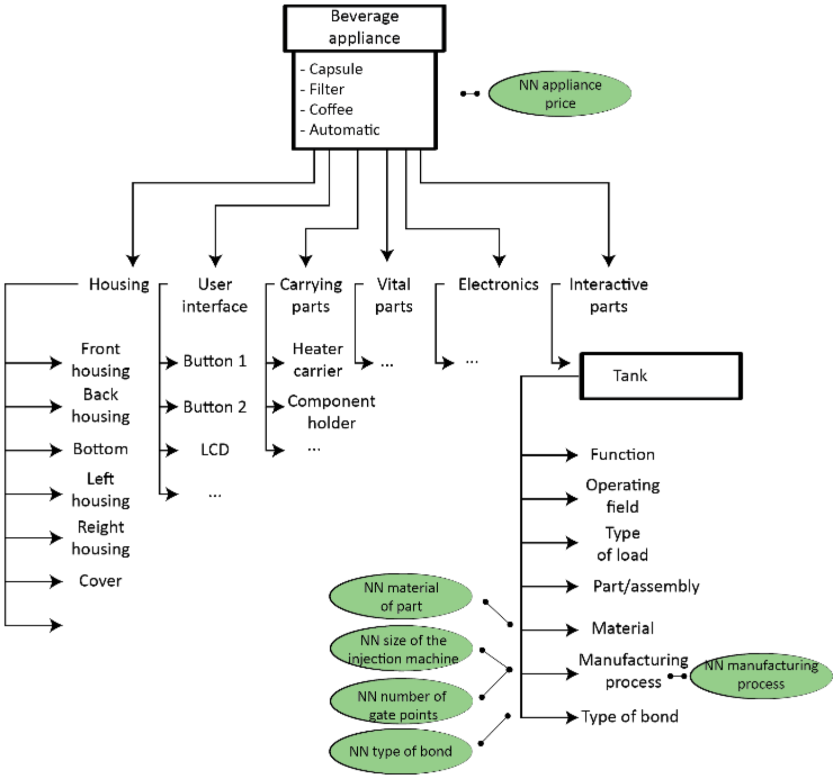

Fig. 4 Support system with implemented NN modules

4.2 Creating NN modules

Implementation and training of neural networks was done with the software framework Multiple backpropagation (MBP). This software framework allows easy and fast implementation of the network topology itself and learning. After implementation it is possible to test the network with the patterns that were initially not introduced during training. So it is possible to see how the system reacts on the real life examples and therefore 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. This meant the aim to lower the *RMS* value as much as possible. In practice this meant retraining the network over and over again from the acceptable configuration onwards. Training the same network again with the same parameters almost never gives identical end results. Therefore the end quality of the network can vary even though all the input data are the same. The following Table 1 shows the end configurations regarding number of input data, hidden neurons, output data, needed iterations to achieve end network, *RMS* of the network and the number of learning patterns.

Table 1 Table of NN 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

5. 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 leads 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.

5.1 Price of the appliance

In this module there were 6 previously unknown appliances presented to the system. Expected end result was approximate price of the appliance in regards to the input data. Following Table 2 shows the actual system outputs in regards to the expected ones.

The biggest deviation of the module was 26 %. The average deviation was 12 % based on expected results. This kind of results which is based upon input data that take into account basic specifications and visual appearance of the appliance is more than good. Module therefore efficiently predicts the price of the appliance from the input specification and gives adequate guidelines for further development and optimization of appliances.

Table 2 Results of testing module price of the appliance

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

5.2 Material of the part

Because this module is of quantitative nature the results are provided quantitatively. Therefore the task of the module is to provide adequate materials for needed application from the database of 43 basic materials with 24 input parameters. From the possible 301 possible expected materials which system should propose, the system itself proposed or wrongly proposed 3 materials. This in sum means an error of 1 %. The result itself is more than adequate since it brings good enough decision support during development work. With introduction of more learning patterns inside NN the result can be even improved.

5.3 Manufacturing process

This module is similar to previous one quantitative. It operates with the choice of 17 basic possible manufacturing processes. With the help of 13 given input parameters it offers the list of possible suitable processes. From 68 possibilities the module should offer, it proposed or wrongly proposed 3 processes. This combined means an error of 4 %. Deviation is greater than in previous module but a 96 % accuracy is still sufficient for the approximate use. System is also possible to improve under additionally presented learning patterns.

5.4 Type of bonding

Also this module is quantitative. From the selection of 13 possible basic types of bonding with regards to 16 input parameters, the module proposes selection of types of bonding that should be suited for a given application. From 65 possibilities that the module should offer it proposed or wrongly proposed 2 types of bonding. This means the combined error of 3 %. Percentage of the error is adequate for the development purposes. With retraining and introducing new learning patterns the error can be improved.

5.5 Injection machine size

On this module the aim was to test 5 before unknown configurations. The goal of the system was to get the clamping force needed for the part to inject with regards to 12 input parameters. With the help of clamping force estimation it is therefore possible to select the required injection machine size (Table 3).

The biggest deviation of the module was 39 kN. Average deviation was calculated at 25.8 kN based on the expected results. The range of error is acceptable since the calculated errors don't affect choosing procedure too much as the size range of the machines is quite big.

Table 3 Results of testing module injection machine size

Sample	Clamping force (kN)
1	23
2	30
3	187
4	89
5	305

5.6 Gate point number

In this module there was 5 previously unknown configurations tested. The aim of the system was to determine the number of the gate points needed based on the information given by 13 input parameters (Table 4). With the help of this information it is later possible to choose the injection system and also determine the price of it.

Here the system in regards to the test samples didn't deviate which means there was no error present.

Table 4 Results of testing module gate point number

Sample	Number of gate points
1	1
2	1
3	1
4	1
5	1

5.7 Snap fit check

In this module 6 previously to the system unknown configurations were presented. Task of the system was to provide in regards to 15 input parameters the maximum force of deflection needed for snap fit, maximum stress and give recommendation about the suitability of the snap fit for the given application (Table 5).

The maximum bending force deviation here was 16.4 N. Average deviation was 6.2 N. Maximum deviation of tensile stress was 30.2 MPa. Average stress deviation was 12.7 MPa. System correctly predicted suitability of all the snap fit solutions that were in the test portfolio. There was no mistake. Based on the deviation of values shown the system itself is effective enough for prediction of snap fit adequacy. With retraining and presenting of new patterns during learning it is possible to further optimize the module.

Table 5 Results of testing module snap fit check

Sample	Force of push	Tensile stress	Suitability
1	112.70	242.8791	0.00
2	22.52	30.5939	0.99
3	18.066	30.2434	0.98
4	130.85	184.3562	0.03
5	31.35	78.30119	0.00
6	49.52	110.2825	0.03

6. Conclusion

For the companies that tend to make a step ahead in the direction towards appliance development process improvement is searching for ever new solutions crucial. One of the possible steps is the implementation of the support system that is based around neural networks. Not only is the concept appealing in regards ease of use, it is also taking into account the existing knowledge. The concept itself uses the existing knowledge for its work, which is otherwise in most companies shared verbally or other channels. The later concept almost never transfers the knowledge to the right place. The information mostly gets lost.

On the case study of support system it was shown that the system itself is efficient enough to provide solid 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. Also because of the module assembly of the whole system it is possible at any time to easily swap or upgrade any certain module. Therefore it is possible in case of demands increase in a certain area occurs the parameters into modules can be added or even output requests. This is also a logical future path as there are always new demands for new knowledge during development. Therefore a system grows and knowledge database is not getting lost but is constantly upgraded. With simple implementation we also avoid unreliable methods for knowledge transfer. Since the system itself is quick it also means we gain time during some phases which can then be allocated to different areas in need. A mention about quality increase is also in place as the system based on the previous knowledge warns about the potential mistakes on new products. We can conclude that the proposed system I effective way of development process optimization in the future. This could also mean more time in the future could be spent on the most challenging tasks, since the supporting systems could take over some other tasks.

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