Natalja Fjodorova[1], Marjana Novič[1], Tamara Diankova[2] and Olga Baskova[2]
[1]National Institute of Chemistry, Laboratory of Chemometrics, Hajdrihova 19, SI-1000 Ljubljana
[2]St. Petersburg State University of Technology and Design, Department of Chemical Engineering and Textile Design, Bolshaya Morskaya Str. 18, RU-191186, St. Petersburg, Russia

New Approach for Optimising the Impregnations of Individual Batches of Aramid Fabrics

Nov pristop pri optimizaciji različnih serij aramidnih tkanin

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Abstract

Innovate textile materials for special clothing are intended for providing trauma protection for the wearer. Fabrics made from high performance aramid fibres are widely used nowadays for manufacturing athletic sportswear for extreme sports due to their high specific tensile modulus and strength. The aim of our study was to illustrate a new approach when searching for optimal settings for impregnating individual batches of textile materials on the basis of para aramid fibres. We demonstrate a feed-forward bottleneck (FFBN) neural network mapping technique that makes it possible to see all optima (optimal settings for best quality) in the studied process. The selections of optimal settings are based on making decisions allowing us to choose optimal settings for processes in relation to the best quality and smallest (minimal) expense. This new approach can be applied for searching optimal settings regarding different chemical treatments. If a standard statistical regression model (in the cases of non-linear relationships) experiences lack of fit, it can be successfully substituted with the FFBN neural network mapping technique. This method can also be recommended as a double check of a studied process when we use other approaches.
Keywords: aramid fabrics, optimisation, impregnation, feed-forward bottleneck neural network, design of experiment

Izvleček

Inovativni tekstilni materiali za specialna oblačila so namenjeni za zaščito telesa pred poškodbami. Tkanine, narejene iz visokozmogljivih aramidnih vlaken, se dandanes na široko uporabljajo za izdelavo atletskih športnih oblačil za ekstremne športe, ker imajo visoko natezno trdnost in elastični modul. Cilj naše študije je bil prikazati nov pristop pri iskanju optimalnih nastavitev za impregnacijo posameznih serij tekstilnih materialov na osnovi paraaramidnih vlaken. V raziskavah je predstavljena metoda 2D (2-dimenzionalnega) nevronskega mapiranja s tako imenovanim pristopom »feed foward bottleneck neural network (FFBN NN)«, ki omogoča vizualno ugotovitev optimalnih rešitev (optimalnih nastavitev procesa, pri katerih dobimo najboljšo kakovost). Optimalne nastavitve procesa izberemo s pomočjo odločitev, pri katerih lahko izberemo najboljšo kakovost pri najnižjih stroških. Takšen pristop je uporaben za ugotovitev optimalnih nastavitev pri različnih kemijskih obdelavah. V primerih, ko pri standardnem regresijskem modelu (zaradi nelinearnih zvez) pride do nezadostnega ali pomanjkljivega ujemanja, ga lahko uspešno nadomestimo z modelom v obliki nevronske mreže FFBN. Metodo mapiranja FFBN NN lahko uporabljamo sočasno s standardnimi statističnimi metodami. Tako omogočimo dvojno kontrolo sistema.
Ključne besede: aramidna vlakna, optimizacija, impregnacija, feed-forward bottleneck neural network, načrtovanje poskusa

Corresponding author/ *Korespondenčna avtorica:*
D.Sc. Natalja Fjodorova
Telephone: +386 1 4760441
E-mail: natalja.fjodorova@ki.si

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1 Introduction

Aramid fibres have been produced in Russia since 1970. The history of the first Russian para aramid fibres under the name SVM (super high-modulus fibre) is given on the web-page of the Alchemie Group [1]. This group was founded in 1999 to commercialise Russian materials' technologies focusing on unique materials' processes and materials that enable the Alchemie Group to supply ultra-efficient, ultra-light, ultra-high strength materials, composites, components, solutions, systems and products for the 21st century. Aramid fibres are currently in production as AuTx-WE fibre based on Rusar (Russian Aramid) technology with a tenacity of over 250 cN/tex. The process of fibre forming is principally different from that used while forming Kevlar and Twaron aramid fibres. The SVM fibre has high strength (190–220 cN/tex), high modulus (75–100 GPa), and elongation at break (3,0–4,0%). This fibre is used for the manufacturing high strength lightweight composites and as a fabric was applied in the creation of the first flexible Russian bullet proof vests.

The current generation of fibres that have become the base for AuTx materials appeared in 1997 under the tradename RUSAR (an abreviation for Russian Aramid). This fibre has very high strength (230–270 cN/tex for AuTx WE and >300 cN/tex for AuTx DWE), high modulus (100–140 GPa), elongation at break at (2,6–3,0%) and is extremly environmentally resilient. The technology of AuTx has a large potential for development [1].

Nowadays the high interest for goods produced from aramide fibres and fabrics has been proved by numerous research [2–8].

In this paper we examined the impregnation processes of high performance fabrics made from aramid fibres designed for the manufacturing of athletic sportswear for extreme sports using the neural network mapping technique when searching for optimal conditions regarding the studied process.

Traditional statistical methods based on the designing of experiments (for example, surface response method or others) are often used for improving the properties of textile materials [9–11]. In some cases the artificial neural network methods have been employed for predicting the properties of fabrics [12–13].

The application of the feed-forward bottleneck neural network (FFBN NN) mapping technique for optimisation is a relatively new method that is easy to use and non-time consuming [14–19]. The projection of multidimensional data into a 2D map enables obtaining of the input and output parameters within the same coordinates. Thus, a contour plot of output parameters (responses) overlapping with locations corresponding to the combinations of input parameters (setting points) enables visualisation of the optimal setting parameters of the technological processes in the 2D map. Implementation of the FFBN NN mapping technique enables the finding of several optimal solutions during the development of the new products, as well as to improve the qualities of industrial products. Application of the FFBN neural network mapping technique for pigment dyeing of aramid and arimid fibres was published in a paper [20]. It was of interest for considering optimisation of the impregnation process of aramid fabrics using the FFBN NN method. The FFBN NN approach in combination with the criteria functions for plotting coded diagrams is innovative within the field of enhancing textile properties via the adjusting of impregnation parameters.

2 Materials and methods

2.1 Materials

Aramid fabrics (Russian name SVM) with mass per unit areas of 131 g/m^2 (*fabric 1*) and 216 g/m^2 (*fabric 2*) produced from polyamide benzimidazole (PABI) filaments were used during the impregnation treatment.

The PABI fibres have extremely high modulus and strength, and are heat-resistant. They are widely

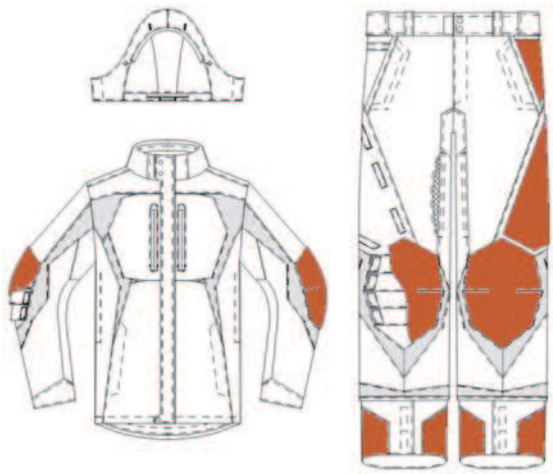

Figure 1: A pattern of a sport jacket and trousers with the pieces of aramid fabrics (darker coloured)

used for the production of protective clothing (i.e. bulletproof vests) [21] as well as for the recreational industry in a variety of applications ranging from boating to skiing. In this paper we studied those aramid fabrics used for the manufacturing of athletic sport wear for extreme sports, particularly sport jackets and trousers (see Figure 1).

The quality of lighter *fabric 1* (131 g/m^2) was evaluated using output parameters (responses) Y1–Y4, where Y1 represents weight gain I (%), Y2 stiffness (mm), Y3 tensile strength (daN) and Y4 elongation (%). The quality of *fabric 2* (216 g/m^2) was evaluated using output parameters Y5–Y7 where Y5 designates weight gain II (%), Y6 wear-resistance (cycles) and Y7 tear force (daN).

2.2 Plan of experimental design for the impregnation process

The diagram of the impregnation process of aramid fabrics considered in this study is represented in Figure 2. The fabric passes through a bath (2) and subsequently through squeeze rollers 3, then is directed towards drying in the air and thermo-fixation at 150°C.

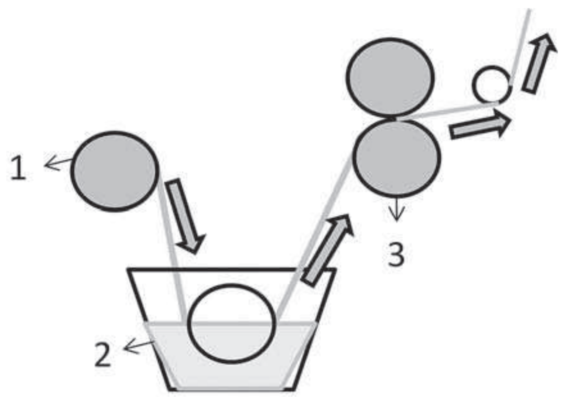

Figure 2: A diagram of the impregnation process

Statistical designs of experiments (DOEs) is commonly used in many industries (chemical, polymer, car manufacturing, biotech, food and dairy, pulp and paper, steel and mining, plastic and paints, electronic, telecom, etc.). DOEs can be used for the developments of new products and processes, enhancements of existing products and processes, optimising the qualities and performances of products, screening important factors, minimization of products' costs and pollution, robustness testing of products and processes, and so on. The goal of our study was improvement of the impregnation process.

The following five independent variables (which affect the qualities of impregnated fabrics) were chosen for the study: the concentration of latex (AH7) (x_1, g/l), concentration of gelatin (x_2, g/l), concentration of binder (Carbamol) (x_3, g/l), concentration of catalyst, $MgCl_2$ x 6 H_2O (x_4, g/l), and heat fixation time, (x_5, s).

Each of the 5 independent variables were explored on 5 levels: –2, –1, 0, +1 and +2. The contents and concentrations of components in the impregnation bath used during this study as coded and non-coded values are represented in Table 1. The parameters were varied according to the specification requirements of the technological impregnation process.

A design matrix including the 32 runs (number of experiments) was composed and is represented in Table 2, where Y1–Y4 are response variables related to *fabric 1* while Y5–Y7 relate to *fabric 2*. The input parameters X1–X5 are represented in the coded units (as code levels).

The relationships were examined between the output properties of fabrics (Y1–Y7) depending on the concentrations of the ingredients in the impregnating bath and conditions (times) of the heat settings of film-forming compositions. The goal of optimisation was to discover the maximal or minimal values of the

Table 1: Coded and non-coded values of the independent input variables X1–X5 at 5 levels (–2, –1, 0, +1, +2) for the impregnating of aramid fabrics

Input	Factors/Coded levels	–2	–1	0	+1	+2
X1	Latex (AH7) (g/l)	100	80	60	40	20
X2	Gelatin 4%-solution (g/l)	0	20	40	60	80
X3	Binder 50%-emulsion (g/l)	20	40	60	80	100
X4	Catalyst $MgCl_2$ x 6 H_2O (g/l)	0	2	4	6	8
X5	Heat fixation time (s)	150	180	210	240	270

Table 2 Experimental layout of the design matrix employed for five independent variables (X1–X5) and output responses (Y1–Y7) for the impregnation process of aramid fabrics

№	Factors					***Fabric 1*** *(131 g/m²)*				***Fabric 2*** *(216 g/m²)*		
	X1	X2	X3	X4	X5	Weight gain I (%) Y1	Stiffness (mm) Y2	Tensile strength (daN) Y3	Elonga-tion (%) Y4	Weight gain II (%) Y5	Wear resistance (cycles) Y6	Tear force (daN) Y7
1	+1	+1	+1	+1	+1	5.7	82	228	6.2	4.3	270	40
2	−1	+1	+1	+1	−1	10.8	90	244	6.5	5.8	280	42
3	+1	−1	+1	+1	−1	7.5	96	204	6.5	6.5	212	40
4	−1	−1	+1	+1	+1	8.1	93	250	6.3	10.2	216	40
5	+1	+1	−1	+1	−1	8.5	73	216	6.0	3.4	285	25
6	−1	+1	−1	+1	+1	7.2	70	242	5.7	6.7	216	36
7	+1	−1	−1	+1	+1	6.2	64	214	5.3	4.2	220	40
8	−1	−1	−1	+1	−1	8.6	70	252	5.7	6.1	225	49
9	+1	+1	+1	−1	−1	8.1	67	211	5.8	6.1	177	54
10	−1	+1	+1	−1	+1	11.6	54	243	4.7	6.5	277	57
11	+1	−1	+1	−1	+1	10.2	49	228	6.4	7.8	192	58
12	−1	−1	+1	−1	−1	11.0	56	238	6.2	8.2	289	56
13	+1	+1	−1	−1	+1	9.6	52	228	5.9	4.2	221	50
14	−1	+1	−1	−1	−1	9.6	51	229	6.5	5.6	270	67
15	+1	−1	−1	−1	−1	5.0	51	233	6.4	4.3	199	60
16	−1	−1	−1	−1	+1	7.4	46	220	6.0	4.7	216	64
17	−2	0	0	0	0	10.8	57	224	5.0	7.9	325	63
18	+2	0	0	0	0	6.0	54	228	6.5	4.3	258	55
19	0	−2	0	0	0	13.3	52	198	4.5	6.5	234	56
20	0	+2	0	0	0	7.1	53	238	6.5	5.7	206	53
21	0	0	−2	0	0	8.3	52	220	5.8	4.3	227	52
22	0	0	+2	0	0	11.7	52	222	5.9	7.0	203	61
23	0	0	0	−2	0	4.8	65	198	6.0	3.5	188	51
24	0	0	0	+2	0	16.	47	236	6.2	8.8	367	62
25	0	0	0	0	−2	9.2	53	220	6.5	6.0	242	50
26	0	0	0	0	+2	6.2	95	232	5.5	3.2	140	60
27	0	0	0	0	0	8.8	97	252	6.5	4.6	281	60
28	0	0	0	0	0	9.0	98	248	6.5	4.6	304	59
29	0	0	0	0	0	9.2	96	248	6.4	4.6	288	65
30	0	0	0	0	0	8.7	96	247	6.4	4.6	279	62
31	0	0	0	0	0	8.9	97	252	5.7	4.5	291	60
32	0	0	0	0	0	8.8	93	251	6.0	4.5	295	63
	Target					min	min	max	max	min	max	max

objective functions in order to reach the best qualities for the products. In this case the generalised response should be determined. Normalisation of the data was performed in order to obtain a generalised response.

In order to obtain the normalized values of the response variables (y_n), each y value was divided by its maximal value ($y_{n1} = y_1/y_{1max}$, $y_{n2} = y_2/y_{2max}$, ..., $y_{nk} = y_k/y_{kmax}$). As a result values no greater than one were obtained for each of the response and could be compared.

The goal of our optimisation was the maximisations of Y3, Y4, Y6 and Y7 and the minimisations of Y1, Y2 and Y5. Therefore, the generalised values of the response variables was obtained using Equations 1 and 2 for *fabric 1* and *fabric 2*, correspondingly.

$$(Y_{n\_gen1}) = y_{n3}{}^{*}y_{n4}/\ y_{n1}{}^{*}y_{n2} \quad (1)$$

$$(Y_{n\_gen2}) = y_{n6}{}^{*}y_{n7}/\ y_{n5} \quad (2)$$

It should be noted that the normalised values of "Y" were used in the neural network method described below.

2.3 Feed-forward bottleneck (FFBN) neural network

The general concept of artificial neural networks (ANN) is based on simplified imitation of the human nervous system.

A simple network has a feed-forward structure: signals flow from inputs forward through any hidden units, eventually reaching the output units. Input data are organised as vectors (based on linear algebra). In other words the input layer serves for introducing the values of the input variables. (In Figure 3 one can see fragments of vectors from the design matrix). Neural networks are typically organised in layers. The hidden and output layer neurons are connected to all the units in the preceding layer. In the study we applied the FFBN NN-containing input layer, hidden layer and de-mapping of input (output layer) (see Figure 4). Layers are made up of a number of interconnected "nodes" which contain an "activation function".

The FFBN neural network applied in the study refers to an auto associative neural network. The feed-forward nets here are trained to produce an approximation of the identity mapping between network inputs and outputs using back propagation or similar learning procedures [14–19]. This neural network can deal with linear and nonlinear correlation amongst variables. Multidimensional data sets are difficult to interpret and visualise. The FFBN neural network was used for compression and visualisation of the data in 2D maps. The FFBN neural network is formed by means of mapping and demapping the hidden layer. The signals in the two hidden nodes are taken as two coordinates for each input object, enabling a 2D projection of experimental objects onto a 2D map.

The architecture of FFBN NN is represented in Figure 3. The DOE matrics containing »*m*« factors (X1–Xm) with »*k*« numbers of runs is shown at the top of Figure 3. The principle of bottleneck layer mapping: the two neurons within the hidden layer produce, for each input object x_i, a corresponding pair of coordinates ($h_i = \{h_{i,1}, h_{i,2}\}$). The run number »*i*« marked as a vector $xi = \{x_{i1}\ x_{i2}\ x_{i3}...x_{im}\}$. In the FFBN each *i-th* object is projected onto a two dimensional map with coordinate h_{i1}/h_{i2} (see blue arrow). In our experiment we have got 32 projection points (k = 32) corresponding to 32 experimental settings.

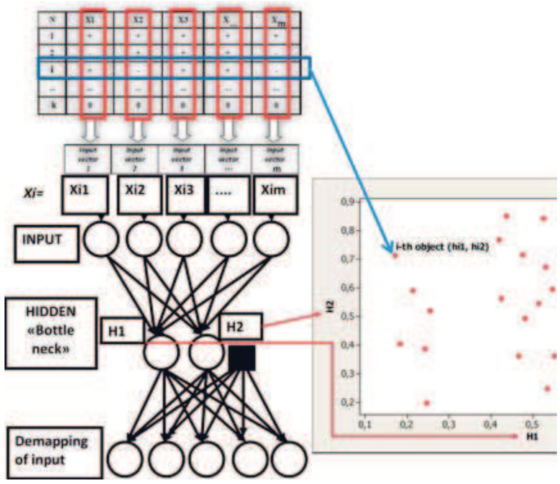

Figure 3: The architecture of feed-forward bottleneck (FFBN) neural network

The 2D map with distribution of 32 experimental settings (as was determined in the plan of the experiment) is shown at the right side of Figure 4 in coordinate H1/H2.

For each of the 32 experimental settings the corresponding value of response Y was determined during the course of the experiment. The projection of Y onto H1/H2 coordinates gave the contour plots of response Y. Overlapping the projections of 32 experimental objects (obtained from the FFBN neural network 2D map) with responses' contour plots in the same coordinates (H1/H2) enables visualisation and the determining of optimal settings (the dark colour in the 2D map corresponds to the highest values of response Y).

3 Results and discussions

3.1 Searching optima using FFBN neural network mapping

The architecture of the FFBN neural network with input matrix (X1–X5) applied in the study and projection of experimantal setting points (1–32) is shown in Figure 4. It complemented the projection of generalised response Ygen1 (for *fabric 1*) onto a 2D map with the same coordinate H1/H2. The right (bottom) side of Figure 4 illustrates the contour plot of Ygen1 overlapped with 32 input setting points.

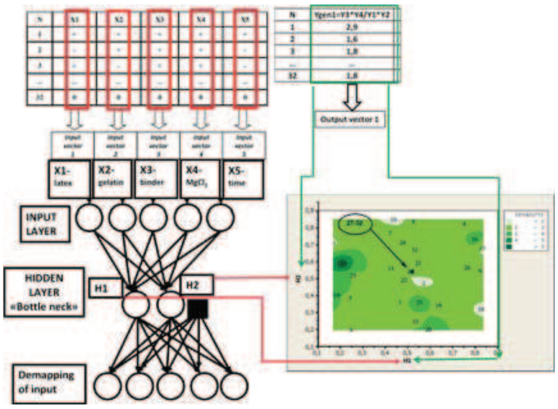

Figure 4: The architecture of FFBN neural network with input matrix (X1–X5) and projection of experimental setting (points 1–32), as well as values of generalised response Ygen1 (for fabric 1) onto 2D map with coordinate H1/H2

Input data are represented as vectors X1–X5 corresponding to 5 columns in the design matrix with 32 rows related to the 32 setting points (see Table 2).

A special architecture of error back-propagation neural network was used (5, 2, 5), in which the data are fed into the 5-nodes input layer and then transferred through the 2-nodes hidden layer (compared to a bottleneck) to the 5-nodes output layer. The number of nodes in the input and output layers correspond to the number of independent variables which is equal to 5 (number of factors in DOE). During the training process we are able to get within the output nodes, the values more similar to the input variables of the samples, after passing the bottleneck of the two-node hidden layer. The signals in the two hidden nodes are then taken as two coordinates for each input object acting as a 2D projection of samples into a map.

For each of the 32 experimental settings the corresponding value of Y (Y1–Y7) was determined in the course of the experiment. The projection of 32 combinations of experimental conditions and values of response within the same coordinates H1/H2 enables determination of optima in the impregnation process.

Figure 5 illustrates the experimental data for fabric 1 with surface density 131 g/m^2. It represents the 34 setting points overlapped with the contour plots of responses: Y1- weight gain, Y2- stiffness, Y3- tensile strength, Y4- elongation and generalised values Ygen1 = Y3*Y4/ Y1*Y2.

The dark green (in colour picture)/grey (in the grey scale picture) area corresponds to maximal values. For *fabric 1* it corresponds to combination 15. Thus, for *fabric 1* optimal condition settings correspond to levels of X1–X5 (+,–,–,–,–) with parameter X1 at level +1 and parameters X2–X5 at the level –1. Thus, the optimal settings for *fabric 1* enable obtaining of the following quality characteristics: Y1 = 5.0%, Y2 = 51mm, Y3 = 233daN; Y4 = 6.4%.

Figure 6 represents the experimental data for *fabric 2* with surface density 216 g/m^2. The thirty two (32) experimental setting points are overlapped with the contour plots of responses: Y5- weight gain, Y6- wear resistance, Y7- tear force; and generalised values Ygen2 = Y6*Y7/ Y5.

For *fabric 2* optima for generalised response correspond to combination 14, 18 and central values (zero level (27–32)) (marked with red circles in Figure 6). Non-coded values of Y5–Y7 in that points are seen in Table 2.

We can also select the optimal settings by taking into account individual responses Y6, Y7 and Y5 (not generalised). If the weight gain (Y5) is insignificant (or the values for Y5 at point 24 satisfy our requrements) and we would like to get the highest wear resistance (Y6) and tear force (Y7) we obviously would select point 24 (see Figure 6). This point 24 corresponds to the highest values of Y7 (Y7 = 62daN) and Y6 (Y6 = 367cycles) keeping the Y5 at the middle level (Y5 = 8.8%).

Thus, three (multimum) optima were recommended for *fabric 2*. The first optimum corresponds to the setting point **14** (–,+,–,–,–); the second optimum belongs to point **18** (2,0,0,0,0); and the third

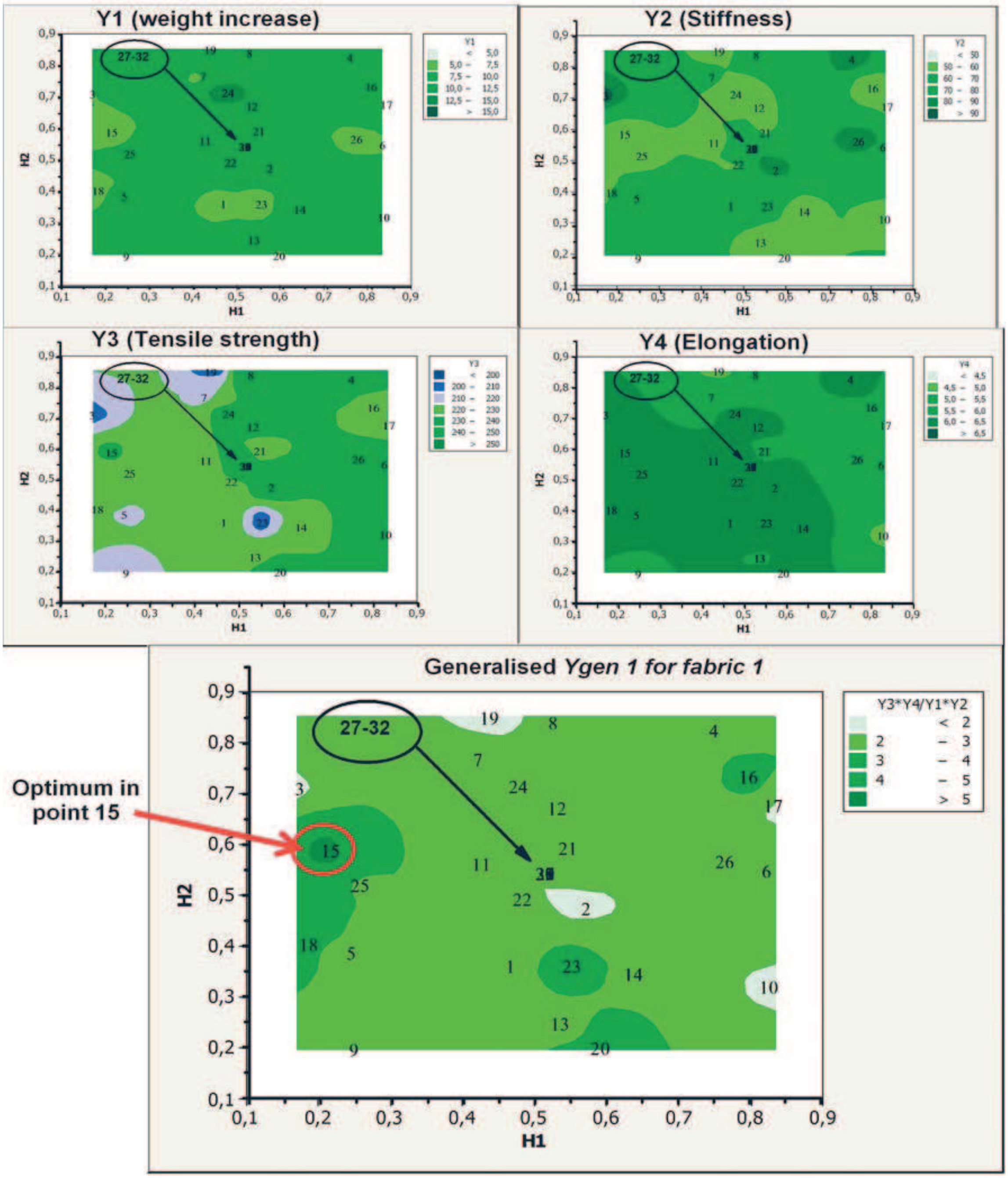

*Figure 5: Experimental data for fabric 1 with surface density 131 g/m². Thirty two (32) setting points overlapped with the contour plots of responses: Y1- weight gain; Y2- stiffness; Y3- tensile strength; Y4- elongation, and generalised values Ygen1 = Y3*Y4/ Y1*Y2*

optimum is located at the centre point **27–32** (0,0,0,0,0).

To obtain the highest wear resistance and tear force keeping the weight gain at the middle level we recommend setting point number **24** (0,0,0,+2,0).

Visualisation of the process in the 2D map provides significant information for making decisions and selecting a suitable condition for the experiment.

An optimal solution was chosen on the basis of a compromise decision.

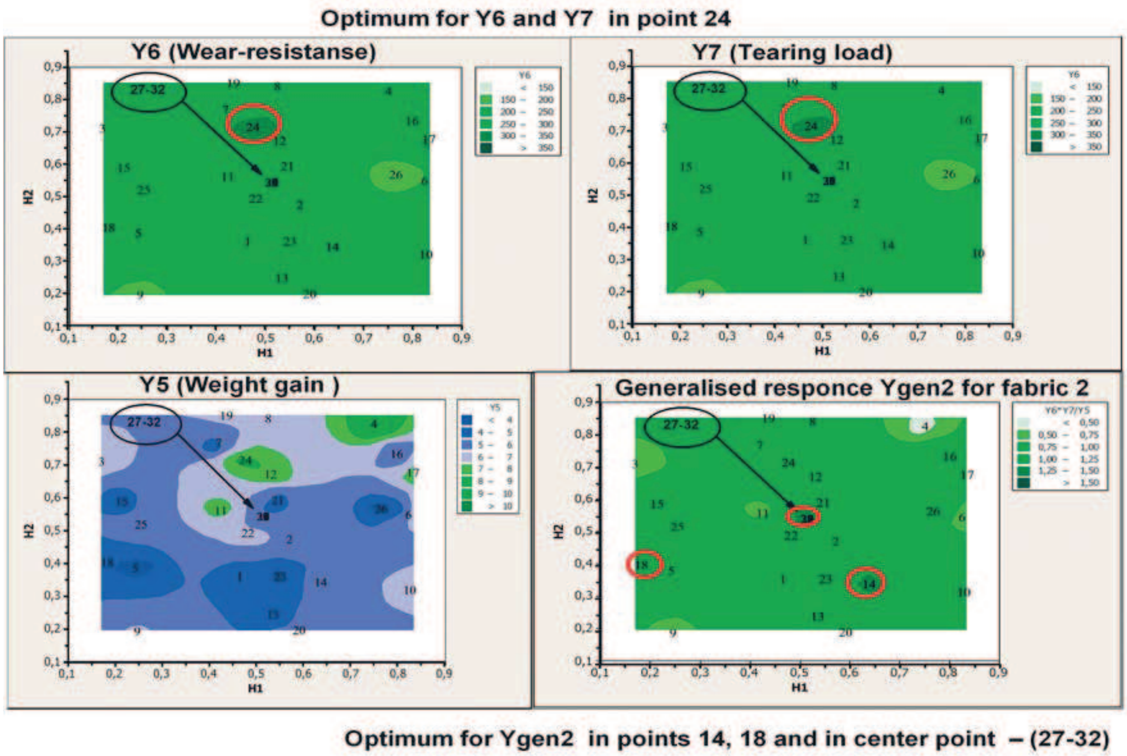

*Figure 6: Experimental data for fabric 2 with surface density 216 g/m². Thirty two (32) setting points overlapped with the contour plots of responses: Y5- weight gain; Y6- wear resistance; Y7- tear force, and generalised values Ygen2 = Y6*Y7/ Y5*

4 Conclusion

Implementation of the feed-forward bottleneck neural network technique enabled the finding-out of one optimum for *fabric 1* that corresponded to setting parameters in setting point **15** (+,–,–,–,–) with parameter X1 at level +1 and parameters X2–X5 at the level –1. For *fabric 2* three (multimum) optima were recommended: corresponding to the setting points **14** (–,+,–,–,–), **18** (2, 0,0,0,0) and centre point **27–32** (0,0,0,0,0). To get the highest wear resistance and tear force keeping the weight gain at the middle level and recommended setting point number **24** (0,0,0,+2,0).

The FFBN mapping technique enables the finding-out multiple optima that could be selected upon compromise decisions by taking into account the desired quality of material, as well as the technical and economic viewpoint and safety of the process. Translation of the multidimensional process input parameter's space into the 2D coordinate system and application of the criteria function as a combination of the process output parameters can be very informative and opening a whole new area of finding optimal conditions in the field of the textile impregnation industry.

References

1. Alchemie Group home page [online], [accessed 22. 4. 2015]. Available on Word Wide Web: <http://alchemie-group.com/core-materials-technology/autx-aramid-fibre/compliance/>.
2. KIM, Hyun Ah and KIM, Seung Jin. Physical properties of para-aramid/nylon hybrid air textured yarns for protective clothing. *Fibers and Polymers*, 2014, **15**(11), 2428–2436, doi: 10.1007/s12221-014-2428-5.
3. ZHENG, Huanda and ZHENG, Laijiu. Dyeing of meta-aramid fibers with disperse dyes in supercritical carbon dioxide. *Fibers and Polymers*, 2014, **15**(8), 1627–1634, doi: 10.1007/s12221-014-1627-4.

4. BILISIK, Kadir. Experimental determination of yarn pull-out properties of para-aramid (Kevlar®) woven fabric. *Journal of Industrial Textiles January,* 2012 **41**(3), 201–221, doi: 10.1177/1528083711413411.
5. UPPAL, Rohit, RAMASWAMY, Gita N. and LOUGHIN, Thomas. A novel method to assess degree of crystallinity of aramid filament yarns. *Journal of Industrial Textiles*, 2013, **43**(1), 3–19, doi: 10.1177/1528083712444648.
6. LIN, Lantian, SHEN, Yiping and ZHANG, Qiuping. Analysis of environmental impact on mechanical properties of aramid filaments. *Journal of Industrial* Textiles, 2013, **42**(4), 489–500, doi: 10.1177/1528083712446383.
7. PARK, Jong Lyoul, YOON, Byung Il, PAIK, Jong Gyu and KANG, Tae Jin. Ballistic performance of *p*-aramid fabrics impregnated with shear thickening fluid. Part I – Effect of laminating sequence. *Textile Research Journal*, 2011, **82**(6), 527–541, doi: 10.1177/0040517511420753.
8. ZIELINSKA, Dorota, DELCZYK-OLEJNICZAK, Bogumila, WIERZBICKI, Lukasz, WILBIK-HAŁGAS, Bożena, STRUSZCZYK, Marcin Henryk and LEONOWICZ, Marcin. Investigation of the effect of para-aramid fabric impregnation with shear thickening fluid on quasi-static stab resistance. *Textile Research Journal*, 2014, **84** (15), 1569–1577, doi:10.1177/0040517514525881.
9. LI, Ting-Ting, WANG, Rui, LOU, Ching Wen and LIN, Jia-Horng. Evaluation of high-modulus, puncture-resistance composite nonwoven fabrics by response surface methodology. *Journal of Industrial Textiles*, 2013, **43**(2), 247–263, doi: 10.1177/1528083712452900.
10. ZHIYING, Cui, YANMIN, Wan and WEIYUAN, Zhang. Thermal protective performance and moisture transmission of firefighter protective clothing based on orthogonal design. *Journal of Industrial Textiles*, 2010, **39**(4), 347–356, doi: 10.1177/1528083709347126.
11. LEE, Kyulin and CHO, Gilsoo. The optimum coating condition by response surface methodology for maximizing vapor-permeable water resistance and minimizing frictional sound of combat uniform fabric. *Textile Research Journal*, 2014, **84**(7), 684–693, doi: 10.1177/0040517513509870.
12. SARAVANA, kumar T. and SAMPATH, V. R. Prediction of dimensional properties of weft knitted cardigan fabric by artificial neural network system. *Journal of Industrial Textiles,* 2013, **42**(4), 446–458, doi: 10.1177/1528083712444296.
13. BEHERA, B. K. and GOYAL, Y. Artificial neural network system for the design of airbag fabrics. *Journal of Industrial Textiles*, 2009, **39**(1), 45–55, doi: 10.1177/1528083708093335.
14. KRAMER, Mark A. Nonlinear principal component analysis using autoassociative neural networks. *AIChE Journal*, 1991, **37**(2), 233–243, doi: 10.1002/aic.690370209.
15. NOVIČ, Marjana and GROŠELJ, Neva. Bottleneck type of neural network as a mapping device towards food specifications. *Analytica Chimica Acta*, 2009, **649**(1), 68–74, doi: 10.1016/j.aca.2009.07.018.
16. DASZYKOWSKI, M., WALCZAK, B. and MASSART, D.L. A journey into low-dimensional spaces with autoassociative neural networks. *Talanta,* 2003, **59**(6), 1095–1105, doi: 10.1016/S0039-9140(03)00018-3.
17. DASZYKOWSKI, M., WALCZAK, B. and MASSART, D.L. Projection methods in chemistry. *Chemometrics and Intelligent Laboratory Systems,* 2003, **65**(1), 97–112, doi: 10.1016/S0169-7439(02)00107-7.
18. LIVINGSTONE, D. J., HESKETH, G. and CLAYWORTH, D. Novel method for the display of multivariate data using neural networks. *Journal of Molecular Graphics*, 1991, **9**(2), 115–118, doi: 10.1016/0263-7855(91)85008-M.
19. KOCJANČIČ, Robert and ZUPAN, Jure. Application of a feed-forward artificial neural network as a mapping device. *Journal of Chemical Information and Modeling,* 1997, **37** (6), 985–989, doi: 10.1021/ci970223h.
20. FJODOROVA, Natalja, NOVIČ, Marjana and DIANKOVA, Tamara. Optimization of pigment dyeing process of high performance fibers using feed-forward bottleneck neural networks mapping technique. *Analytica Chimica Acta***,** 2011, **705**(1–2), 148–154, doi: 10.1016/j.aca.2011.04.041.
21. *High-performance fibres*. Edited by J. W. S. Hearle. Cambridge: Woodhead Publishing, 2001, pp. 329, doi: 10.1533/9781855737549.

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