Blending Process Optimization into Special Fat Formulation by Neural Networks[1]

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ABSTRACT: Computer programs are used to manage, supervise, and operate production lines of oil, margarine, butter, and mayonnaise in the fats and oils industry. Automation allows for lower-cost and better-quality products. The present paper shows a multilayer perceptron-type, second-generation neural network that was built based on a desirable product solid profile and was designed to formulate fats from three ingredients (one refined oil and two hydrogenated soybean-based stocks). This network operates with three sequential decision levels, technical, availability and costs, to furnish up to nine possible formulations for the desired product. Upgrading verification was accomplished by soliciting to the formulation network all 63 products used in the upgrading (the answers were evaluated by a panel of experts and considered satisfactory) and 17 commercial products. It was possible to formulate more than 50% of the products in the network with only the three bases available. The results demonstrate the possibility of using neural networks as an alternative to the automation process for the special fats formulation process.
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KEY WORDS: Blending, fat formulation, hydrogenated fats, neural networks, shortenings.

The final characteristics of hydrogenated products, such as margarine, spreads and fats, for specific uses depend on the physical and chemical properties of the oils and fats used in their formulation. To obtain the appropriate specification for each product, different hydrogenated base stocks are produced and mixed in adequate proportions (blending process). When necessary, refined oils are also used. The number and complexity of bases used primarily depend on the finished product specifications.

Nowadays, the formulation of a fat involves a series of steps in which experts, on the basis of solid profiles of the raw materials and the desired product, make use of methods, such as statistical equivalence, where blend components are determined by computer from the results of a great number of blends with known composition. Other methods, such as linear programming or selecting from previously developed formula files stored in a data base, are used as well (1).

However, linear programming methods are based on linearization (each component contributes in a linear way to the solid contents of the final blend) and have restricted application to formulations that do not have liquid oils and/or fats with high solid contents, due to the eutectic effect, nor fats with a particular crystallization behavior (e.g., palm oil) (1,2).

For the development of new products, calculations to determine the resulting characteristics of several base combinations are made, and the next step is formulation on a laboratory scale, where the calculated chemical mixture data are confirmed, then determination of the solid fat content, among other characteristics (2).

The automation process for special fats formulation involves a long and laborious process. Besides the calculations, many trial-and-error procedures and determinations of the physical characteristics of the final products are needed. If the procedure is not carried out in the appropriate way, clients may reject the product, resulting in economic losses or reprocessing. It also involves economic questions related to raw material availability, which, owing to price fluctuations, can cause a significant economic impact (2).

Computer programs are used to manage, supervise, and operate the controls of production lines for oil, margarine, butter, and mayonnaise in the fats and oils industry. Automation allows for lower costs and better-quality products. Two areas stand out in process control, the specialist systems and the neural networks (3,4).

Neural networks are computer systems that are based on the structure and behavior of biological systems (Figs. 1 and 2) and can be defined as a group of computer units of low capacity that are intensively connected. Besides working in parallel, these systems are able to learn and spread knowledge, showing a performance that is somewhat akin to that of human beings, which allows for the substitution of the latter in different tasks (5).

Neural networks have been studied for use in control tasks, such as self-guided vehicles (6), robots (7), and failure diagnosis (8). In the food area, they have been used for chemical and sensorial analyses (9,10) and in biotechnology (11,12).

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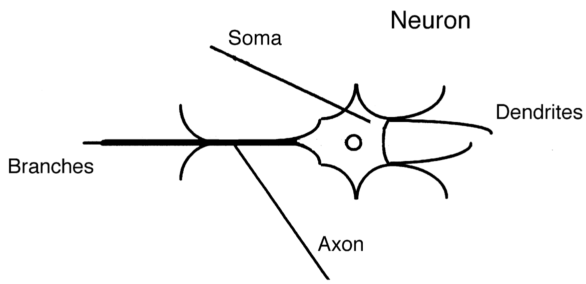

FIG. 1. Biological neuron model.

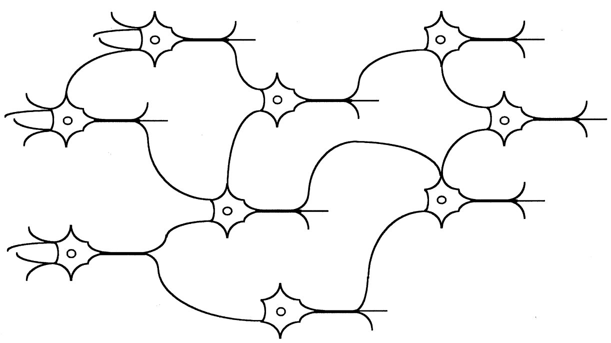

FIG. 2. Biological neural network.

In the most common proposal for artificial neurons, signals enter the neural network and stimulate the neurons through the dendrites. First, they are weighed and added, and after that, the signal is recoded by a sigmoidal function before being sent to the rest of the network (Fig. 3).

The neuron interconnection gives the neural network its structure. The synapses set the connection among the neurons and store the network knowledge, which is distributed to all of the synapses. Upgrading is the name of the process of neural network learning and storing of knowledge. Several proposals are available in the literature about the architecture of neural networks and neural network learning methods (6,13). The learning method chosen depends on the problem to be solved by the network.

In the fats and oils field, the neural network has been used to classify oils (5) and to detect olive oil adulteration (14).

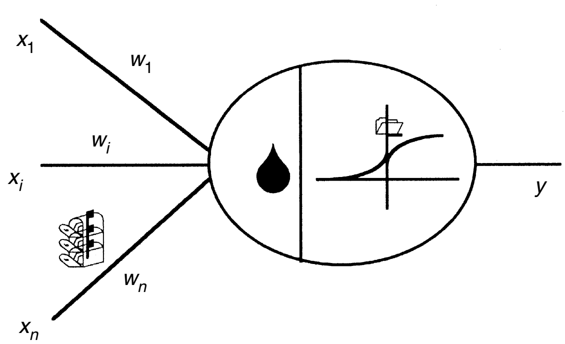

FIG. 3. Artificial neuron. *x* = inputs; *w* = synaptic weights; *y* = outputs.

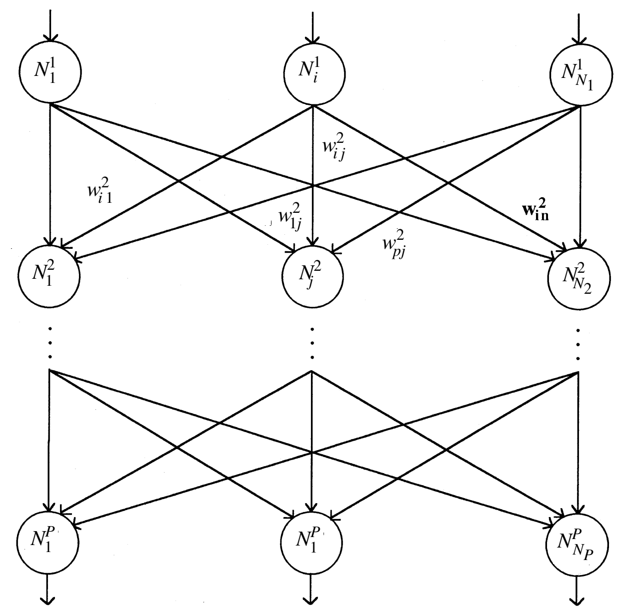

FIG. 4. Neural network perceptron topology. *P,* network layer; *N,* neuron.

The automation process for hydrogenated products formulation can present many advantages for the industry by solving problems related to production and cost restrictions and by making the process faster and more economical.

The present research studies an alternative proposal to conventional formulation through neural network application, so that process automation becomes possible. A perceptron-type neural network (Fig. 4), associated with the backpropagation learning process, was chosen because of its ease of implementation and the good results achieved with this structure in this type of problem (15–17).

EXPERIMENTAL PROCEDURES

Raw materials. Hydrogenated bases, made from soybean oil and refined soybean oil (Cargill Agrícola, S.A., Mairinque, São Paulo, Brazil) and for which some physical and chemical characteristics are shown in Table 1, were used as raw materials**.**

Analytical methods. Solid fat content (SFC) was determined by AOCS Cd 16-81 (18) serial method at temperatures of 10, 20, 25, 30, 35, and 37.5°C**.** Softening points were measured by AOCS Cc 3-25 (18); iodine values by AOCS Cd 1b-87 (18); and *trans* isomers by the AOAC (19) method.

Neural net. The neural net main characteristics are described in Table 2.

Formulation method and neural network training. Neural network training was carried out with the following entrance data: SFC curve of 63 formulated fats with three different raw materials (two hydrogenated bases plus refined soybean oil). The formulations were produced with a compound percentage change of 10 units (Fig. 5 and Table 3). The exit layer represents the percentage of mass of each raw material that must

TABLE 1
Some Physicochemical Characteristics of the Raw Materials[a]

				SFC (%)					
Sample	IV	SP	*Trans*	10°C	20°C	25°C	30°C	35°C	37.5°C
Base A	62.9	42.0	54.7	71.7	51.6	44.0	35.2	18.3	11.7
Base B	79.2	32.2	42.3	29.5	13.7	9.7	5.4	2.3	1.22
Oil	124.9	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.	n.d.

[a]Abbreviations: IV = iodine value (meq/k); *Trans* = *trans* fatty acids (%); SP = softening point (°C); SFC = solid fat content; n.d., not determined.

TABLE 2
Neural Net Characteristics

Net used: Multilayer perceptron
Net structure:
- Input layer: six variables standing for the solids profile (SFC × temperature)
- Hidden layers: two layers with six neurons each
- Output layer: three neurons standing for the proportion of raw materials that must be used in formulation
- Activation function: a sigmoid-like function
- Training factor: 0.05
- Training algorithm
  - Step 1: present input data *x* (inputs)
  - Step 2: compute the net output *y* (outputs)
  - Step 3: compute the error between the desired net output and current net output *y*
  - Step 4: if the error is ≤0.001, then go to step 5, otherwise go to step 1
  - Step 5: stop learning

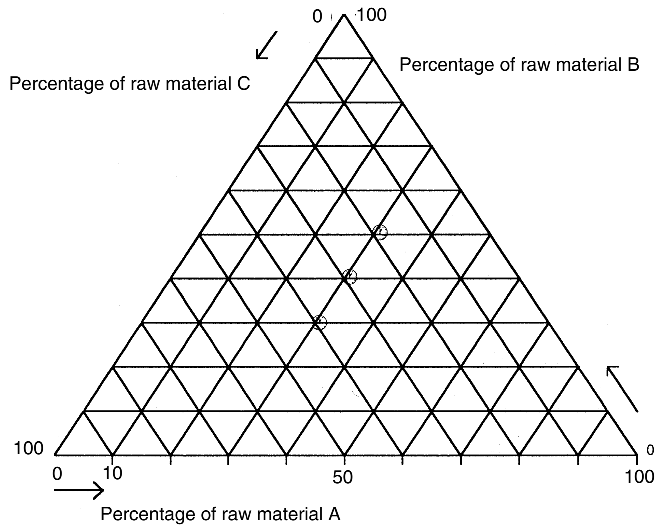

FIG. 5. Formulation triangle.

be used in the desired product formulation (Fig. 6 and Table 4).

The answers obtained by the network were compared to the compositions set for each curve. The training factor used was 0.05, and the learning phase was concluded when the adjustments were smaller than 0.001.

After training, the network was put into a computer system to support the decision, so that it became possible to visualize the desired curves and those obtained by the network, and make storage and cost analysis.

RESULTS AND DISCUSSION

To observe the network learning process, formulations of all products used were required and the answers obtained were evaluated experimentally by using a fewer error formulation (the network gives up to nine answers for the same product formulation, depending on the range of variation). The solid profile obtained was compared to those required by the network. This evaluation was made on the 63 curves used in the learning process. The curves obtained were evaluated by two specialists and found satisfactory. The results can be observed in Table 5, which shows the required curves, the network answer (theoretical value), and the experimental curves.

To check neural network efficiency, the formulations of 17 commercial products (soft and hard margarines, spreads, and shortenings) were submitted to the network. With the available raw materials, it was possible to formulate about 50% of the required products properly (Table 6), as judged by the normal limitations of the raw materials (bases).

As the network operates at three distinct levels (technical, raw material availability, and costs), after solving the techni-

TABLE 3
Examples of Data Used in Learning of Neural Network

Learning (solids profile, composition)								
Solids profile						Composition (%)		
10°C	15°C	20°C	25°C	30°C	37.5°C	A	B	C
34.37	23.05	19.17	12.95	5.61	3.39	20	50	30
31.95	19.38	15.05	9.98	3.54	2.12	30	40	30
28.99	16.45	12.17	7.31	2.70	1.56	40	30	30

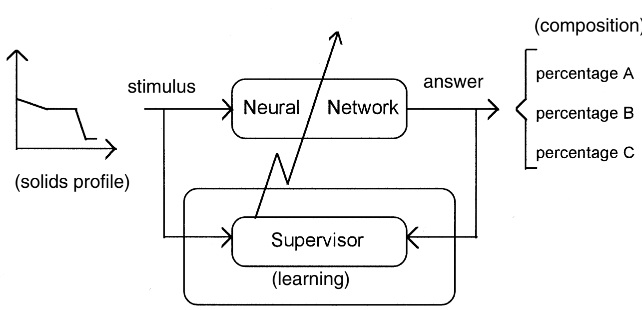

FIG. 6. Training process for a neural network.

TABLE 4
Answers from Neural Network After Training

Solids profile (required)						Answer (composition, %)		
10°C	15°C	20°C	25°C	30°C	37.5°C	A	B	C
34.37	23.05	19.17	12.95	5.61	3.39	20.65	51.00	28.35
31.95	19.38	15.05	9.98	3.54	2.12	32.02	40.11	27.87
28.99	16.45	12.17	7.31	2.70	1.56	40.02	30.84	29.14

cal restriction, it is possible to select the formulation by considering raw material availability and price.

The obtained results show that is possible to use neural networks as an alternative for automation of special fats formulation. This formulation system considers the food industry worker's real needs. Besides showing many options for the same formulation, the system gives the solid profile for each product, to allow better quality control of the final product. The user works with the system by giving restrictions regarding raw material costs and storage. Automation of the formulation process presents many advantages for the industry, making the process faster, more economic, and independent of the conventional system's problems.

TABLE 5
Verification of Neural Network Upgrading *via* the Solids Profile of the Formulated Products

	SFC[a] (%)					
	10°C	20°C	25°C	30°C	35°C	37.5°C
Sample 1						
Required	50.90	36.19	30.15	22.28	10.49	6.26
Network estimate	51.90	36.20	30.00	22.20	9.80	5.90
Experimental	52.25	36.76	31.41	22.32	10.72	6.27
Sample 2						
Required	43.46	30.02	25.18	17.11	7.94	4.81
Network estimate	44.20	31.10	25.60	18.40	7.70	4.60
Experimental	45.63	32.13	27.32	18.91	9.00	5.04
Sample 3						
Required	35.00	23.43	18.79	13.06	5.63	2.81
Network estimate	35.20	24.00	19.40	13.20	5.20	3.10
Experimental	36.30	24.94	20.29	13.84	5.88	3.43
Sample 4						
Required	27.73	17.85	13.75	9.11	3.11	1.77
Network estimate	27.90	17.90	14.10	9.00	3.60	2.10
Experimental	27.31	17.52	13.90	8.46	3.42	1.43
Sample 5						
Required	21.53	12.96	9.64	6.11	2.25	1.00
Network estimate	21.30	12.50	9.50	5.80	2.30	1.30
Experimental	21.15	12.94	9.99	6.10	2.09	1.05
Sample 6						
Required	15.35	8.29	5.98	3.36	0.95	0.47
Network estimate	16.00	7.20	4.80	2.80	1.20	0.70
Experimental	16.24	7.20	4.53	2.46	0.57	0.26
Sample 7						
Required	48.51	31.73	25.77	18.36	7.85	4.66
Network estimate	47.70	31.70	25.70	18.20	7.70	4.60
Experimental	47.99	31.83	26.48	18.20	8.52	4.73
Sample 8						
Required	43.82	27.88	21.91	15.24	6.02	4.22
Network estimate	44.70	27.80	22.00	14.90	6.20	3.60
Experimental	43.47	27.09	21.59	14.17	6.08	3.51
Sample 9						
Required	36.66	21.18	16.48	10.57	4.11	2.36
Network estimate	36.70	21.10	16.00	10.20	4.10	2.40
Experimental	36.66	21.17	16.12	10.08	4.23	2.54
Sample 10						
Required	33.19	18.19	13.35	8.00	3.15	1.71
Network estimate	33.20	17.80	13.00	8.00	3.20	1.90
Experimental	33.04	18.07	13.24	8.33	2.93	1.91

[a]For abbreviation see Table 1.

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TABLE 6
Verification of the Neural Network Formulating Commercial Products

	SFC[a] (%)					
	10°C	20°C	25°C	30°C	35°C	37.5°C
Sample 1						
Required	43.24	24.14	18.52	12.66	5.08	2.83
Network estimate	40.30	24.00	18.50	12.10	4.90	2.90
Experimental	40.66	23.83	18.19	12.35	5.55	2.85
Sample 2						
Required	32.90	19.32	12.60	9.94	4.44	2.52
Network estimate	33.30	19.30	14.60	9.20	3.70	2.10
Experimental	33.64	19.22	14.18	9.19	3.72	2.31
Sample 3						
Required	26.23	17.29	11.82	7.22	3.16	1.23
Network estimate	26.00	15.80	12.20	7.60	3.00	1.70
Experimental	26.04	16.29	12.05	8.09	3.08	1.41
Sample 4						
Required	29.95	14.54	9.87	4.41	0.18	0.00
Network estimate	29.40	14.60	10.20	6.10	2.40	1.40
Experimental	29.94	14.96	10.04	6.18	2.60	1.20
Sample 5						
Required	22.80	14.26	8.98	4.62	1.89	1.38
Network estimate	23.20	12.30	8.80	5.30	2.10	1.20
Experimental	23.71	12.76	8.82	5.20	1.80	0.83
Sample 6						
Required	35.02	22.68	14.51	8.14	3.42	1.85
Network estimate	35.50	19.60	14.60	9.10	3.70	2.10
Experimental	36.22	20.12	14.61	9.30	3.77	2.20
Sample 7						
Required	37.52	22.60	18.23	10.60	4.01	1.98
Network estimate	38.00	22.80	17.60	11.40	4.60	2.70
Experimental	38.56	22.95	17.26	11.25	4.66	2.64
Sample 8						
Required	32.29	20.99	13.32	7.00	3.06	1.65
Network estimate	33.50	17.40	12.60	7.70	3.10	1.80
Experimental	34.27	17.84	12.32	7.74	3.16	1.81

[a]For abbreviation see Table 1.

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