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Application of Bayesian Networks to Diagnostics of Hot Dip Galvanized Coasts

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Abstract

This study presents an output of the application of a probabilistic method of inference based on Bayes' rule in the diagnosis of defects formed during hot-dip galvanising process of casting products. Bayesian cause-effect network for given group of surface defects and its causes was build. Many factors causing defects was taken into consideration like: technological parameters, technological nodes and character of cause. The advantages and drawbacks of a probabilistic method of representation of the incomplete and uncertain empirical knowledge were highlighted.

Keywords: Formalization of knowledge, Uncertain knowledge, Bayesian networks, Reasoning in a Bayesian network, Faults of metal products, Hot-dip galvanizing

1. Introduction

The modern, demanding market forces producers of casting products (fittings, automotive cast, etc) to take actions to assure its competitiveness. The buyers are interested mostly in prices and quality of products. This two notions aren't independent. Improvement of the quality most often increases costs of a production those have significant influence on the price of products. However it is not a rule. For example, giving appropriate functional characteristics of the cast surface is much more profitable from the technical and economical point of view then usage of materials having in all its bulk requested properties (anticorrosive, antiabrasive or/and decorative). Modern technologies in surface engineering give ability to replace expensive materials with cheaper ones, decrease of losses (ex. caused by corrosion if iron alloys), decrease of tools and devices parts damages etc. One of the best and widely used methods of casting products protection, against corrosion for example is the hot dip galvanising

The main idea of this process consist in proper physico-chemical preparation of the product's surface, the iron coast for example and then in immersion in the bath of melted zinc or zinc alloy. As a result of the diffusion process an zinc-iron alloy in the surface layer is created. This coat has high mechanical resistance, anticorrosive properties, aesthetic look and requires no maintenance. The average working life of 70-150 mm thick zinc coat is 35-50 years in normal environment. and could be increased. The treatment of cast products surface is used to increase the lure of products and in a result its competitiveness. [1].The problems of the surface quality in production of hot dip galvanising products are the subject of the presented work. The issues of products quality are directly related with the notion of defect. According to Polish Foundry Standard [2]*"...all exceptions from values of parameters (physical, chemical or geometrical) recommended by technology, causing decrease of its quality, usability or market value is called the casting fault. ..."*

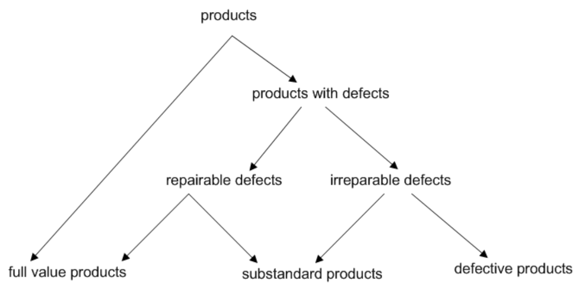

Fig. 1. The Classification of products based value and quality of products

The figure 1 shows schema of products classification based on the products quality. It is an illustration of relationships between quality and value of the product. Defective products are the pure loss for producers. The value of substandard products is decreased by cost of repair and difference between prices of full quality and repaired products. The value of fully repaired products is decreased by the price of repair. Decrease of defects is economically measurable. In the contemporary quality management, used for among others to decrease of production defectiveness, the advantages of mathematical apparatus and computer tools are taken. In this paper the probabilistic evaluation method based on Bayes' theorem (Netica toolkit) concerning influence of technological parameters on quality of final (galvanised) products is presented. The advantage of the Bayesian network is a possibility of implementation both in diagnostics systems and defects preventing systems. The diagnostics consists in pointing with specific probability what was the cause or causes driving to creation of defect and gives information on node in galvanising process where correction must be made or where technological regime must be corrected.

In defects preventing actions the Bayesian networks could be applied to prediction possibility (probability calculations) of the specific defect occurrence using real (measured in production node) values of parameters having essential influence on creation of specific defects

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2. Bayesian network as a method of knowledge representation

One of formalisms used to represent knowledge in expert systems, diagnostics systems, or decision support systems are cause-effect networks, known as Bayesian networks (*belief network, probabilistic network*) [3].

In such type of networks relations between variables are represented by an acyclic graph:

- nodes represent events (random variables) , each have finite numbers of states (finite number of variables),
- arcs represent direction of influence between adjacent variables,
- every node has an assigned conditional probability table defining what influence on it have its predecessors (parents) in the graph, this mean, for each variable Y and set of all its parents $X_1,...X_k$, distribution $P(Y/X_1,X_2,....X_k)$ is determined

To define properly probability distribution following appointment is made :

- two nodes in Bayesian network are conditionally independent if them are d-separated,
- two nodes X i Y in Bayesian networks are d-separated if for each path between them node A exists, which is serial connected or divergent and the state of node is known (observable) or connection is convergent and neither node A nor its descendants were observed.
- if nodes X i Y are d-separated then changes X had no influence on changes Y
- two nodes in Bayesian network are d-connected if they are d-separated .

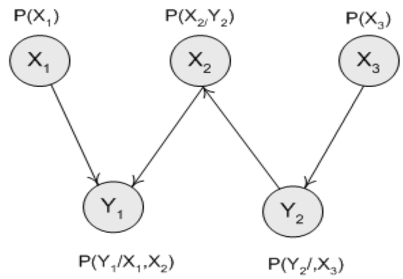

Fig. 2. An example of cause-effect network

Presented of Fig 1 graph conveys knowledge about relationships between analysed variables X_1, X_2, X_3, Y_1, Y_2:

- variable Y_1 depends simultaneously from X_1, X_2.
- variables X_1, X_2 are independent one from other
- X_1, X_2 are d-separated (d-connected by Y_1).
- variables X_2, X_3 are depended indirectly by Y_2,
- pair of variables X_2, Y_2 is d-separated by variables Y_1, X_3.

For presented example the probability of the specific values occurrence for each variable could be calculated, basing on knowledge of local probabilities as shown in equation (1).

$$P(X_1,X_2,X_3,Y_1,Y_2)=P(X_1)P(Y_1/X_1,X_2)P(X_2/Y_2)P(Y_2/X_3)P(X_3) \quad (1)$$

The cause-effect networks in its being contain information on probability distribution. In the practice such networks are not used to describe precise distributions, rather to extraction of information in the case of unknown distributions where information is taken from available samples or static experiments. In the intelligent computer systems, as a base of probabilistic inference supported by the knowledge contained in the form of cause-effect, Bayes' rule (2) is used.

$$P(H/S) = \frac{P(S/H)P(H)}{P(S)} \quad (2)$$

where:

P(H) - the probability of occurrence of an event H which is the hypothesis;

P(S) - the probability of occurrence of an event S which is the symptom;

P(E|H) - the probability of occurrence of a symptom, if the event which is a hypothesis has occurred.

P(H|S) - the probability that a hypothesis H will be true, if symptom E has occurred;

In practice there are usually more complex problems. In the case where exists many hypothesis for one single symptom ($H_1...H_m$ are mutually exclusive) the probability is expressed by equation (3)

$$P(H_i / S) = \frac{P(S / H_i)P(H_i)}{\sum_{k=1}^{m} P(S / H_k)P(H_k)} \tag{3}$$

In the case where may hypothesis exist equation (4) is used

$$P(H_i / S_1, S_2, ..., S_n) = \frac{P(S_1, S_2, ..., S_n / H_i)P(H_i)}{\sum_{k=1}^{m} P(S_1, S_2, ..., S_n / H_k)P(H_k)} \tag{4}$$

Hypothesis $H_1...H_m$ and symptoms $S_1...S_n$ as well must be mutually exclusive.

The probability of combination of all symptoms for given hypothesis is usually impossible to obtain and then expression (4) is reduced to equation (5).

$$P(H_i / S_1, S_2, ..., S_n) = \frac{P(S_1 / H_i)P(S_2 / H_i)...P(S_n / H_i)P(H_i)}{\sum_{k=1}^{m} P(S_1 / H_k)P(S_2 / H_k)...P(S_n / H_k)P(H_k)} \tag{5}$$

Thus determined Bayes' rule will express a prior probability, if there are conditions for existence of posterior probabilities, which are in many cases easier to derive or calculate.

3. Knowledge representation for defects of hot dip galvanized products and causes of faults

For the hot dip galvanising process detailed research concerning knowledge acquisition and representation for the defects of zinc coat was made. This assume:

- analysis and evaluation of knowledge sources in the domain of the galvanised products defects and causes of coat faults ,
- chose of criteria for evaluation of zinc coat quality,
- identification of coat defect set,
- identification of cause set,
- location of node in the technological process where cause of defect occurs and where individual technological parameters are controlled or set up,
- determination of relationship between defects and place of its creation and values of technological parameters,
- development of structural model of relations between defects and its causes.

As a basic source of the knowledge needed to identification cause of defects in galvanized products standards, products catalogues, published data and experts knowledge (consultation in research institutes and galvanising plants). According to standard [4] ” the *zinc coat must be continuous without trace of defects causing effects on functional properties of product*”, This requirements are expressed too generally and then relaying on the research [1,5,6,7] and consultation with industrial experts the following basic conditions of zinc coat evaluation were chosen:

- thickness of coat and its evenness
- adhesion
- continuity,
- brittleness,
- appearance of surface (colour, tarnish)
- defects caused by improper structure of galvanised elements.

Analysis of mentioned earlier sources of the knowledge and experience in quality control of final products in the hot dip galvanising plant leads to identification of the most often occurring which are shown i the table 1.

Table 1.
Chosen items from set of the zinc coat defects

	Name of defect
A	Discontinuity of coating
B	Excessive riser
C	Ash
D	Excessive thickness of zinc coating
E	Too thin thickness of zinc coating
F	Cracks of coat
G	Cracks in area of welding
H	Orange peel
I	Blowholes
J	Overpikling
K	Plastic deformations

It is more important for the technologists to find a cause of the defect then the defects itself. The causes of defects could be any incorrectness in the realization of the technological process. This are usually deviations from required by the technology properties of materials used in the production process like chemical composition of base material, structural requirement of galvanised elements and also the non-observance of a technological regime like deviation from required physical and chemical parameters of the technological process. Based on the real data concerning causes of the specific defects, registered in a chosen galvanising plant, table 2 was worked out. It present the frequency of simultaneous occurrence of defects and causes. With the occurrence of defect “excessive thickness of coat”, cause “improper chemical composition” in 70% was found

With the occurrence of defect “excessive thickness of coat”, “improper chemical composition of galvanised element” in 70%, in 17% “improper immersion time” and in 10% “improper chemical composition of galvanising bath” where found. In the case of the defect “discontinuity of zinc coat” the chemical composition is rather unimportant because its influence is only

1% and the impurities of surface give 80% of all possible causes of this defect.

Table 2
Classification of causes with assigned nodes and frequency of occurrence

defect	cause	node	[%]	rank
Discontinuity of coating	Chemical composition	P0_1	1	3
	Quality of surface	P0_2	80	1
	Technological holes	P0_5	6	2
	Structure suspension	P1_1	1	6
	Degreasing bath composition	P2_1	1	3
	Degreasing bath temperature	P2_2	1	
	Degreasing time	P2_3	1	
	Pickling bath composition	P3_1	1	4
	Pikling bath temperature	P3_2	1	
	Pikling time	P3_3	1	
	Fluxing bath composition	P5_1	1	5
	Fluxing bath temperature	P5_2	1	
	Fluxing time	P5_3	1	
	Drying time	P6_2	1	8
	Galvanising bath composition	P7_1	1	7
Excessive riser	Technological holes	P0_5	30	2
	Structure suspension	P1_1	25	1
	Galvanising bath temperature	P7_2	10	4
	Galvanising bath composition	P7_1	5	7
	Withdrawal rate	P7_4	5	5
	Out-of- furnace treatment	P7_5	25	6
Ash	Technological holes	P0_5	60	1
	Fluxing bath composition	P5_1	20	3
	Galvanising bath composition	P7_1	20	2
Excessive thickness of zinc coating	Chemical composition	P0_1	70	1
	Pickling bath composition	P3_1	1	4
	Pikling bath temperature	P3_2	1	4
	Pikling time	P3_3	1	4
	Galvanising bath composition	P7_1	10	3
	Immersion time	P7_3	17	2

For the unambiguous localisation of faults causes in the hot dip galvanising process eight point were distinguished where the parameters of the process are set up or controlled. This points will be called nodes and are listed in table 3.

Table 3.
The control measurement modes

Node	Points of measuring and control
P0	Parameters of charge
P1	Preparation of charge
P2	Degreasing bath
P3	Pickling bath
P4	Rinsing
P5	Fluxing bath
P6	Drying
P7	Galvanising
P8	Dismantling

The relationship cause-defect-node is presented on figure 3.

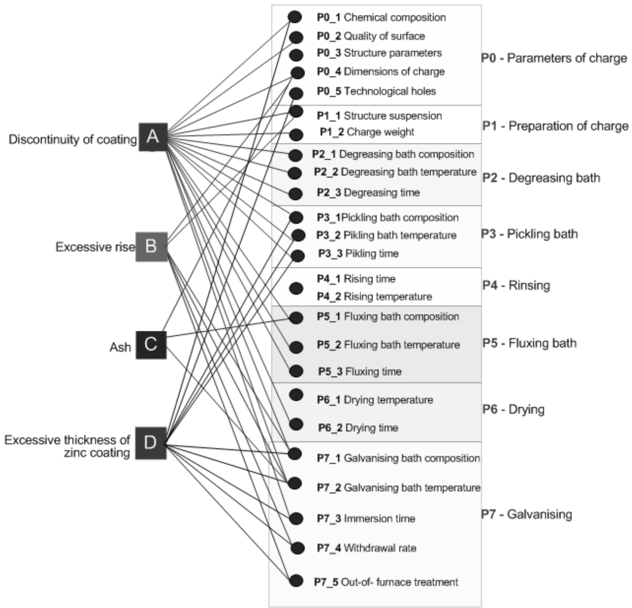

Fig. 3. Schema of defect-cause-node relationship

A structural model of the process was created. Each node is the root level in the notions hierarchy describing the causes of defects. The schema of the multilevel cause-effect relationships network between chosen defects and technological parameters is presented on the figure 4.
Specifying knowledge about causes of defect creation in given node (P7 – GALVANISING) , characteristic groups of parameters was determined like P7_1 - chemical composition of galvanising bath, P7_2 – temperature of galvanising etc., for each group a detailed list of basic technological parameters (physical or chemical quantities) like those presented in table 4 for the group P7_1.

Table 4.
A set of permitted values of parameters for the chemical composition of the galvanizing bath.

Assigned symbol	Elements	Value or brackets [%]
P7_1_1	Al	0.001-0.005
P7_1_2	Ni	0.045-0.05
P7_1_3	Fe	0.03-0.4
P7_1_4	Bi	0.08-0.1
P7_1_5	Zn	the best purity 99.99

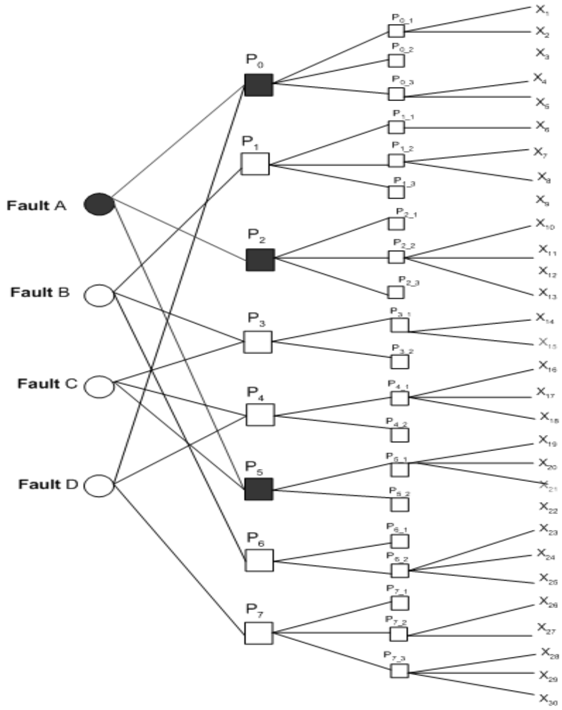

Fig. 4. The schema of the cause-effect relationship between defects and its causes

4. Bayesian network in diagnostic of the hot dip galvanising process

The Bayesian networks seem to be the mostly used formalism for the knowledge representation in a case of complex cause-effect relationships like in the example of defects and its causes. The reasoning is based on the Bayes' theorem (equations 3-5). The event S called symptom consists in affirmation of existence of the specific defect.(a blister in the zinc coat for example). Let H is one of the possible causes of the specific defect's formation (bad surface preparation). To calculate the probability that the bad surface preparation is the cause of the blister existence values of the following probabilities are needed:

- P(S/H) conditional probability of a blister existence on improperly prepared galvanised surface.
- P(S) unconditional probability of blister existence on the galvanised surface
- P(H) probability that the improperly prepared element was galvanised.

Those probabilities was determined on the base of experts knowledge and the experimental results (some of them are presented in table 2).
In the testing environment the Norsys Netica toolkit was used [8].
The fragments of implemented networks is presented on the figure 4 and 5.

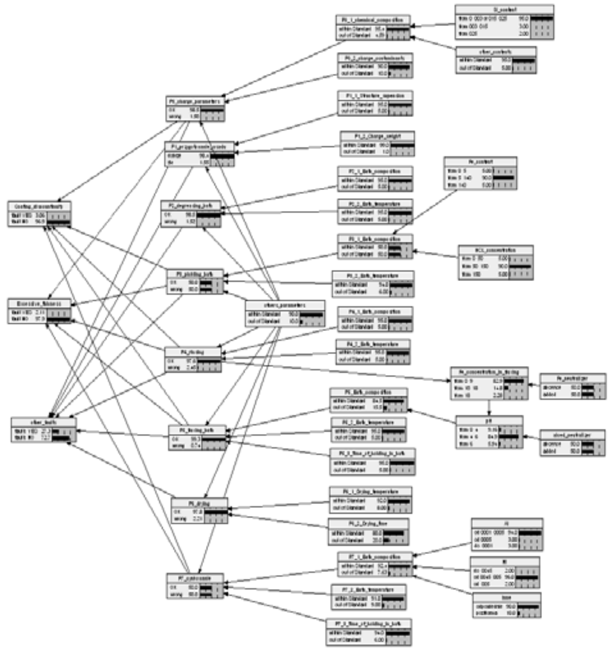

Fig. 5 Graphical form of a network of causal-resultant relationships from as implemented in the Netica toolkit

A random variable called *defects* having linguistic values from the set of defects names (table 1) is in the network represented by a random variable which in all probability will take the value YES (the presence of this specific defect has been ascertained) or NO. YES means the existence of defect, NO means lack of the defect. Technological parameters, that is the most specific causes of given defect usually take the form of numerical sets (intervals) with attributed units of measurement (content of elements [%], temperature [^{o}C], time [mn]. In the network rather the membership in the given range is taken into account then the specific values. For example, the parameters of the bath chemical composition of bath (P1_7) have assigned tree values bellowStandard, withinStandard and overStandard. The figure 6 shows a notation of the probabilities in networks calculated and accepted a priori: IF P(0.001<Al <0.005)= 0.94 , P(Al >0.005)= 0.03 P(Al <0.001)= 0.0.03 and P(0.045<Ni <0.05)= 0.96 , P(Ni >0.05)= 0.02, P(Ni <0.045)= 0.02 and for others components the probability of out-of-Standar is equal 0.9. In such case the calculated result presents information that the composition of the galvanising bath is within acceptable range with probability 0.924.

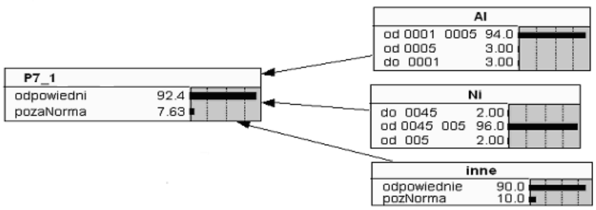

Fig. 6. Example of the conditional probability calculation in theindirect node

The technological nodes labelled P_i and P_{i_j} are the middle layer between the direct causes (technological parameters) and defects

If in a group of technological parameters (P_{i_j}) all parameters taken into account (X_i) conform with the standard then direct node P_{i_j} could have values: withinStandard or outofStandard

The value of the random variable P_i depends of the values of the specific elements P_{i_j}. The variables take values from the set {good, bad}. In the nodes P_i and P_{i_j} the probabilities are conditional, defined on the base of the unconditional probabilities. In development of such knowledge representation the main problem consist in determination of the input probabilities (a priori) needed in a inference process. The subjective estimations (based on the experts knowledge), or the statistical data could be used (how often the parameters are exceeded, which causes was diagnosed in the case of defect existence)

5. Summary

An advantage of the Bayesian network as applied in this study is the fact that an algorithm used for the computation of probabilities enables both forward and backward reasoning, that is, making diagnosis about the faults when the event of occurrence of a specific defect has already been acknowledged. Some of the variables are therefore event variables. These are the variables whose exact values (e.g. taken from measurements or observations) are known. The remaining variables in the network are the query variables, for which the conditional probability is computed in respect of the event variables. The choice of the inference direction is left at the discretion of the packet user when he is introducing the input data. If, on entry, the algorithm receives information that the probability of occurrence of a defect(s) is 1, and some values of the technological process parameters are given, the algorithm is capable of computing the probability of occurrence of the individual faults of the indicated defect. This is an example of the diagnostic reasoning. Quality control of a technological process uses forward reasoning, which means that, basing on the recorded real values of the technological parameters, one can compute the probability of occurrence of some specific defects in final products. This information can be used in preventive measures taken to avoid the occurrence of these defects (current adjustments).

The Bayesian network has also some drawbacks. Probably the most important one is the fact that it is necessary to possess some knowledge about many probabilities, not always easy to estimate. The prior probabilities determined from statistical data (frequencies of occurrence) have to be supported by a sufficiently great number of the data representative of a given population, and when they are determined by humans, may these be the best experts even, an error resulting from subjective evaluation is always possible.

Moreover, in this approach, the computations are based on the use of some formulae (e.g. equations 3-5), which are true only under certain conditions, e.g. when independence or mutual exclusion of events exists, which need not always be true in practice.

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