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The application of Bayesian networks to estimate the marginal probability of leakage in dental composite reconstructions

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Highlights

- The application of the Bayesian classifier to the diagnosis of marginal leakage
- The analysis was carried out for four different load cycles
- Critical leaks occurring in the subsurface layers were investigated

Abstract

This study presents the application of the Bayesian method to estimate the probability of critical marginal leakage in dental restorations. Aim of the study was to evaluate the effectiveness of the Bayesian method in estimating the probability of leakage associated with gap in the subsurface layers of composite restorations, based on observations of their surfaces. The study, involving the construction of a Bayesian network model and probabilistic inference, was based on the results of experimental research. These results were used to verify the a priori and a posteriori probabilities of damage to the tooth-restoration system in three zones of the tooth's anatomical structure and across four load level intervals; using a Bayesian classifier, the study demonstrated the potential for diagnosing critical subsurface leaks. The results obtained show that surface fissure parameters can support the probabilistic diagnosis of leakage throughout the entire volume of the restorative filling, thereby assisting in clinical decision-making regarding the replacement of damage fillings.

Keywords

Bayesian networks, reliability forecasting, dental material reconstructions, marginal leakage, surface and subsurface observations

1. Introduction

Material biomedical reconstructions include a large group of therapeutic procedures involving the restoration of defects in hard tissues of the human body. This applies, among other things, to the restoration of carious cavities in teeth [1,2,3]. The development of the effectiveness and efficiency of treatment procedures in this area depends on many interdisciplinary aspects, including advances in materials engineering and the development of methods for forecasting material consumption. In this article, as an example of material research on biomedical reconstructions, the study of composite restorations in mineralized tooth tissue cavities is described. From a physical point of view, the composite reconstructive filling creates a physico-chemical connection with enamel and dentin in the tooth (Fig. 1). The following elements are involved in the connection of the filling with the tooth tissues: the edge of the outer surface of the filling body with the occlusal surface of the tooth, the surface of the joint in the enamel zone and the surface of the joint in the dentin zone.

The mechanism of adhesion of the surface of the tooth elements and the filling is based on the phenomenon of adhesion.

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Adhesion is the joining of dissimilar materials by attracting atoms or molecules. The stresses that weaken the adhesive joints are caused by differences in thermal expansion coefficients and changes in volume during the bonding of the material to be adhesed. Some authors distinguish two mechanisms of adhesion: chemical and mechanical [4]. Chemical adhesion involves bonding at the atomic or molecular level. Mechanical adhesion is based on retention by hooking or penetrating one phase into another. In many cases, chemical and mechanical adhesion occur together. Regardless of how the adhesion phenomenon is explained, each of these theories requires that the two elements to be connected are as close to each other as possible. The strength and durability of a reconstructive dental joint depends mainly on the physicochemical properties of the filling material and the tissues of the tooth and the intermediate layer.

The oral environment also plays a big role. When a composite filling is applied, the polymerization process causes polymerization contraction to form in the material. Contraction can cause significant structural stresses [5,6]. These stresses most often exceed the strength of the bonding system and lead to damage to the adhesive connection between the filling and the tooth and the formation of a marginal gap between the filling and the walls of the cavity. The term marginal gap is understood as an empty space between the tooth tissues and the filling, through which fluids, microorganisms, toxins and substances contained in saliva penetrate [7,8]. During use, under the influence of mechanical stress related to chewing forces and changing temperature, the gap expands. The marginal fissure is the main factor initiating bacterial microleakage [9], which can lead to marginal discoloration, post-operative hypersensitivity, secondary caries and endodontic complications [10,11,12]. In clinical practice, diagnosing reconstructive fillings in teeth is a major challenge, as access to observation of the contact between the filling body and hard tooth tissues in the subsurface zones is particularly difficult [13]. As a consequence, clinical decisions regarding whether to replace or retain existing reconstructive fillings are made without full knowledge of the actual state of tooth-filling contact [11,12,13]. It is known from literature reports that an effective direction for the development of clinical diagnostic methods in this area may be the use of a probabilistic approach to assessing the condition of the test object and its reliability hazards using Bayesian networks [14]. The use of the Bayesian network enables cause-and-effect interpretation and inference under conditions of incomplete observations [14,15], which is of particular importance in clinical diagnostics. Examples of research work in which the authors used Bayesian inference methods to solve problems in dentistry are described, among others, in the following works: [15,16] - an overview of practical applications, [17] - statistical analysis of the phenomenon of dental fluorosis, [18,19] - an overview of artificial intelligence and deep learning tools in dentistry, and [20,21,22] - examples of applications of Bayesian networks to diagnose toothache, caries and support treatment planning. The method of Bayesian probabilistic modeling is also presented in the paper [23] as a way to standardize the development of strength measurement results of dental composites and replace routine testing with an adaptive knowledge accumulation model.

The paper discusses the problem of using the Bayesian method for probabilistic inference about the threshold expansion of the marginal gap of composite reconstructive fillings in unobservable zones of the tooth structure.

The aim of the study was to evaluate the effectiveness of the Bayesian method for estimating the probability of emergency marginal leakage in the subsurface layers of dental composite fillings based on surface observations. The computational part of this work, including the construction of a Bayesian lattice model and probabilistic inference, was based on the results of our own experimental research described in earlier works on the degradation of the tooth-filling system [24,25].

2. Test method

2.1. Criterion of failure (degradation) of the tooth-filling system

In a composite filling system, the reconstructed tooth is treated as an object to be renewed, which means that it is assumed to regain its full ability to perform physiological functions without damage. The malfunction of this system is defined as the loss of seal integrity between the filling and the tooth to the extent that fluid leakage is possible. It has been assumed, based on the literature [24,25], that the criterion of failure (degradation) of the filling determines the width of the marginal gap above 5 μm. Previous studies have indicated that penetration is significantly limited if the gap width is less than 5 μm [24,25,26].

Qualitative observations of leakage formation indicate two dominant factors determining the propagation of leakage [24,25]:

- polymerization shrinkage of the filling material (composite),
- fatigue of the filling material (oscillating stresses during the physiological chewing process).

The curing process of a polymer-ceramic composite is a chemical process combined with the phenomenon of shrinkage [27,28,29]. In most cases, the volumetric shrinkage of the material is a few percent, and its clinical consequences depend on the modulus of elasticity, the geometry of the defect and the photopolymerization procedure [5,27,28]. It has been experimentally shown that the average value of linear contraction, measured in vitro, is usually in the range of about 0.2% to 2.0%, while volumetric contraction can be several times higher, reaching values of several percent and leading to displacement of nodules and an increase in the risk of microleakage [29,30,31,32,33,34].

2.2. A priori leakage probability distribution studies

The object of in vitro studies were human teeth with dental composite fillings. Molars and premolars removed for orthodontic and surgical purposes were used (Fig. 1).

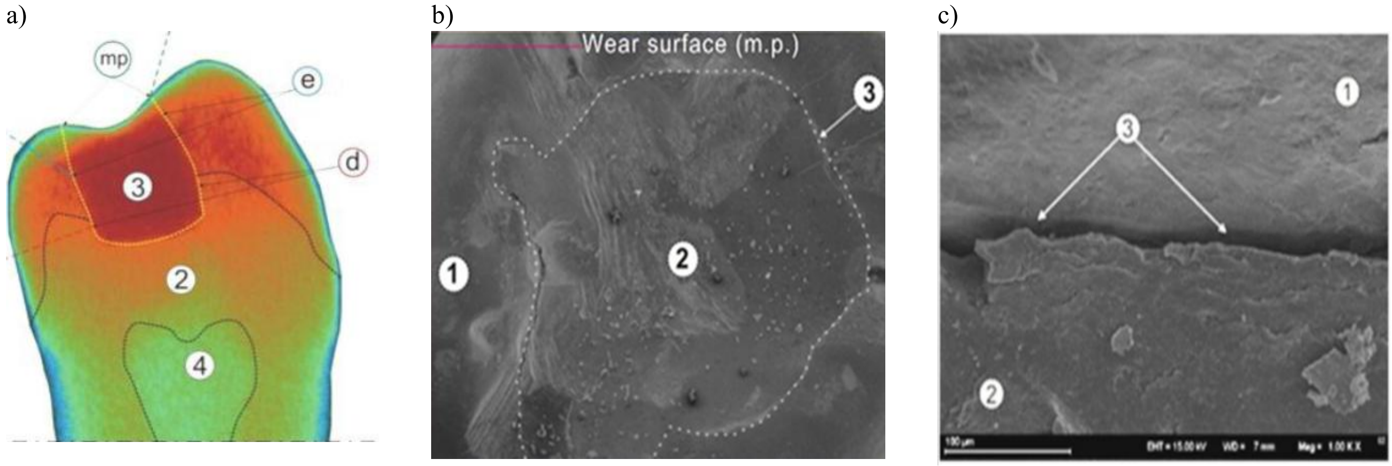


Figure 1. Tooth with Class I filling according to the Black classification: a) Diagram of microscopic observation areas: m.p. – chewing surface, e. – enamel and composite filling separation zone, d. – dentine and composite filling separation zone, 2 – dentin, 3 – composite filling, 4 – tooth pulp, b) SEM image of the chewing surface of the tooth: 1 – tooth (enamel), 2 – composite filling, 3 – edge of the filling, c) SEM image of the marginal gap on the chewing surface of the tooth: 1 – composite filling, 2 – enamel, 3 – marginal gap.

A total of 25 teeth were used in the study. The sample size was determined based on previous studies that showed that 25-30 specimens in the sample were sufficient to detect differences in marginal gap width at the significance level of $\alpha = 0.05$.

Experimental reconstructive fillings were placed in specially prepared cavities in the teeth. Tooth samples prepared in this way were subjected to cyclic mechanical loads on a test device that simulates the physiological conditions of the oral cavity (Fig. 2). The chewing simulator generated cyclic vertical and horizontal loads of tooth samples, mimicking the natural chewing cycle described in the literature [35]. The test bench was developed in accordance with previous solutions for degradation analyses of composite fillings [36,37], and the use of cyclic loads corresponded to the approach used in studies using chewing simulators [38]. The total number of cycles ranged from 0 to 100,000, divided into four load series (0, 30,000, 60,000, 100,000 cycles).

A special computer program has been developed to regulate the parameters of the chewing cycle. This allowed for a random change in the trajectory of movement of the examined teeth [36, 37]. After each series of loads, the width of the gap between the filling and the tooth was measured in the zones: MP (chewing surface), D (dentin) and E (enamel), which corresponds to the step-by-step approach also used in other microleakage studies conducted at subsequent time intervals [26]. Measurements were made using a scanning electron microscope LEO 1430VP in the chewing surface zone and using a Neophot optical microscope in zones D and E. Images obtained from microscopic observations were subjected to computer analysis (Image-Pro Plus, Media Cybernetics). In the case of observations of zones D and E, a longitudinal cross-section of tooth samples was previously performed.

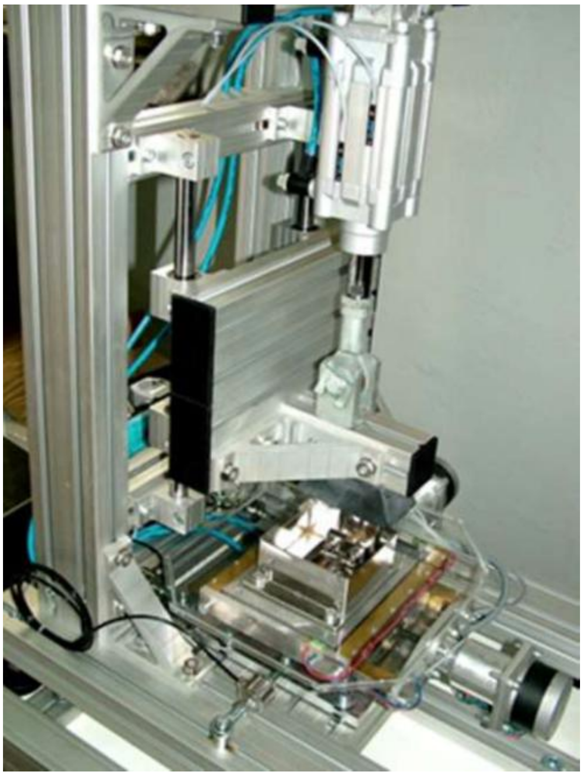


Figure 2. Chewing simulator [36,37].

2.3. Bayesian network as a model of diagnostic testing

A Bayesian lattice (BN) is an acyclic directed graph whose nodes represent directly or indirectly observable quantities W1, W2, ..., Wn used in the concept of the modeled process, and the arcs represent the causal relationships between these quantities. BN represents the shared probability distribution of the variables used in the model [14]:

$$P(W_1, W_2, \cdots, W_n) = \prod_{i=1}^{n} P\big(W_i \mid parents(W_i)\big) \quad (1)$$

where the Wi *nodes* immediately precede the parents node *(Wi)*

Probabilistic inference in the form of a Bayesian network is more intuitive than the classical scheme of statistical inference [15].

A diagnosis is a hypothesis concerning the unobservable (in the diagnostic process) condition of the object that is being diagnosed (Fig. 3).

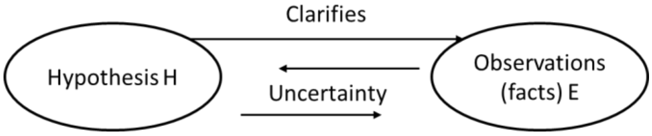


Figure 3. Diagnostic inference scheme.

The measure of diagnosis is the probability of the occurrence of a negative event (failure) based on Bayes' theorem, written in the form (2), where the a priori measure of the uncertainty of the hypothesis *H* is the probability, *P(H)* and the a'posteriori measure is the conditional probability *P(H│E)H.*

$$P(H|E) = \frac{P(E|H)P(H)}{P(E|H)P(H) + P(E|\neg H)P(\neg H)} \quad (2)$$

If *H* is a variable with *n* possible values *{h1, h2,... hn}* then:

$$P(h_i|E) = \frac{P(E|h_i)P(h_i)}{\sum_{i=1}^{n} P(E|h_i)P(h_i)} = \frac{P(E|h_i)P(h_i)}{P(E)} \quad (3)$$

Given the previous observations of E, we choose the a'posteriori maximum-likelihood hypothesis (MAP):

$$h_{MAP} = \underset{h_i \in H}{argmax} P(h_i|E) = \underset{h_i \in H}{argmax} \frac{P(E|h_i)P(h_i)}{P(E)} = \underset{h_i \in H}{argmax} P(E|h_i)P(h_i) \quad (4)$$

Assuming that all hypotheses are equally likely:

$$\forall_{h_i, h_j \in H} P(h_i) = P(h_j) \quad (5)$$

Next, the maximum probability hypothesis of ML (the hypothesis with the highest likelihood of the highest plausibility) is selected:

$$h_{ML} = \underset{h \in H}{argmax} P(E|h) \quad (6)$$

Diagnostic models, understood as symbolic representations of knowledge in real time, are inherently data-driven [14,15]. This means that the model becomes a product of machine learning based on process data. In the process of decision-making based on knowledge and real-time information, the model can act as an inference machine in clinical decision support systems [20,21,22]. In this context, a modeling method and technology using Bayesian networks are used.

2.4. Building a reliability model

The process of leakage formation between the tooth and the filling is stochastic. The analysis of this issue is based on the methodology of Bayesian networks. To this end, a model was constructed to determine the common probability distribution of the development of the marginal fissure. The key factor is that the gap between the tooth and the filling already occurs at time 0 (zero chewing cycles), as it is mainly the result of polymerization contraction. As a consequence, one of the elements of the experiment was the measurement of leaks with zero chewing cycles, i.e. in the newly made filling. The second cause of gap development is the fatigue process of the material during use resulting from the stresses associated with chewing cycles.

The width of the gap between the tooth and the filling is naturally visible and measurable only on the surface of the tooth. Therefore, in order to investigate the depth of penetration of the gap, measurements were carried out in three tooth zones: MP, D, E and for four load count ranges: 0, 30 k, 60 k, 100 k cycles, respectively.

The gap width between zones E and D was measured regardless of whether the gap was observed in the outer MP layer. The tests were carried out according to 12 scenarios – 4 levels of the number of chewing cycles and for each level (0 cycles, 30000 cycles, 60000 cycles and 100000 cycles), and for each range of the number of cycles, 3 zones (MP, D and E) were tested, in which the width of the gaps was measured.

Figure 4 shows the Bayesian network, which is an adequate model of the problem under study. The two parent nodes **of the network, n_c** (number of workloads) and **w** (layer), represent the context of the process. The node that represents the condition of the dental filling system is the gap size **s**. In addition, a binary node is attached to the s node, which indicates a state of unfitness (failure), seal_fill. The unsuitability of this system is defined by a binary assessment of the gap width (good-bad). It is a binary system, in which if the gap is larger than 5 μm, the filling is considered unsuitable. The topology of the Bayesian network (Fig. 4) was defined on the basis of qualitative knowledge of the degradation process. The number of chewing cycles (**n_c**) and the measurement layer (**w**) have been introduced as parent nodes because they represent independent experimental conditions affecting the width (widths) of the gaps. The s-node was placed as a child because the width of the gap is directly measured and depends on both **the n_c** and the w. The seal_fill binary node, attached to **the s**, forms the clinical failure criterion (> 5 μm gap), which is the main diagnostic outcome. This structure reflects a causal chain with respect to load and location conditions, through physical damage to functional failure. The choice of the truncated normal distribution for **s** was motivated by physical constraints (the gap width cannot be negative).

Reasoning with accuracy defined by probability distributions is a well-documented area of Bayesian network (BNT) technology. This network is a graph where nodes represent the variables being measured, and arcs represent the causal relationships between nodes. Network topology results from qualitative knowledge of a particular problem, while a quantitative measure of uncertainty for the variables represented by nodes, in the form of a common posterior probability distribution, is the result of a machine learning process based on process data. In this case, the data is generated through experiments.

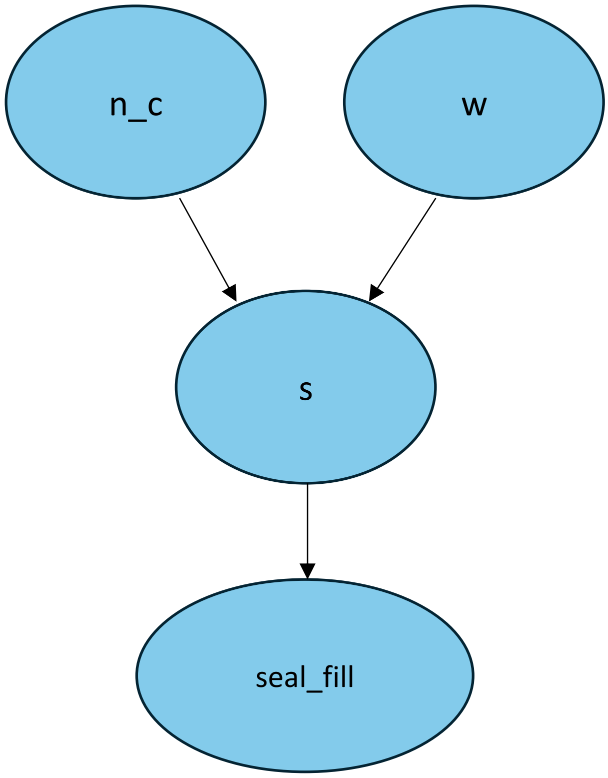


Figure 4. Topology Bayesian network.

The topology of the Bayesian network was also derived from a simple cause-and-effect scheme between the width of the gap and the number of cycles and the depth of the filling layer in the tooth. To determine the common probability distribution of the gap width, it was necessary to establish conditional probability density functions for all 12 scenarios. These distributions were determined in a manner typical of Bayesian networks, specifically through data-driven Bayesian learning [14,23]. The Bayesian approach assumes that the measured values of the studied quantity are treated as empirical data, while the values of the probability distribution parameters are not directly measured and are therefore assigned a specific uncertainty quantified by means of a probability distribution.

Gap width measurements, analysed in the context of three depth levels and four chewing cycle count ranges, yield twelve learning scenarios for the network. These scenarios yield twelve "posterior" conditional probability distributions. The process of training the network with examples is illustrated in Fig. 5. the effect of the training was a truncated normal a posteriori distribution.

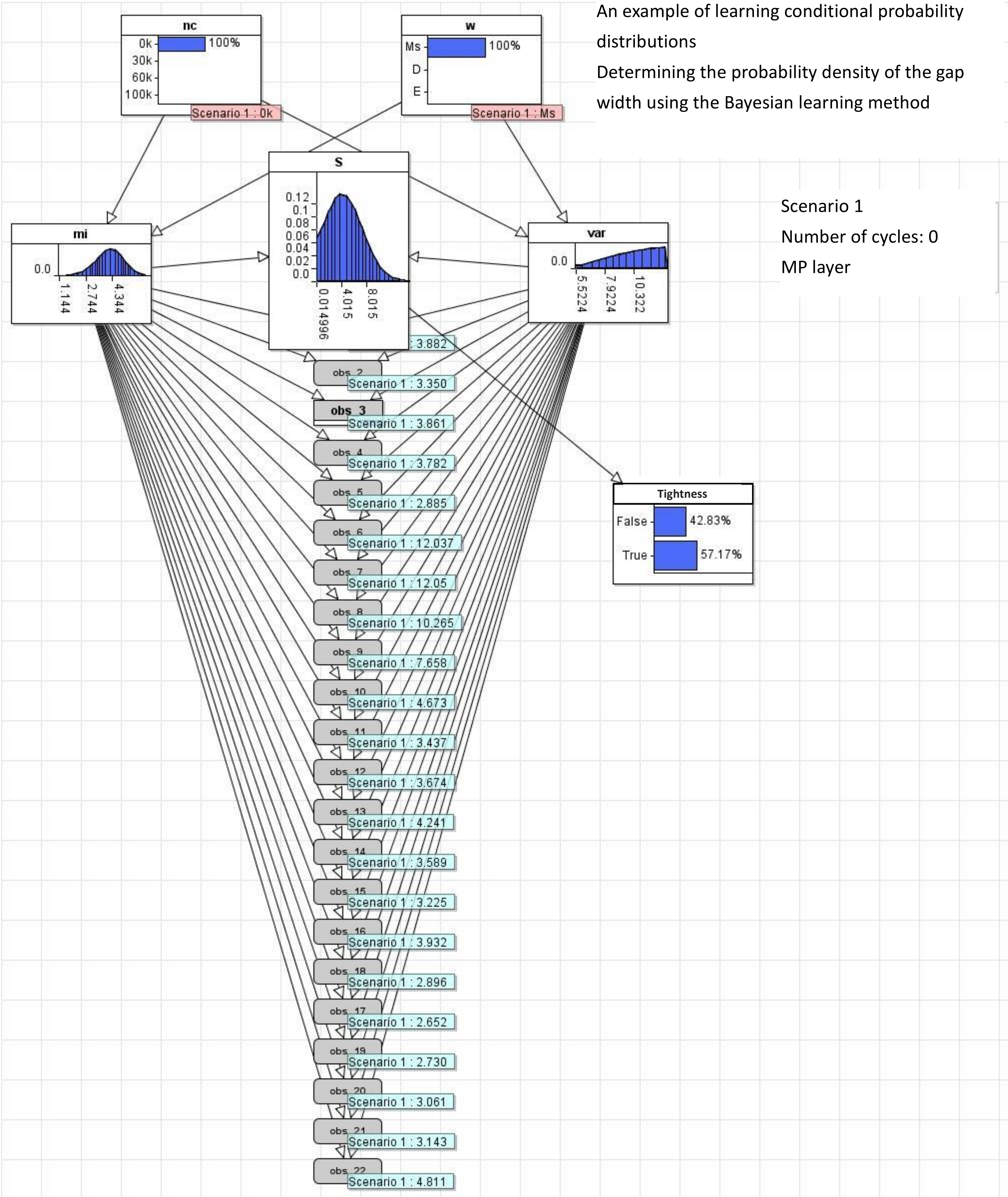


Figure 5. Example of network learning for scenario 1 – MS layer, 0 chewing cycles.

3. Results

3.1. Probability a proiri and a posteriori (experimentally verified)

The parameters of the fitted a priori probability distributions of marginal gap width are shown in Table 1. The table shows the minimum and maximum values at which the distribution was truncated (for example, for 0 cycles in the MP layer, the observed minimum value was 2.652 μm and the maximum value was 12.056 μm). The truncated normal distribution was adjusted, and as a result of machine training, the mean value, the variance and the standard deviation were determined. For each analysed layer, four chewing cycle counts of 0k, 30k, 60k and 100k were taken into account.

The construction of the Bayesian network as a model of reliability of the tested fillings divided into tooth zones and ranges of the number of fatigue loads is presented in Figure 6. The results of 12 Bayesian inference scenarios are presented, including binary diagnoses (fit – unfit, i.e. good – bad) fissures in the area of 3 anatomical layers MP, E, D and in the intervals of the number of chewing cycles 0k, 30k, 60k, 100k. According to these scenarios, the gap measurements were carried out. On the basis of the results of measurements and network training, a posteriori probability distributions of the width of the marginal gap were determined. Figure 8-10 shows the probability graphs for the scenarios corresponding to each layer and taking into account all chewing cycle count ranges.

The conditional distributions for all scenarios studied show that the number of chewing cycles results in an increase in the gap width, with an accuracy to the probability distribution in all tested layers (Fig. 7-9). This indicates the occurrence of the fatigue process, according to the results of experimental studies and prognostic models on dental composites and restorations subjected to cyclic loads [39,40,41,42,43,44,45]. The question of whether it is possible to infer the width of the gap in the deeper layers (D and E) from the observation of the presence or absence of a gap greater than 5 μm in the MP layer has a binary answer (YES or NO), but with probabilities differing only slightly.

The answers to the decisive questions indicate whether the width of the gap increases with the increase in the number of chewing cycles. Probability distributions show, with precision up to the probability distribution, that the number of chewing cycles contributes to widening the gap. In other words, the more chewing cycles, the greater the difference becomes, which remains consistent with comparative studies of microleakage of restorative materials [46,47].

Table 1. Parameters of truncated probability distributions a priori of the gap width [μm].

Tooth zone	Average	Variance	StdDev	Min	Max
		n_c=0k			
MP	4.811	8.478	2.912	2.652	12.056
D	5.478	7.694	2.774	1.812	19.295
E	5.011	12.660	3.558	1.440	16.250
		n_c=30k			
MP	5.596	55.563	7.454	0.368	28.501
D	6.803	11.038	3.322	0.000	21.648
E	7.476	16.343	4.043	1.689	22.980
		n_c=60k			
MP	10.598	60.625	7.786	0.394	27.382
D	12.062	26.943	5.191	3.063	42.756
E	11.167	42.239	6.499	0.629	41.455
		n_c=100k			
MP	16.337	37.202	6.099	6.666	36.832
D	14.627	50.639	7.116	4.384	49.234
E	15.678	70.084	8.372	4.460	39.968

3.2. Bayesian classifier

A Bayesian classifier is a system in which empirical data describing the diagnosed objects is provided at the input, and a list of possible diagnoses is generated at the output, ordered according to their conditional probabilities. Examples of Bayesian classifier applications in dentistry can be found, among others, in the articles [16,20,21,22].

Data on classified objects are collected in the form of:

$$D = \{(x_i, y_i) | i = 1,2, \cdots, n\} \tag{7}$$

x_i: $description\ of\ the\ i-th\ object\ in\ the\ m-dimensional\ attribute\ space$

$$x_i = (x_1, x_2 \ldots x_m)_i, i = 1,2, \cdots, n$$

y_i: *'attribute purpose', for example here as an indicator of leakage* $specifying\ the\ state\ of\ the\ i-th\ object$:

$$y_i = \begin{cases} 0\ if\ the\ i-th\ object\ is\ suitable \\ 1\ in\ the\ opposite\ case \end{cases}$$

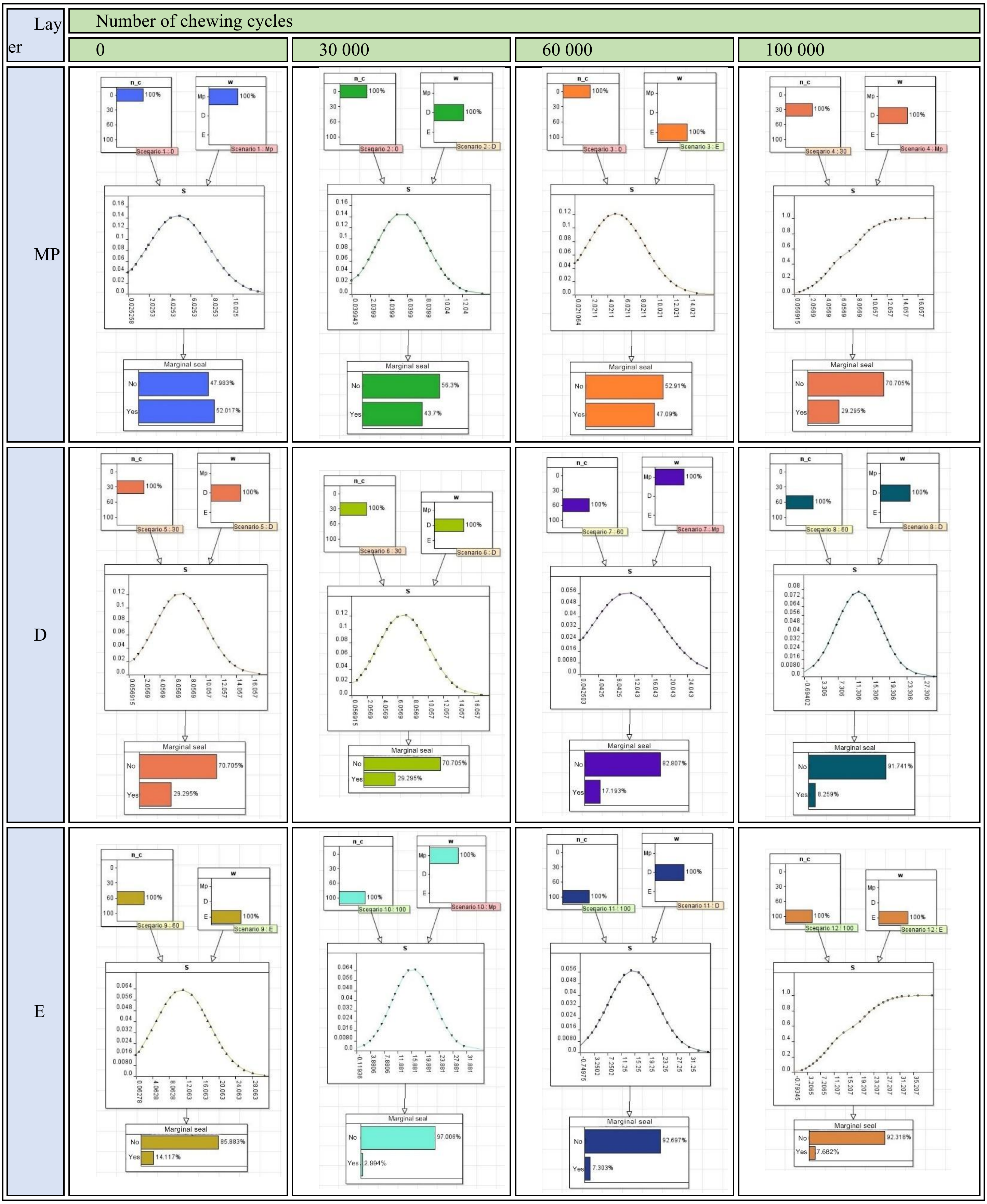


Figure 6. Bayesian networks for 12 gap diagnosis scenarios, **n_c** – number of load cycles, **w** – measurement depth layer, **s** – gap width.

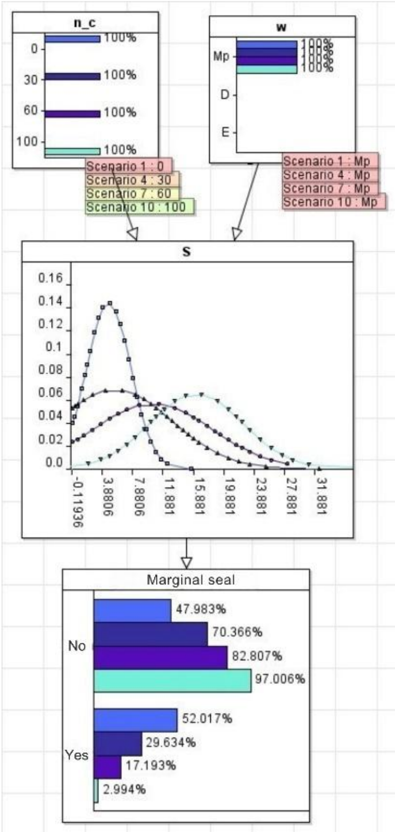


Figure 7. Probability density plots for scenarios 1, 4, 7, and 10 (MS layer, comparison for all chewing cycle counts).

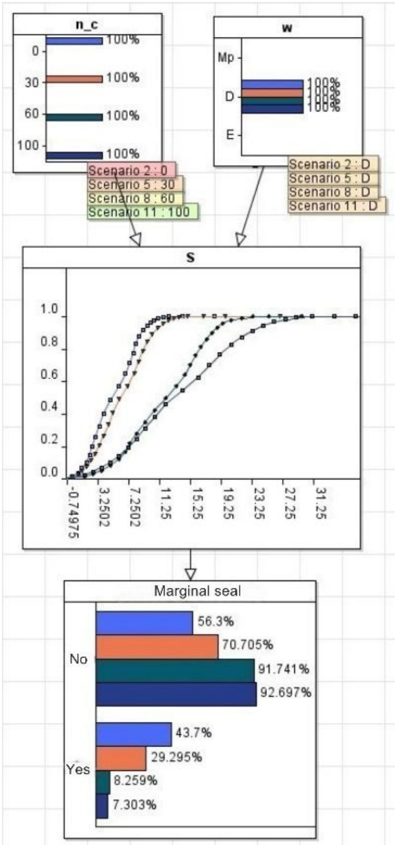


Figure 8. Probability density plots for scenarios 2, 5, 8, and 11 (layer D, comparison for all chewing cycles).

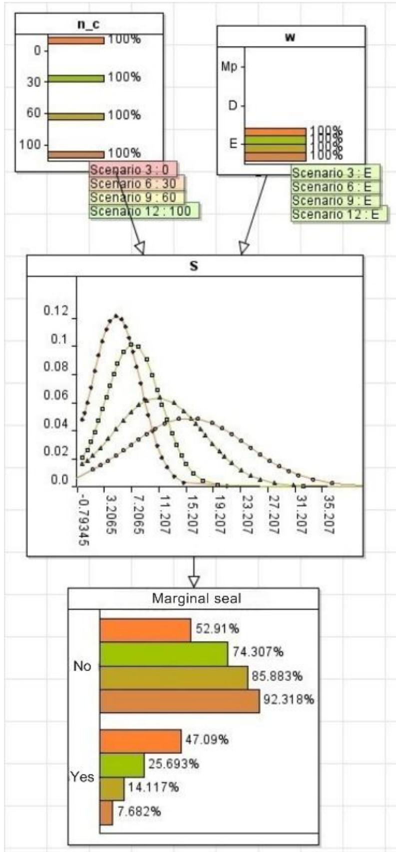


Figure 9. Probability density plots for scenarios 3, 6, 9, and 12 (Layer E, comparison for all chewing cycle counts).

Here, the target attribute YES is a categorical (nominal) quantity, and the purpose of classifying objects is to diagnose them. This data can be used directly as training data. The corresponding BN (Bayesian network) has m nodes representing the object in the attribute space and y nodes representing the diagnosed state of the object. Examples of the use of Bayesian networks in this area can be found in many publications [15,16,20].

In the problem of diagnosing the functional suitability of the "tooth-filling" system, the attributes were the width of the marginal gap at three levels in the context of the time of use of the filling, expressed by the number of chewing cycles. In the case of diagnosis, however, this condition was defined as a leak at each level (zone). The width of the gap was discreetly discreetized according to the leakage criterion. It was assumed that each of the three layers could be either leaky or leaky, which is why there are eight (23) leakage states:

$$LF \stackrel{\text{def}}{=} (000,001,010,011,100,101,110,111) \stackrel{\text{def}}{=} (L0, L1, l2, L3, L4, L5, L6, L7) \quad (8)$$

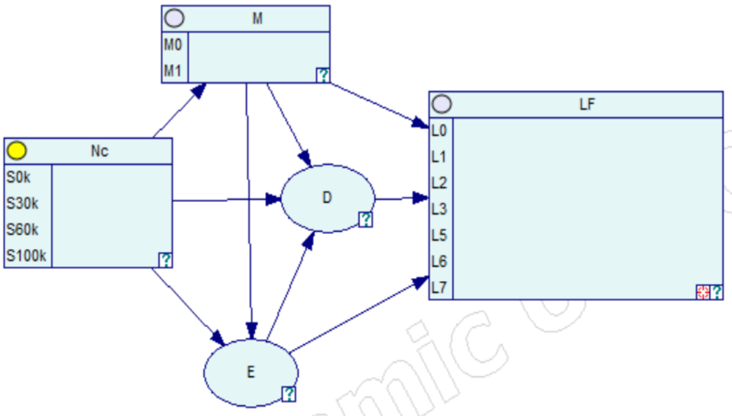
Hence, the topology of the classifier is a five-node BN. The collected data and qualitative knowledge of the causal relationships between the five quantities Nc, M, D, E, LF} represented by the network nodes of the studied problem indicate the factorization method presented in Figure 10.

Fig. 10. Classifier topology (the model was created using GeNIe Academic Version 3.0).

Once the data is loaded and the learning process in GeNIe begins, the classifier is ready to work in knowledge base mode, i.e. a question is asked and an answer is received. A question is about a sentence function in which variables represent what is being queried. The question triggers an inference algorithm (search algorithm) that calculates the values of the sentence variables that answer the questions asked.

In the developed model, the condition of the external surface M is observed as M0 (leaky) or M1 (leaky). Questions are asked about the general condition of the reconstructive LF filling and the probable time Nc that has elapsed since the filling was placed. The answers are formulated with accuracy to probability distributions. This method is illustrated in Figures 11 and 12.

$$P(Nc, M, D, E, LF) = P(LF|M, D, E)P(D|M, E, Nc)P(E|M, Nc)P(M|Nc)P(D|Nc)P(E|Nc)P(Nc)$$



M - a node representing the observable outer surface of the tooth and filling.

D, E – nodes representing layers unobservable during clinical diagnosis

LF – a node representing the hypothetical state of the object to be diagnosed, the purpose of the diagnosis.

Nc – a node representing the hypothetical operating time after recovering the object, expressed in the number of chewing cycles.

Figure 10. Classifier topology (the model was created using GeNIe Academic Version 3.0).

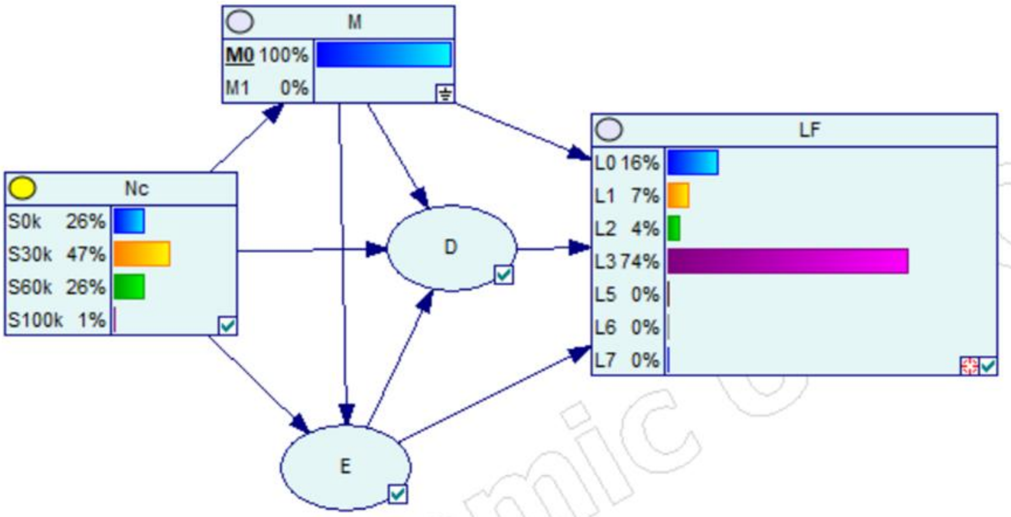


Figure 11. Diagnosis of the condition of the tested object when observation indicates that the outer layer is fit (tightness, no failure).

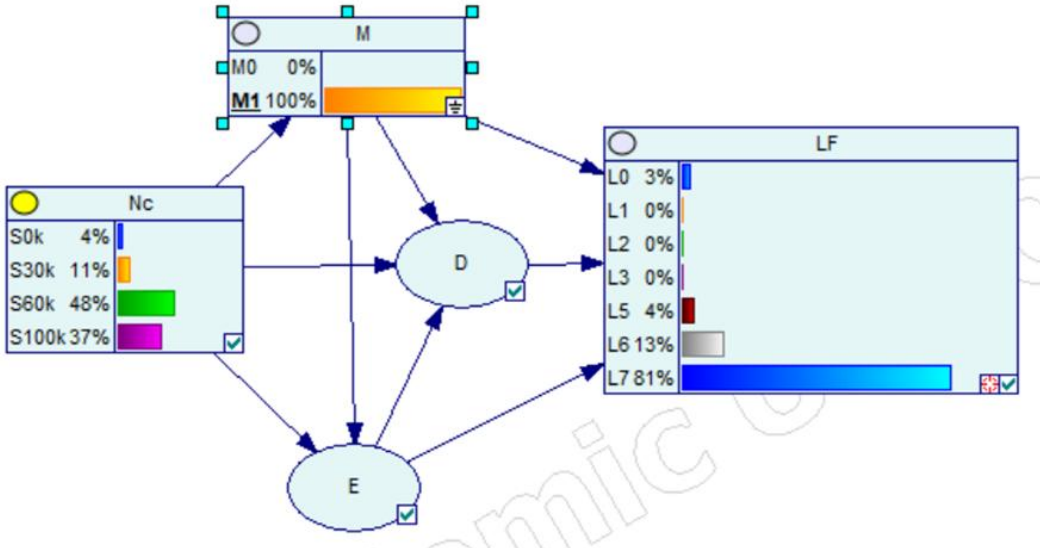


Figure 12. Diagnosis of the condition of the tested object, when observation indicates that the outer layer is unfit (leakage, failure).

Observations indicate that the outer layer is intact, and the most likely condition of the object (74%) is L3 (M0, D1, E1). The probability that both the surface and the layers are intact, L0 (M0, D0, E0), is 16%. The most likely operating time of the object is 30 kilocycles of chewing (47%).

Observations indicate that the exterior surface is leaking, and the most likely condition of the object (81%) is L7 (M1, D1, E1), where all three levels are leaky (Fig. 12). The most likely operating time is 60 kilocycles of chewing (48%), followed by 100 kilocycles with a slightly lower probability (37%). In particular, there is a 4% probability that an object in the same condition, leaking in all layers, can be new after 0 kilocycles of chewing.

4. Discussion

The structure of the Bayesian network allows for causal interpretation and inference under conditions of incomplete observations [14,15], which is particularly important in clinical diagnostics, where decision support increasingly combines classical probabilistic models with machine learning tools [18,22].

In clinical practice, in the case of reconstructive restorations in the teeth, diagnosing the physical and biological condition is a challenge, because access to observations about the integrity of the bond between the filling body and the hard tissues of the tooth is particularly difficult [11,12,13]. The marginal gap between the tooth walls and the filling develops in the invisible zones of enamel and dentin and cannot be assessed in real time during the restoration procedure [9,13]. As a consequence, clinical decisions regarding whether to replace or keep restorations are made without full knowledge of the actual state of tooth-filling contact [10,11,12,13].

This paper proposes an approach based on probabilistic modeling using Bayesian networks as a tool to estimate the probability of a tooth-filling failure that exceeds a critical threshold for the formation of a marginal leak based on the observable features of the gap. The estimation of the probability of a threshold leak here concerns the subsurface layers and is based on the results of surface observations and the prior recognition of the a priori probability relationship between the layers. This approach is consistent with fatigue analyses of restored teeth with cracks subjected to cyclic loads [48] and with Bayesian models of degradation of technical composites, which simultaneously take into account many mechanisms of damage and sources of uncertainty [49,50,51,52]. Researchers emphasize the importance of this method because it allows for the determination of a posteriori probability distribution instead of a single value and the ongoing updating of knowledge with incomplete data [14,51].

Process data (a priori and a posteriori probability) were verified by in vitro experimental studies described in Chapters 2.2 and 3.1. It is necessary to continuously expand the clinical database in order to improve the accuracy of probabilistic predictions and the future validation of models in clinical settings [18,19].

Bayesian approaches have been successfully applied to predict the fatigue life of innovative materials, allowing multiple failure mechanisms and sources of uncertainty to be considered simultaneously [49,52,53]. The ability of dynamic Bayesian networks to incorporate data from current checks and update reliability predictions makes them particularly suitable for diagnostic applications where the intrastructural states of complex material and bioengineering systems cannot be directly observed [51,54].

The presented results show that measurable parameters of the surface gap of the tooth-filling system can support probabilistic leak diagnosis in the entire restoration volume and may form the basis for clinical decision support systems aimed at reducing unnecessary replacement of composite fillings [22,46,47].

Bayesian approaches have been shown to be an effective tool for assessing reliability in complex systems, as they allow the integration of experimental data and a priori knowledge and the continuous updating of predictions as new evidence emerges. This ability is particularly important in dentistry, where diagnostic decisions often have to be made under conditions of uncertainty and based on a limited number of observable indicators. The ability to infer states of internal degradation on the basis of surface measurements is a significant step towards the development of non-invasive diagnostic methods [14,15].

5. Conclusion

The paper presents the application of Bayesian modeling of the probability of critical leakage formation in the material connection between the tooth and the reconstructive composite filling. Two criteria were taken into account in the evaluation: polymerization contraction of the filler material and the process of material fatigue associated with the number of chewing cycles. The aim of the study was to evaluate the effectiveness of the Bayesian method for estimating the probability of emergency marginal leakage in the subsurface layers of dental composite fillings based on surface observations. The presented paper presents a proposal for an adequate model of the Bayesian network and a design of the author's Bayesian classifier. Inputs describing the diagnosed objects were entered into the classifier, and the result was a list of potential diagnoses ordered according to the conditional probabilities of their agreement with the empirical data.

It has been shown that the Bayesian classifier under the conditions of the experiment presented in the paper effectively allows for generating a ranking of possible diagnoses based on conditional probabilities using data on diagnosed objects.

The developed reliability model used to determine the probability distribution of the critical width of the marginal gap and the results of the calculations are the basis for the formulation of the following detailed conclusions:

1. Changes in the probability distribution of the gap width in subsequent layers are poorly targeted. For example, in a new reconstruction fill (scenarios 1, 2, 3), the probability that the MP surface will remain intact is 52.17%, for layer D is 43.7%, and for layer E it is 47.9%. However, after 100,103 chewing cycles (scenarios 10, 11, 12), the probability of an intact MP layer drops to 2.994%, for layer D to 7.303%, and for layer E to 7.682%.
2. The width of the gap in all layers increases with the number of chewing cycles. For example, for a new unused fill, the probability of all zones (levels) being sealed at the same time (a condition that represents the functional state of the system at 0 load cycles) is 10.92%. However, after 100 × 103 cycles, this probability is 1.68%, i.e. after this time, the model practically becomes unusable.

The results obtained in the presented study suggest that probabilistic inference may help overcome current diagnostic limitations and support more evidence-based decision-making in restorative dentistry.

Nevertheless, the approach proposed in the article requires continued research. Future research should focus on the integration of experimental material fatigue data with advanced imaging techniques, clinical observations, and evaluation of new composite materials, including self-healing systems.

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