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# Development of Decompression Tables and Models: Statistics and Data Analysis

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## Abstract

The pioneering work of J.S. Haldane with the first decompression table in 1906 has generated considerable research and effort towards the development of safer and more rapid decompression procedures. The deterministic approach is governed by a fixed set of rules that defines the boundary between safe and unsafe dives and includes a model for gas exchange and an ascent criterion, such as gas supersaturation, to calculate the "safe" decompression depth. These decompression models are essentially empirical and provide "safe" decompression only over a limited range of depth and bottom times. The statistical approach considers DCI to be a probabilistic event and uses a risk function consisting of a gas exchange component and an ascent criterion to estimate or predict the risk of DCI. The ascent criterion can be based on supersaturation or bubble growth. To determine the risk function, a large data set of precise dive data, including time, depth, gas composition, and DCI outcome, must be available to match the predicted risk with the observed data. Probabilistic models of decompression can be used to analyze dive tables and procedures, compare different tables, and develop decompression tables with a given risk level. The probabilistic approach for decompression is a very powerful technique that could lead to a better insight into the physics and physiology of decompression because of its objectivity and potential for implementing a variety of models in the design of the risk functions for DCI. This review compares both approaches and discusses current and future challenges in the quest for a universal decompression model.

**Key Words:** diving, decompression, decompression models, probabilistic risk model, decompression sickness, decompression illness

## Introduction

Since the development of the first decompression tables in 1906 by J.S. Haldane, considerable research and effort have been expended in the development of safer and more rapid decompression procedures and tables. Haldane was the first to define a decompression schedule in terms of depth and time exposures (Hempleman 1993). The approach taken by Haldane can be considered to be deterministic and most models/tables of decompression that have since been developed have taken a similar approach. However, such tables are valid only over a limited range of depth and bottom times. The development of the universal decompression table has not yet been achieved, in part due to an incomplete understanding of the response to decompression and of decompression illness (DCI). There are many factors that can directly and indirectly influence decompression safety, and in many cases, their exact contributions are not known. More recently, a different and more promising approach to the decompression problem has been proposed by Weathersby et al. (1984) that uses statistical methods to analyze real dive data to develop probabilistic models. These models can subsequently be used to develop decompression tables based on a calculated risk of DCI.

Decompression tables based on deterministic methods are governed by a fixed set of rules that define the boundary between safe and unsafe dives. The No-Decompression limit is a good example (Fig. 1). It is generally assumed that dive bottom times less than and up to the no-decompression boundary are safe. On the other hand, if this boundary is violated, it is assumed that DCI would result. However, the incidence of DCI is not so sharply observed; that is, some divers can develop DCI on the "safe" side of the boundary, while others on the "unsafe" side have no apparent symptoms. One individual may incur DCI while others on the same profile may not. In addition to this between subject variability, a given individual may respond differently on different days to the same profile.

Consequently, it is natural to consider DCI as a probabilistic event (Fig. 2). It is no longer a case of being just safe or unsafe. Increasing the time-depth dose increases the risk of DCI and vice-versa. Thus, in the example given above, a dive table that has conservative no-decompression limits will have a lower risk of DCI than a table that has more liberal no-decompression limits. This concept leads to the statistical approach for developing probabilistic models of decompression to estimate or predict the risk of DCI. While the statistical approach is the focus of current research and development efforts in decompression theory, the deterministic approach is the basis of most decompression tables and dive computers; hence both approaches will be reviewed in this paper.

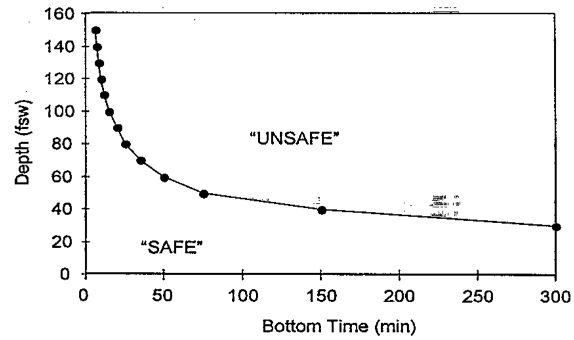



Fig. 1. No-decompression limit boundary.

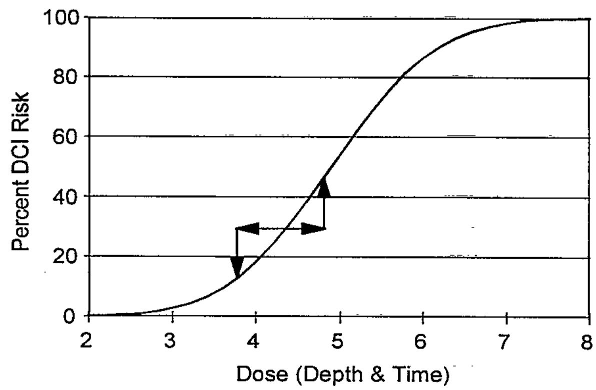



Fig. 2. Example of risk as a function of a depth/time dose.

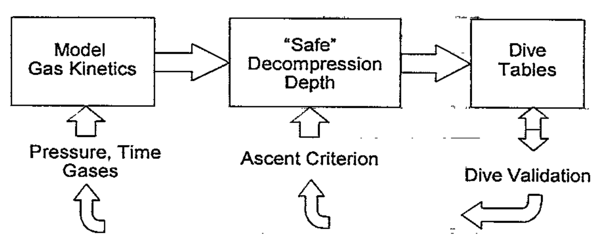



Fig. 3. Elements of a deterministic decompression model.

## Deterministic Approach

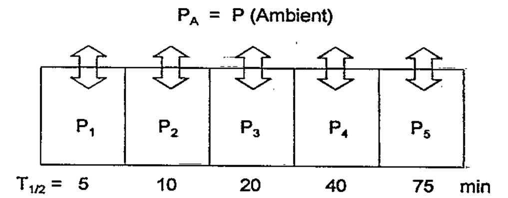
The deterministic approach (Fig. 3) requires a model for gas exchange that takes into account the pressure, time and inspired gases to calculate the gas loading or time-depth dose for an individual exposed to that pressure (Vann and Thalmann 1993). There must also be an ascent criterion to enable the individual to return safely back to the surface. The ascent criterion defines the "safe/unsafe" boundary and is used to calculate the allowable or "safe" decompression depth at any given time. These calculations are used to generate a decompression profile or a set of dive tables for safe guidance back to the surface. The model and ascent criterion must be tested, and in the event that the resultant decompression is inadequate, modifications are made and the validation process is repeated.

The Haldane model (Hempleman 1993)

is the classic example of a deterministic model (Fig. 4). Haldane assumed that the body could be represented by a set of parallel tissue compartments with different half-times selected to represent a spectrum of tissues characterized as fast to slow. The half-times ranged from 5 to 75 min and govern the exponential kinetics of inert gas uptake and elimination. Haldane's ascent criterion assumed that the body could tolerate a certain degree of gas supersaturation, and that this supersaturation, the ratio between the allowable tissue pressure and the safe decompression depth, was a factor of 2.

The US Navy found that the Haldane tables were not safe for deep or long dives (Workman and Bornmann 1975, Hempleman 1993). Between 1930 and 1950, it was demonstrated that the faster tissues could tolerate a much higher supersaturation ratio than the slow tissues; for example, a value of 5.5 was used initially for the 5 min compartment (Table 1). Continuing research also showed that a 120 min half-time compartment was required for prolonged exposures at deeper depths and that the ratios were depth dependent, being smaller at deep decompression stops. This was formulated into the M-value system of calculating decompression tables by Workman in 1965 (Hempleman 1993) and further extended by Schreiner (Schreiner and Kelley 1971) to include multiple inert gases that could be breathed simultaneously or sequentially.

The Haldane/Workman/Schreiner model and its many derivatives form the basis of most of the decompression tables and dive computers that exist today. Table 2 presents some examples, mostly for air diving, showing the number of compartments and range of half-times used. For example, the US Navy uses 6 compartments with a maximum half-time of 120 min. Tonawanda II represents a Schreiner version that is used for developing deep trimix tables, with 11 compartments each for nitrogen and helium. The maximum half-times are 670 min for air and 240 min for helium. Buhlmann's air diving model uses 16 compartments (Buhlmann 1984). Other versions and/or combinations are often applied in dive com-




$$\frac{dP_n}{dt} = k(P_A - P_n)$$

$$P_n = P_i - (P_i - P_A)\left[1 - e^{-0.693\frac{t}{T_{1/2}}}\right]$$

Ascent Criterion
Supersaturation Ratio

$$\frac{P_n}{P_A} = 2$$

Fig. 4. Parallel tissue compartments decompression model (Haldane Model).

Table 1. Supersaturation ratios used by the US Navy

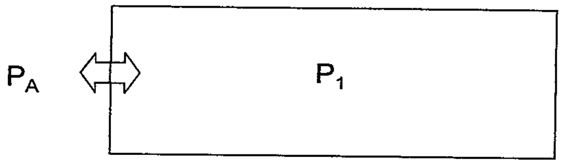
| Tissue Half-Times (min) | Haldane (1906) | Hawkins, Shilling, Hansen (1935) | Van der Aue (1951) | Dwyer (1956) | Workman M-Value* (1965) | |
|---|---|---|---|---|---|---|
| | | | | | $M_0$ | $\Delta M$ |
| 5 | 2.0 | 5.5 | 3.8 | | 104 | 1.80 |
| 10 | 2.0 | 4.5 | 3.4 | | 88 | 1.60 |
| 20 | 2.0 | 3.2 | 2.8 | depth-dependent | 72 | 1.50 |
| 40 | 2.0 | 2.4 | 2.3 | | 56 | 1.40 |
| 75 | 2.0 | 1.8 - 2.0 | 2.1 | | 54 | 1.30 |
| 120 | | | 2.0 | | 52 | 1.20 |
| 160 | | | | | 51 | 1.15 |
| 240 | | | | | 50 | 1.10 |

* $M_0$ is the allowable nitrogen pressure in feet of seawater, $\Delta M$ is change per feet

Table 2. Examples of Haldane/Workman/Schreiner decompression models

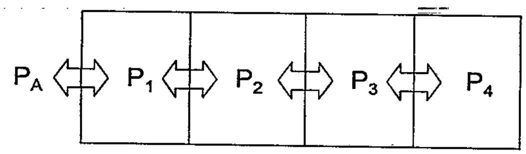
| Implementation | No. of Compartments | Half-time Range (min) | Application |
|---|---|---|---|
| US Navy | 6 | 5-120 | Standard Air |
| Tonawanda II (Hamilton) | 11 Nitrogen<br>11 Helium | 5-670<br>5-240 | Trimix Tables |
| Buhlmann | 16 | 2.65-635 | Swiss Air Tables |
| Rogers | 14 | 5-480 | DSAT RDP (PADI) |
| Buhlmann-Hahn* | 6 | 4-397 | MICROBRAIN |
| Buhlmann (modified)* | 6 | 4-320 | ALADIN, US DIVERS |
| Powell* | 12 | 5-480 | OCEANIC |
| Nikkola* | 9 | 2.5-480 | SUUNTO |
| Huggins/Spencer* | 12 | 5-480 | ORCA |
| Lewis Multi-level* | 6 | 5-120 | OCEANIC |
| Lewis Modified, Spencer, Powell-Rogers* | 12 | 5-480 | DACOR |

*SOURCE: DIVE COMPUTERS, a Comparison by DACOR, January 1990




$$P_1 = P_A - \frac{8}{\pi^2}(P_A - P_0)\left[e^{-kt} + \frac{e^{-9kt}}{9} + \frac{e^{-25kt}}{25}\right]$$

Fig. 5. Single slab bulk diffusion model (British).




$$\frac{dP_n}{dt} = A[(B + P_{n-1} + P_n)(P_{n-1} - P_n) - (B + P_n + P_{n+1})(P_n - P_{n+1})]$$

where $P_0 = P_A$ and $P_5 = 0$

Fig. 6. Serial compartments decompression model - Kidd-Stubbs Model (Canadian/ DCIEM).

puters, and all differ in their ascent criteria.

Although the Haldanian model is the most widely used model for calculating decompression tables, other types of models have been proposed. These non-Haldanian models tend to be more complex mathematically. Of the several that have been developed, only two have been used to develop operational diving tables. The first is the single slab, bulk diffusion model (Fig. 5) that uses an approximation of the diffusion equation to calculate the uptake and elimination of gas (Hills 1977, Hempleman 1993). This model has been used to develop the Royal Navy air decompression tables, the British Sub Aqua Club tables, and Underwater Engineering Group commercial diving tables in the UK.

The second is the Kidd-Stubbs model (Kidd and Stubbs 1969) used to develop the DCIEM air and helium decompression tables (Nishi 1992). It uses an arrangement of four compartments in series (Fig. 6) and, similar to the single slab model, has an ascent criterion that is depth dependent. The four differential equations that define the uptake and elimination of gas into the model compartments are nonlinear and need to be solved by numerical techniques on a digital computer.

The deterministic models used for calculating decompression tables are empirical and non-physiological, and have been referred to as decompression calculation methods, or decompression algorithms, rather than decompression models (Hills 1977). The tissue compartments do not represent real tissues. There is no prerequisite for successful decompression table calculations to have a precise knowledge of the physiology or causes of decompression illness (Hempleman 1969). In these deterministic approaches, the equations and constants of the model have been selected to fit the data. If the equations or constants prove to be inadequate, then other equations or constants are introduced until an acceptably low incidence of DCI is achieved.

There is an abundance of model parameters (usually 3 times the number of compartments in a Haldane/Workman/Schreiner model) and they can be altered independently to extend the operational envelope of the tables or to correct local problems. If a Workman/Schreiner formulation is used to expand the model to a matrix of M-values, then up to several hundred parameters can be adjusted to rectify difficult profiles. Although such models appear to have great flexibility, they are mathematically cumbersome and provide little insight of DCI or guidance for the development of a more realistic decompression model. Non-Haldanian models are generally better in this respect, having fewer parameters or degrees of freedom.

Deterministic models are generally restricted to a limited range of depths and bottom times. Hence, the development of a universal model capable of prediction for dives ranging from no-decompression to saturation appears unattainable. In addition, with any deterministic model, it is impossible to calculate the risk if the ascent criterion is inadvertently violated, or to determine what corrective action should be taken.

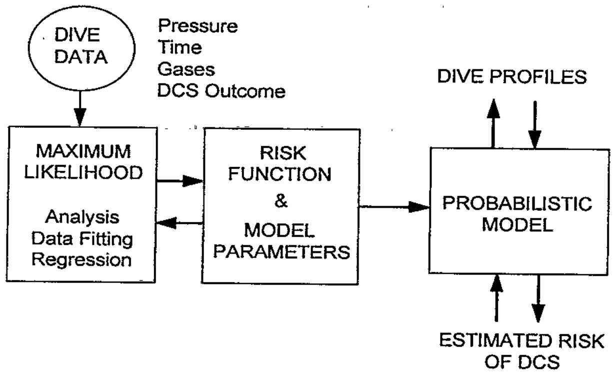



Fig. 7. Statistical model of decompression.

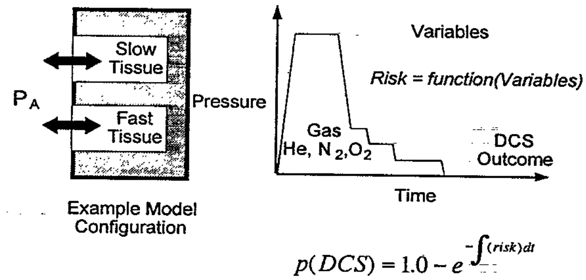



Fig. 8. Elements of the risk function for probabilistic model of decompression.

Because DCI is considered a binary event (i.e., either DCI occurs or does not occur), testing or validating profiles is costly in time and resources. The validation process for decompression tables requires testing profiles in several different stages, through chamber testing, operational evaluation of provisional tables, and field use (Hamilton and Schreiner 1989). There is a detailed analysis and review at each stage, sometimes necessitating a new validation process. How many dives must be conducted to declare a profile to be safe and advance to the next stage is often a practical consideration rather than a statistical one. Twenty dives without a DCI incident is generally considered to be an acceptable compromise.

Statistical theory indicates that the true incidence of DCI based on the above practice can range anywhere from 0% to 16.8% at the 95% confidence level as indicated by Weathersby (1990). Upper confidence limits of other examples are 52.2, 30.9, 7.1, and 3.6% if no cases of DCI occur in 5, 10, 50, and 100 trials, respectively. To achieve 95% confidence that the true incidence would be less than 1% would require that 400 tests be conducted on that profile alone with no cases of DCI. The implications of such a requirement are staggering, especially considering that different divers must be used for statistical validity and without any occurrences of DCI. If DCI were to occur, then many more dives would have to be conducted to assure the 1% incidence at the 95% confidence level.

Obviously, it is unacceptable to spend that much effort and resources on only one profile. As indicated above, 20 dives without an incident of DCI on one profile is often accepted as a practical compromise. Fortunately, other cues are available to aid decisions, including past experience and a knowledge of the safety of other existing tables or related profiles. Doppler ultrasonic monitoring of bubbles is also available to provide further information on the decompression stress of the dives (Nishi 1993).

## Statistical Approach

The statistical approach to decompression modeling was developed at the US Naval Medical Research Institute (Weathersby et al. 1984, Weathersby et al. 1985a) and it has had a very large impact on how decompression is analyzed and treated. In this approach, DCI is viewed as a probabilistic event and a risk function based on the time-depth dose is defined to estimate the risk or probability of DCI (Fig. 7). The risk function can also be used to compute an ascent profile such that the risk of DCI does not exceed a preselected acceptable level of risk, unlike the deterministic approach that calculates a "safe" ascent profile. To determine the risk function, a large set of real dive data containing a mixture of outcomes with and without DCI is required and the risk function must be fitted to the observed data.

The risk function contains both the gas

kinetics and the ascent criterion. These are similar to those used in the deterministic approach. For example, gas kinetics based on a two-compartment model consisting of a fast and slow tissue can be assumed (Fig. 8) and the ascent criterion could be based on gas supersaturation or bubble growth. Instead of preselecting the parameters of the risk model as in the deterministic approach and using trial and error until the best fit to the data is achieved, the parameter estimation program only requires a reasonable estimate of the parameters as an initial starting point. It then regresses the values that give the best fit to the data iteratively by comparing the predictions of DCI with the observed data. This method of parameter estimation is based on the principle of maximum likelihood (Edwards 1972).

The likelihood procedure can be extended to any number of compartments and statistical tests can be applied to determine the optimum number of compartments and/or parameters that should be used. There is no restriction to the configuration of compartments [parallel (e.g., Haldane) or series (e.g., Kidd-Stubbs)], to the kinetics of inert gas exchange (linear, exponential, etc.), or to the ascent criteria (gas supersaturation or bubble growth). The parameters of existing models such as the Kidd-Stubbs or a Haldanian version (Vann 1987, Tikuisis et al. 1988, Parsons et al. 1989) can be optimized against data using maximum likelihood. The best model that the US Navy has found for air diving is one where the uptake of nitrogen is exponential and its elimination is linear (Parker et al. 1992). Several recent investigations have focused on the evolution of bubbles and the correlation of their size/density to the incidence of DCI (Ball et al. 1995, Burkard and Van Liew 1993, Gerth and Vann 1997, Srinivasan et al. 1998, Tikuisis et al. 1994, Van Liew 1991).

Normally, the predictions of DCI from the risk function are fitted against observed DCI values. If bubble growth is used as the ascent criterion, the estimated bubble size could be fitted against the Doppler bubble scores observed after decompression (Gault et al. 1995). Doppler-detected bubbles can give an indication of the decompression stress of dives. No detectable bubbles or few bubbles are indicative of low decompression stress, whereas large quantities of bubbles are always associated with high decompression stress, and a higher risk of DCI. Although high bubble levels do not necessarily result in DCI, experience has shown that DCI is almost always associated with high bubble levels (Nishi 1993). Therefore, the probabilistic method could also be applied in this instance to develop a model for decompression stress.

The dive data set used to calibrate the statistical model is critical to its success. Dive profiles as well as the outcome must be accurately defined, whether or not DCI occurred and when, if it did occur. The database should be large (> 1000 dives) with and without incidences of DCI. In fact, many cases of DCI (5 - 10%) are required so that the parameter estimation procedure can distinguish between "safe" and "unsafe" dives with increased confidence (Albin 1992).

The requisite quality of the data, considered as primary, must provide a detailed account of the dive profile from the start of the dive to the end of the decompression profile including any delays and depth variations (Fig. 9). Not all data meet these requirements. Using the nominal depth and bottom time reported by a diver and assuming that decompression occurred according to the stop times

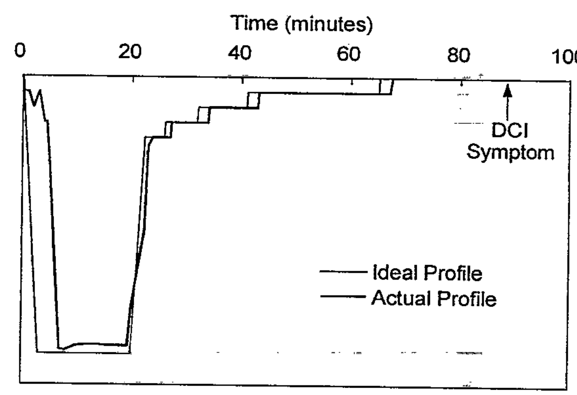



Fig. 9. Data requirements for probabilistic modeling - actual dive profile vs. ideal table profile.

taken from the decompression table that was used is too crude. Gas composition must be known to within 1%, the time resolution must be within 0.3 min during depth and for gas mixture changes, and depths must be precise to within 1.5 feet of seawater (Weathersby and Survanshi 1991). Operational dive logs generally do not give sufficient detail whereas chamber logs that have been medically monitored as to DCI outcome are ideal. The time when the first definite symptom of DCI occurred is critical to the parameter estimation of the model (Weathersby et al. 1992a).

Historical chamber logs from dives preceding 1970 contain many cases of DCI, but are generally not suitable because the criteria for DCI were less conservative at that time [i.e., symptoms had to be far more severe than today's standards before they were acknowledged as DCI and treated (Weathersby et al. 1986a)]. Open water dives conducted with data logging dive computers could qualify if the times and depths are recorded several times a minute. However, unless the DCI outcome has been reported accurately and truthfully, and preferably by a qualified diving medical specialist, such data are suspect. Unfortunately, symptoms of DCI are sometimes ignored or not reported, wilfully or through a lack of recognition of symptoms of DCI. Marginal symptoms of DCI are particularly valuable in defining the "gray" zone between no DCI and DCI, but these are often ignored since they may not require treatment. While it is tempting to use data from dive recorders, the risk of serious error is too great. Incorrect information could lead to highly inappropriate and incorrect parameter estimates that may grossly underestimate the risk of DCI, leading to the development of hazardous decompression tables or procedures. Ultimately, bad data are worse than no data.

The power of the statistical approach is that data can be combined from a wide variety of depth-time exposures even though individual profiles in the data set may constitute only a very small number of actual trials (Weathersby 1989). This overcomes the problem faced with the deterministic approach of having to do many more tests on a single profile. For example, the air data set used by the US Navy which forms the basis of their new air and nitrogen-oxygen probabilistic decompression tables (Parker et al. 1992, Survanshi et al. 1997) consists of more than 3300 man dives from DCIEM, the US Navy and the Royal Navy, completed from 1977 to 1990 (Weathersby et al. 1992b). The data range from submarine escape profiles from depths as great as 600 feet with a total exposure time of less than 2 min, to saturation dives exceeding one week at pressure.

As more dive data become available, they can be combined to further improve the model parameter estimates and increase confidence in the model prediction. If helium or trimix dive data, both non-saturation and saturation, are added to an air diving data set, a multiple-gas probabilistic model could be developed. It conceivably has the potential of being the universal model that can take into account any combination of gas and depth-time exposure. However, high quality "primary" dive data are required to attain this goal.

Once a probabilistic model is formulated and calibrated with data, different dive profiles or dive procedures can be theoretically tested (i.e., predicting the risk of DCI for dives with known outcomes). Conversely, new dive profiles or decompression tables can be generated with pre-selected degrees of risk

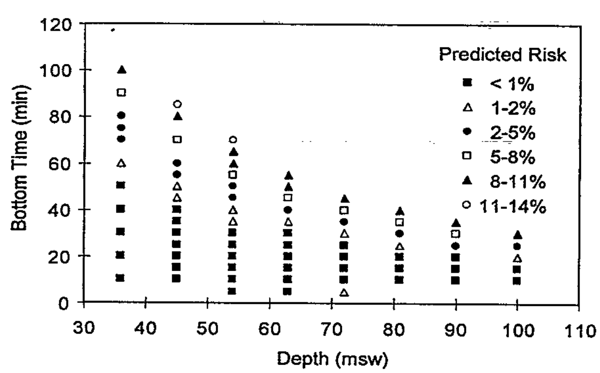



Fig. 10. Example of risk prediction - predicted risk of DCI for DCIEM 84/16 Surface-Supplied $HeO_2$ Table.

(Weathersby et al. 1985b). Figure 10 gives an example of calculating the risk of DCI for the individual profiles in a set of tables. This figure shows the results for the DCIEM helium-oxygen decompression table with in-water oxygen decompression (DCIEM 1992). The risk model that was used took both helium and nitrogen into account (Tikuisis et al. 1991a) and was based on a preliminary data set of approximately 3500 man-dives, of which approximately 30% were air dives. The estimated risk of DCI for the profiles of each bottom time/depth combination in the tables is divided into several different ranges of risk. The risk increases as the bottom time is increased at each depth. The high risks at the outer limits of the tables are a result of insufficient data for long and deep exposures in the preliminary helium data set. As a result, this model over-predicts the risk at the extreme limits of the table. The actual observed incidence of DCI in this range was around 3 to 5% during the validation trials for the helium decompression tables.

The same type of analysis can be used to compare different decompression tables and to estimate the relative risks of DCI (Weathersby et al. 1986b). Profiles that give a high risk of DCI can be modified to decrease the risk. Dive procedures such as repetitive diving (Tikuisis and Nishi 1992, Gerth et al. 1992) can also be analyzed. Another possibility is to look at the relative risks of different dive conditions, for example, between wet and dry chamber divers (Weathersby et al. 1990), and to introduce into the risk function a factor that takes this difference into account for future predictive purposes. This method may also be applied to estimate the risk of DCI for divers with predisposing conditions (Tikuisis et al. 1991b).

Table 3 shows an example of equal risk decompression tables developed by the probabilistic method (Survanshi et al. 1997) as part of the development of the USN93 decompression tables. These are no-decompression limits for air dives with a 1, 2.3 and 5% estimated risk of DCI. Selecting a 1% risk severely restricts the allowable time at depth; for example, at 100 feet, only 11 min is allowed. This is shorter than, for example, the 15 min allowed by the DCIEM air table, or the 25 min allowed by the older 1957 US Navy tables. However, if a higher risk such as 5% is acceptable, a much longer period, 50 min in this case, can be spent at 100 fsw. The choice of the acceptable risk level will generally be an operational decision. For example, a 2.3% risk defines the operational limit in the USN93 tables which allows 27 min in the case of a 100 foot dive.

Table 3. Statistically-based decompression tables: equal risk no-decompression limits (Survanshi et al. 1997)

| Depth (fsw) | No-Decompression Limit (min) | | | Depth (fsw) | No-Decompression Limit (min) | | |
|---|---|---|---|---|---|---|---|
| | 1% | 2.3% | 5% | | 1% | 2.3% | 5% |
| 30 | 146 | 245 | 387 | 90 | 14 | 32 | 59 |
| 40 | 63 | 144 | 232 | 100 | 11 | 27 | 50 |
| 50 | 40 | 93 | 156 | 120 | 7 | 21 | 38 |
| 60 | 29 | 64 | 113 | 140 | 4 | 16 | 31 |
| 70 | 21 | 48 | 87 | 160 | 4 | 14 | 26 |
| 80 | 16 | 38 | 70 | 180 | 0 | 12 | 22 |

Although probabilistic models have been successful in predicting the observed DCI in a wide range of air and nitrogen-oxygen dive data, they have tended to underpredict the risk of DCI for dives with prolonged breathing of 100% oxygen. Studies have shown that it is highly possible that oxygen may have to be considered as a contributor to DCI risk at high partial pressures (Tikuisis and Nishi 1994, Parker et. al. 1996).

In addition to tables of equal risk, tables can also be developed with variable risk in different depth/bottom time ranges depending on operational requirements. Unlike the deterministic model which gives only one path back to the surface, the probabilistic model can give an infinite number of paths back to the surface, depending on the risk that the user is willing to tolerate or accept. One obvious choice is to generate tables which minimize the decompression times for a given risk. Regardless, any decompression table or profile developed from probabilistic models will still require validation testing under controlled conditions. Fortunately, strategies can be devised for minimizing the number of trials and cases of DCI while still retaining the statistical power of the method [e.g., by using a sequential trials design (Homer and Weathersby 1985, Lehner and Palta 1989, Survanshi et al. 1992 and 1998)]. Another promising development is the use of animal models for decompression validation. Lehner et al. (1997) have reported strong similarities between sheep and human responses to decompression.

Probably the greatest advantage of the probabilistic model is that it can be designed into a real-time dive computer to give considerable flexibility and decompression options (Survanshi et al. 1996). For example, the computer can calculate the instantaneous risk as the dive progresses and determine the optimum decompression profile to minimize the total decompression time for a given risk level (Survanshi et al. 1996). Such a real-time algorithm requires considerable processing power; at present, unlike the deterministic counterpart, implementing the probabilistic program in a miniature diver-portable computer is not possible.

Another application of the probabilistic approach has been the development of a model for predicting maximum bubble size calibrated against Doppler-detected bubbles in divers (Gault et al. 1995). Remarkably, the predictions agree closely with those from an independently-derived bubble model calibrated against the incidence of DCI that has been used to generate a Bubble Growth Index (BGI, Gernhardt 1991). Fig. 11 shows a comparison of the maximum bubble size predicted from the DCIEM model and the BGI for no-stop decompression dives. The close agreement strongly supports an inherent connection between bubble size and the incidence of DCI, and by extension, the application of bubble models for safe decompression. Preliminary

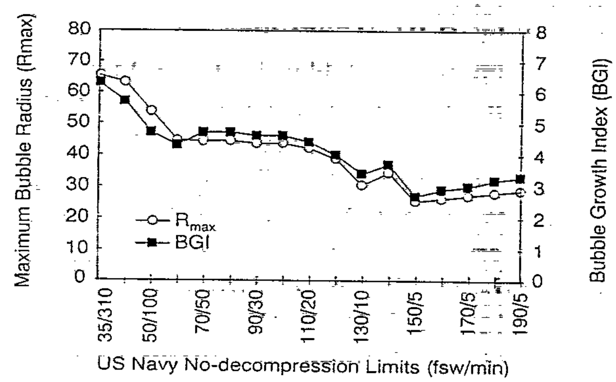



Fig. 11. Comparison of predicted maximum bubble size based on Doppler-detected bubbles with the Gernhardt Bubble Growth Index based on DCI data, for US Navy no-decompression dive limits.

investigations indicate that decompression is incident-free if the maximum bubble size or BGI is below a specific threshold. This potentially provides a very convenient method for developing safe surface decompression procedures.

In summary, the statistical approach for decompression is a very powerful technique that has opened up the potential for an entirely new concept in table design, analysis, and dive testing. It is highly desirable because of its objectivity and its potential for implementing gas kinetics, bubble growth, or other natural phenomena in the description of the risk function for DCI. By being able to investigate different risk criteria, for example, gas supersaturation vs. bubble growth, bubble size vs. gas volume, etc., and matching the results to actual dive data, better insight into the physics and physiology of decompression will be attained. The present work is still largely developmental, deriving the best risk model, establishing well-calibrated dive data for helium/trimix dives, and exploring the potential uses of the probabilistic decompression models. There are still many problems to be overcome before the universal decompression model emerges.

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