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DIPLOMA THESIS

Ανάλυση Μοντέλου Ροής Γεγονότων Συστήματος για την Εκτίμηση του Ρίσκου σε Επιλεγμένες Διαδικασίες σε Πλοίο

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Abbreviations

AHP - Analytical Hierarchy Process
AI - Artificial Intelligence
BE - Basic Events
BN - Bayesian Networks
BWM - Ballast Water Management
CCFA - Common Cause Failure Analysis
CPT - Conditional Probability Table
DAG - Direct Acrylic Graph
DBN - Dynamic Bayesian Network
ETA - Event Tree Analysis
EU - European Union
FMEA - Failure Modes and Effect Analysis
FSA - Formal Safety Assessment
FTA - Fault Tree Analysis
HAZOP - Hazard and Operability Analysis
HELSTAT - Hellenic Statistical Authority
IMO - International Maritime Organization
ISM - International Safety Management
LPG - Liquified Petroleum Gas
RCOs - Risk Control Options
TE - Top Event

Περίληψη

Η παρούσα εργασία επικεντρώνεται στη διαχείριση κινδύνων κατά τη διαδικασία του δεξαμενισμού πλοίων, εστιάζοντας στους κινδύνους που σχετίζονται με τα ατυχήματα κατά τη διάρκεια του δεξαμενισμού, όπως οι πτώσεις από ύψη και οι πυρκαγιές ή εκρήξεις. Ο δεξαμενισμός αποτελεί μια κρίσιμη διαδικασία συντήρησης για τα πλοία, κατά την οποία πραγματοποιούνται επισκευές και επιθεωρήσεις που δεν είναι εφικτές όσο το πλοίο βρίσκεται σε λειτουργία. Παρόλο που λαμβάνονται αυστηρά μέτρα ασφαλείας, τα ατυχήματα σε ναυπηγεία είναι συχνά, λόγω της πολυπλοκότητας των εργασιών και των επικίνδυνων συνθηκών.

Η εργασία δομείται γύρω από την εφαρμογή δύο κύριων μεθοδολογιών εκτίμησης κινδύνων: την Ανάλυση Δέντρου Αστοχιών (Fault Tree Analysis - FTA) και τα Bayesian Networks (BNs). Μέσα από αυτές τις μεθοδολογίες, επιχειρείται να παραχθεί ένα δυναμικό μοντέλο εκτίμησης κινδύνου, το οποίο λαμβάνει υπόψη τόσο στατικές όσο και δυναμικές πιθανότητες, με στόχο την κατανόηση και τη μείωση των κινδύνων στον δεξαμενισμό. Τα δύο κύρια είδη ατυχημάτων που εξετάζονται είναι οι πτώσεις από ύψη και οι πυρκαγιές ή εκρήξεις, τα οποία είναι από τα πιο συχνά περιστατικά που συμβαίνουν κατά τη διάρκεια αυτής της διαδικασίας.

Το τρίτο κεφάλαιο της εργασίας επικεντρώνεται στη θεωρία του δεξαμενισμού, αναλύοντας τις διαφορετικές φάσεις και διαδικασίες που εμπλέκονται σε αυτόν. Σε αυτό το σημείο, γίνεται αναφορά στο πρόγραμμα εργασιών ενός LPG (Liquified Petroleum Gas) Carrier, με στόχο την παροχή μιας σαφούς εικόνας για τις διάφορες εργασίες που πραγματοποιούνται στο πλοίο. Παράλληλα, αναλύεται ο τρόπος με τον οποίο αυτές οι εργασίες αλληλεπιδρούν μεταξύ τους μέσα σε ένα προκαθορισμένο χρονικό πλαίσιο. Η ανάλυση αυτή βοηθά στην καλύτερη κατανόηση της οργάνωσης και του συντονισμού των εργασιών, καθώς και της σημασίας τους για την ασφαλή και αποδοτική λειτουργία του πλοίου κατά τη διάρκεια των εργασιών. Ο δεξαμενισμός είναι μία από τις πιο σημαντικές λειτουργίες συντήρησης και επιθεώρησης ενός πλοίου, καθώς παρέχει την ευκαιρία για λεπτομερή επιθεώρηση της γάστρας, των βοηθητικών συστημάτων (ηλεκτρομηχανές, purifiers, αντλίες, συστήματα ψύξης, κ.α.) και άλλων χώρων που δεν είναι προσβάσιμα όσο το πλοίο βρίσκεται στο νερό. Οι εργασίες που πραγματοποιούνται περιλαμβάνουν καθαρισμό και βαφή της γάστρας ο οποίος αποτελεί από τις πιο σημαντικές εργασίες καθώς η ρύπανση της γάστρας μπορεί να αυξήσει την απαίτηση σε ισχύ από την κύρια μηχανή εώς και 15%. Επίσης γίνονται επισκευές μηχανολογικού εξοπλισμού, καθώς και εγκατάσταση νέων τεχνολογιών για τη βελτίωση της λειτουργικότητας, της ασφάλειας του πλοίου και κυρίως την συμμόρφωση με κανονισμούς.

Η διαδικασία αυτή απαιτεί προσεκτικό σχεδιασμό και συντονισμό ανάμεσα στη διαχείριση του ναυπηγείου και των ιδιοκτητών του πλοίου. Επιπλέον, το κεφάλαιο εξετάζει και τις προκλήσεις που αφορούν τη συμμόρφωση με τους κανονισμούς ασφαλείας που θέτουν οργανισμοί όπως ο Διεθνής Ναυτιλιακός Οργανισμός (IMO), καθώς και τις κατευθυντήριες γραμμές που καθορίζουν οι εθνικές αρχές και οι νηογνώμονες.

Σε αυτό το κεφάλαιο πραγματοποιείται ανάλυση των συχνότερων ατυχημάτων που λαμβάνουν χώρα κατά τη διάρκεια του δεξαμενισμού, με βάση στατιστικά δεδομένα και μελέτες περιπτώσεων. Τα πιο συνήθη ατυχήματα περιλαμβάνουν πτώσεις από ύψη, πυρκαγιές και εκρήξεις, ηλεκτροπληξίες και τραυματισμούς από εξοπλισμό. Κάθε τύπος ατυχήματος εξετάζεται διεξοδικά για να εντοπιστούν τα βασικά αίτιά του και να αναδειχθούν μέτρα πρόληψης. Επιπλέον, γίνεται αναφορά σε ιστορικά περιστατικά για κάθε είδος ατυχήματος, προσφέροντας μια ολοκληρωμένη εικόνα των προκλήσεων και των κινδύνων που σχετίζονται με τον δεξαμενισμό.

Η ανάλυση βασίζεται στην βιβλιογραφία και δεδομένα από διάφορες ναυπηγοεπισκευαστικές ζώνες, όπως αυτή της Δυτικής Αττικής και τα ναυπηγεία της Τουρκίας, και αποκαλύπτει πως η ανεπαρκής επίβλεψη και οι παραβιάσεις των προτύπων ασφαλείας αποτελούν κύριους παράγοντες που συμβάλλουν στην εμφάνιση αυτών των ατυχημάτων. Αξίζει να σημειωθεί ότι, βάσει των δεδομένων της παρούσας μελέτης για τη ναυπηγοεπισκευαστική ζώνη στη Δυτική Αττική, η συχνότητα των ατυχημάτων πτώσης από ύψη και φωτιάς/έκρηξης υπολογίζεται σε 3.56*10^-3 *και* 1.3610^-3 ανά δεξαμενισμό, αντίστοιχα. Αυτές οι τιμές θα χρησιμοποιηθούν για τη σύγκριση με τα αποτελέσματα του μοντέλου, συμβάλλοντας στην αξιολόγηση και τεκμηρίωση της αξιοπιστίας του. Η σύγκριση με πραγματικά δεδομένα είναι κρίσιμη για την επικύρωση του μοντέλου και την αποδοχή του ως εργαλείου πρόβλεψης και ανάλυσης κινδύνων. Μέσω της Ανάλυσης Δέντρου Αστοχιών (FTA), καταδεικνύεται ότι τα ατυχήματα μπορούν να αποδοθούν σε συγκεκριμένα βασικά γεγονότα, όπως η χρήση ακατάλληλου εξοπλισμού και η έκθεση των εργαζομένων σε επικίνδυνα υλικά, αναδεικνύοντας την ανάγκη για ενισχυμένη τήρηση των κανονισμών και καλύτερη εκπαίδευση του προσωπικού για τη μείωση των κινδύνων.

Το τέταρτο κεφάλαιο επικεντρώνεται στη θεωρία του ρίσκου και στις μεθοδολογίες που χρησιμοποιούνται για την εκτίμηση των κινδύνων στη ναυτιλία, δίνοντας ιδιαίτερη έμφαση στις διαδικασίες του δεξαμενισμού. Η εκτίμηση κινδύνων αποτελεί θεμελιώδες εργαλείο για τη διαχείριση της ασφάλειας στον ναυτιλιακό τομέα, καθώς συμβάλλει στην ταυτοποίηση πιθανών κινδύνων, στην κατανόηση της σοβαρότητας και της πιθανότητάς τους, και στην αξιολόγηση των μέτρων που μπορούν να εφαρμοστούν για τη μείωση ή εξάλειψη των κινδύνων αυτών. Μέσω της ανάλυσης κινδύνων, είναι δυνατή η δημιουργία ενός ασφαλέστερου περιβάλλοντος εργασίας για το πλήρωμα και τους τεχνικούς, ενώ παράλληλα βελτιώνεται η αποδοτικότητα των εργασιών συντήρησης. Οι μέθοδοι εκτίμησης κινδύνων που χρησιμοποιούνται περιλαμβάνουν την ανάλυση δέντρου αστοχιών, την ανάλυση επικινδυνότητας και λειτουργικότητας καθώς και την ανάλυση τρόπων αποτυχίας και επιπτώσεων, οι οποίες προσφέρουν δομημένες προσεγγίσεις για την κατανόηση των πιθανών αποτυχιών και των συνεπειών τους στη λειτουργία του πλοίου. Η Ανάλυση Δέντρου Αστοχιών χρησιμοποιείται για τη διάσπαση των αιτίων ενός ατυχήματος σε βασικά γεγονότα, βοηθώντας στην ταυτοποίηση των κύριων παραγόντων που οδηγούν σε μια επικίνδυνη κατάσταση. Ωστόσο, η FTA παρουσιάζει περιορισμούς. Σε αυτό το σημείο, τα BNs αποκτούν κεντρικό ρόλο, επιτρέποντας την ενσωμάτωση κατανομών πιθανοτήτων και τη διενέργεια πιο ακριβών υπολογισμών. Μέσω της χρήσης τους, καθίσταται δυνατή αντιμετώπιση της αβεβαιότητας, η διεξαγωγή σεναρίων, συμβάλλοντας έτσι στην

καλύτερη κατανόηση της ευαισθησίας των παραμέτρων και της αλληλεπίδρασης μεταξύ τους.

Η μετατροπή από Ανάλυση Δέντρου Αστοχιών σε Bayesian Networks πραγματοποιείται με τη χρήση καθιερωμένης θεωρίας και μεθοδολογίας που διατηρεί τη βασική δομή των FTs. Αυτή η προσέγγιση εισάγει στα Conditional Probability Tables (CPTs) των αντίστοιχων κόμβων τιμές που αντικατοπτρίζουν τη λογική των πυλών AND και OR του Δέντρου Αστοχιών. Έτσι, η μετατροπή επιτρέπει τη διατήρηση των εξαρτήσεων και των αιτιωδών σχέσεων του FTA, ενώ ενισχύει την ικανότητα ανάλυσης μέσα από τις πιθανότητες που εισάγονται στα BNs. Αυτή η σύνθεση καθιστά τα BNs κατάλληλα για τη διεξαγωγή ποσοτικών αναλύσεων και την εκτίμηση της ευαισθησίας των παραμέτρων, διατηρώντας παράλληλα την απλότητα και τη σαφήνεια της αρχικής ανάλυσης FTA.

Τα BNs αποτελούν ένα ισχυρό εργαλείο μοντελοποίησης που βασίζεται στη θεωρία πιθανοτήτων και στη Bayesian στατιστική. Χρησιμοποιούνται ευρέως για την αναπαράσταση και ανάλυση πολύπλοκων συστημάτων, όπου οι αλληλεπιδράσεις και οι σχέσεις μεταξύ των παραμέτρων είναι δύσκολο να κατανοηθούν με παραδοσιακές μεθόδους. Τα BNs αναπαριστούν τις αιτιώδεις σχέσεις μεταξύ γεγονότων μέσω ενός γραφήματος, όπου οι κόμβοι αντιπροσωπεύουν μεταβλητές ή γεγονότα, και οι συνδέσεις μεταξύ των κόμβων αντιπροσωπεύουν τις εξαρτήσεις τους. Αυτό επιτρέπει την εκτίμηση των πιθανοτήτων για διάφορες καταστάσεις, ακόμα και όταν υπάρχουν αβεβαιότητες ή ελλιπή δεδομένα. Επιπλέον, τα BNs διευκολύνουν την ανάλυση ευαισθησίας, βοηθώντας τους αναλυτές να προσδιορίσουν ποιες παράμετροι επηρεάζουν περισσότερο τις τελικές πιθανότητες, προσφέροντας έτσι πολύτιμη πληροφόρηση για τη λήψη αποφάσεων και τη βελτίωση των διαδικασιών ασφάλειας.

Στο πέμπτο κεφάλαιο το οποίο αποτελεί το κύριο κομμάτι των υπολογισμών και εφαρμογή της προαναφερόμενης θεωρίας προχωράμε στην δημιουργία των Fault trees για τα ατυχήματα που θα μελετήσουμε, την πτώση από ύψη και την φωτιά/έκρηξη. Στη συνέχεια, ακολουθώντας τη δομή του Δέντρου Αστοχιών και τη θεωρία μοντελοποίησης σε BN, διαμορφώνονται τα απαραίτητα δίκτυα. Κάθε γεγονός και εξάρτηση στο FT μετατρέπεται σε κόμβο ή σχέση μέσα στο BN, διατηρώντας τη λογική των πυλών AND και OR του FT.

Αφού διαμορφωθεί η βασική δομή του BN, το επόμενο βήμα είναι ο καθορισμός των πιθανοτήτων για κάθε γεγονός και των δεσμευμένων πιθανοτήτων μεταξύ τους. Στην περίπτωση του ατυχήματος φωτιάς/έκρηξης, δημιουργήθηκαν δύο διαφορετικά μοντέλα: το ένα με στατικές πιθανότητες στους κόμβους (Chance Nodes) και το άλλο με παραμέτρους που ακολουθούν κατανομή πιθανοτήτων (Equation Nodes) για τα γεγονότα που σχετίζονται με την Εμπειρία και τον Φόρτο Εργασίας. Οι κατανομές αυτές υπολογίστηκαν χρησιμοποιώντας θεωρία πιθανοτήτων και ιστορικά δεδομένα. Η εισαγωγή αυτών των δυναμικών παραμέτρων στο BN έχει ως αποτέλεσμα να επηρεαστούν και άλλα γεγονότα, τα οποία πλέον ακολουθούν κατανομή καθώς εξαρτώνται από τα δεδομένα των κύριων παραμέτρων. Η κατανομή αυτή υπολογίστηκε με τη βοήθεια ενός προγράμματος Matlab, το οποίο εντοπίζει την καταλληλότερη κατανομή για μία σειρά δεδομένων, χρησιμοποιώντας το Kolmogorov-Smirnov test για να αξιολογήσει την ακρίβεια της προσαρμογής. Οι υπόλοιπες πιθανότητες

καθορίζονται με βάση την υπάρχουσα βιβλιογραφία, η οποία παρέχει καθιερωμένες εκτιμήσεις και κατευθυντήριες γραμμές για τη ναυτιλιακή ασφάλεια. Σε περιπτώσεις όπου δεν υπάρχουν διαθέσιμα δεδομένα ή σχετικές εκτιμήσεις στη βιβλιογραφία, οι πιθανότητες ορίζονται από μια εξειδικευμένη ομάδα που αποτελείται από επαγγελματίες με εμπειρία στον χώρο της ναυτιλίας. Η συμβολή της ομάδας αυτής είναι καθοριστική για την ακριβή αξιολόγηση των κινδύνων, καθώς χρησιμοποιεί την πρακτική γνώση και την εμπειρία από πραγματικές συνθήκες και περιστατικά στον ναυτιλιακό τομέα, ενισχύοντας την αξιοπιστία και την ακρίβεια του μοντέλου.

Με τα τρία μοντέλα πλήρως ανεπτυγμένα (ένα για πτώσεις από ύψη με Chance Nodes και δύο για φωτιά/έκρηξη — ένα με Chance Nodes και ένα με Equation Nodes), μπορούμε να προχωρήσουμε στην εκτέλεση των υπολογισμών.

Αρχικά, πραγματοποιούμε **ανάλυση ευαισθησίας** για τον εντοπισμό των γεγονότων στα οποία μικρές μεταβολές στις τιμές τους προκαλούν τη μεγαλύτερη ποσοστιαία αλλαγή στο τελικό αποτέλεσμα του ατυχήματος, συγκριτικά με άλλα nodes. Εφαρμόζοντας αυτή τη διαδικασία στο μοντέλο φωτιάς/έκρηξης, διαπιστώνεται ότι οι πιο ευαίσθητοι παράγοντες είναι η ελλιπής επίβλεψη, το κάπνισμα σε επικίνδυνες ζώνες και η αμελής τοποθέτηση και αποθήκευση εύφλεκτων υλικών στους χώρους εργασίας. Αυτοί οι παράγοντες συμβάλλουν σημαντικά στην πιθανότητα ατυχήματος, επισημαίνοντας κρίσιμα σημεία ελέγχου για την πρόληψη κινδύνων.

Στη συνέχεια, εκτελείται ο **υπολογισμός της πιθανότητας** του ατυχήματος με βάση τα CPTs που αναπτύχθηκαν στα προηγούμενα στάδια του μοντέλου. Αφού ολοκληρωθούν οι υπολογισμοί, τα αποτελέσματα συγκρίνονται με τα ιστορικά δεδομένα για την αξιολόγηση της ακρίβειας και της αξιοπιστίας του μοντέλου. Αυτή η σύγκριση είναι ουσιώδης, καθώς επιτρέπει την επικύρωση του μοντέλου και αποδεικνύει σε ποιον βαθμό οι προβλέψεις του ευθυγραμμίζονται με τα πραγματικά περιστατικά, παρέχοντας μια τεκμηριωμένη βάση για τη διαχείριση και πρόληψη κινδύνων.

Στο τελικό στάδιο, πραγματοποιούνται **προσομοιώσεις** με διαφορετικές τιμές για τις παραμέτρους που έχουν εισαχθεί, με στόχο την εκτίμηση της επίδρασης αυτών των παραλλαγών στην πιθανότητα ατυχήματος σε διάφορα σενάρια. Συγκεκριμένα, εκτελούνται έξι προσομοιώσεις με διαφορετικές τιμές στις παραμέτρους Εμπειρίας και Φόρτου Εργασίας, τέσσερις προσομοιώσεις που τροποποιούν τα Chance Nodes για τις ευαίσθητες παραμέτρους που αναφέρθηκαν προηγουμένως, και μία προσομοίωση στην οποία τροποποιούνται τόσο τα Equation Nodes όσο και τα Chance Nodes. Αυτή η προσέγγιση επιτρέπει την ανάλυση των πιθανών μεταβολών στην εκτίμηση κινδύνου ανάλογα με τις συνθήκες, παρέχοντας έτσι μια πιο ολοκληρωμένη εικόνα για τους κινδύνους και διευκολύνοντας τον σχεδιασμό κατάλληλων στρατηγικών πρόληψης σε κάθε σενάριο.

Τα συμπεράσματα που προκύπτουν από την αναλυτική διερεύνηση της δομής και ανάπτυξης του μοντέλου, καθώς και από τα αποτελέσματα των προσομοιώσεων, συνιστούν κρίσιμα ευρήματα αυτής της διπλωματικής εργασίας, αποτυπώνοντας τις βασικές πτυχές της ερευνητικής διαδικασίας. Αρχικά, αποδεικνύεται ότι οι μέθοδοι του Δέντρου Αστοχιών και των Bayesian Networks ανταποκρίνονται επιτυχώς στις απαιτήσεις μοντελοποίησης σύνθετων συστημάτων, όπως τα ατυχήματα πτώσης από ύψη και φωτιάς/έκρηξης στον δεξαμενισμό πλοίων. Επιπλέον, η ανάλυση ευαισθησίας

και οι προσομοιώσεις αναδεικνύουν τις παραμέτρους που επηρεάζουν σημαντικά τα αποτελέσματα, παρέχοντας βαθύτερη κατανόηση των κρίσιμων παραγόντων κινδύνου.

Το μοντέλο αυτό αποτελεί ένα πρακτικό εργαλείο για τους εμπλεκόμενους φορείς στη διαδικασία του δεξαμενισμού, όπως οι ναυτιλιακές εταιρείες και τα ναυπηγεία. Οι φορείς αυτοί μπορούν να προσαρμόσουν τις τιμές των κόμβων του μοντέλου σύμφωνα με τις δικές τους παρατηρήσεις και εκτιμήσεις, αντιπροσωπεύοντας καλύτερα τις συνθήκες λειτουργίας τους. Με τον τρόπο αυτό, είναι σε θέση να εντοπίσουν τα σημεία του συστήματος που απαιτούν βελτίωση και να λάβουν μέτρα για την ελαχιστοποίηση της πιθανότητας ατυχημάτων, ενισχύοντας έτσι την ασφάλεια και την αποτελεσματικότητα των διαδικασιών δεξαμενισμού.

Για μελλοντική έρευνα, προτείνεται η ανάπτυξη μοντέλων εκτίμησης κινδύνου για επιπλέον τύπους ατυχημάτων που μπορεί να προκύψουν σε επικίνδυνες ναυτιλιακές διαδικασίες, όπως η φόρτωση και εκφόρτωση φορτίων, το bunkering, και η πλοήγηση σε πολυσύχναστα λιμάνια. Αυτές οι διαδικασίες αποτελούν κρίσιμα σημεία ρίσκου στη ναυτιλία και απαιτούν εξειδικευμένες προσεγγίσεις μοντελοποίησης για την πλήρη αποτίμηση των κινδύνων.

Επιπλέον, συνιστάται ο προσδιορισμός και η ποσοτικοποίηση των συνεπειών των ατυχημάτων, προκειμένου να εκτιμηθεί το συνολικό ρίσκο των διαδικασιών αυτών. Με βάση αυτή την εκτίμηση, είναι δυνατόν να υπολογιστούν τα λεγόμενα Risk Control Options (RCOs), δηλαδή τα μέτρα ελέγχου ρίσκου, τα οποία θα αξιολογούνται με βάση το κόστος και την αποδοτικότητά τους. Η ανάπτυξη μιας τέτοιας ανάλυσης μπορεί να ενισχύσει τη λήψη τεκμηριωμένων αποφάσεων για την ασφάλεια στη ναυτιλία, προσφέροντας ένα ισχυρό πλαίσιο για την ιεράρχηση των μέτρων πρόληψης και μετριασμού των κινδύνων.

1. Abstract

This thesis focuses on risk management during ship drydocking, addressing accident risks falls from heights, and fires/explosions. Drydocking is essential for ship maintenance and safety, allowing repairs and inspections that can't occur while the vessel is operational. Despite rigorous safety protocols, shipyards often see accidents due to the complexity and hazards involved in drydocking tasks.

Chapter 3 provides an in-depth look at the drydocking process itself, detailing the stages of a typical drydocking operation, such as that of an LPG (Liquified Petroleum Gas) Carrier. The chapter analyzes specific tasks like hull cleaning, machinery repairs, and safety upgrades, explaining how these are coordinated and managed under tight timelines.

Chapter 4 explores risk theory and assessment methodologies in the maritime context, particularly as they apply to drydocking. This chapter highlights methods like Fault Tree Analysis (FTA) and Bayesian Networks (BNs), which allow systematic identification and quantification of accident causes. These tools are critical for understanding the likelihood and severity of potential accidents.

Chapter 5 presents the core modeling work. Fault trees for falls and fire/explosion risks are constructed and then converted into Bayesian Networks to integrate conditional probabilities, enabling more dynamic risk assessments. Here, models are tested with both static and probabilistic variables to reflect varying conditions, like worker experience or workload.

Sensitivity analyses reveal key risk factors, like supervision quality and safe material storage, which substantially affect accident probabilities. Simulations on these models help evaluate different risk scenarios, enhancing decision-making on safety improvements.

2. Literature Review

Risk assessment and safety methodologies in the maritime industry have evolved substantially over the years, impacting operations such as drydocking. The book Drydocking: Theory and Technical Aspects of the Operation (Lamb, 2003) provides foundational knowledge about the technical and theoretical aspects of drydocking, covering essential topics such as shipyard operations, the drydocking process, and the unique challenges posed by this critical maintenance procedure. This work is pivotal for understanding the operational baseline of drydocking and its associated risks, making it an essential reference for professionals involved in ship maintenance and safety management.

Complementing this, Adland discusses the efficiency of hull painting, highlighting its significant impact on both maintenance schedules and risk reduction during drydocking (Roar Adland, 2018). Adland's research emphasizes the economic and safety benefits of optimal hull coating procedures, explaining how advanced techniques reduce maintenance costs, extend the lifespan of the vessel, and minimize potential safety hazards. This understanding of hull maintenance plays a crucial role in enhancing the overall effectiveness and safety of the drydocking process.

Safety regulations play a pivotal role in maritime operations, as underscored by the International Maritime Organization (IMO), which introduced significant policies such as the Ballast Water Management (BWM) Convention and the Sulphur Cap Regulations. These standards have reshaped compliance and risk management practices by ensuring ships meet environmental and operational safety standards that reduce risks to both personnel and the environment. The International Safety Management (ISM) Code (Marine Insight, 2023) further elaborates on the regulatory framework, setting clear guidelines for safety management. These guidelines are essential for ensuring that drydocking procedures meet safety and operational standards, providing ship operators with a structured approach to minimizing risks in shipyard environments.

The Safety in Docks: Approved Code of Practice and Guidance (HSE, 2015) addresses risk assessment and safety planning specific to drydocking, ensuring that practices meet the required safety standards. It offers comprehensive guidance on ensuring the safety of personnel during drydocking and ship repairs, with a focus on safe working practices, risk identification, and accident prevention. Tsaraklis contributes to this by providing theoretical insights into shipyard hazards and accident causation (Z. Tsaraklis, 2019). His work is critical for identifying potential failure points and understanding the root causes of accidents in drydocking operations, thus providing a foundation for comprehensive safety planning and risk mitigation strategies.

Historical accident data, such as the statistical analyses by Mineadis on ship repair zones (Mineadis, 2009) in West Attica and by Barlasa and Burak Izci on the Tuzla shipyards (Barlasa & Burak Izci, 2018), emphasize the prevalence and types of accidents that occur in these high-risk areas. These studies provide invaluable data for understanding risk trends over time and offer insight into the recurring factors that contribute to accidents. Similarly, Baginsky reviews accident causes in California shipyards, providing comparative insights into incident patterns and offering lessons that can be applied to current risk management practices (Baginsky, 1976). Statistics

from HELSTAT (Hellenic Statistical Authority) further highlight the frequency and nature of drydock incidents in Greece, providing a regional perspective that enhances the overall understanding of safety in shipyards.

The application of formal safety assessment (FSA) in drydock accident analysis is elaborated by Njumo, who presents methodologies and risk management strategies tailored to this context. Njumo's work is essential for understanding how formal safety assessment tools can be employed to reduce risk in shipyard environments by systematically identifying and addressing hazards before they lead to incidents (Njumo, 2015). Mr. Ventikos his book Study and Management of Risk in Maritime Transport delves deeper into Formal Safety Assessment (FSA) methodologies FTA and BNs), establishing a theoretical framework for understanding complex risk structures in maritime operations (Ventikos N. , 2013). Rausand and Lundteigen's work on Common Cause Failure Analysis (CCFA) further enriches the discussion by providing insights into correlated failure events, which are critical for understanding how multiple failures may interact and compound safety risks in drydocking operations (Rausand & Lundteigen, 2011).

Methodologies for hazard identification are discussed by Mousavi, Ghazi, and Omaraee, whose paper Risk Assessment in the Maritime Industry outlines key approaches for pinpointing potential hazards. Their work provides a detailed look at various risk assessment techniques, such as qualitative and quantitative risk analysis methods, helping professionals better identify and mitigate risks before they escalate. Bayesian networks, extensively analyzed by Jensen and Nielsen (2007) in Bayesian Networks and Decision Graphs, offer a powerful tool for probabilistic risk modeling and decision-making in maritime safety scenarios. Jensen and Nielsen demonstrate how Bayesian networks can be used to model complex risk scenarios, allowing operators to make data-driven decisions that minimize risk and enhance safety.

Additionally, Risk-based Maintenance (Cullum et al., 2018) and Risk-based Maintenance—Techniques and Applications (Arunraj & Maiti, 2007) offer methodologies that can be adapted for the shipyard context, focusing on maintenance strategies that improve operational safety and reliability. These works discuss how risk-based maintenance approaches can be used to prioritize maintenance tasks based on the likelihood of failure and the severity of consequences, thus ensuring resources are allocated efficiently to areas with the highest risk.

The transformation of fault trees into Bayesian networks is a method that has been used with the purpose of integrating these two models to enhance the analytical capabilities of risk assessments (Medkour et al., 2020). By combining the logical structure of fault trees with the probabilistic reasoning of Bayesian networks, Medkour et al. present a more robust framework for identifying and assessing risk in maritime operations. Theoretical support for statistical methods, such as the Weibull distribution, provide essential tools for reliability analysis (Vadya & Srivastav, 2024) (Dunn & Shultis, 2023). These statistical methods are crucial for predicting the failure rates of ship components and systems, which is vital for effective risk management in shipyards. The Kolmogorov-Smirnov test, a non-parametric method for assessing distribution fit, is explained by Hajek and Sen in "Theory of Rank Tests", offering a tool for verifying the appropriateness of the chosen statistical distribution in risk assessments (Hajek & Sen, 1999).

Furthermore, the application of risk-based planning for inspections using dynamic Bayesian networks is explored by Nielsen & Sorensen, illustrating the importance of adaptable planning in maritime safety (Nielsen & Sorensen, 2017). Their work emphasizes how dynamic risk models can help adjust inspection schedules in real-time based on changing conditions, improving efficiency and reducing the likelihood of missed maintenance tasks that could lead to accidents.

Practical applications of risk analysis methods are illustrated in various studies. Tuncel et al. apply FTA to analyze fire and explosion risks on bulk carriers, showcasing the use of theoretical models (Tuncel et al., 2023). Their work demonstrates how FTA can be applied to specific maritime risks, providing a structured method to identify root causes of hazardous events and improve safety measures. Annetis demonstrates a Bayesian approach for condition monitoring of marine diesel engine lubrication, bridging theoretical frameworks with practical outcomes (Annetis, 2020). His research underscores the role of BNs in predictive maintenance, allowing for early detection of potential failures and reducing the risk of catastrophic engine failures during maritime operations. Similar methodologies are applied in the dynamic hull inspection model presented by Ventikos et al., where dynamic risk modeling is used to optimize the inspection process and enhance ship safety (Ventikos et al., 2018).

Additionally, Risk Assessment Methodologies FTA and BNs (Chemweno et al., 2018) delve into the integration of these tools for more precise maritime risk management. They discuss how combining FTA and BNs allows for a more comprehensive approach to identifying and mitigating risks in the maritime industry. Furthermore, Dikis et al. tackle the issue of ship inspection, emphasizing the need for safety improvements to avoid accidents, promote maritime safety, and protect the environment (Dikis et al., 2015). Their work advocates for a systematic approach to ship inspection, which incorporates risk-based methodologies to enhance the efficiency and safety of shipyard operations.

The study by Riposo & Alkire focuses on cost-effective operations and planning for overtime and workload management in shipyards, discussing strategies for improving shipyard capacity and flexibility (Riposo & Alkire, 2008). Their research highlights the importance of balancing operational costs with safety considerations, ensuring that shipyards can handle unexpected workloads without compromising safety. The investigation of human risks in shipyards through a Gaussian fuzzy Analytical Hierarchy Process (AHP) approach is used to examine the relationship between individual characteristics and workplace accidents in shipyards (Turk & Ozkok, 2022) (Acuner & Cebi, 2016). These studies are critical for understanding the human factors that contribute to workplace accidents, offering insights into how to reduce human error and improve safety outcomes in shipyards.

Zaman et al. apply Fault Tree and fuzzy theory to assess risks in abandoned leaking oil wells and natural gas wells, highlighting the importance of these techniques in situations with limited data (Zaman et al., 2021). Their work demonstrates how fuzzy logic and Fault Tree Analysis can be used to model complex risk scenarios, even when access to detailed data is limited. Lavasani et al. provide a detailed review of fire and explosion accidents in the maritime industry from 1990 to 2015, proposing preventative measures for similar future incidents (Lavasani et al., 2015). Their analysis is crucial

for developing better safety standards and policies to prevent such accidents in the future.

Finally, Classification Societies by Eyres & F.R.I.N.A. play an integral role in risk-based methodologies, with works from DNV-GL and Lloyd's Register further supporting the application of these strategies in maritime risk management. These classification societies have been instrumental in introducing and promoting risk-based approaches to ship construction, inspection, and maintenance, ensuring that vessels meet safety standards that mitigate risks across their operational lifespan (Eyres & F.R.I.N.A., 2007) (Lloyd's Register, 2015) (DNV-GL, 2016).

3. Drydock Theory

3.1 Drydocking

Drydocking is a crucial procedure in the maritime industry, providing a unique opportunity to inspect, maintain, and repair ships. This process involves removing a vessel from the water to access areas below the waterline that are not reachable when the ship is afloat. The significance of drydocking extends beyond maintenance, playing a vital role in ensuring a ship's operational efficiency, compliance with international maritime safety and environmental standards, and ultimately, its lifespan. In order to understand the operation of a ship drydock here are some of its most important components:

Inspection and Repair: Essential for assessing the condition of the hull, propellers, rudders, and other underwater parts. It allows for the identification and rectification of damages, ensuring the vessel's structural integrity (Lamb, T - Society of Naval Architects and Marine Engineers, 2003)

Cleaning and Painting: This involves removing biofouling using high-pressure water or sandblasting and applying new anti-fouling paints to reduce drag and improve fuel efficiency. This is crucial for both operational performance and environmental protection.

Upgrades and Modifications: Drydocking provides an opportunity to enhance a ship's capabilities through the installation of new technology or the modification of existing systems, improving efficiency and compliance with new regulations. A good and relevant example is the installation of ballast water treatment systems in order to comply with the BWM Convention of IMO (International Maritime Organization, 2020)

Safety and Compliance: Ensuring that ships meet the safety standards set by international bodies such as the IMO is a critical aspect of drydocking. It is required for every vessel to go through the Special Survey. The Special Survey is a thorough inspection of a ship's condition, including its structure, machinery, and equipment, to ensure that it meets safety and environmental standards.

With over 50 classification organizations worldwide, each society sets rules focused on a ship's structural integrity, equipment adequacy, and machinery reliability (Eyres & F.R.I.N.A., 2007).

Planning and Logistics: The successful execution of drydocking requires meticulous planning, including the selection of a suitable drydock facility, scheduling of repairs, and management of resources.

In order to have a better understanding of the works done in a drydocking a Gant chart of the operations done in a Fully Pressurized LPG is shown in Figure 1: Drydocking Timeline - Tasks.

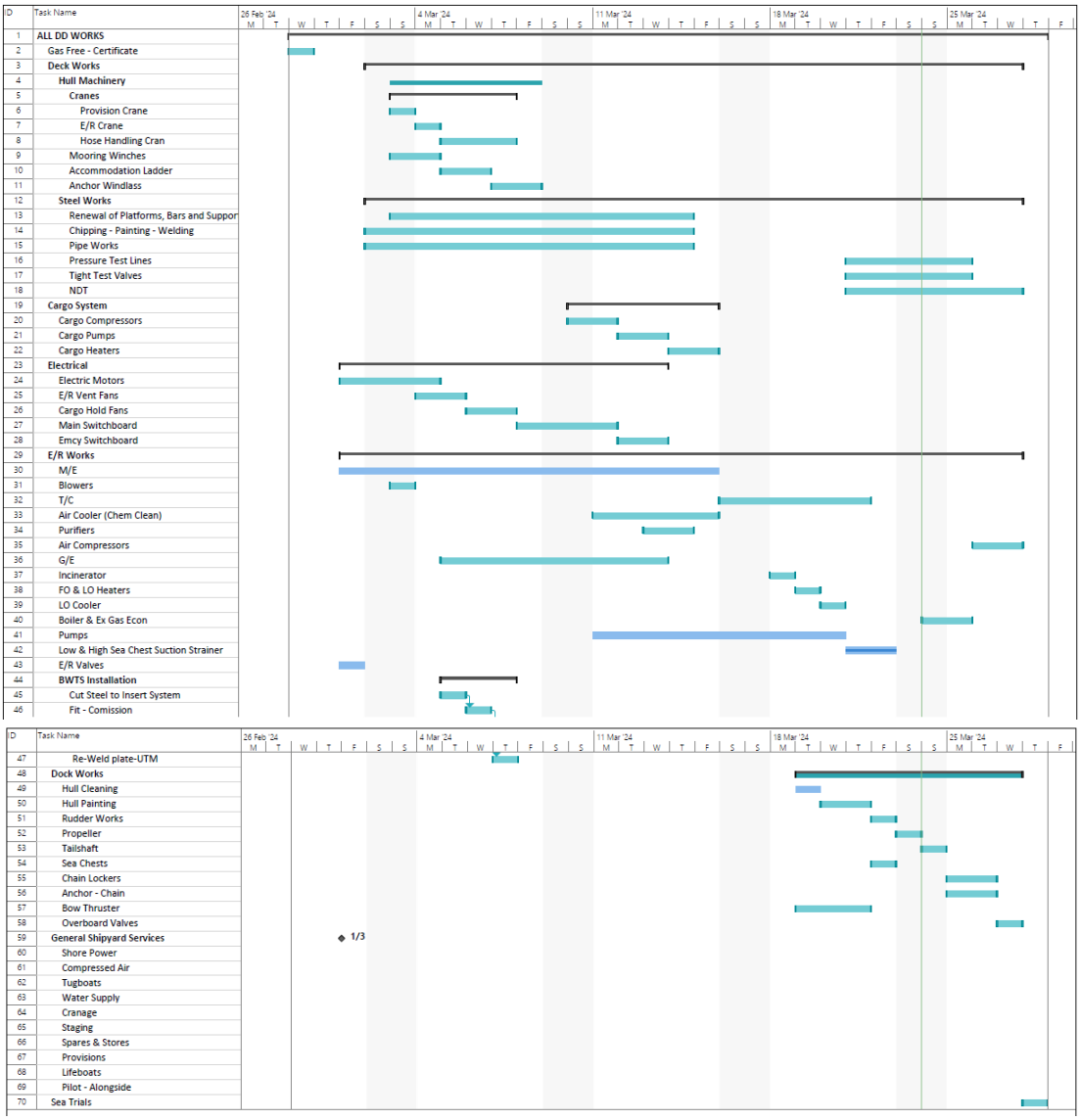


Figure 1: Drydocking Timeline - Tasks

Deck machinery: This type of work involves servicing auxiliary machinery located on deck, including mooring winches, anchor windlasses, cranes, lifeboats, and others. It also extends to key components of the cargo system such as cargo heaters, compressors, and specialized valves. These items are thoroughly inspected and, if necessary, overhauled to ensure optimal performance and safety.

Steel Works: This project involves identifying and restoring rust-affected areas on pipes, flanges, and other steel components. The restoration process includes using specialized tools to chip away the rust, followed by thorough cleaning. Afterward, the treated surfaces are painted to prevent further rust accumulation.

Engine room works: The main engine and generators are overhauled, see Figure 3: Generator Overhaul, along with any auxiliary machinery that has exhibited issues. Key components such as purifiers, air compressors, pumps, heaters, and coolers are also thoroughly examined. During the overhaul, measurements are taken of parts that could potentially cause poor performance. Spare parts are either reconditioned or entirely replaced to ensure optimal functionality and reliability. Additionally, system retrofits

may occur during this phase. For instance, during this drydock period for the LPG vessel, a ballast water treatment system was installed to ensure compliance with ballast water management regulations.

Dock works: At this stage, the vessel enters the dock and its hull is cleared of water. The most critical task at this point is cleaning the hull of biofouling and applying a fresh coat of paint, see Figure 2: Hull Painting. This operation has proven to significantly enhance the ship's performance by reducing hull resistance, which effectively decreases fuel consumption by 17%. (Roar Adland, 2018). This is also an ideal opportunity to inspect the general condition of the hull and take ultrasonic thickness measurements. Other major tasks may include polishing the propeller, inspecting the rudder and rudder stock, replacing anchor chain shackles, and cleaning the sea chests and overboard valves to remove clamps.

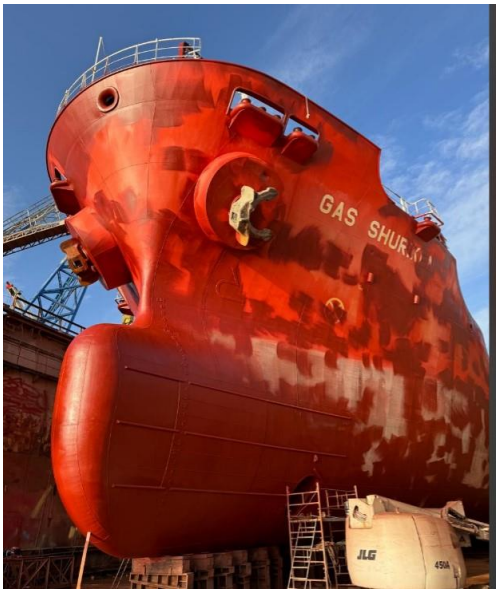


Figure 2: Hull Painting

Figure 3: Generator Overhaul

Other general services: These services provided by the dock consist of the tugboats that are used, shore electric power, compressed air, cooling water, staging, cranage, and others.

This complex operation can be identified as a project since it has a specified period in which it should be completed, a precalculated budget, and a required quality result. The superintendent of the owning company is the defined project manager and is responsible for the coordination and effective cooperation of the shipyard, the crew, third-party engineers, attending classes, etc.

Another important responsibility of the shipyard and the ship-owning company is to make sure the project is carried out with the highest safety standards possible. This is done with different methods:

Regulatory framework and guidelines: The establishment of safety standards is governed by a combination of international regulations, classification society standards, and national/local government laws. IMO sets global standards for maritime safety and environmental protection. Classification societies, such as Lloyd's Register, DNV GL, and the American Bureau of Shipping (ABS), provide specific guidelines and standards for ship construction, maintenance, and safety. National and local regulations further tailor these guidelines to address regional specifics (International Maritime Organization, 2020). For example to achieve the sulphur cap of 0.1% (Figure 4: IMO Sulphur Cap Regulations through the years) in the ECAs many shipping companies installed a scrubber, this was done in the drydock.

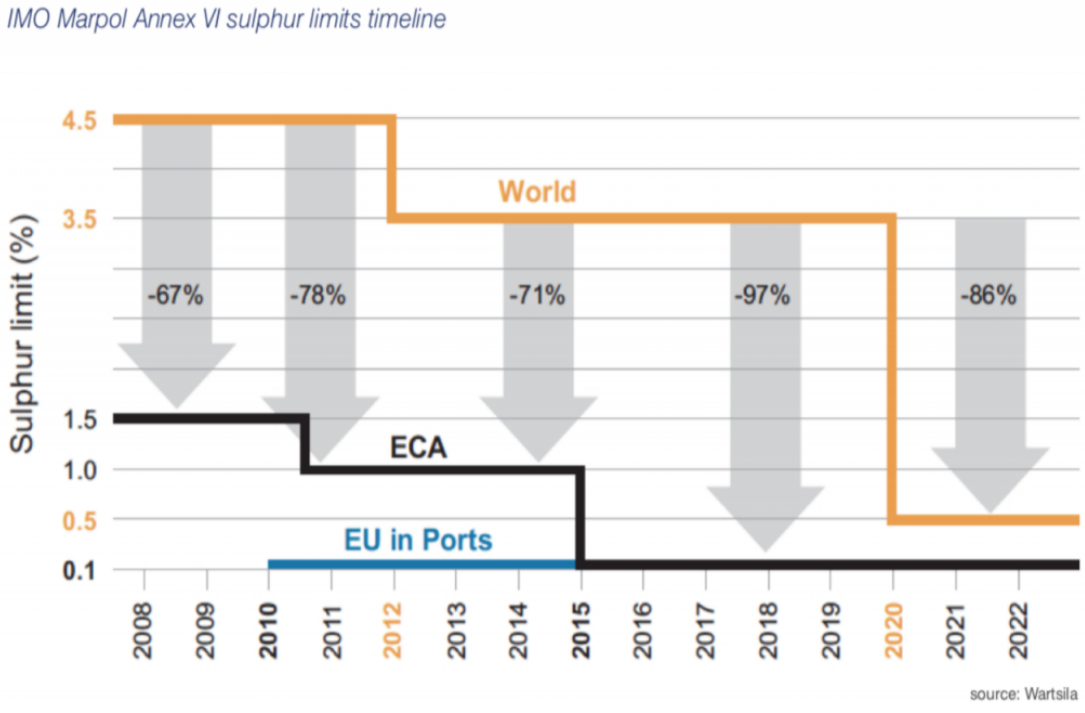


Figure 4: IMO Sulphur Cap Regulations through the years

Drydock safety plan and risk assessments: The development of a detailed safety plan includes hazard identification and risk assessments. These plans are designed to

preemptively identify potential risks and propose strategies for mitigating these hazards (HSE, 2015).

Also, there must be effective communication between the involved parties, close monitoring and supervision, safety training, and emergency safety plans for reactive treatment.

3.2 Accidents

It is unavoidable that a complex and dangerous operation like that will lead to several accidents despite all the protective measures taken. In the shipyard of Tuzla in Istanbul -which is a major drydocking location in the eastern Mediterranean – in the period of 2004-2014 126 workers lost their lives due to workplace accidents (Barlasa & Burak Izci, 2018).

To have a better understanding of the cause of these accidents and thus lower the potential risk it is helpful to categorize them. The most common accidents are (Z. Tsaraklis, 2019):

- Fall from heights
- Fire & Explosions (flammable gasses, fumes, residue gases in tanks, etc.)
- Electrocution
- Damage from equipment (cutting tools, fall of heavy objects from cranes, etc.)
- Physical (Radiation, vibration, heat, etc.)
- Chemical (toxic residues from cargo, chemicals in paint, etc.)
- Ergonomic (long hours working in tough conditions)
- Biological

Fall from heights is the most common fatal accident in the European Union (EU). In a ship repair yard, extensive work is conducted at heights, significantly increasing the risk of accidents, see Figure 5: Work in Dangerous Heights. These incidents often result from unsafe scaffold operations, precarious hanging structures, unguarded floor openings, slippery work surfaces, and tasks performed on high structures like chimneys or masts. Additionally, work on scaffolds typically involves complex tasks at considerable heights, including the handling and placement of heavy objects (Mineadis, 2009). Falling from heights is among the most likely accidents to result in death or serious injury in shipyards and similar construction industries. While these accidents cannot be completely prevented, their occurrence can be minimized (Turk & Ozkok, 2022).

Figure 5: Work in Dangerous Heights

Fire and explosions are common accidents during ship drydocking due to the presence of flammable substances such as fumes in enclosed spaces, poorly maintained gas cylinders, cargo residues, and vapors, alongside various ignition sources including sparks from hot works like grinding or welding, and cigarettes. These hazards can lead to tragic outcomes including loss of life, environmental damage, and significant property damage. Between 1990 and 2007, a total of 18 fire incidents occurred during the docking of oil tankers for repairs. Out of these 18 incidents, 8 resulted in a significant number of injuries and fatalities. In 4 of these 8 cases, it was explicitly reported that the fires were caused by 'hot works' (Njumo, 2015).

Electrocution: During complex operations in the ship repair and construction zones, workers frequently encounter electrical currents. These currents may originate from various sources including the ship's power generation engines, the ship's electrical and electronic devices, the ship's permanent wiring, handheld electric tools, lighting extension cords, and other wiring from various tools or machinery (Mineadis, 2009). Workers should be trained and continuously reminded of the hazardous environment of their workplace to prevent as many accidents as possible.

Damage from equipment is a frequent cause of injuries in shipyards. Misuse or poor maintenance of any tool, ranging from simple items like hammers to large machinery found in the yard's workshop, can result in accidents. The greatest risk when using machinery and equipment is the workers' contact with moving parts of the machines (such as rotating or reciprocating cutting tools, cutting points, pressure points, friction or molding areas, cylinders for material intake or output, endless screws, gears, chains, wheels, belts, and conveyor belts, etc.), or with materials, chips, or sparks that are ejected (Z. Tsaraklis, 2019).

Physical hazards, including vibrations and heat, can lead to injuries if safety guidelines are neglected. Such risks are prevalent in activities like painting, hull cleaning, or hot works.

Chemical hazards include toxic residues from inadequately cleaned tanks, paint, and others. Regular inhalation of these substances by workers can lead to chronic health issues.

Ergonomic hazards encompass workplace conditions that threaten muscle and skeletal health, including repetitive movements leading to strain injuries, awkward postures causing disorders, and forceful exertions resulting in overexertion injuries. Additionally, static positions can impair circulation and exacerbate discomfort, while continuous exposure to vibrations from tools or machinery may lead to long-term physical ailments.

Biological hazards refer to risks associated with exposure to harmful biological substances. These include bacteria, viruses, fungi, and other microorganisms that can cause infections or diseases. Workers may encounter these hazards in environments where they are exposed to bodily fluids, contaminated surfaces, medical waste, or through interaction with infected individuals. This is typically the case when the ship's crew has been exposed to contaminants and has not undergone proper testing.

See Table 1: Percentage of accidents in California Shipyards 1970-1971 (Baginsky, 1976).

The percentage of fatalities in each category that happened in Turkish Shipyards from 2004-2014 is seen in Table 2: Accidents in Turkish Shipyards 2004-2014. As we can see a very dangerous activity that causes the biggest percentage of accidents is a fall from height (Barlasa & Burak Izci, 2018).

Table 1: Percentage of accidents in California Shipyards 1970-1971

Struck by, struck against	29.2
Falls, slips	24.6
Strain, overexertion	21
Foregin substance in eye	7.7
Caught in between	7.2
Contact with toxic substances	4.6
Other or not reported	5.7
Total Percent	**100**
Accidents	**1466**

Table 2: Accidents in Turkish Shipyards 2004-2014

Fall from height	30.2
Struck by/ against - caught in between	23
Fire and/or explosion	16.7
Exposure to electric shock	13.5
Drowining	11.1
Other causes	5.6
Total percent	**100**
Fatalities	**126**

In the associated case study on accidents in Turkish shipyards, a questionnaire was distributed to workers to identify the primary causes of these incidents. The responses

are presented in Table 3: Questionnaire about the safety conditions in Turkish shipyards below (Barlasa & Burak Izci, 2018).

Table 3: Questionnaire about the safety conditions in Turkish shipyards (Barlasa & Burak Izci, 2018)

Question	Yes%	No%
Are the precautions taken sufficient in the workplace against parts falling from a height?	69.7	30.3
Do you use personal protective equipment (PPE) (helmet, mask, etc.)?	100.0	0.0
Is the use of PPE checked regularly at work?	98.5	1.5
Have you taken any courses and training in occupational safety?	98.5	1.5
Do you think the training you received is beneficial?	93.0	7.0
Do you believe that your working area is safe?	62.0	38.0
Do you believe you have adequate training about the equipment you use?	81.2	18.8
Do you get your equipment checked on a regular basis?	65.3	34.7
Are precautions taken to prevent falling from a height enough for you?	67.5	32.5
Are you afraid that you will be exposed to an accident by falling at heights?	63.1	36.9
Do you use safety harness while working at heights?	90.8	9.2
Does safety harness complicate your job while working at heights?	60.8	39.2
Are the precautions taken against electrical contact hazard enough?	60.1	39.9
Are you afraid to get exposed to an accident by electrocution?	68.7	31.3
Are the electrical cables scattered around in the workplace environment?	44.4	55.6
Do you pay attention to the low voltage and high voltage difference while using equipment (sockets, lighting, etc.)?	98.5	1.5
Do you have any information about static electricity?	72.4	27.6
Are adequate precautions taken to deal with fire and/or explosion in the workplace?	70.9	29.1
Are you afraid to get exposed to an accident by fire and/or explosion?	70.5	29.5
Has your workplace implemented a hot work permit?	95.5	4.5
Have gas measurements been made in indoor environments before working?	70.6	29.4
Do the gas hoses spread around in the workplace environment?	36.2	63.8
Have you done enough training and exercises on fire safety?	64.6	35.4
Do you find training and exercises useful?	92.9	7.1
Do you pay attention to the exits in your workplace environment?	78.0	22.0

Mr. Mineadis Andreas carried out a study on accidents in the West Attica ship repair zone, gathering data from 1989 to 2008. The results highlight the types of accidents and their consequences, which are presented in Table 4: Injury for each accident type in West Attica Shipyards(Mineadis, 2009)

.

Table 4: Injury for each accident type in West Attica Shipyards

TYPE OF ACCIDENT	WITHOUT DETAILS	MINOR INJURIES	SERIOUS INJURIES	DEATHS	TOTAL
Falls from height	12	48	30	10	100
Hits from falling objects	4	32	10	2	48
Stepping on dangerous objects, hit by or from objects	1	17	3	0	21
Crushed inside or between objects	0	16	8	1	25
Overexertion or awkward movements	0	2	1	0	3
Exposure to or contact with high or low temperature	2	6	15	15	38
Exposure to or contact with electricity	1	1	0	1	3
Exposure to or contact with harmful substances or radiation	5	8	12	1	26
Other accident categories	4	11	15	11	41
TOTAL	29	141	79	47	296

In the database of this paper, it is found that from 2000 to 2008 there have been 21 Falls from Height and 8 Fires and/or Explosions. The database used in this study reveals that between 2000 and 2008, there were 21 incidents of falls from height and 8 cases of fire and/or explosions. During this same period, HELSTAT records indicate a total of 5895 drydock operations in this region (Hellenic Statistical Authority, 2024). Based on this information, the frequency of each type of accident has been calculated as follows.

- Fall from Heights = 3.56*10^-3 per drydock
- Fire and/or Explosion = 1.36*10^-3 per drydock

Workers are operating in environments where they are consciously exposed to significant risks. By comprehending the underlying causes of these accidents and prioritizing the most frequent ones, it is possible to mitigate the risks associated with drydocking operations.

4. Risk Theory

4.1 Risk Assessment

Risk assessment is a critical practice in the maritime industry, a sector characterized by numerous hazards. This approach is essential not only for ensuring the safety of crew members but also for protecting the environment and safeguarding the interests of all stakeholders involved in maritime operations.

Risk assessment can be either quantitative or qualitative. Quantitative risk assessment involves estimating both the frequency of events and their potential consequences. This method is suitable when it is feasible and justified, meaning the cost of conducting the assessment is proportional to the benefit of addressing the issue, and there is sufficient information and data available. On the other hand, qualitative risk assessment is appropriate when the risks are minimal, well-understood, and the site is not near potential conflicting developments (Arunraj & Maiti, 2007).

In the maritime industry, this has succeeded with risk assessments following the standards of the International Safety Management Code. The ISM code is a part of IMO's efforts to ensure and maintain safety for seafarers and prevent pollution (Marine Insight, 2023) and ship managing companies should integrate a safety management system in their operations to comply with the regulations of the code.

A **Formal Safety Assessment** includes 5 steps (Ventikos N. , 2013):

1. Identify the hazards associated with a specific operation.
2. Assess the risks posed by these hazards.
3. Evaluate the available tools that could mitigate the risks (RCOs).
4. Analyze the financial implications of implementing these ROCs.
5. Make informed decisions based on the above analyses.

Hazard Identification is done using different methods:

What if analysis:

A What-if Analysis consists of structured brainstorming to determine what can go wrong in a given scenario; and then judge the likelihood and consequences that things will go wrong.

Checklist analysis:

Checklist analysis is a systematic technique used to evaluate systems against predefined criteria. This method structures interviews, document reviews, and field inspections by creating qualitative lists of conformance and non-conformance, along with recommendations for remediation (Mousavi et al., 2017).

HAZOP (Hazard and Operability Analysis):

The HAZOP analysis method uses special words (high, low, no, etc) to help experts spot possible safety and operational issues in systems or equipment. These words are formed by combining set adjectives with key process aspects like flow or pressure. The team discusses how these issues could happen and makes sure there are safety measures

to prevent them. Mainly, HAZOP provides a basic, qualitative review and is mostly used to check systems in continuous processes (Mousavi et al., 2017).

FMEA (Failure Modes and Effect Analysis):

FMEA is a systematic approach used to identify and analyze potential failures in system components. This method helps safety and reliability engineers determine the impact of component malfunctions, aiming to prevent undesirable outcomes such as production halts, injuries, or accidents (Njumo, 2015).

Risk calculation.

During this stage, we aim to thoroughly investigate the failure mechanisms of a system while simultaneously calculating the frequency with which each failure model occurs and potentially leads to an accident. Specific, structured techniques are used for this purpose, often complementing each other. Below are the main methods employed (Ventikos N. , 2013):

Historical Data Analysis utilizes data of similar events that took place in the past to calculate the frequency of the event and thus the probability of it happening.

Event Tree Analysis (ETA) looks forward from an initial event and maps out what could happen next, showing different possible outcomes depending on whether safety systems work or fail. It helps understand the effects of an event and plan how to handle it.

Fault Tree Analysis (FTA) works backward from a bad event, like a system failure, to figure out what could cause it. It uses diagrams to trace all the paths that lead to the failure, helping to find the root causes. An example is shown in Figure 6: FTA for motor overheating.

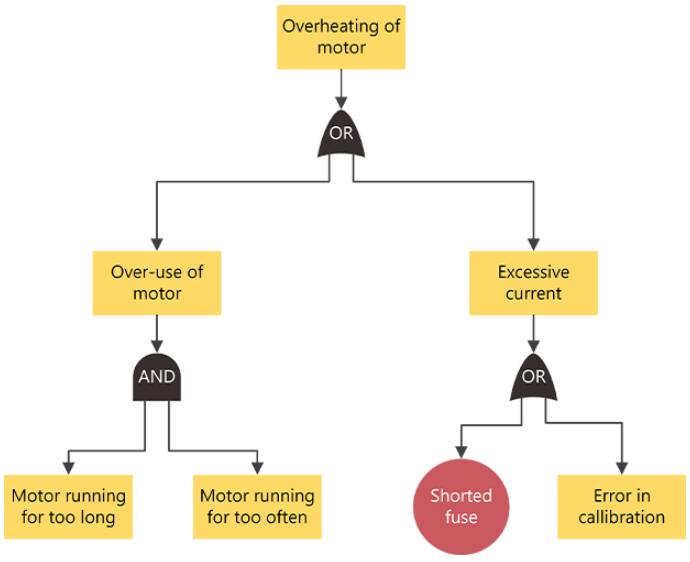


Figure 6: FTA for motor overheating

Common Cause Failure Analysis (CCFA) is a method used to identify events where multiple system components fail simultaneously due to a shared cause. This analysis is essential for recognizing how such failures can undermine system redundancies and

lead to larger systemic failures. CCFA involves identifying potential common causes, such as environmental influences, design errors, or operational mistakes, and analyzing how these causes could affect multiple components at once (Rausand & Lundteigen, 2011).

Reliability analysis is used to assess the dynamics of probability outcomes, evaluating how likely it is for a predetermined statistical model to fail. This analysis helps in understanding the consistency and dependability of system performance under various conditions.

After determining the consequences and the probability of the event it is possible to complete the risk assessment. Depending on the gathered data the FSA can be quantitative or qualitative. Usually in the maritime industry, it is qualitative. For a better understanding see Figure 7: Risk Assessment on Oil Leakage after collision/grounding (Marine Insight, 2023).

Depending on the frequency of these accidents and their severity they are categorized as negligible risk, acceptable risk, or unacceptable risk.

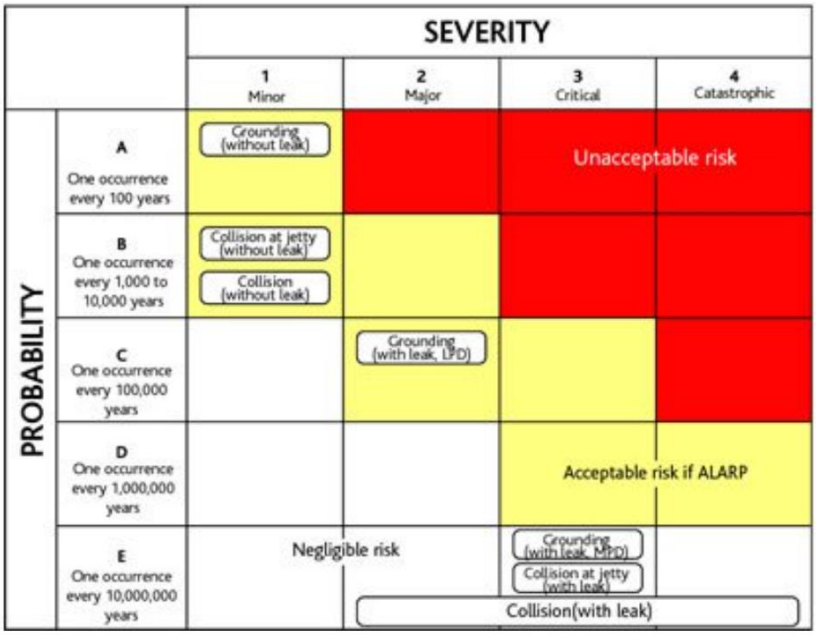


Figure 7: Risk Assessment on oil leakage after collision/grounding

4.2 Fault Tree Analysis

In this paper, FTA will be employed to investigate the events that lead to accidents caused by falls from heights and fire/explosions. These particular types of incidents have been identified as the most prevalent and dangerous during drydocking operations.

Fault trees are perhaps the most well-known method in safety analysis. They originated in the 1960s (from Bell Laboratories) and have since become a powerful tool for realistic risk analysis across many industries, such as aerospace, and nuclear, and, more recently, efforts are being made for the maritime industry (Ventikos N. , 2013).

FTA is utilized to investigate various factors that can cause malfunctions in complex systems or lead to accidents. In this method, the primary undesired outcome is referred

to as the top event (TE), while the simplest failure modes that trigger the Top Event (TE) are known as basic events (BE). FTA is a widely used technique in literature for both quantitative and qualitative risk assessments. It has also been applied extensively in numerous risk analyses within the maritime transportation sector. This method uses the probabilities associated with each BE, combined with the mathematical principles of AND and OR logic gates, to calculate the likelihood of the TE occurring. This capability is crucial as it enables the quantitative evaluation of the risk associated with the occurrence of the TE (Tuncel et al., 2023).

In the highly complex and hazardous environment of drydocking operations, where various dangers such as equipment malfunctions, human error, and environmental factors are present, it becomes crucial to thoroughly analyze risks and identify their root causes. This allows for effective mitigation and reduction of operational risks, enhancing both safety and efficiency.

Fault Tree Analysis provides an intuitive, qualitative method to deconstruct potential failure points in drydocking operations. By mapping out how individual failures can lead to larger, systemic issues, FTA helps safety engineers focus on preventive actions. This systematic approach not only reduces the chance of incidents but also aids in creating robust contingency plans, ensuring that risks are managed proactively. FTA's logical structure captures complex interactions, making it a valuable tool in navigating the intricacies of drydocking procedures and safeguarding personnel and assets.

The formation of a fault tree analysis is presented as a structured process consisting of five main stages. Some even argue that creating a fault tree is a form of art (or a combination of art and science), with the final result heavily depending on the skills and knowledge of the person in charge. The stages include:

1) **Preparation**, where the initial conditions are defined before the analysis begins, including selecting the specific top event (e.g., an explosion on the Irenes Serenade) and gathering known causes, potentially using results from methods.

2) **Fault Tree Construction**, which requires careful attention to the analysis process and proper use of logical gates;

3) **Review, Addition, and Check**, where the safety analysis follows an iterative approach, ensuring that no critical causes are overlooked;

4) **Evaluation of Results**, which involves assessing outcomes, preparing a list of primary causes, ranking them, and calculating probabilities, representing the classic application of fault trees.

(Ventikos N. , 2013)

There are various reasons to consider using or avoiding fault tree analysis. By evaluating its advantages and disadvantages, one can determine whether it is suitable for a particular application.

Advantages of fault trees include:

- They help in identifying risks within complex systems.

- They allow focusing on a specific fault without losing sight of the bigger picture.
- They provide a clear overview of how faults can lead to undesirable outcomes.
- If someone is familiar with this type of analysis, they can understand the results relatively easily and quickly.
- They support quantitative analysis (probabilities/frequencies), which is crucial for risk assessment.

Disadvantages of this method include:

- It is relatively detailed and time-consuming.
- It requires specialized skills and training.
- It can sometimes create an illusion of high accuracy but may contain multiple potential sources of errors.
- It cannot be applied mechanically or automatically and does not guarantee that all potential faults have been identified.
- Its application demands the support of detailed certification.

(Ventikos N. , 2013)

Fault trees are widely utilized in the maritime sector due to their straightforward approach, making them an effective tool for deconstructing accidents and understanding the simple errors that contribute to them. For example, this methodology was applied in the Analysis of Fire and Explosion Accidents Occurring in Tankers Transporting Hazardous Cargoes , where a fault tree was used to identify the primary causes of such incidents, the results of this study are shown in Figure 8: Hierarchical structure of Fire and Explosion Accidents (Ugurlu, 2016).

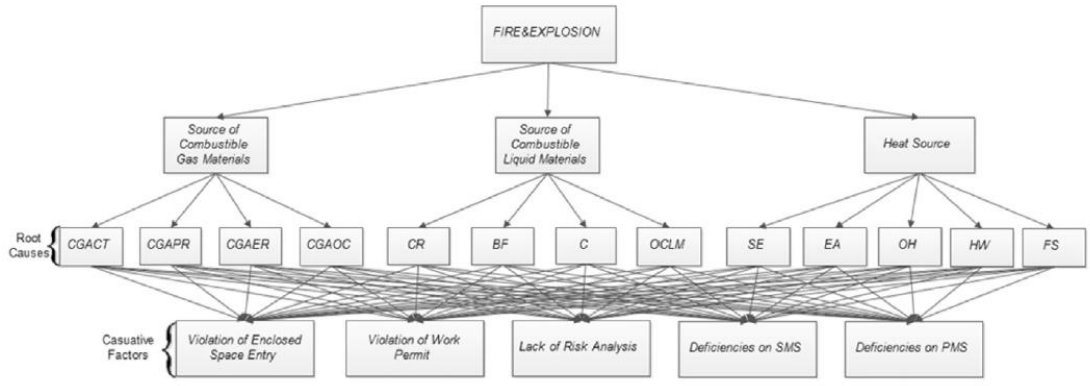


Figure 8: Hierarchical structure of Fire and Explosion Accidents

4.3 Bayesian Networks

Risk-based approaches integrate both probability and consequence, allowing for a comprehensive assessment that considers the extent of failure rather than just the likelihood of occurrence. While defining consequences is often straightforward due to their specific and limited nature, the more complex task lies in determining event probabilities within a system and estimating posterior probabilities, particularly when variables are interdependent or influenced by temporal factors. Posterior probability refers to the updated likelihood of an event after accounting for relevant evidence or background information. This estimation process is inherently complex and involves reasoning under uncertainty (Annetis, 2020).

Bayesian Networks (BN), also known as Bayesian Belief Networks, are powerful tools that facilitate this type of analysis. As an artificial intelligence (AI) technique, BNs help manage the computational challenges associated with causation and probability modeling. They enable the calculation of posterior probabilities, streamlining reasoning under uncertainty and simplifying complex probabilistic relationships (Jensen & Nielsen, 2007).

To compute the risk associated with these accidents, the Fault Tree Analysis will be modeled into Bayesian networks. This transformation allows for a more dynamic evaluation of the interconnected probabilities and dependencies influencing the likelihood of accidents occurring during drydocking operations.

Bayesian networks are widely used for both classification and probabilistic modeling tasks. These networks are graphical models that depict the probabilistic relationships between variables using nodes and directed edges. Each node in a Bayesian network represents a stochastic variable, which can either be observed (measured), unknown (parameters to be estimated), or latent (unobserved). The relationship between the variables is represented using Conditional Probability Tables (CPTs) that define how each variable depends on its "parent" variables in the network. An example of how a CPT of dependent variables is computed is shown in Table 5: CPT Example (Jensen & Nielsen, 2007).

Table 5: CPT Example (Jensen & Nielsen, 2007)

	$Fu = yes$	$Fu = no$
$Sp = yes$	(0.99, 0.01)	(0,1)
$Sp = no$	(0.01, 0.99)	(0,1)

$P(St \mid Fu, Sp)$

	$Fu = yes$	$Fu = no$
$FM = full$	0.39	0.001
$FM = \frac{1}{2}$	0.60	0.001
$FM = empty$	0.01	0.998

$P(FM \mid Fu)$

The structure of a Bayesian network is a directed acyclic graph (DAG), meaning it consists of nodes (variables) and directed edges (dependencies) with no loops. The graph's edges indicate the direction of influence from parent to child nodes, and this structure is crucial for representing conditional dependencies. If a variable (node) is

instantiated with specific values (e.g., evidence), it updates the probability distributions of all dependent nodes, refining predictions or risk assessments.

In addition, Bayesian networks follow the local Markov property, where each node is conditionally independent of its non-descendant nodes, given its parent nodes. This allows for efficient probabilistic inference—updating beliefs about one node based on new information.

When applied to dynamic systems, a Bayesian network can be extended to a dynamic Bayesian network (dBN), where time is modeled explicitly by connecting identical Bayesian networks across time steps. This extension is crucial in applications where the system evolves (e.g., system reliability analysis or forecasting). Static BNs usually are utilized for diagnosis and detection, while dynamic BNs (dBN) are utilized for prediction models (Annetis, 2020).

BNs are particularly useful in risk analysis, anomaly detection, diagnosis, and decision-making. The networks allow users to compute joint probabilities and perform inference using Bayesian statistics. They are versatile tools that can handle both static and dynamic systems, making them applicable across many fields, including system failure modeling, medical diagnosis, and predictive analytics (Anke Meyer-Baese, 2014).

In Bayesian Networks, probability events are represented by variables, which correspond to values that can change across different states or measurements. These variables can be either discrete or continuous. Discrete variables take on one of several distinct states, while continuous variables can assume any real-valued measurement. The probability of a specific event A occurring is represented by a single numerical value. However, a variable itself does not have a single probability value; it is characterized by a probability distribution. For discrete variables, each state (e.g., low, normal, high) has an associated probability value, forming a discrete distribution. Continuous variables, on the other hand, are described by continuous distributions (e.g., Gaussian, Weibull). In both cases, the sum of the probabilities for discrete distributions and the integral over continuous distributions must equal one. Continuous variables can be discretized by creating bins within the distribution to represent value ranges. This process can simplify the model or may be necessary for certain algorithms that do not support continuous variables or all types of distributions (Jensen & Nielsen, 2007).

In BNs, instantiation occurs when a variable is set to a specific state, making it constant. This changes the network's posterior probabilities, as the certainty of that variable affects its child nodes and continues through the network. Instantiation, also known as giving evidence or hard evidence allows for updating beliefs in the network with new information, which is essential for recalculating probabilities (Jensen & Nielsen, 2007).

Bayesian networks are named after Thomas Bayes, a British theologian and mathematician who pioneered probability theory. The fundamental principle is based on **Bayes' theorem**, which is used to update the probability of an event A given the occurrence of another event B. Bayes' theorem is mathematically expressed as:

$$P(A/B)=P(B/A)\cdot P(A)/P(B)$$

Where:

- P(A)) is the **prior** probability of event A,
- P(B/A) is the **likelihood** of A given B, and
- P(A/B) is the **posterior** probability of A after considering B.

Additionally, **conditional independence** is used in Bayesian networks to indicate that the occurrence of one event (e.g., B) does not affect the probability of another event A unless mediated by a third event C (Annetis, 2020). This is represented as:

P(A/B)=P(A) , P(A/B,C)=P(A/C)

An example of the structure of a BN is shown in Figure 9: Example of a Bayesian network with three nodes A, B, and C with their associated probability tables.

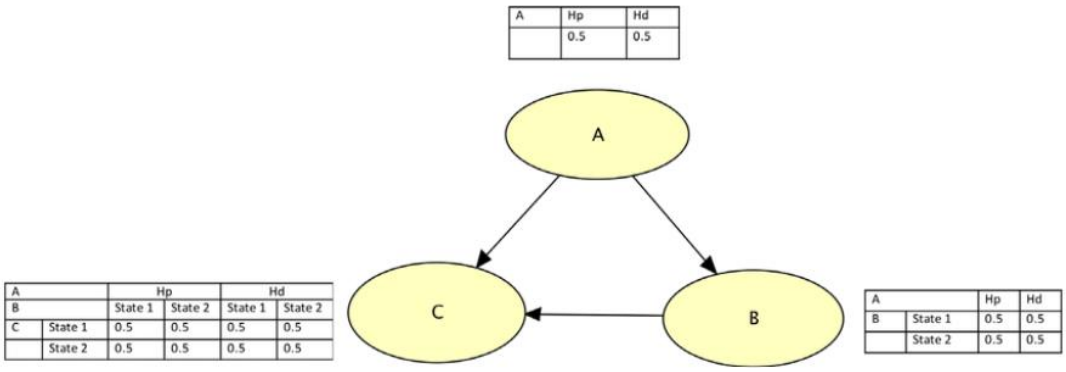


Figure 9: Example of a Bayesian network with three nodes A, B, and C with their associated probability tables.

Brualdi (1992) defines a graph as a set of nodes (also called vertices) and a set of edges (also called arcs), where each edge connects two nodes. This is also referred to as an undirected graph. If the two nodes connected by each edge are ordered, then the edges are directed, and the graph is called a digraph (Directed Graph). Brualdi also discusses multigraphs and general directed graphs, which allow multiple connections between any two nodes in directed and undirected graphs, respectively. The following properties of a graph deal with the arrangement of edges between nodes in a graph or directed graph (Ventikos et al., 2018).

A chain is a sequence of nodes where each consecutive node in the chain is connected to the previous one by an edge (regardless of the direction, if any, of the edge). A path is a chain with additional restrictions, where each connected edge in the chain must have the same direction as the direction of the chain. A cycle is a path that starts and ends at the same node. A simple path is a path where all the nodes are unique. A simple cycle is a cycle where, except for the initial/final node, all other nodes are unique. A DAG is a directed graph that has no cycles (Ventikos et al., 2018).

The parent/child relationship in a directed graph occurs when there is an edge (X1, X2) from X1 to X2, where X1 is the parent and X2 is the child. The ancestor/descendant relationship is an extension of the parent/child relationship. For example, if X1 is a parent of X2 and X2 is a parent of X3, then X1 is an ancestor of X3 and X3 is a descendant of X1. A genealogical chain is a sequence of nodes where each ancestor

precedes its corresponding descendant. This situation is always the only possible one in the case of a DAG (Jensen & Nielsen, 2007).

In a BN, Bayesian inference relies on belief-updating algorithms. For simple chain-connected BNs, basic matrix product calculations are sufficient, utilizing fundamental principles such as the chain rule, Bayes' rule, and marginalization. In more complex networks, the most common and efficient method is the Junction Tree algorithm. This algorithm requires understanding key concepts related to belief updating, including moral graphs, node elimination, cliques, and join trees (Jensen & Nielsen, 2007).

A moral graph is derived by adding links between all pairs of variables that share a common child and by removing the directionality from all arcs. Once the moral graph is obtained, node elimination becomes possible. Graphically, node elimination is achieved by connecting each pair of non-eliminated neighboring nodes. Mathematically, it is accomplished by marginalizing the node from the joint probability of the node and its neighbors. The choice of which nodes to eliminate first results in different elimination sequences. A perfect elimination sequence occurs when no additional links are inserted between non-eliminated variables. See Figure 10: Moral Graph Transformation (Annetis, 2020).

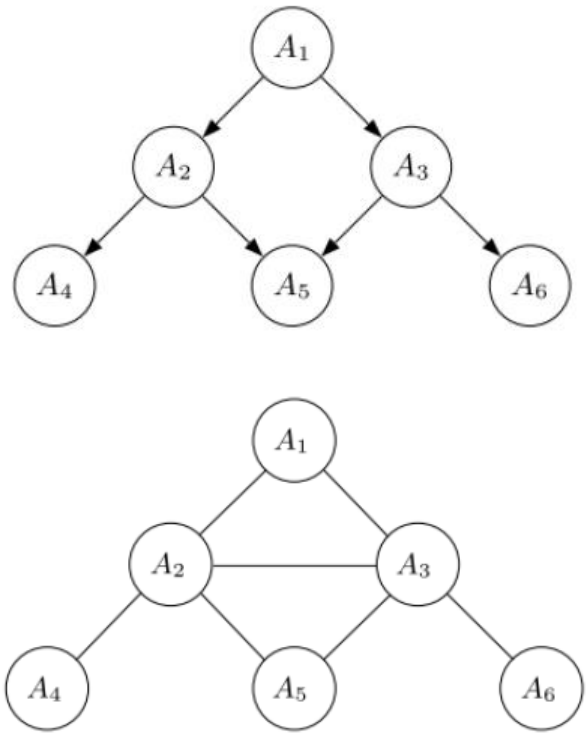


Figure 10: Moral Graph Transformation

The probability of event A4 can be calculated as follows using the chain rule:

$$P(A_4) = \sum_{A_1,A_2,A_3,A_5,A_6} P(A_1) \cdot P(A_2/A_1) \cdot P(A_3/A_1) \cdot P(A_4/A_2) \cdot P(A_5/A_2, A_3) \cdot P(A_6/A_3)$$

Graphs that are undirected and have at least one perfect elimination sequence are referred to as triangulated graphs. A graph that is not triangulated can be transformed

into one by adding more links. Perfect elimination sequences yield the same complete set of variables, where a complete set is considered a clique if it is not a subset of another complete set. When cliques are organized into a tree structure, they form what is called a join tree (Annetis, 2020). See examples Figure 11: Example of a join tree (a) and a not join tree (b) (Jensen & Nielsen, 2007).

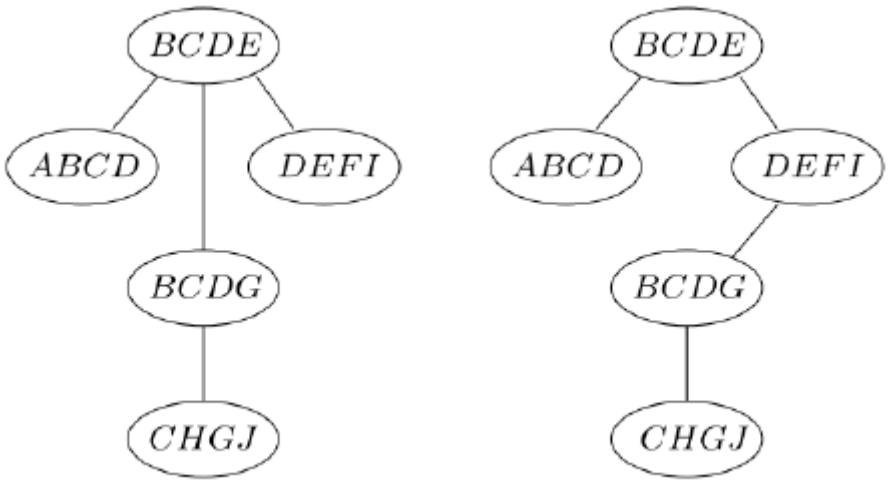


Figure 11: Example of a join tree (a) and a not join tree (b) (Jensen & Nielsen, 2007)

The junction tree algorithm simplifies a Bayesian network by eliminating cycles (cliques) and grouping them into single nodes, gradually reducing the complexity of the network. This process allows the junction tree to handle large Bayesian networks, enabling efficient inference and the computation of posterior probabilities.

Bayesian networks are widely used in various research and industrial fields due to their graphical structure, which enhances understanding, and their ability to calculate posterior probabilities in uncertain conditions. Often regarded as a lightweight form of AI, BNs are particularly valuable in reasoning applications (N. P. Ventikos et al., 2018). Some of their primary uses include:

- **Anomaly detection**: Identifying unusual data, such as outliers or faults, in applications like condition monitoring or signal processing.
- **Prediction**: Once a BN is constructed and calibrated with data or expert judgment, it can predict future system conditions. A prediction model is presented in (N. P. Ventikos et al., 2018) and (Nielsen & Sørensen, 2018).
- **Diagnostics**: By inputting data on symptoms, a BN can facilitate diagnostic processes.
- **Risk modeling**: BNs enable the calculation of posterior probabilities under uncertainty, making them essential for risk estimation and decision-making.

Additionally, BNs support a range of other applications, such as decision automation, latent variable modeling, automated insights, mixture models, and time-series analysis. In the context of risk-based approaches, BNs, including dynamic Bayesian networks

(dBNs), are effective for modeling uncertainty and risk. dBNs are especially useful for simulating time dependencies and degradation trends.

An efficient BN model must be developed and quantified for the system at hand, which can be implemented in different programming languages or software tools. In this paper, the GENIE program has been utilized.

4.4 FTA to BNs modelling

In modern systems, machines and installations are becoming increasingly complex, and their potential failures can lead to significant production consequences. While constructing a Bayesian network can be labor-intensive and intricate, it can be simplified by utilizing a fault tree to establish causal relationships between components. The process of constructing a fault tree facilitates the creation of a Bayesian network by deriving its graphical structure, which represents the causal relationships among the different events within the system, leveraging existing data.

Transforming a fault tree into a Bayesian network involves converting the graphical representation of the fault tree into a network. The basic elements of the fault tree, such as events and logic gates (AND, OR), are mapped onto the Bayesian network. the network, nodes represent events, and arcs depict dependencies and cause-effect relationships between these events.

OR gates are converted into CPTs where the output is true (mathematically represented as 1) when any of the input events occur. In contrast, AND gates are true only when all of their input nodes are true simultaneously. The output values for these gates can be more nuanced; specifically, for an AND gate, even if all input events needed for it to be true are true, the resulting probability of the output node may range from 0 to 1. This indicates that the occurrence of the event is not always guaranteed at 100% certainty but instead reflects a probability that the event will occur.

An example of this conversion is shown in Figure 12: Graphical and digital transformation of Fault tree into Bayesians network (Njumo, 2015).

Various methods exist to transform fault trees into Bayesian networks. These methods often involve converting logical gates into nodes, which increases the number of nodes and complicates calculations. The method adopted in this work focuses on transforming the different types of fault tree events into corresponding nodes in the Bayesian network, while excluding logic gates from the network's graphical structure.

The next stage in constructing a Bayesian network from a fault tree involves estimating probabilities. This involves assigning prior probabilities to the basic (primary) events of the fault tree, which correspond to the root nodes in the network. In contrast, the probabilities associated with intermediate and final events (undesired outcomes) are determined through the calculation of conditional probabilities (Medkour et al., 2020).

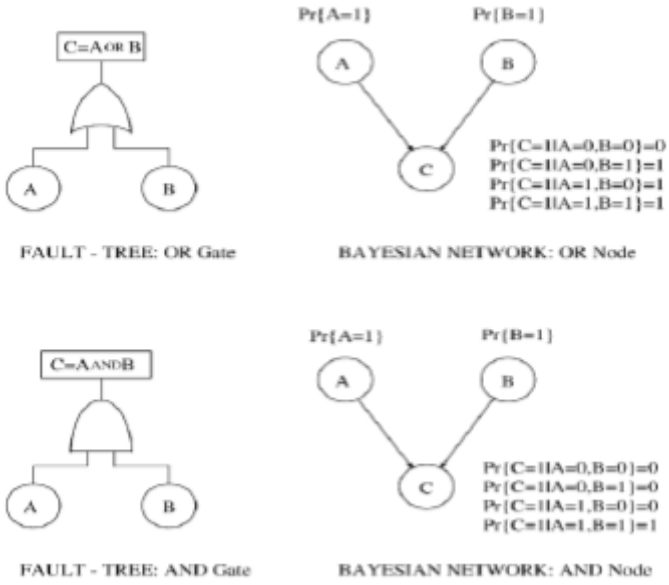


Figure 12: Graphical and digital transformation of Fault tree into Bayesians network

5. Main Model

In this project, the focus is on 2 types of accidents: Fall from height and Explosion/Fire. By integrating the theories of Fault Tree Analysis and Bayesian Networks, we aim to gain a deeper understanding of the risks associated with these hazards. This approach will help in identifying the root causes and visualizing the interdependencies between different failure points.

5.1 Model FTA and BN

Presented in the following figures are the fault trees created for the mentioned drydocking accidents. Figure 13: Fault Tree of Faire and/or Explosion Accident, Figure 14: Fault Tree of Fall from Heights Accident.

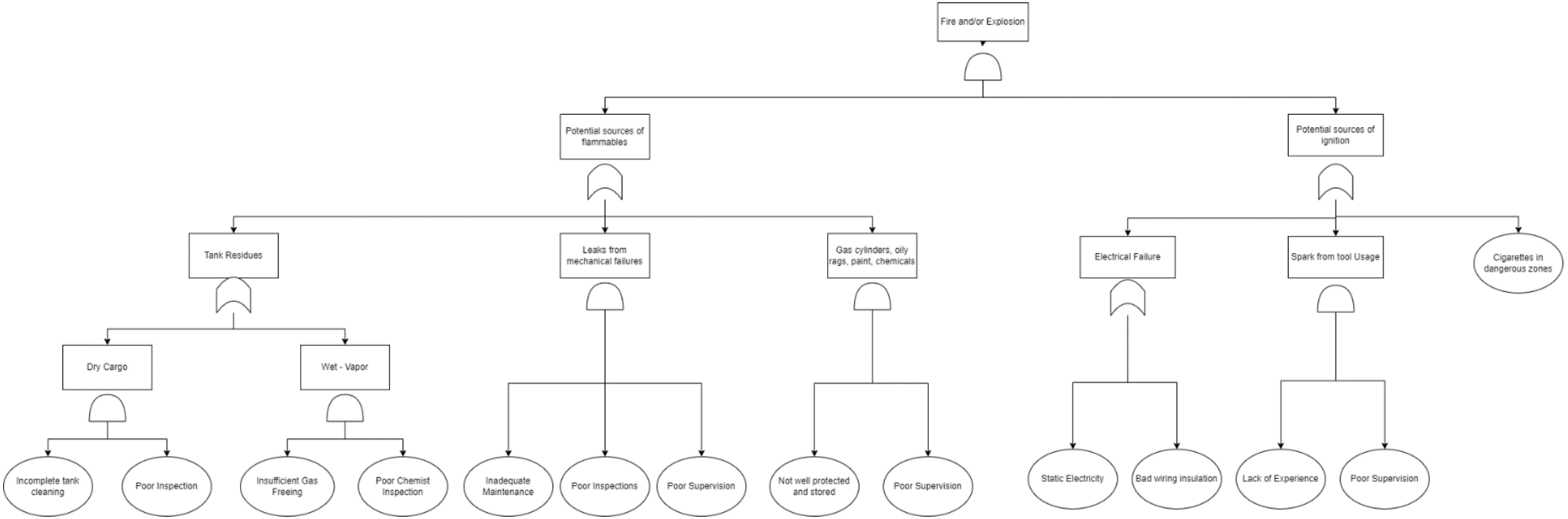


Figure 13: Fault Tree of Faire and/or Explosion Accident

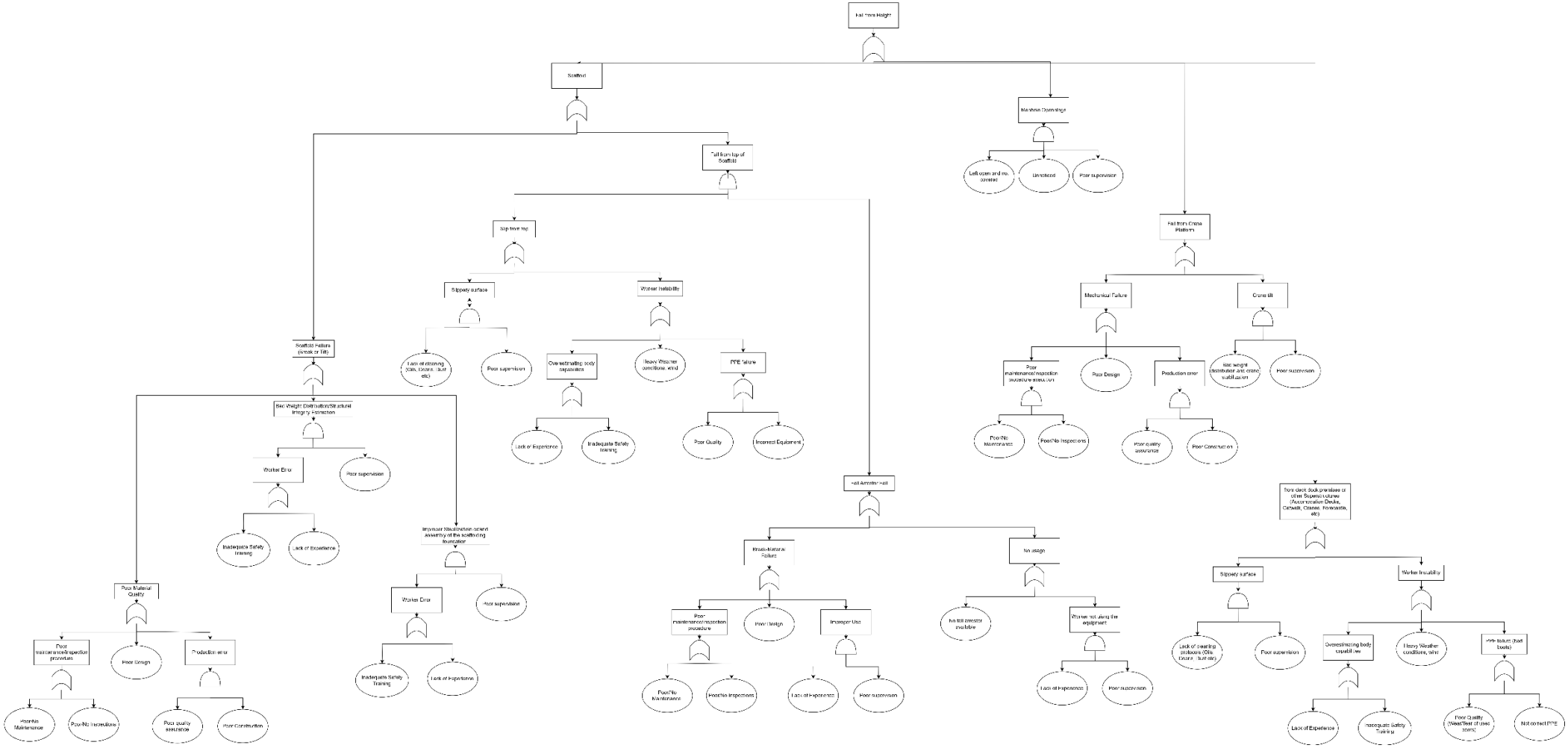


Figure 14: Fault Tree of Fall from Heights Accident

5.2 Quantification of the model

To determine the probability of the two types of accidents for integration into the Bayesian network, various methods have been employed. For static probabilities, such as the likelihood of insufficient gas-freeing, extensive research has been conducted using available literature and expert estimations from technical professionals.

To create a more dynamic model, suitable for simulations where variables can be adjusted to observe varying outcomes for specific events, probability distributions have been implemented. This approach allows for greater flexibility and accuracy in the modeling process, providing more realistic estimations under changing conditions.

5.2.1 Chance Nodes

For events that are relatively unaffected by other variables and are more static, their probabilities were determined using established resources. In instances where the available resources lacked sufficient information, the quantification was based on expert judgment (Lavasani et al., 2015). This judgment was reached through guided discussions, ensuring that a consensus was achieved before proceeding. The panel consisted of multiple experts, selected to ensure a diverse range of maritime safety expertise. The expert group included six individuals with the following backgrounds:

- Expert A: An academic expert in maritime risk assessment.
- Expert B: A safety Designated Person Ashore of a Greek shipping
- company operating general cargo ships and tankers.
- Expert C: A chief engineer at a Greek shipping company operating
- containerships and bulkers vessels.
- Expert D: A representative of the Greek flag authority.
- Expert E: A technical manager of a Greek shipping company.
- Expert F: An inspector of a classification society.

The results of the probability research are shown in Table 6: Basic Events Probabilities

Table 6: Basic Events Probabilities

Fire and/or Explosion Basic Events	Probability	Resource
Incomplete Cleaning	0.1	"Probabilistic assessment of the risk of accidents in the shipbrepair zone" Papakostas Aggelos, Papazoglou 2010
Insufficient Gas Freeing	0.1	Expert Group
Poor Chemist Inspection	0.01	Expert Group
Inadequate Maintenance and Renewals	0.05	"Probabilistic assessment of the risk of accidents in the shipbrepair zone" Papakostas Aggelos, Papazoglou 2010
Poor/No Inspections	0.2	Expert Group
Poor Supervision	0.3225	Calculated in 5.2.2 using available data
Not well Portected and Stored	0.4	Expert Group
Static Electricity	0.0175	"Analysis of fire and explosion accidents occurring in tankerstransporting hazardous cargoes" Ozkan Ugurlu, 2016
Bad wire Insulation	0.0203	fire fta tanker
Lack of Experience	0.3	"Analysis of fire and explosion accidents occurring in tankerstransporting hazardous cargoes" Ozkan Ugurlu, 2016
Cigarettes in Dangerous Areas	0.2	Expert Group
Fall from Heights Basic Events	**Probability**	**Resource**
Poor/No Maintenance	0.02	"Application of FSA for dry docking evolution " Atehnjia Denis Njumo, 2015
Poor/No Inspections	0.05	Expert Group
Poor Design	0.015	"Application of FSA for dry docking evolution " Atehnjia Denis Njumo, 2015
Poor Quality Assurance	0.01	Expert Group
Poor Construction	0.005	Expert Group
Inadequate Safety Training	0.07	"Application of FSA for dry docking evolution " Atehnjia Denis Njumo, 2015
Lack of Experience	0.3	Calculated in 5.2.2 using available data
Poor Supervision	0.3225	Calculated in 5.2.2 using available data
Lack of Cleaning	0.2	Expert Group
Heavy Weather Conditions	0.1	"Analysis of fire and explosion accidents occurring in tankerstransporting hazardous cargoes" Ozkan Ugurlu, 2016
Poor PPE Quality	0.1	"Application of FSA for dry docking evolution " Atehnjia Denis Njumo, 2015
Incorrect PPE	0.1	"Application of FSA for dry docking evolution " Atehnjia Denis Njumo, 2015
Manholes left open	0.05	Expert Group
Unnoticed	0.1	Expert Group

5.2.2 Equation Nodes

The variables **Workload** and **Experience** have been selected to follow probabilistic distributions in the dynamic Bayesian network model for fire and explosion accidents. These distributions will influence the outcome of the model by introducing variability based on these factors.

These variables influence the outcomes of interconnected events, with each connection represented by a mathematical equation. The rationale behind the choice of each equation, along with an explanation of how it was selected, is provided.

Workload:

The workload is a significant factor contributing to increased risk in shipyards. When workers are under pressure to complete tasks more quickly due to heavy workloads, safety protocols may be overlooked or rushed. This urgency can lead to mistakes, poor decision-making, or the use of unsafe practices, all of which increase the likelihood of accidents. Additionally, physical and mental fatigue caused by excessive workload can reduce a worker's ability to stay focused, further elevating the risk of incidents such as falls, equipment malfunctions, or human errors during critical operations. Shipyards need to match their workload and the available workforce for the most cost-effective operation (Riposo & Alkire, 2008).

The probabilistic distribution of workload was modeled using the variable of daily work hours. Based on input from the technical expert team, the average workday was identified as 8 hours, with a standard deviation of 2 hours. Using a normal distribution with these parameters, the probability density function was constructed. The histogram of this distribution, constrained to an equation domain from 8 to 12 hours, is presented in Figure 15: Working hours in Shipyards Distribution.

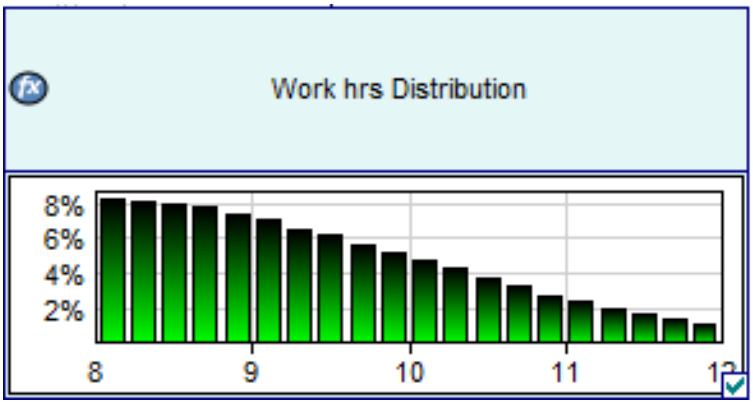


Figure 15: Working hours in Shipyards Distribution

To integrate this distribution into the existing model, a function must be developed to convert work hours into a probability of high workload, yielding values between 0 and 1. This probability will serve as a common variable along the x-axis of the Bayesian network.

In this context, the probability of a high workload is 0.1 when the work hours are set at 8 hours, while it increases to 0.8 at 12 hours. These probabilities were established based on assessments conducted by the technical expert team. This is possible through the following function. $P(High\ Workload) = 0.175 * Work_Hours - 1.3$

The PDF using this equation is seen in the following Figure 16: Probability of High Workload Distribution.

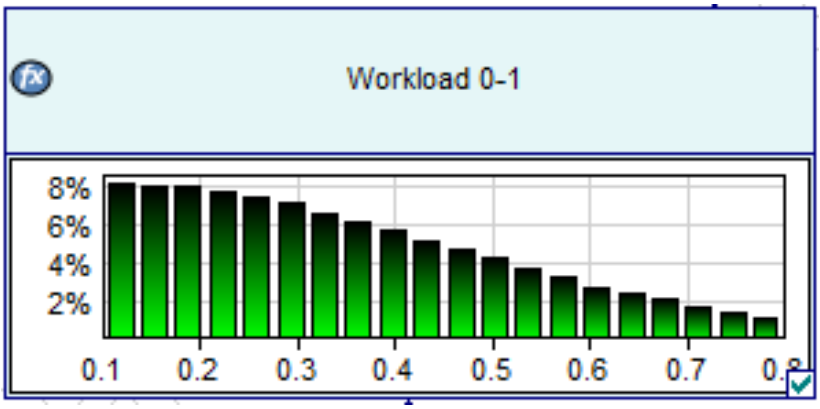


Figure 16: Probability of High Workload Distribution

The mean value of the probability that there is a high workload in the yard is ~0.35

Experience

Experience plays a crucial role in the mitigation of accidents in shipyards. An Experienced worker is significantly less likely to find themselves in hazardous situations, as they have encountered a variety of operational environments and challenges throughout their careers. This exposure allows them to develop a deeper understanding of safety protocols, recognize potential risks, and respond effectively to unexpected circumstances. Experienced workers are often better equipped to assess situations quickly, make informed decisions, and implement safety measures that prevent accidents. Additionally, their familiarity with equipment and procedures

enables them to identify and mitigate hazards proactively, contributing to a safer work environment overall. In this way, experience not only enhances individual worker safety but also promotes a culture of safety within the entire organization.

The variable utilized to quantify the probability distribution of experience is the number of years in the profession. The average years of experience and the standard deviation were derived from a questionnaire administered to shipyard workers in Turkish shipyards, as part of a study conducted by Baris Barls and Fatih Burak Izci in their research titled "Individual and Workplace Factors Related to Fatal Occupational Accidents Among Shipyard Workers in Turkey."

Mean Value(μ) = 13.6 , StDev(σ^2) = 7.37

The distribution that best fits this data is the **Weibull Distribution**. This distribution is particularly suitable for modeling years of experience among workers, as it captures the characteristic pattern where experience is more concentrated in the initial years and tends to diminish over time. The flexibility of the Weibull function allows it to effectively represent the rapid accumulation of experience early in a worker's career, followed by a gradual decline in the rate of experience gain as time progresses. This behavior aligns with findings in reliability analysis, where the Weibull distribution is commonly employed to model varying failure rates over time (Vadya & Srivastav, 2024).

The required parameters β and α are calculated by combining the data and the theory of the Weibull distribution.

$$\mu = \beta * \Gamma(1 + \frac{1}{\alpha})$$

$\sigma^2 = \beta^2 * \left(\Gamma\left(1 + \frac{2}{\alpha}\right) - \Gamma^{2\left(1+\frac{1}{\alpha}\right)}\right)$ Where Γ is the gamma function

(Dunn & Shultis, 2023)

β=15.3316 and α=1.9215

The output of the graph using these parameters is shown in Figure 17: Distribution of Experience in years of Shipyard Workers.

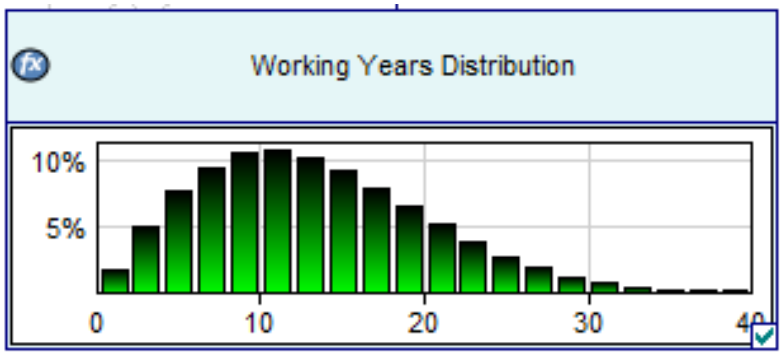


Figure 17: Distribution of Experience in years of Shipyard Workers

To integrate the distribution in the network a function that calculates the Probability of Experience (0-1) has to be determined. The technical expert's team evaluated that the

average probability of an experienced worker is 0.7. The function that coverts the above distribution in an Experience distribution is the following.

$$P(Experience) = \left(\frac{ExperienceYears}{40}\right)^{0.3}$$

By using this function the node that is in the network is shown in Figure 18: Probability Distribution of Experience.

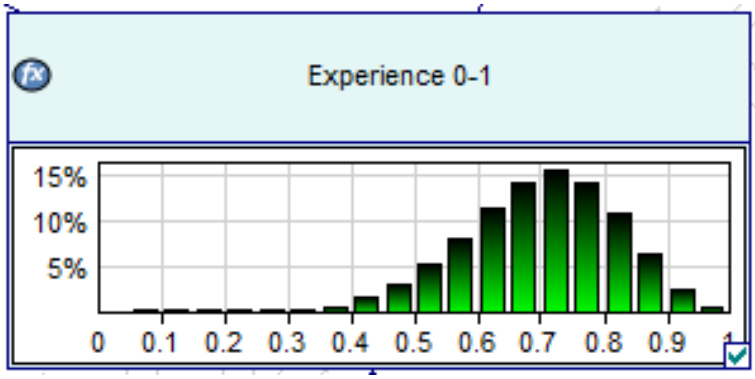


Figure 18: Probability Distribution of Experience

The mean value of the probability that the worker is experienced is ~0.7

The node Poor Supervision (the probability that there is poor supervision in the operations in the yard) that is dependent on the corresponding nodes of Experience and High Workload is calculated by an equation as follows:

$$P(Poor\ Supervision) = 0.6 * (1 - Experience) + 0.4 * Workload$$

Experience plays a more crucial role than the workload since an experienced worker can handle a high workload better than an inexperienced worker. That is the reason more gravity is given to the Experience factor. The distribution of the probability of poor supervision is shown in Figure 19: Probability Distribution of Poor Supervision.

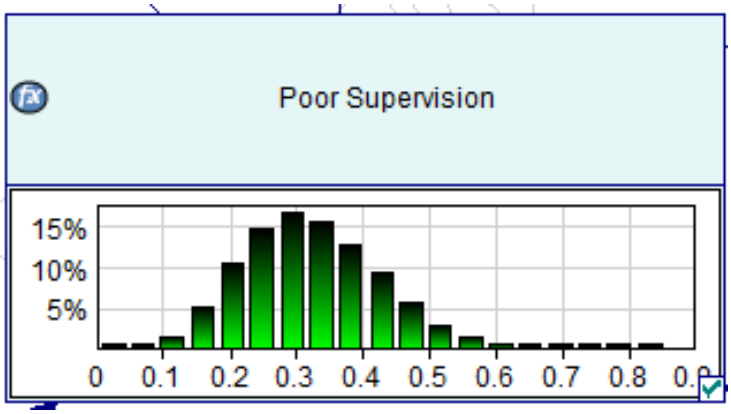


Figure 19: Probability Distribution of Poor Supervision

The mean value of the probability that there is poor supervision in the yard is ~0.322.

Lastly, the event of Spark from Tool Usage is possible when the events of poor supervision AND lack of experience (1-Exp) are true. If both of these events are true then there is a 50% chance that spark will occur (according to the technical expert team). Keeping that in mind, the equation that calculates the probability of this event is as follows.

$$P(Spark\ from\ Tool\ Usage) = 0.5 * Poor\ Supervision * (1 - Experience)$$

Using this equation the result is shown in Figure 20: Probability Distribution of Spark from Tool Usage.

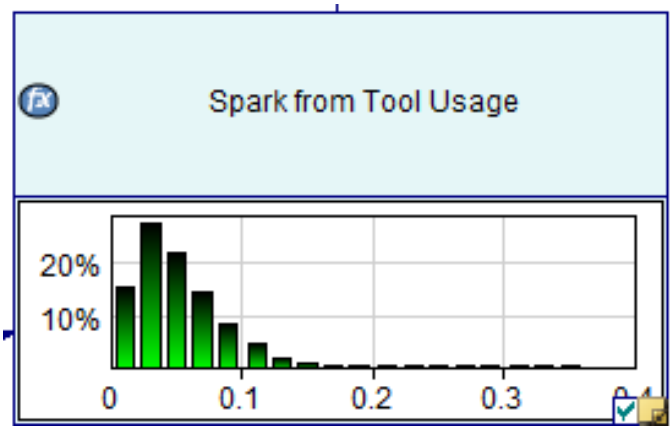


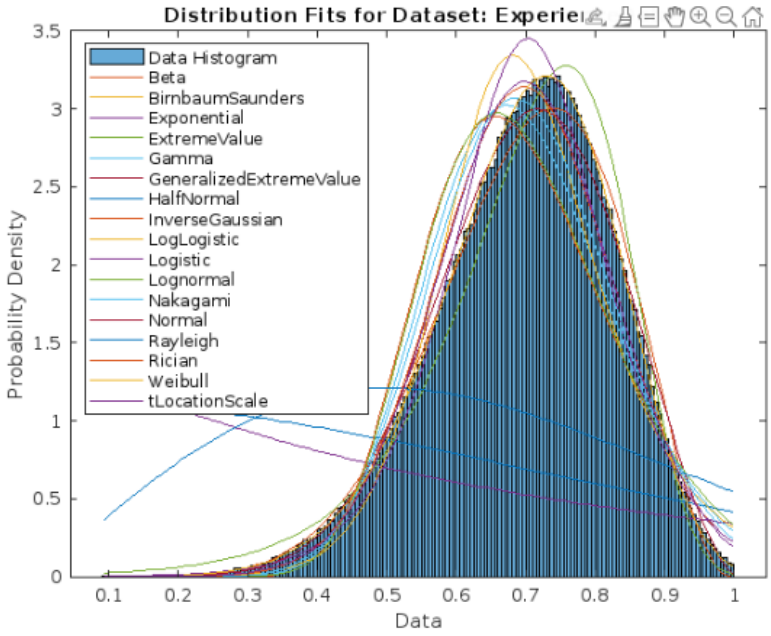
Figure 20: Probability Distribution of Spark from Tool Usage

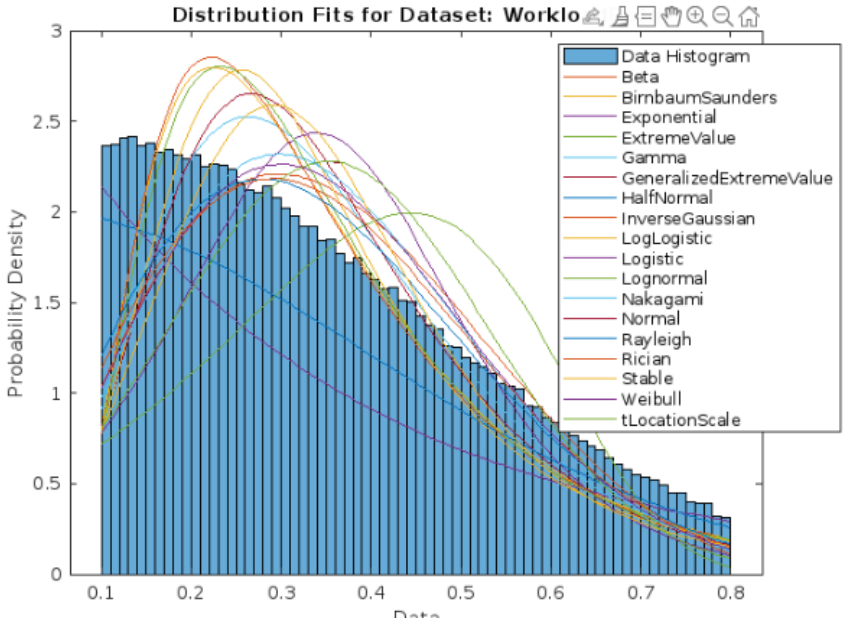
To have a better understanding of the distribution of these events (Workload, Experience, Poor Supervision, and Spark from Tool Usage) a Matlab code is used that fits several different distributions (ex. Weibull, Normal) and by using the Kolmogorov-Smirnov Test the most accurate one is computed (Hajek & Sen, 1999). The code is shown in the annex.

Shown in Table 7: Best Fitting functions for each distribution are the results, the best fitting distribution, and the parameters that define each one of them. The graphic results from the program are shown in Figure 21: Histogram and the Fitted distributions for each variable from the Matlab code execution.

Table 7: Best Fitting functions for each distribution

Data Set	Distribution	Parameters	Kolmogorov-Smirnov stat
Experience	Weibull	a=0.749439, b=6.47078	0.003157
Workload	Gamma	a=3.92411, b=0.0897768	0.038028
Poor Supervision	Beta	a=6.30262, b=13.271	0.003464
Spark From Tool Usage	Burr	a=0.14955, c=1.7108, k=5.57767	0.006496


Distribution Fits for Dataset: Experie
Data Histogram
Beta
BirnbaumSaunders
Exponential
ExtremeValue
Gamma
GeneralizedExtremeValue
HalfNormal
InverseGaussian
LogLogistic
Logistic
Lognormal
Nakagami
Normal
Rayleigh
Rician
Weibull
tLocationScale
Probability Density
Data


Distribution Fits for Dataset: Worklo
Data Histogram
Beta
BirnbaumSaunders
Exponential
ExtremeValue
Gamma
GeneralizedExtremeValue
HalfNormal
InverseGaussian
LogLogistic
Logistic
Lognormal
Nakagami
Normal
Rayleigh
Rician
Stable
Weibull
tLocationScale
Probability Density

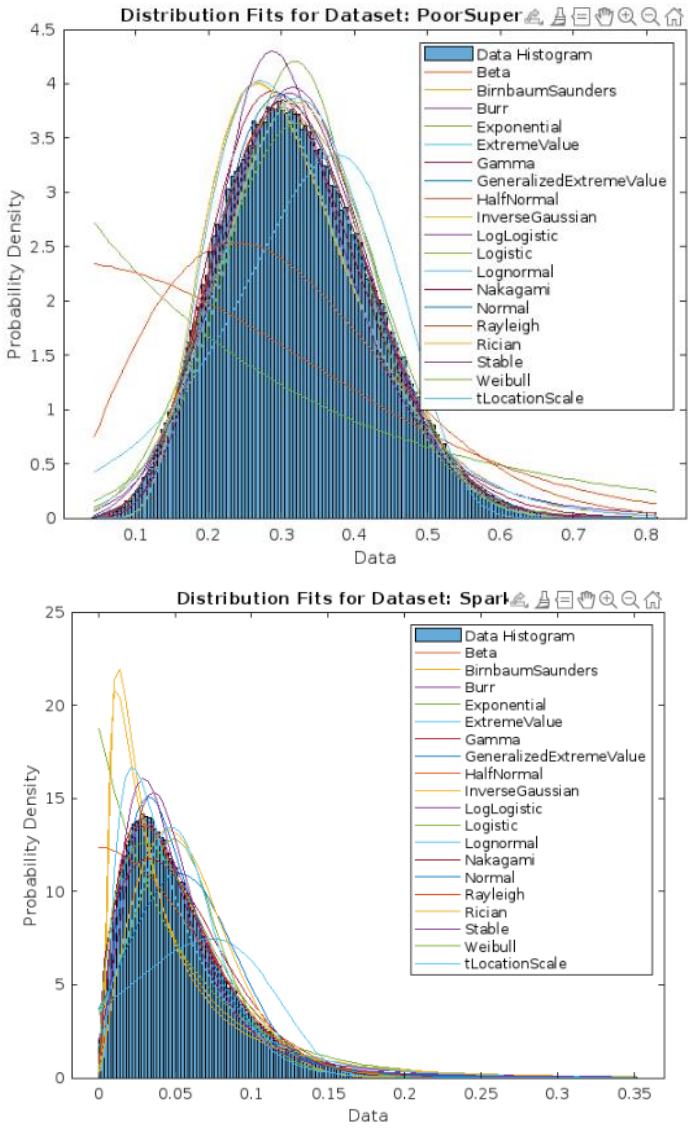


Figure 21: Histogram and the Fitted distributions for each variable from the Matlab code execution

5.3 Calculations - Results

After constructing the Bayesian network of each model (Fall from Heights – Fire/explosion) and assigning the probability calculated in the previous chapter for each node the results are available.

There are 3 BNs. 1 static model of Fall from heights 1 static model of Fire/Explosion and 1 dynamic model of Fire/Explosion with the probability distributions integrated.

5.3.1 Sensitivity Analysis

A sensitivity analysis of the Bayesian Network estimates is now conducted to the model variables. This analysis examines the impact on a target variable when evidence is systematically introduced for a specific state of a model variable while keeping all other variables constant. The goal is to identify the key variables in the BN model—those that exert the greatest influence on the target variables of interest (Sotiralis et al., 2016).

The sensitivity analysis is conducted on the Fire/Explosion model to identify the critical events that contribute to the occurrence of such accidents. By systematically introducing evidence for specific states of various events within the model while holding others constant, the analysis aims to pinpoint which factors have the most significant influence on the likelihood of fire or explosion incidents. This process is essential for understanding the underlying causes, prioritizing preventive measures, and improving safety protocols in high-risk environments such as shipyards, where multiple hazards can interact to cause catastrophic outcomes. Identifying these key events allows for more focused interventions, ensuring that resources are directed toward mitigating the most influential risks.

The program is run on the GenIE application and the graphic results are shown in Figure 22: Graphic Result of Sensitivity Analysis in Fire/Explosion Accident.

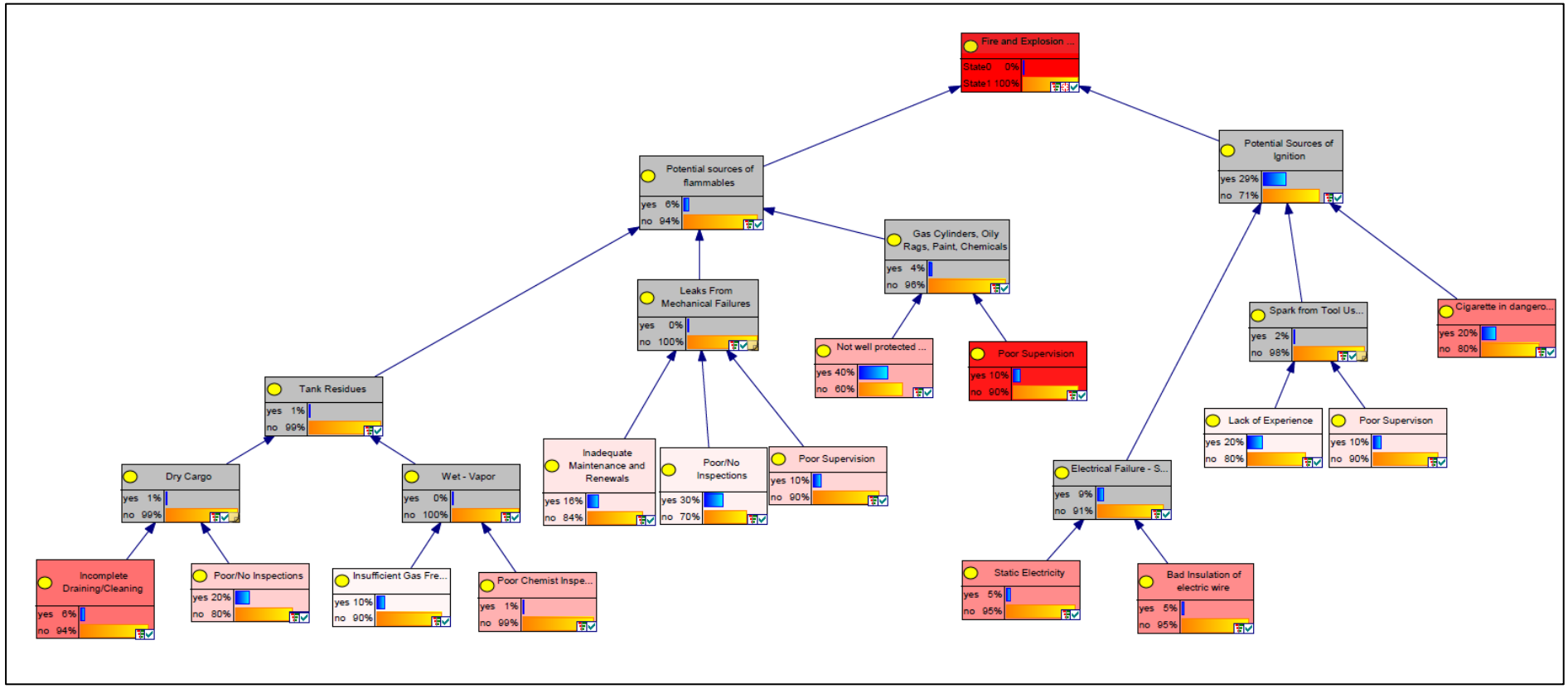


Figure 22: Graphic Result of Sensitivity Analysis in Fire/Explosion Accident

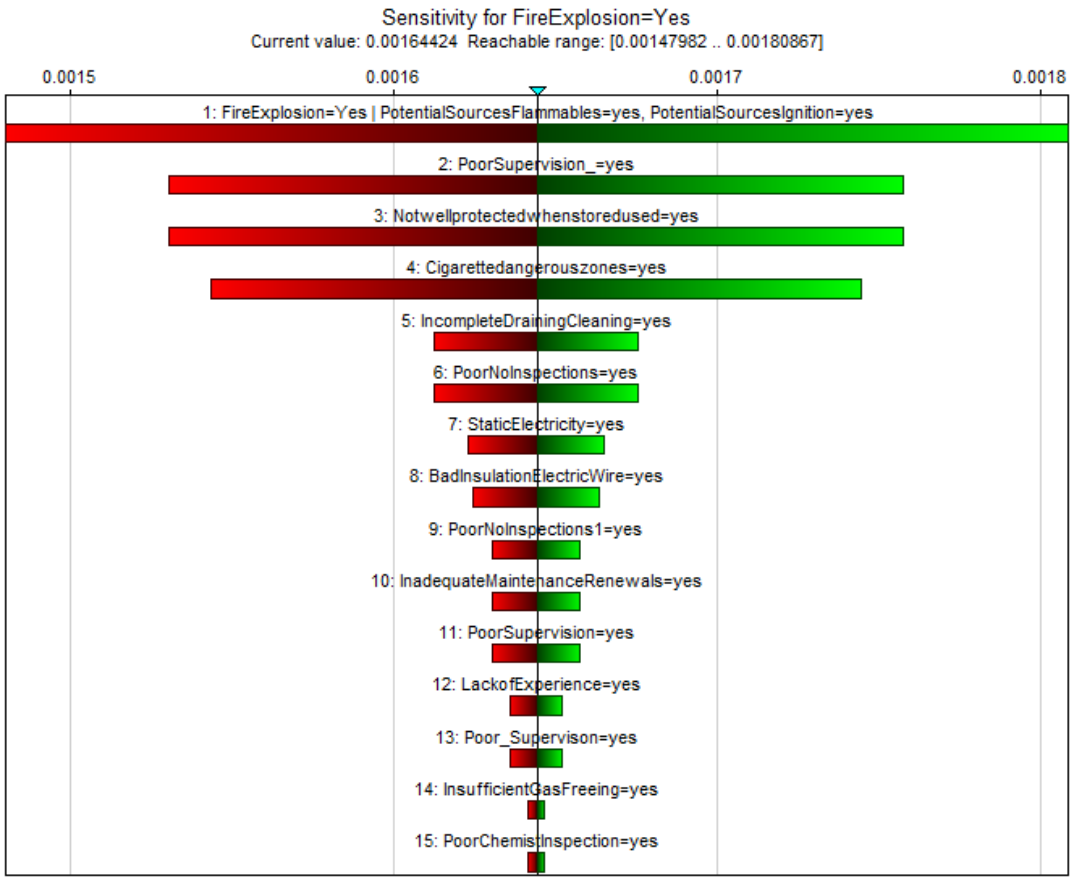


Figure 23: Sensitivity Analysis Tornado of Fire/Explosion Accident

The sensitivity analysis tornado chart (Figure 23: Sensitivity Analysis Tornado of Fire/Explosion Accident) visually represents the influence of key parameters on the probability of fire or explosion in the risk model. Each bar in the chart quantifies the effect of varying a particular parameter by ±10% on the target variable—specifically, the likelihood of fire or explosion. The chart is structured such that the parameters with the greatest impact are positioned at the top, while those with less influence are shown progressively lower. The results are shown in Table 8: 10% increase in each event result on the TE.

Table 8: 10% increase in each event result on the TE

if + 10%	leads to	
Poor Supervision	0.00175819	6.93%
Not well protected/stored equipment	0.00175819	6.93%
Cigarettes	0.00174493	6.12%
Incomplete Cleaning	0.00167623	1.95%

This dual representation allows for a comparative understanding of how both positive and negative shifts influence the model. The analysis reveals that the Potential Sources of Flammables and Potential Sources of Ignition have the largest impact, demonstrating that even a small increase in the probability of these factors significantly raises the

overall risk of fire or explosion. This is expected since these are the two preconditions for the event to occur.

Parameters such as “Equipment Not Well Protected When Stored” and “Cigarettes in Dangerous Zones” are the top contributors. Further down the chart, variables such as Poor Supervision, Incomplete Draining/Cleaning, and Static Electricity show lower sensitivity, meaning their impact on the model's outcome is comparatively modest. Although these parameters contribute to the overall risk, they are less critical than the top-ranked factors, indicating that interventions targeting these lower-impact variables will yield smaller reductions in fire/explosion probability.

The tornado chart provides clear insight into prioritizing risk mitigation strategies. Parameters with high sensitivity should be the primary focus of control measures, as reducing their likelihood will have the most significant effect on decreasing the risk of fire or explosion. Conversely, parameters with lower sensitivity, while still important, may require less immediate attention, given their limited influence on the overall risk profile. Thus, the sensitivity analysis provides a systematic approach to identifying and addressing the most influential factors in fire and explosion risk management.

5.3.2 Calculated probability of each accident by the BN

Once all nodes have been assigned values and the equations are completed, the GenIe application can be executed to calculate the probability of the top event in each model. Notably, for the two models composed solely of chance nodes, the result is a single probability value. In contrast, for the Bayesian Network that incorporates distributions, the outcome will be represented as a probability distribution.

Results:

- P(Fall from heights)=5.84*10^-3
- P(Fire/Explosion) =1.64*10^-3 (Static Model)

Results of the dynamic model for fire/explosion are shown in Figure 24: Probability Distribution of Fire/Explosion Accidents Genie result.

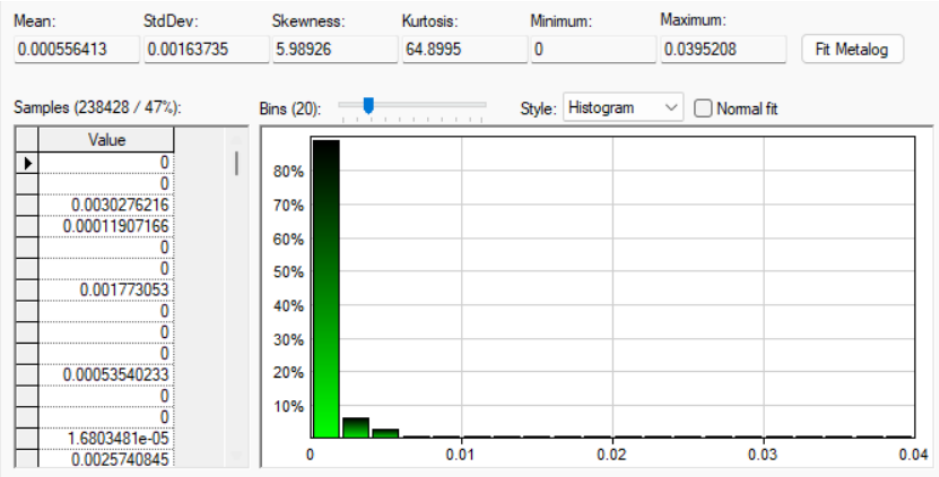


Figure 24: Probability Distribution of Fire/Explosion Accidents Genie result

With the computed results available, it becomes possible to compare these outcomes with the accident frequencies calculated in Chapter 3.2, using data from incidents in the West Attica ship repair zone, Table 9: Probability comparison between the Model and the available data.

Table 9: Probability comparison between the Model and the available data

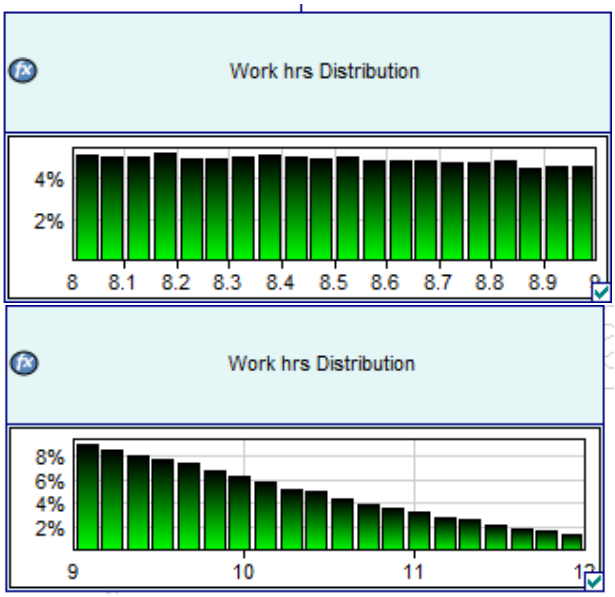
Accidents probability per Drydock	Fire/Explosion	Fall from Heights
Chance Node	0.00164	0.00584
Equation Node (mean)	0.0005564	-
Frequency of Accidents (West Attica yards)	0.00136	0.00356

The comparison shows that the model is accurate, and the conclusions drawn from the study are reliable.

5.3.3 Simulation Results

Next, various scenarios that reflect realistic conditions are tested to observe how the probabilities change and to assess the influence of different variable groups on the overall result. This analysis is applied to the dynamic Bayesian Network (BN) for fire/explosion accidents, as the variables "workload" and "experience" are modeled across different ranges. The workload varies from 8 to 12 hours, and experience ranges from 0 to 40 years.

Six scenarios are evaluated, based on combinations of workload and experience levels. The workload is divided into medium (8-9 hours) and high (9-12 hours), while experience is categorized as low (0-4 years), medium (4-15 years), and high (15-40 years). The graphic results are found in Figure 25: Distributions with Evidence The results of these simulations, both in numerical values and as percentages relative to the average computed probability, are presented in the accompanying tables, Table 10: Different Scenarios Results.



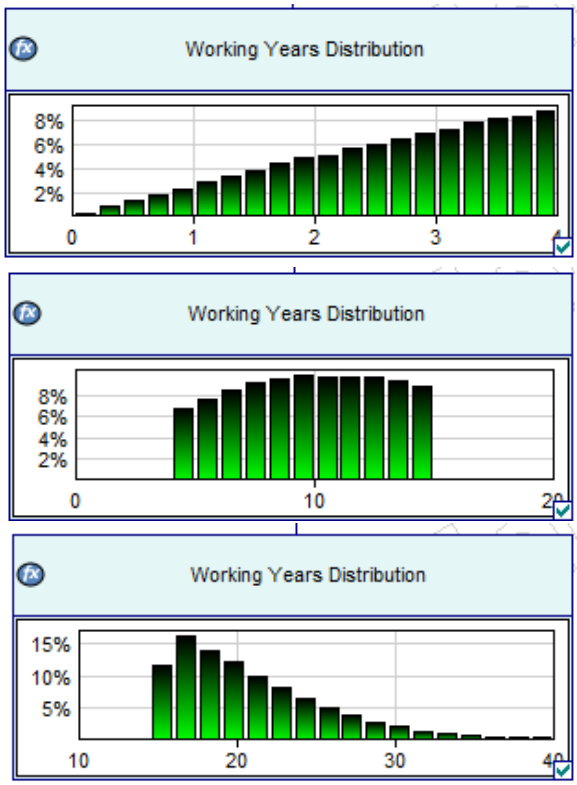


Figure 25: Distributions with Evidence

Simulations (probabiltiy of fire/explosion)		Workload (hours)	
		Low(8-9)	High(9-12)
Experience (years)	Low(0-4)	0.000837546	0.00108782
	Medium (4-15)	0.000437292	0.000693359
	High(15-40)	0.000308401	0.000465734

Simulations (probabiltiy of fire/explosion %)		Workload (hours)	
		Average(8-9)	High(9-12)
Experience (years)	Low(0-4)	50.22%	95.11%
	Average(4-15)	-21.57%	24.36%
	High(15-40)	-44.69%	-16.47%

Table 10: Different Scenarios Results

Also, a randomized model was run with the following evidence: Work hours (11), Years experience (30), cigarettes in a dangerous zone (yes, P=1), results in Figure 26: Graphic results with given evidence.

The mean probability of the TE is: 0.001624

The analysis of the simulation results demonstrates that experience plays a more critical role than workload in reducing the likelihood of accidents. While higher workloads increase the probability of fire or explosion incidents, the experience level of workers has a more substantial impact on mitigating these risks. Workers with low experience face a significantly higher accident probability under high workloads, nearly doubling

the risk. Conversely, as workers gain experience, they can handle more demanding conditions with fewer incidents, and in the case of highly experienced workers, the influence of workload diminishes. Experienced workers may even experience a decrease in accident probability under high workloads. These insights suggest that to minimize risks, it is essential to align workloads with workers' experience levels and prioritize ongoing training. Additionally, avoiding excessive workloads for inexperienced workers and offering guidance and supervision can significantly enhance safety. This approach will allow for better risk management and safer working conditions in high-risk environments such as shipyards.

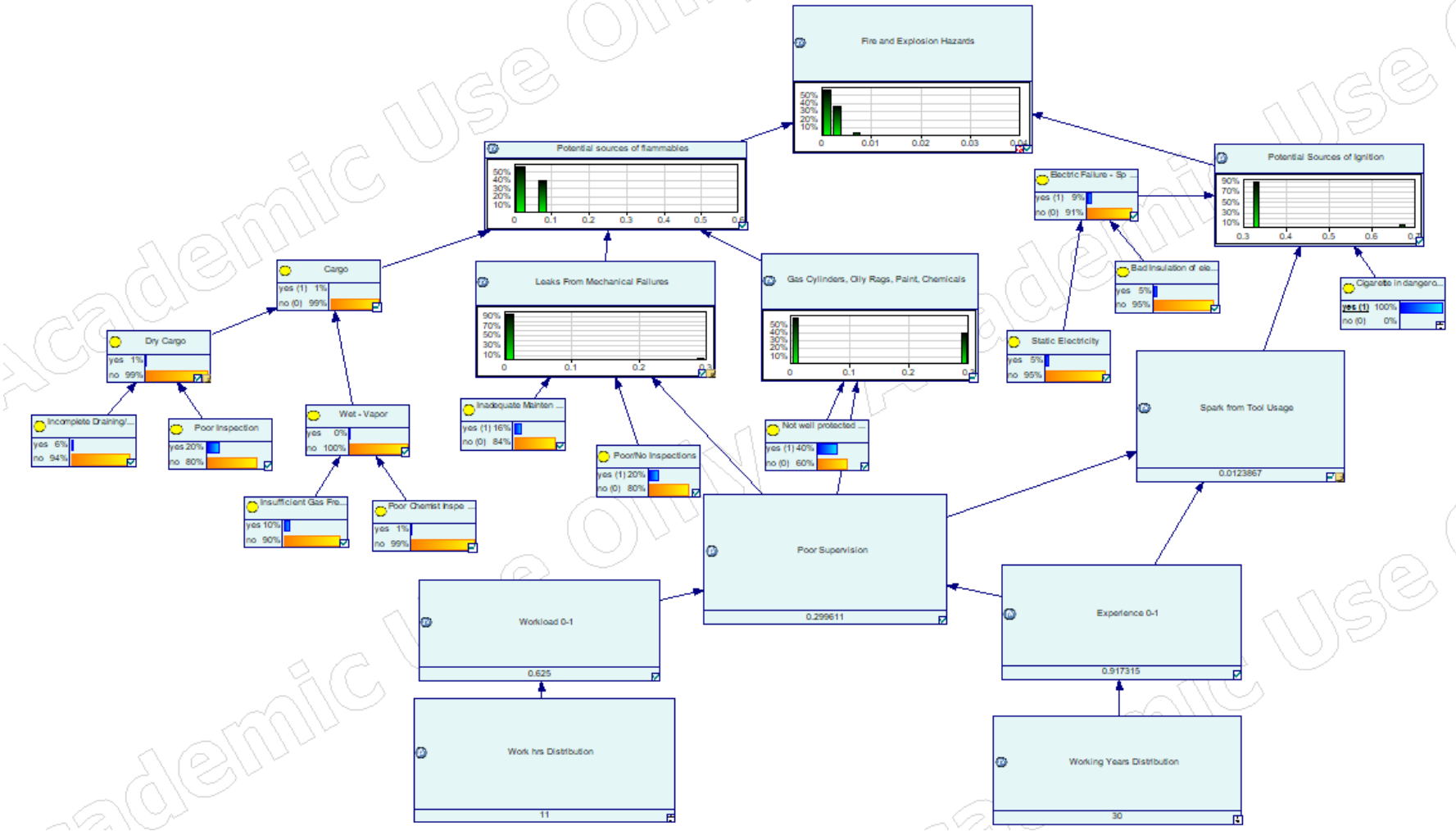


Figure 26: Graphic results with given evidence

6. Conclusions – suggestions for future work

In conclusion, the developed model has proven to be accurate, with its results aligning closely with historical data. This validation is a direct result of comprehensive research, which included an extensive review of existing literature and valuable expert input. The Bayesian Network (BN) model, derived from a Fault Tree Analysis (FTA), has been rigorously verified, and the probabilities in each node have been demonstrated to be realistic. The model's equation nodes also provide reliable outputs, ensuring that they can be applied not only in maritime contexts but also across various industries to assess and mitigate risk.

The findings indicate that while the overall probability of accidents is relatively low, certain parameters have the potential to significantly increase this probability. Specifically, changes in key variables can double the likelihood of an incident, highlighting the importance of these factors in risk assessment and safety planning.

The integration of FTA with Bayesian Networks has proven to be a highly effective approach. The creation of the fault tree was straightforward, and the advanced capabilities of the BN allowed for further refinement and more precise results. This combination of methodologies provides a powerful tool for understanding complex risk scenarios and enhances the accuracy of risk assessments.

Additionally, it has been demonstrated that incorporating equation nodes with probability distributions, rather than relying on static chance nodes, provides a more realistic approach. This is particularly important as various parameters can fluctuate between shipyards, leading to different risk profiles. By using probability distributions, the model can account for these variations, resulting in more accurate and dynamic risk assessments that better reflect real-world conditions.

As a result, the model can be effectively utilized by stakeholders involved in drydocking operations—including shipping companies, shipyards, and other relevant entities—to improve safety standards. Its adaptability is a key strength, as users can modify the model's variables to reflect their specific operational conditions. For instance, a shipyard with a highly experienced workforce can adjust the model to incorporate data that better reflects their unique operational environment. This flexibility allows for the identification of potential vulnerabilities within existing processes, enabling stakeholders to take informed actions toward enhancing safety and reducing the risk of accidents.

Future research should focus on quantifying the consequences of various accidents to provide a more comprehensive understanding of their impacts. For example, it is essential to assess the potential outcomes of incidents, such as minor injuries, fatalities, or environmental risks like oil spills in the sea. By quantifying these consequences, researchers can develop risk control strategies that enable a detailed cost-benefit analysis, facilitating more effective decision-making in safety practices. This approach would not only guide the development of targeted mitigation measures but also provide practical recommendations for reducing the severity and frequency of accidents in maritime operations.

The use of methodologies like Fault Tree Analysis (FTA) combined with Bayesian Networks (BN) proves invaluable in such research. Specifically, the incorporation of equation nodes with probability distributions enhances the ability to model different scenarios, offering a more nuanced understanding of how various factors interact in risk assessment. By simulating various conditions, this approach helps identify potential risks and predict the consequences of different accident types, providing a more realistic and dynamic view of potential hazards.

Furthermore, extending this research to encompass other types of significant accidents—such as collisions, fires, or structural failures—could further improve safety practices within the maritime industry. By broadening the scope of the analysis, stakeholders can better understand the full range of risks they may face and implement more robust safety protocols. Collectively, these efforts will contribute not only to safer drydocking operations but also to the overall enhancement of maritime safety standards, driving continuous improvement across the industry.

Resources

(2024). Retrieved from Hellenic Statistical Authority: https://www.statistics.gr/

Acuner, O., & Cebi, S. (2016). An effective risk-preventive model proposal for occupational accidents at shipyards.

Anke Meyer-Baese, V. S. (2014). *Statistical and Syntactic Pattern Recognition.*

Annetis, E. (2020). *A Risk-based approach and computational Bayesian framework for off-line condition monitoring of marine diesel engine crankcase lubrication.* Laboratory for Maritime Transport, National Technical University of Athens, Greece.

Arunraj, N., & Maiti. (2007). Risk-based maintenance—Techniques and applications. In *Journal of Hazardous Materials.*

Baalisampang, T., Abbassi, R., Garaniya, V., Khan, F., & Dadashzadeh, M. (2018). Review and analysis of fire and explosion accidents in maritime transportation. In *Ocean Engineering.*

Baginsky, E. (1976). *Occupational Illness and Accidents Reported fom California Shipyards* . California: Berkeley.

Barlasa, B., & Burak Izci, F. (2018). Individual and workplace factors related to fatal occupational accidents. In *Safety Science.* Istanbul, Turkey.

Chemweno, P., Pintelon, L., Muchiri, D., & Horenbeek, A. (2018). Risk assessment methodologies in maintenance decision making: A review of dependability modelling approaches. In *Reliability Engineering & System Safety.*

Cullum, J., Binns, J., Lonsdale, M., Abbasi, R., & Garaniya, V. (2018). Risk-Based Maintenance Scheduling with application to naval vessels and ships. In *Ocean Engineering.*

Dikis, K., Lazakis, I., Taheri, A., & Theotokatos, G. (2015). Risk and Reliability Analysis Tool Development for Ship Machinery.

DNV-GL. (2016).

Dunn, W., & Shultis, J. (2023). Some Common Probability Distributions.

Eyres, D., & F.R.I.N.A. (2007). Classification Societies. In *Ship Construction* (pp. 35-41).

Hajek, J., & Sen, P. (1999). Selected rank tests. In *Theory of Rank Tests.*

HSE. (2015). Safety in Docks: Approved Code of Practice and Guidance.

International Maritime Organization. (2020).

Jensen, & Nielsen. (2007). *Bayesian networks and decision graphs. Statistics for engineering and information science.*

Lamb, T - Society of Naval Architects and Marine Engineers. (2003). *Ship Design and Construction.* Jersey City.

Lavasani, S., Ramzali, N., Sabzalipour, F., & Akyuz, E. (2015). Utilisation of Fuzzy Fault Tree Analysis (FFTA) for quantified risk analysis of leakage in abandoned oil and natural-gas wells. In *Ocean Engineering.*

Lloyd's Register. (2015).

Marine Insight. (2023, June). Retrieved from https://www.marineinsight.com/maritime-law/what-is-international-safety-management-code-or-ism-code-for-ships/.

Medkour, M., Bouzaouit, A., Khochmane, L., & Bennis, O. (2020). *Transformation of Fault Trees into Bayesian Networks.*

Mineadis, A. (2009). *Statistical Analysis of Work Accidents in the Shipreparing Zone.* Athens.

Mousavi, M., Ghazi, I., & Omaraee, B. (2017). Risk Assessment in the Maritime Industry. In *Engineering, Technology & Applied Science Research* (pp. 1377-1381).

Nielsen, J., & Sorensen, J. (2017). Computational framework for risk-based planning of inspections, maintenance and condition monitoring using discrete Bayesian networks. In *Structure and Infrastructure Engineering.*

Njumo, A. D. (2015). *Application of Formal Safety Assessment for Dry Dock Evolution.*

Rausand, M., & Lundteigen, M. (2011). *Common Cause Failures (CCFs).*

Riposo, J., & Alkire, B. (2008). An Evaluation of Workload- and Workforce Practices. In *U.S. Navy Shipyards.*

Roar Adland, P. C.-C. (2018). The energy efficiency effects of periodic ship hull cleaning. In R. A. a, *Journal of Cleaner Production.*

Sotiralis, P., Ventikos, N., Hamann, R., Golyshev, P., & Teixeira, A. (2016). Incorporation of human factors into ship collision risk models focusing on human centred design aspects. In *Reliability Engineering and System Safety* (pp. 210-227).

Tuncel, A., Bal Bes Ikci, E., Akyuzz, E., & Arslan, O. (2023). Safety analysis of fire and explosion (F&E) accidents risk in bulk carrier. *Safety Science*.

Turk, A., & Ozkok, M. (2022). A Comprehensive Risk Assessment Analysis of Accidental Falls in Shipyards Using the Gaussian Fuzzy AHP Model. In *Journal of Maritime Science.*

Ugurlu, O. (2016). Analysis of fire and explosion accidents occurring in tankers.

Vadya, D., & Srivastav, A. (2024). Retrieved from Wallstreet Mojo: https://www.wallstreetmojo.com/weibull-distribution/

Ventikos, N. (2013). *Study and Management of Risk in Maritme Transport.* Zografou.

Ventikos, N., Sotiralis, P., & Drakakis, M. (2018). A dynamic model for the hull inspection of ships: The analysis and results.

Z. Tsaraklis. (2019). *Health and Safety in Shipyard Repair Works.* Athens: Symetria.

Zaman, M., Baheramsyah, A., & Ashari. (2021). Analysis of Work Accident Factors in the Shipyard. In *IOP Conference Series: Earth.*

7. Annex

CPT of Nodes

Fall from heights:

yes	0.0046576485
no	0.99534235

Manhole Openings	yes								no							
Fall from Crane Platform	yes				no				yes				no			
Fall from deck, dock premises or other...	y..		no		yes		no		yes		no		yes		no	
Scaffold	yes	no	yes	no	yes	no	yes	no	yes	no	yes	no	yes	no	yes	no
yes	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0
no	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1

Fall from Scaffold:

Scaffold Failure...	yes		no	
Fall from Top of...	yes	no	yes	no
yes	1	1	1	0
no	0	0	0	1

yes	0.0029132629
no	0.99708674

Fall through manhole:

Left open and ...	yes				no			
Unnoticed	yes		no		yes		no	
Poor Supervision	yes	no	yes	no	yes	no	yes	no
yes	0.1	0	0	0	0	0	0	0
no	0.9	1	1	1	1	1	1	1

yes	0.00016125
no	0.99983875

Fall from Crane platform:

Mechanical Fail...	yes		no	
Crane Tilt	yes	no	yes	no
yes	1	0.1	0.2	0
no	0	0.9	0.8	1

yes	0.00015471027
no	0.99984529

Fall from Deck, dock premises or other superstructures (ABC – Deck, Catwalk, Forecastle)

Slippery surface	yes		no	
Worker Instability	yes	no	yes	no
yes	0.01	0.005	0.005	0
no	0.99	0.995	0.995	1

yes	0.001434
no	0.998566

Scaffold Failure (Break/Tilt):

Poor Material Quality	yes				no			
Poor Weght Distribution and Structural ...	yes		no		yes		no	
Improper Stabiization or Assembly	yes	no	yes	no	yes	no	yes	no
yes	0.05	0.05	0.05	0.01	0.05	0.01	0.01	0
no	0.95	0.95	0.95	0.99	0.95	0.99	0.99	1

yes	0.0028854968
no	0.9971145

Fall from Top of Scaffold:

Slip from top	yes		no	
Fall Arrestor Failure	yes	no	yes	no
yes	0.1	0	0	0
no	0.9	1	1	1

yes	2.7846485e-05
no	0.99997215

Poor Material Quality:

Poor Maintena...	yes				no			
Poor Design	yes		no		yes		no	
Production Error	yes	no	yes	no	yes	no	yes	no
yes	1	1	1	1	1	1	1	0
no	0	0	0	0	0	0	0	1

yes	0.083010852
no	0.91698915

Poor Weight Distribution and Structural Integrity Estimation:

yes	0.1125525
no	0.8874475

Worker Error	yes		no	
Poor Supervision	yes	no	yes	no
yes	1	0	0	0
no	0	1	1	1

Improper Stabilization or Assembly:

Worker Error	yes		no	
Poor Supervision	yes	no	yes	no
yes	1	0	0	0
no	0	1	1	1

yes	0.1125525
no	0.8874475

Slip from top:

Slippery surfac...	yes		no	
Worker Instability	yes	no	yes	no
yes	0.01	0.01	0.01	0
no	0.99	0.99	0.99	1

yes	0.00087728718
no	0.99912271

Fall Arrestor Failure:

Material Failure	yes		no	
No Usage	yes	no	yes	no
yes	1	1	1	0
no	0	0	0	1

yes	0.31741585
no	0.68258415

Poor Maintenance/Inspections :

Poor/No Maintenance	yes		no	
Poor/No Inspections	yes	no	yes	no
yes	1	0	0	0
no	0	1	1	1

yes	0.001
no	0.999

Poor/No maintenance:

yes	0.02
no	0.98

Poor/No inspections:

yes	0.05
no	0.95

Poor Design:

yes	0.015
no	0.985

Production Error:

Poor Quality As...	yes		no	
Poor Construction	yes	no	yes	no
yes	1	0	0	0
no	0	1	1	1

yes	5e-05
no	0.99995

Poor quality assurance:

yes	0.01
no	0.99

Poor construction:

yes	0.005
no	0.995

Worker Error:

Inadequate Safety Training	yes		no	
Lack of Experience	yes	no	yes	no
yes	1	1	1	0
no	0	0	0	1

yes	0.349
no	0.651

Inadequate Safety Training:

yes	0.07
no	0.93

Lack of Experience:

yes	0.3
no	0.7

Poor supervision:

yes	0.3225
no	0.6775

Slippery surface inadequate cleaning:

Lack of Cleanin...	yes		no	
Poor Supervision	yes	no	yes	no
yes	1	0	0	0
no	0	1	1	1

yes	0.0645
no	0.9355

Lack of cleaning:

yes	0.2
no	0.8

Worker Instability:

Heavy Weathe...	yes				no			
Overestimating ...	yes		no		yes		no	
PPE failure	yes	no	yes	no	yes	no	yes	no
yes	0.2	0.1	0.1	0.05	0.1	0.05	0.05	0
no	0.8	0.9	0.9	0.95	0.9	0.95	0.95	1

yes	0.02483027
no	0.97516973

Overestimating body capabilities:

Lack of Experie...	yes		no	
Inadequate Saf...	yes	no	yes	no
yes	1	1	1	0
no	0	0	0	1

yes	0.349
no	0.651

Heavy weather conditions:

yes	0.1
no	0.9

PPE failure:

Poor Quality	yes		no	
Incorrect Equip...	yes	no	yes	no
yes	1	0.2	0.2	0
no	0	0.8	0.8	1

yes	0.046
no	0.954

No Fall Arrestor Usage:

No Fall Arrestor...	yes		no	
Worker not usi...	yes	no	yes	no
yes	1	1	1	0
no	0	0	0	1

yes	0.187075
no	0.812925

No fall arrestore available in yard:

yes	0.1
no	0.9

Worker not using fall arrestor:

Lack of Experie...	yes		no	
Poor Supervision	yes	no	yes	no
yes	1	0	0	0
no	0	1	1	1

yes	0.09675
no	0.90325

Manhole openings left open:

yes	0.05
no	0.95

Unnoticed:

yes	0.1
no	0.9

Crane tilt:

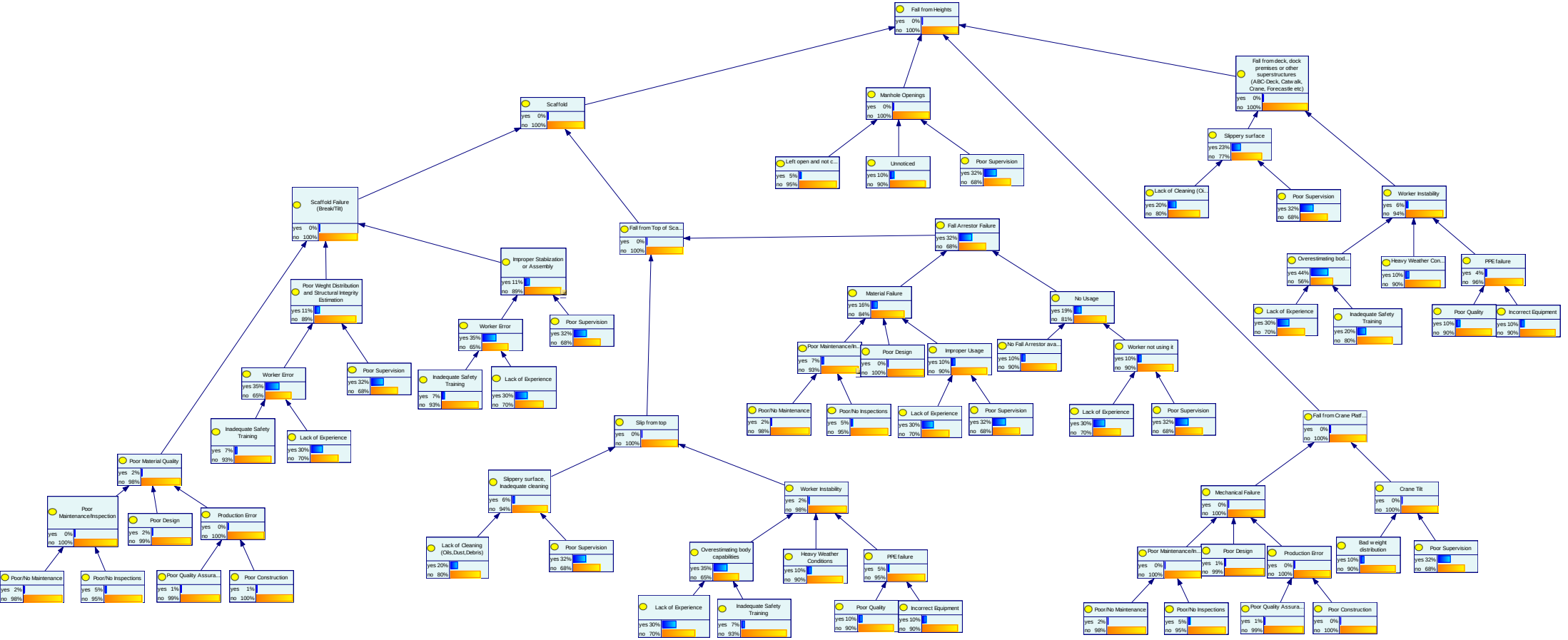
Bad weight dist...	yes		no	
Poor Supervision	yes	no	yes	no
yes	0.01	0	0	0
no	0.99	1	1	1

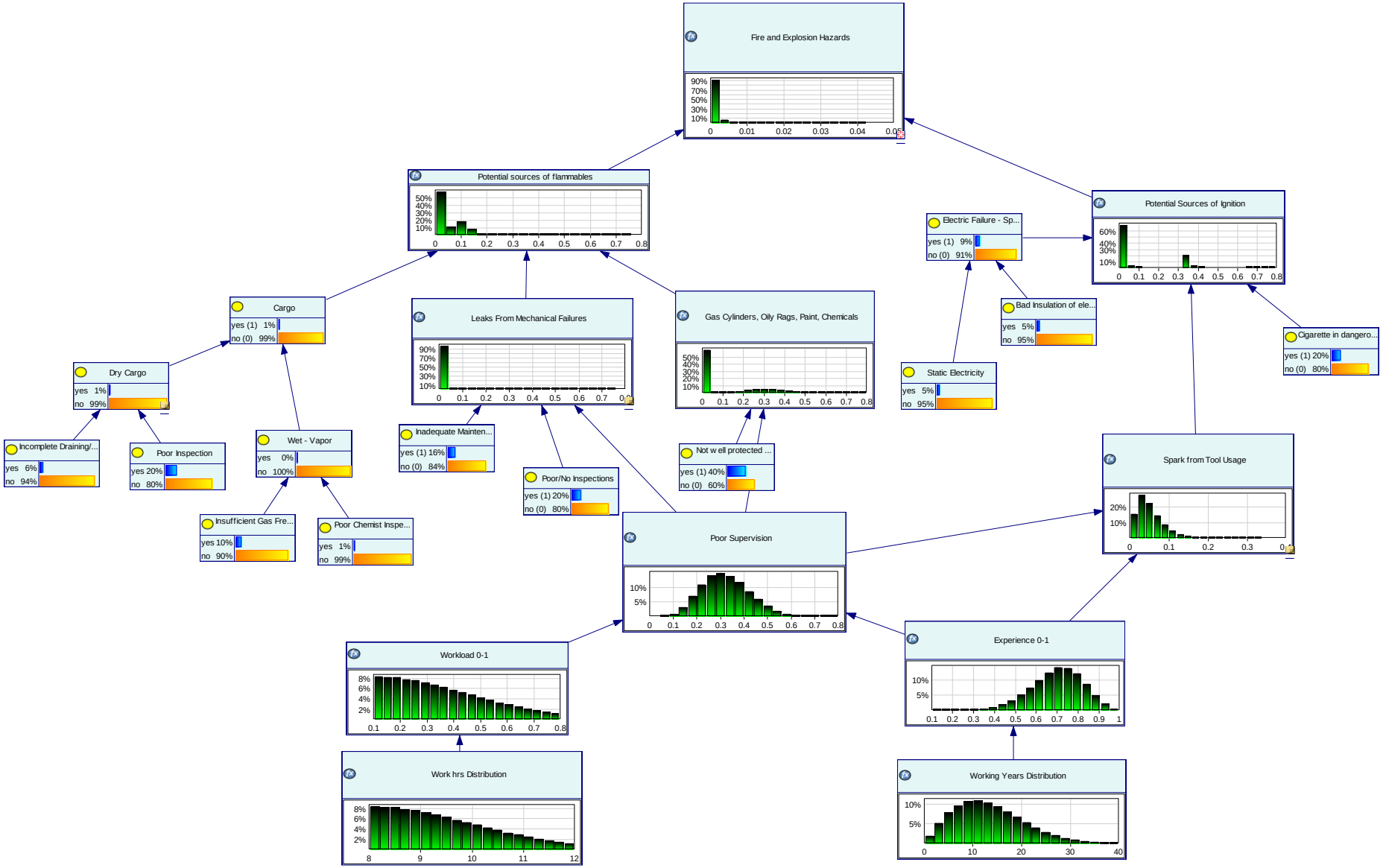
yes	0.0003225
no	0.9996775

Bad weight distribution:

yes	0.1
no	0.9

Bayesian Networks




Fire and Explosion Hazards
Potential sources of flammables
Potential Sources of Ignition
Electric Failure - Sp...
yes (1) 9%
no (0) 91%
Bad Insulation of ele...
yes 5%
no 95%
Cigarette in dangero...
yes (1) 20%
no (0) 80%
Static Electricity
yes 5%
no 95%
Cargo
yes (1) 1%
no (0) 99%
Dry Cargo
yes 1%
no 99%
Incomplete Draining/...
yes 6%
no 94%
Poor Inspection
yes 20%
no 80%
Wet - Vapor
yes 0%
no 100%
Insufficient Gas Fre...
yes 10%
no 90%
Poor Chemist Inspe...
yes 1%
no 99%
Leaks From Mechanical Failures
Inadequate Mainten...
yes (1) 16%
no (0) 84%
Poor/No Inspections
yes (1) 20%
no (0) 80%
Gas Cylinders, Oily Rags, Paint, Chemicals
Not well protected ...
yes (1) 40%
no (0) 60%
Spark from Tool Usage
Poor Supervision
Workload 0-1
Work hrs Distribution
Experience 0-1
Working Years Distribution

Matlab code

```
clear all
close all

% List of distributions to evaluate
distributions = {'Beta', 'BirnbaumSaunders', 'Burr', 'Exponential',
'ExtremeValue', 'Gamma', ...
    'GeneralizedExtremeValue', 'HalfNormal', 'InverseGaussian',
'LogLogistic', ...
    'Logistic', 'Lognormal', 'Nakagami', 'Normal', 'Rayleigh', 'Rician',
'Stable', 'Weibull', ...
    'tLocationScale'};

% Names of your Excel files (make sure these files are in your working
directory)
files = {'ExperienceData.xlsx', 'WorkloadData.xlsx',
'PoorSupervisionData.xlsx', 'SparkData.xlsx'}; % Replace with actual file
names

% Loop through each file (each dataset)
for i = 1:length(files)
    % Load dataset
    data = xlsread(files{i});

    % Initialize variables to store best fitting distribution info
    bestDist = '';
    bestParams = [];
    bestKStat = Inf;

    % Create a new figure
    figure;

    % Plot the actual data histogram
    histogram(data, 'Normalization', 'pdf', 'DisplayName', 'Data
Histogram');
    hold on;

    % Loop through each distribution
    for j = 1:length(distributions)
        % Fit the distribution to data
        try
            pd = fitdist(data, distributions{j});

            % Plot the PDF of the fitted distribution
            x_values = linspace(min(data), max(data), 100);
            y_values = pdf(pd, x_values);
            plot(x_values, y_values, 'DisplayName', distributions{j});

            % Perform Kolmogorov-Smirnov test
            [~, ~, ksstat] = kstest(data, 'CDF', pd);
```

```
            % Check if this distribution is the best fit
            if ksstat < bestKStat
                bestKStat = ksstat;
                bestDist = distributions{j};
                bestParams = pd;
            end
        catch ME
            % If the fit fails, display a message and skip this
distribution
            fprintf('Could not fit %s distribution: %s\n',
distributions{j}, ME.message);
        end
    end

    % Display the best fitting distribution, its parameters, and KS
statistic
    fprintf('Dataset %d - Best fitting distribution: %s\n', i, bestDist);
    fprintf('Kolmogorov-Smirnov statistic: %f\n', bestKStat);
    disp(bestParams);

    % Set plot labels and legend
    xlabel('Data');
    ylabel('Probability Density');
    legend show;

    % Set the title of the figure using the name of the Excel file (without
extension)
    [~, fileName, ~] = fileparts(files{i});
    title(sprintf('Distribution Fits for Dataset: %s', fileName));

    hold off;

    % Save the figure
    saveas(gcf, sprintf('%s_DistributionFit.png', fileName));
end
```