DYNAMIC RISK-BASED ANALYSIS OF PETROLEUM RESERVOIR PRODUCTION SYSTEMS

By

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Dedication

This work is dedicated to God Almighty, the most gracious for his infinite mercy, undeniable blessings, and unlimited favour and to my father Aliyu Mamudu, my mother Awawu Mamudu, my wife Latifat Mamudu, my kids Ahmad Aliyu Abbas Mamudu, Ali Aliyu Abbas Mamudu, Hawwa Aliyu Abbas Mamudu, and my eldest brother Lawal Mamudu.

ABSTRACT

Petroleum reservoirs are complex process systems defined by intrinsically uncertain data and a distinct pressure gradient. The upstream sector's assets are with huge uncertainties and high risks. Thus, the investments in these complex geologic process systems majorly suffer severe dynamic risks due to the process' complex dynamics, process data's temporal and spatial variabilities, and data/model's uncertainties. Over time, the complex dynamic risks of the reservoir production system have resulted in unforeseen severe production fluctuations, total process system failures, and/or abrupt well shut-in due to uncontrollable circumstances. Hence, the need to introduce a multipurpose dynamic risk-based smart production prognostic approach to address the outlined inherent petroleum production challenges. This thesis presents dynamic risks assessment models for dynamic risks-based analysis of petroleum reservoir production systems. Different possible production scenarios are captured with the developed adaptive hybrid model with the following highlighted novel scientific contributions. Firstly, a dynamic risk-based predictive model is introduced to forecast production and capture the parameters variabilities, data and model's uncertainties, and dynamic risks of primary recovery processes. This is followed with an introduced novel model for dynamic risks monitoring and production forecast of secondary recovery processes. A novel model is also presented to incorporate dual reservoir energy support mechanisms in production predictions and associated dynamic risks forecast under lift mechanisms. In addition, a dynamic economic risks analysis model is proposed to consider economic risk assessment of the reservoir production systems. Lastly, a dynamic risks-based smart model is proposed to capture sand face pressure enhancement influence on the reservoir production system with production pump schemes.

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NOMENCLATURES

Acronyms

AI	Artificial intelligence
ANN	Artificial neural network

API	America Petroleum Institute
AVG	Average
bbl	Barrel
BN	Bayesian network
BHP	Bottom-hole flowing pressure
CPT	Conditional probability table
DBN	Dynamic Bayesian network
EWIS	Early waring index system
EOR	Enhanced oil recovery
GA	Generic algorithm
GLR	Gas-liquid ratio
GOR	Gas-oil ratio
HHP	Heavy warning-high production
HHW	High production heavy warning
HLP	Heavy warning-low production
HLW	High production light warning
HPHW	High production heavy warning
HPLW	High production light warning
LHP	Light warning-high production
LHW	Low production heavy warning
LLP	Light warning-low production
LLW	Low production light warning
LPHW	low production heavy warning

LPLW	low production light warning
MAD	Mean absolute deviation
MAE	Mean absolute error
MAPE	Mean absolute percentage error
MCMC	Markov chain Monte Carlo
MLP	Multilayer-perceptron
MSE	Mean square error
NA	Neighborhood algorithm
NO	Degree of reliability/success
NORP/NOR	Normal production
PCP	Progressive cavity pump
RMSE	Root mean square error
SPE	Society of Petroleum Engineers
WOR	Water-oil ratio
YES	Degree of risk/failure

Variables, Parameters, and Functions

b	Bias
b_1	First bias
b_2	Second bias
B_o	Oil formation volume factor
C_t	Total compressibility
E	Error
E	Evidence

e	Evidence state
f	Transfer/activation function
h	Pay zone thickness/reservoir thickness
H	Reference depth
H^b	Variable
I_{ik}	Input vector
j	Synapse/ordinal
k	Permeability/position
L_2	Quadratic loss
l	Position
m	Neuron
n/N	Total number
o_1	Output neuron
Pa_i	Parent
$P/P_{(t)}$	Probability
P_e	Reservoir pressure
P_i	Initial reservoir pressure
p_{tf}	Tubing head flowing pressure
$P(Q\|Y)$	Likelihood
$P(Y)$	Prior probability
$P(Y\|Q)$	Posterior probability
$P(E\|H^b)$	Likelihood function
$P(E)$	Normalization constant/evidence probability

$P(\theta_e, H^b)$	Prior probability density function
P_{wf}	Bottom-hole flowing pressure
q_o	Oil production rate
q_{max}	Maximum oil production rate
Q	Predicted oil production rate/query variable
Q_{jk}	Hidden layer neuron output
Q_k	Output from the output layer
t	Production time
R^2	Coefficient of determination
T	Target T (MAPE); number of time steps T (DBN)
Δp	Reservoir drawdown/pressure drop
$w_j/w_{k,lm}$	Synaptic weight
$w_{1,1h}$	Synaptic weight (from the input layer 1^{st} neuron to hidden layer 1^{st} neuron)
$w_{2,1h}$	Synaptic weight (from the input layer 2^{nd} neuron to hidden layer 1^{st} neuron)
$w_{1,2h}$	Synaptic weight (from the input layer 1^{st} neuron to hidden layer 2^{nd} neuron)
$w_{2,2h}$	Synaptic weight (from the input layer 2^{nd} neuron to hidden layer 2^{nd} neuron)
$w_{1,1o}$	Synaptic weight (from the hidden layer 1^{st} neuron to output layer 1^{st} neuron)
$w_{2,1o}$	Synaptic weight (from the hidden layer 2^{nd} neuron to output layer 2^{nd} neuron)
X	Random variable
x	Variable
x_j	Input signal
x_m	Net input into a neuron
y	Neuron output signal

Y	Variable Y (BN); Output Y (MSE)
Y_t^i	i^{th} in time-step t
$Y_j^{Predicted}$	Actual variable
Y_j^{Actual}	Predicted variable
z	Sum of all inputs entering the neuron
dz/dz	Pressure gradient
Δp	Reservoir drawdown

Greek Letters

σ	Standard deviation
Δ	Change
δ	Little change
Ղ	Learning rate
μ	Statistical mean/viscosity
θ_e	Parametric variable
θ_i	Vector form of the parametric variable
∞	Infinity
$\rho(x, \alpha)$	Generic adaptive algorithm loss
$\emptyset$	Porosity
α	Alpha
γ_o	Specific gravity

Subscripts and Superscripts

a	Number of states
j	Ordinal

t	Total
o	Oil
k	Position
l	Position
m	Neuron
n	Total number
o_1	Output neuron
T	Target
x_m	Net input into a neuron
x	Variable
$total$	Summation

Chapter 1

Introduction

1.1 Background

The primary energy consumption grew at a rate of 2.9% in 2018, almost double its 10-year average of 1.5% per year, and the fastest since 2010 (Budley, 2019). The consumption growth was reported to be majorly driven by natural gas, which contributed more than 40% of the global increase. All the fuels grew faster than their 10-year averages except renewables. This shows the huge importance of the hydrocarbons in the 21st century. Oil consumption grew by an above average of 1.4 million barrels per day or 1.5%. While natural gas consumption rose by 195 billion cubic meters or 5.3%, one of the fastest growth rates since 1984. The global oil production increased by 2.2 million barrels per day and that of natural gas increased by 190 billion cubic meters or 5.2%. These data demonstrate the need for technological advancement and expansion of exploration activities in the off-stream oil and gas sectors to meet the global demands. The most vital aspect is the production technologies/strategies deployed to ensure optimum hydrocarbons production to meet the consumers' demands. Production engineering is a core area/part of petroleum engineering that attempts to maximize production/injection in a cost-effective manner. The technologies/methods deployed in this engineering area are related to other major areas (formation evaluation, drilling, and reservoir engineering) directly and interdependently. As advancement continues in the industries to meet the growing global energy demands, the complexities and challenges associated with the petroleum production increase. This conducted research attempts to highlight the production challenges involved in meeting these demands and propose solutions to them.

The global demands for fossil fuel are still experiencing increase. Thus, significant advancement in different technologies to be utilized, from the exploration stage to the production/recovery stage in the oil and gas industry, has attained higher implementation in terms of technical, economic, environmental, and safety prospects. The most serious concern of the field operators for decision making and field development is to achieve some of their primary business objectives, which include accurate determination of recoverable reserves through production forecast and asset management. The industry's goal is hence achievable through reservoir simulation and risk analysis. Reservoir simulation is the act of mimicking the behaviour of the reservoir system, where the variations of pressure and flow rate with respect to time and position are targeted. A sound knowledge of the state of reservoir depletion in terms of the remaining time and/or reserves is vital for proper asset management (Khazaeni & Mohaghegh, 2011; Shahkarami et al., 2014). To obtain this important data/information, petroleum engineers typically utilize numerical models to simulate reservoir behaviours (with the aid of adequate adjustment) to match the observed field trends. This is a process termed history matching, wherein a model that is capable of mimicking the available historical data is developed (Costa et al., 2014). This procedure is time consuming, computationally expensive, and requires high processor capability due to the challenges associated with the number of runs required to generate the geological realizations; this is relatively expensive in terms of CPU time (Subbey, Mike, & Sambridge, 2003). In addition, the development and implementation of such field-scale models can be highly financially demanding due to the required computational burden and human resources. These challenges become more pronounced in the remote harsh offshore environment where restricted access remains a posed issue. On the other hand, analytical models typically suffer a lack of adequate representation of the nonlinear complex behaviors and relationships of the reservoir system (Khazaeni & Mohaghegh, 2011). This highlights the need for the development of a dynamic risk-based model to efficiently facilitate the modeling process as presented in the current study.

Hydrocarbon production trends and field experience have proven that the petroleum reservoir is a complex system composed of intrinsically uncertain data. The challenges of the dynamic risks associated with the production variables/dynamic data have become even more alarming, leading to avoidable production downtime or production losses, due to inefficient production risk assessment strategies. It is worth noting that while limited efforts are being made to mitigate the challenges associated with intrinsically uncertain data through history-matching, the approaches used to resolve the dynamic risks remain scarce in the literature (Subbey et al., 2003). Although artificial intelligence (AI) systems are being proposed to tackle the history-matching challenges in some research works, the literature is yet to report any adequate dynamic risk analysis methodology for dynamic risks assessment of the petroleum reservoirs production systems. The dynamic risk prognostic model evaluates and updates current and future production trends and forecasts the oilfield production dynamic risk. It employs real-time and future early warning concept and risk prediction principles, hybridized with the concept of human biological neural structures exercised by a data-driven computational tool. These hindrances posed by history-matching and the challenges associated with dynamic risk analysis of the varying reservoir production rates are solved using the developed hybrid strategy presented in this work.

Inadequate reservoir energy to transport the hydrocarbons to the surface at economic rates leads to the deployment of techniques for production enhancement. The deployment of gas lift systems or production pumps to lift the well or reservoir fluids is only a viable option if water or gas injection is not economically or technically feasible (Guo et al., 2007). Hence, the geologic production system becomes a reservoir system with a dual energy support as the energy supplied by the injected gas improves the insufficient reservoir energy by lowering the sand face pressure. The implementation of the gas lift/production pumps' mechanism for the downhole pressure enhancement increases the system's complexity. These challenges such as technical difficulties and complex dynamics of the process system, have attracted researchers' attentions in the recent times as no existing risk analysis methodologies capture the process' dynamic risks. Thus, the process dynamic risk predictions are vital and would be handy for academic and industrial applications. In this research, a dynamic risk analysis approach to model a reservoir production system with a dual energy support is introduced.

Hydrocarbon reservoirs are complex process systems defined by inherently uncertain data and a distinct pressure gradient. Basically, the upstream sector's assets are with high risks (Khazaeni & Mohaghegh, 2011; Wang et al., 2019). Thus, the investments in these complex geologic systems mainly suffer considerable economic risks due to the process complex dynamics, environmental factors, model's uncertainties, process data's uncertainties, and human errors. The complex challenges with the production variables can be due to unforeseen severe production fluctuations, total process system failures, and/or abrupt well shut-in due to uncontrollable circumstances (environmental factors and/or governmental regulations). In the recent decade, field development planning and several developed optimization strategies have been used to proffer solutions to these challenges. However, their applications in petroleum economics have revealed that these strategies are deficient in mechanisms to handle dynamic risks/dynamic economic risks assessments of the process systems as they are manly designed to predict production and/or quantify production uncertainties. Thus, the mechanisms to incorporate the production variables' dynamics are not incorporated in the existing models. Petroleum economics is a fundamental part of petroleum engineering and science. Petroleum production models, field development models, and reservoir management optimizations strategies are the key economic models in petroleum economics. To the best of the authors' knowledge, while these models have been applied in reserves estimates, production predictions, uncertainties quantifications and/or risks analysis over the past decades, a proper approach for dynamic economic risks assessment of the production system has not been reported in the literature. This leads to the quest in this work to develop multipurpose connectionist models for reservoir production forecast, evidence-based dynamic risks analysis, and dynamic economic risks assessment of the reservoir production systems.

The proposed hybrid model is a connectionist model made up of several component models designed to adequately accomplish the multipurpose modeling methodology's functions. It employs probabilistic and non-probabilistic models for process modeling. The individual models that constitute the presented adaptive hybrid model include: 1) an artificial neural network (ANN) model, 2) a Bayesian network (BN) model, 3) a dynamic Bayesian network (DBN) model, 4|) an early warning index system of oilfield development risk block (EWIS) model, and 5) a loss function (LF) model.

1.2 Motivation

The quest towards ensuring the development of a hybrid connectionist strategy capable of data/model's uncertainties quantifications, reservoir production forecasts, dynamic risk predictions and/or real time monitoring, and dynamic economic risks assessment of the petroleum reservoir production systems led to the design of the multipurpose tools presented in this work primarily for petroleum production related decision-making strategies. Although, extensive efforts have been made in modelling hydrocarbons production (and recovery) processes and the associated process uncertainties in the past decades, the scarcity of adequate models to capture the complex dynamic risks of the recovery systems in process modeling remains a posed serious economic and technical challenge. In addition, the increasing global demand for energy, which has led to exploits, even in the remote harsh offshore environment, has necessitated advancements in the existing methodologies for effective process modelling, economic risks analysis, and dynamic risk profiling of the reservoir production system. Hence, in this work, we present an innovative and adaptive multifunction risk-based model for production forecasts, dynamic risks assessment, and dynamic economic risks analysis of petroleum reservoir production systems to bridge the gaps in the existing methodologies in the literature (in petroleum production economics). To the best of the authors' knowledge, the existing models, whether hybrid or single, lack the potency for dynamic risks/dynamic economic risk assessments. This is because these numerous approaches in the literature were not built/developed to incorporate risks' dynamics. Hence, they should be best referred to as static risks/uncertainties analysis models.

1.3 Current State of Knowledge and the Gaps

Critical/comprehensive study of the existing models reveals obvious flaws which require urgent attentions. These weaknesses include: 1) Dynamic risks are not considered in the models used for production analysis of reservoir systems under natural drive; 2) The models do not incorporate dynamic risk prediction/monitoring for reservoir production systems under pressure support; 3) The models are not applicable to reservoir production systems with dual energy supports; 4) The models do not incorporate dynamic economic risk assessments of the reservoir production systems; and 5) The models are not applicable to dynamic risks assessment of reservoir production systems with pump schemes. These weaknesses are overcome in the current research as detailed in the objectives presented in section 1.4.

1.4 Research Objectives

This research aims at providing dynamic risks-based analysis models for dynamic risk assessment of the petroleum reservoir production systems. The methodologies are designed for production forecasts, associated dynamic risks predictions/monitoring, and resultant dynamic economic risks assessments. The models capture temporal and spatial variability of the data, uncertainty in the data and reservoir models, and most importantly, the impacts of these factors/parameters on the overall production risk profile. The non-linear interactions of the vital flow parameters in the system are also adequately considered/captured with the presented models. The models adequately provide dynamic risks monitoring/assessment, assess dynamic economic risks, and predict real-time daily production economic losses.

Figure 1.1 outlines the tasks conducted to achieve the research objectives. The research goal is achieved through the following research objectives.

i. To conduct dynamic risks assessment of a reservoir production system under natural drive for production forecast and dynamic risk/uncertainties predictions.
ii. To develop a hybrid model for production predictions and dynamic risk monitoring for a reservoir production system under pressure support.
iii. To develop a dynamic risk analysis approach to model a reservoir production system with a dual energy support.

iv. To develop a connectionist model for dynamic economic risk assessment of reservoir production systems.

v. To model a reservoir production system with bottom-hole pressure enhancement scheme using pump systems.

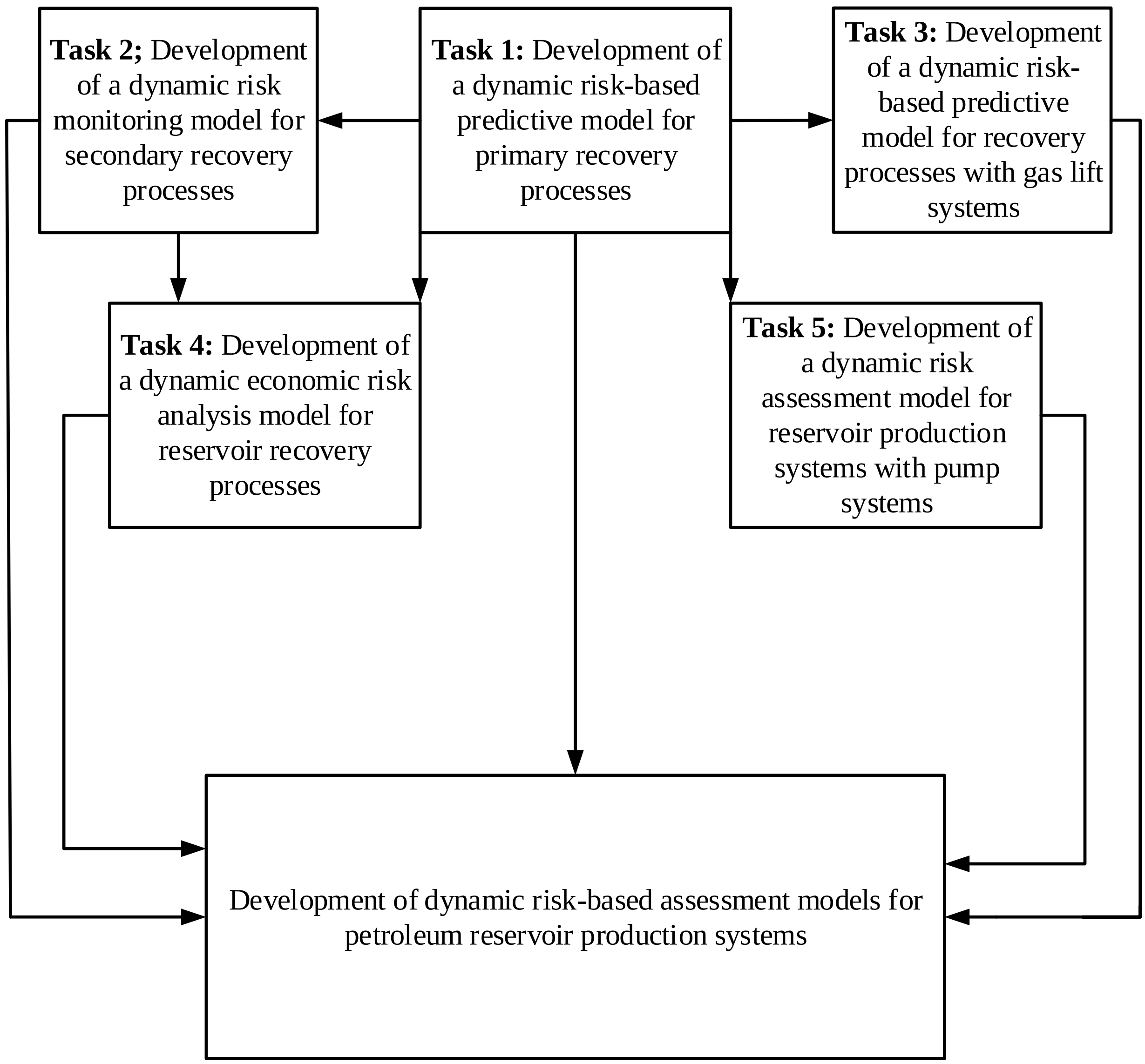

Figure 1.1: Research tasks

1.5 Scope and limitations

This research presents dynamic risks-based methodologies for petroleum reservoir production forecasts, associated dynamic risks predictions/monitoring, and resultant dynamic economic risks assessments. The methodologies are applicable in both offshore and onshore geologic environments. The risk assessment models, deterministic predictive models, dynamic risks monitoring models, and dynamic economic risks assessment models presented in this work are designed for different reservoir production scenarios to enable effective field development planning and adequate reservoir production management related decision-making strategies. Dynamic risks associated with petroleum reservoir productions pose serious challenges in engineering operations in the upstream oil and gas sectors as the existing traditional risks analysis models lack the potency to incorporate the process risks' dynamics and should be best referred to as static risk analysis models. Hence, there is a need to conduct the current research. However, it should be emphasized that the model is only applicable to petroleum reservoirs production systems. In addition, despite the numerous advantages of the proposed connectionist models, it is imperative to emphasize their further limitations, which comprise the weaknesses of the individual sub-models that constitute the presented hybrid models. For instance, the ANN model is restricted by the lack of extrapolation capability and overfitting flaws, while the BN models are faced with the challenge of subjectivity.

1.6 Contributions and the novelty of the current work

The scientific contributions and novelties of this doctoral work are highlighted as follows:

- A dynamic risks-based predictive model is introduced to forecast production and capture the parameters' variabilities, data and model's uncertainties, and dynamic risks of primary recovery processes. The model provides a cost-effective template for production risk assessment and eases the computational burden of history matching processes. The model captures the temporal-spatial dependency and non-linear complex relationships involved in isothermal reservoir flow behaviours. This contribution would be handy in effective reservoir management decision making, enabling a risk-based optimal field performance of reservoir. This scientific contribution is presented in chapter 3 of this thesis.

- A new model is introduced for dynamic risks monitoring/assessment and production forecast of secondary recovery processes. The challenges with reservoir production's dynamic risks assessment under pressure support are addressed with this introduced model. The new approach serves as a multipurpose tool for dynamic risk monitoring and reservoir production managements for systems under pressure support. It facilitates optimization of production schemes to prevent production losses. The model predicts the transition time between successive early-warning-indicated production levels necessary for a change in the production strategy to avoid production downtime. The model captures the pressure maintenance effects using early warning indexes and implements the 3σ mathematical rule to promptly signal the arrival of any production rate variation. This scientific contribution is presented in chapter 4 of this thesis.

- A novel technique is introduced to incorporate dual reservoir energy support mechanism in production predictions and to forecast the associated dynamic risks. The challenges with dual energy production systems are addressed with this model's application. The model yields predictive outcomes at any production time in the well's production life. It offers field operators an early warning system with prognostic capabilities to monitor dynamic risks associated with systems supported with gas lift mechanisms. This enables dynamic risk prediction at any production time in the well's production life. The model offers a means to quantify the reservoir flow parameters' dependencies to enable real-time optimization and adjustment of the uncertain parameters as the well is being produced. The model would enable the operators to evaluate the risks involved in the different production scenarios resulting from the variation of all the key reservoir flow parameters at reservoir engineers' disposal during operations. This scientific contribution is presented in chapter 5 of this thesis.

- A dynamic risk-based smart model is introduced for evidence-based and real-time dynamic economic risks assessment of the reservoir production systems. The hybrid model forecasts production, assesses the dynamic risks, and evaluates the associated production economic losses. The model yields transitional (threshold) production values for effective reservoir management to minimize production losses. It introduces an innovative approach that effectively minimizes the potential for dynamic economic risks and predicts real-time daily production economic losses. It is a connectionist model for dynamic economic risk assessment for production systems with or without pressure maintenance. The model provides the field operators with the means to assess real-time dynamic economic risks, their associated production economic losses, and their impacts on the overall process systems risk profiles. This scientific contribution is presented in chapter 6 of this thesis.

- A dynamic risks-based model is proposed to capture sand face pressure enhancement influence on the reservoir production system with pumps scheme. The introduced operational risk model is designed for the dynamic risk analysis of pressure-augmented downhole petroleum production systems. The model analyzes the progressive cavity pump

(PCP)'s impacts on systems' failures during production and yields risk profiles as a function of time as the production operation proceeds. The model demonstrates adequate downhole process system contributing factors' representations of the PCP system. Hence, the field operators are offered a proper tool for assessment of dynamic risk to ensure effective production management decision-making in pressure-augmented downhole systems. This scientific contribution is presented in chapter 7 of this thesis.

1.7 Co-authorship statement

This Ph.D. thesis is sole authorship of the candidate (Abbas Mamudu) under the guidance of supervisory team comprising of Dr. Faisal Khan, Dr. Sohrab Zendehboudi, Dr. Hodjat Shiri, and Dr. Sunday Adedigba. Detailed roles and contributions of each coauthor in the current research are presented below.

Abbas Mamudu: Conceptualization and concepts ideation, formulation and development of methodology, design and development of risk-based production models, data processing and analysis, models testing and validation, writing the original draft of the manuscripts for publication, reviewing and editing the manuscripts in response to co-authors and journal reviewers' feedbacks.

Faisal Khan: Supervision, research idea formulation, conceptualization and review of the methodologies, reviewing and editing the developed risk-based production models, guidance in data processing and analysis, and review of the manuscripts and thesis.

Sohrab Zendehboudi: Supervision, research idea formulation, conceptualization and review of the methodologies, reviewing and editing the developed risk-based production models, guidance in data processing and analysis, and review of the manuscripts and thesis.

Hodjat Shiri: Guidance in the doctoral work structure/organization and review of the doctoral work and thesis.

Sunday Adedigba: Guidance in the development of the BN and ANN models and review of the manuscripts and thesis.

1.8 Organization of the thesis

This doctoral thesis is written in a manuscript-based format. Hence, the outcomes of the doctoral work are represented in five peer-reviewed journal articles. Figure 1.2 shows the structure of the research thesis. The introduction, literature review, and conclusions are presented in chapters 1, 2, and 8, respectively. Chapters 3 to 7 are developed based on the submitted papers to peer-reviewed journals.

Chapter 2 comprises a comprehensive review of the relevant previous studies. This includes definitions of terminologies and relevant previous works analysis.

Chapter 3 presents production forecasts and associated risk predictions of primary recovery processes using data-driven probabilistic approach. This chapter is published in *Journal of Petroleum Science and Engineering 2020; 184:106486.*

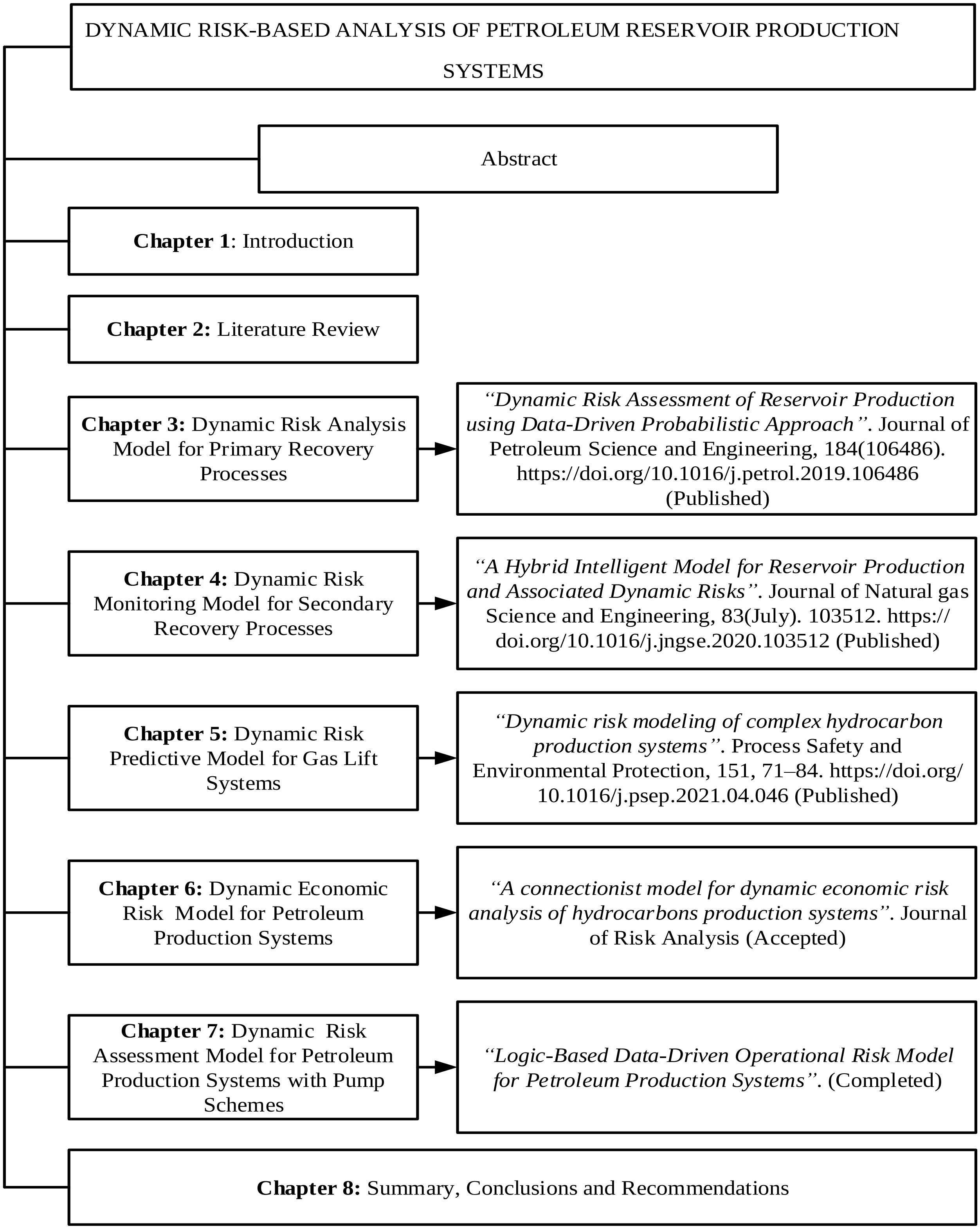

Figure 1.2: Organization of the doctoral thesis

Chapter 4 presents dynamic risks monitoring/assessment and production predictions of secondary recovery processes using a hybrid intelligent strategy (ANN-BN-DBN model). This chapter is published in *Journal of Natural gas Science and Engineering 2020;18July:103512.*

Chapter 5 presents dynamic risks-based predictive models for production systems with gas lift systems. The analysis is designed to offer field operators an early warning system with prognostic capabilities to assess dynamic risks associated with systems supported with gas lift mechanisms. The chapter is published in *Process Safety and Environmental Protection 2021; 151:71-84.*

Chapter 6 presents a dynamic economic risks model for reservoir recovery/production processes. The introduced connectionist model integrates an ANN-BN-DBN model with a loss function model for dynamic economic risks assessment. This chapter is accepted for publication in the *Journal of Risk Analysis*.

Chapter 7 comprises a dynamic risks-based model for reservoir production systems with pump systems. The introduced operational risk model is designed for dynamic risk assessment of pressure-augmented downhole petroleum production systems. This chapter is completed and ready for submission for publication.

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Chapter 2

Literature Review

2.1 Terminologies

The challenges encountered in the upstream sector of oil and gas industries necessitate dynamic risks prediction/monitoring and dynamic economic risks assessments of the petroleum reservoir process systems. The conducted research comprises several relevant terminologies that should be well-introduced to facilitate better understanding.

The petroleum reservoir is known to be a complex, porous, permeable, and saturated sub-surface geologic structure/entrapment that can hold hydrocarbons in commercial quantities under a distinct pressure gradient (Olafuyi & Mamudu, 2015). The process systems are characterized by inherently uncertain data and a unique pressure gradient. Thus, the assets are typified by high risks (Khazaeni & Mohaghegh, 2011). Effective risks analysis methods are needed for these engineering problems. In fact, the existing traditional approaches lack process modeling potency in these complex engineering cases as they are not dynamic risk-based methodologies. Hence, there is a need to develop the proposed methodologies as the viable options. Several possible reservoir production scenarios are considered in the current study.

Risk can be defined as the possibility of losing something of value or broadly described as a measure of economic loss. This refers to both the likelihood of an event (damage, loss or injury) and the magnitude of the loss or damage. In addition, it is also viewed as a state that causes loss or events to be in danger (Zhong et al., 2016). Relative to humans (not events), risk is generally categorized into two classifications in the chemical industries: individual risk and societal or group risk. While the former refers to the rate at which an individual could be exposed to suffer harm or injury from some identified hazards' occurrence, the latter deals with the relationship between the rate and the number of people sustaining a specific degree of injury based on the occurrence of some known hazards.

Dynamic risk assessment is a method that updates the estimated risk of a failing/deteriorating process according to the performance of the control system, safety barriers, inspection and maintenance activities, the human factors, or procedure (Khan et al., 2016). The BN models are the most used in dynamic risk assessment. The BN models have been widely/successfully used in different engineering, science, and health domains as well as risk assessment decision support. The understandable visualization of the complicated relationships among the variables is one of the most appealing characteristics of a BN model, though its mystifying power lies in the ability to encode multivariate probabilistic distributions. The logical networks provide a clear and efficient way to model/visualize complex relationships between unobservable and observable variables. They can integrate data from diverse sources with contrasting degrees of uncertainty. Most interestingly, the BN approach enables the modeling of unique/different dynamic processes under a single and statistically robust framework.

The Bayesian network (BN) is a product of a century's old effort. Bayes' network or the BN can be described as a graphical tool which uses a directed acyclic graph to encrypt probabilistic bonds among random variables and their conditional dependence (Adedigba et al., 2016b). Bayes' rule describes how to update the probabilities of hypothesis, given an evidence. The theorem was introduced in the 1740s. The theorem was developed by conducting a study on the theory of logic and inductive reasoning. The concept provides a mathematical foundation for relating the extent to which a new information (an observation) confirms the different hypothesized states of nature (cause). Bayes' mathematical work, which includes this logical theorem, was first published in 1763, and later supported in 1774 by a more renowned scholar named Pierre Simon Laplace. Pierre Simon Laplace independently rediscovered Bayes' rule in words (without equations); it was claimed that the probability of a cause when the effect is observed is proportional to the probability of the effect given its cause. The researcher continued to exploit, develop, clarify, and prove this new principle for a further period of forty years. Dynamic Bayesian network (DBNs) are Bayes' networks for dynamic processes. DBN introduces appropriate temporal dependencies to model the random variables' dynamic behaviours. DBNs are established to cope with systems having complex dynamics (Zhang et al., 2018). Thus, the DBN can adequately simulate the dynamics of the complex nonlinear reservoir production systems.

Artificial intelligence (AI) is a term used for virtual intelligence, computational intelligence, and/or soft computing in the literatures (Mohaghegh, 2000; Zendehboudi et al., 2018). AI model exhibits an impressive capability to learn and deal with complicated trends in various engineering and science cases. This technique is characterized by its potential to perform the attributes of reasoning such as generalization, discovery, organization, and perception (Mohaghegh, 2000; Zendehboudi et al., 2018).

The artificial neural network (ANN) could be generally considered as a robust computational tool or an information processing system characterized by performance synonymous with biological neural networks (Zendehboudi et al., 2018). It has the capability to relate input and output data in complex systems without process knowledge. The ANN remains one of the paradigms of the artificial intelligent techniques. The discovery of the ANN dated back to 1943 when McCulloch and Pitts introduced the concept of the ANN as the scientific peer of the human biological neural structures (Mohaghegh, 2000; Zendehboudi et al., 2018).

Loss function model is normally used to compute the extent of deviation of an estimated variable/value of a quantity from the true variable or optimal value. The loss function model required for a given process is dependent on the loss type (whether they are classification or regression losses). In the recent times, loss function models have been generally recognized among quality assurance practitioners and researchers due to the inherent features of Taguchi method as it produces suitable quality improvement schemes (Adedigba et al., 2018).

2.2 Previous works

Risk management has been extensively studied in the past decades. Interestingly, the research works have mostly aimed at tackling challenges associated with safety related risks to assure safety and environmentally friendly processes in various chemical and energy industries such as offshore operating systems (Abimbola et al., 2015; Adedigba et al., 2016b, 2016a, 2017a, 2017b, 2018; Adedigba et al., 2018; Zhang et al., 2018). For instance, Khan et al. (2015) presented a comprehensive work on process safety and risk management methods where the past strategies, current status, and future trends of engineering and research activities in this area were highlighted. Based on their work, there are still significant gaps in the safety and risks field that motivate researchers to develop more systematic models. Despite the numerous efforts made in the chemical process facilities in terms of risk management, implementation of similar approaches for reservoir production systems seems very scarce in the literature. The risk associated with reservoir production systems poses theoretical and practical challenges due to a variety of geological complexities, non-linear flow process, and different fluid behaviours. The common techniques to resolve the challenges are rarely cause and effect based but rather based on either stochastic or deterministic uncertainty quantification approaches. One of the most widely used techniques for uncertainties quantification among the stochastic methods is the Markov Chain Monte Carlo (MCMC) method, either as a stand-alone or in combination with other methods. However, the method is computationally expensive as it requires generating a multiplicity of outcomes (reservoir models) in the process of uncertainties assessment. In fact, the model is designed primarily for uncertainties quantifications. Dynamic risks studies are not considered in the category. These represent huge pitfalls addressed in the current research.

Numerical and analytical models are commonly employed for field developments. Numerical simulators are the most used numerical models. These models are only used for reserves estimates, production predictions, and uncertainties quantifications. In fact, the uncertainties quantifications conducted with these simulators are achieved by assuming ranges of values for the model's individual uncertain input parameter(s) (data) and obtaining a corresponding model's output value for each of the assumed values of the set of input data (Costa et al., 2014). Thus, the approach is stochastic, prohibitive, and time consuming. In addition, it does not consider the process dynamic risks. On the other hand, the commonly used analytical models are the decline curves method. They are established models for reserve estimates, and production forecasts (Rahuma et al., 2013). Some operators have deployed this method for decades (Rahuma et al., 2013). However, the models lack adequate process systems representation due to process assumptions made during their development such as system homogeneity, isotropy, flow regime, boundary conditions, and geologic structural shape limitations. The decline curve models are built to yield/define fixed production curves. Therefore, the models have no mechanisms to handle/capture dynamic risks or evidence-based production abnormality such as the consequence of abrupt well shut-in or sever abnormal production losses/fluctuations. Though they do not require huge amounts of data and processor capability, but their applicability is very limited. Yet, solely relying on the availability of huge resources and measurements for the field without an adequate risk assessment is not always a realistic and proactive solution. Therefore, the commercial simulators may not always offer practical strategies/solutions in all scenarios. Also, the numerical and analytical methods might not be beneficial enough technically and economically for proper field development strategy and decision making. The data driven models enable engineers and researchers in the petroleum industries to conduct future field production performance analysis with limited data (Khazaeni & Mohaghegh, 2011). With smart modeling approaches such as ANN, adequate prediction of the process performance/behaviours is feasible if adequate data are provided and if the network is designed in an effective manner with the aid of process knowledge and statistical criteria. Implementation of such an approach can provide useful guidelines/tips for better design and operations as well as optimization of targeted processes or phenomena. In this work, we propose a connectionist modeling strategy to address the identified dynamic risk challenges.

Recent decades have seen significant advances in smart models' applications in the oil and gas industries. A brief review of the relevant previous research studies is presented in this chapter. Bittencourt & Horne (1997) presented a hybrid generic algorithm (GA) for economic analysis and production simulation. Although their model was successfully implemented for production forecast, dynamic risks/dynamic economic risks assessment and evidence-based production losses evaluations were not considered in their work. Subbey et al. (2003) used neighborhood algorithm (NA) in their study to predict production. While the production forecast was a huge success, dynamic risks/dynamic economic risks were not considered in their model. Also, Nicotra et al. (2005) implemented a similar method with an in-built stochastic feature. The model is stochastic and costly. It lacks potency for dynamic risk analysis as it was not primarily designed for such tasks. Lechner et al. (2005) proposed an ANN model to forecast production. Production economics was not included in their analysis. The model is stochastic, and risks were not investigated in their work. Khazaeni and Mohaghegh (2011) applied ANN to predict oil production. They did not consider risks in their work. Zhao et al. (2012) used non-linear programming model for oil production rate optimization. Similarly, they did not analyze dynamic risks in their study. Shahkarami et al. (2014) successfully applied an ANN model for production forecast in their assisted history matching study. Like others, they did not investigate risks in their study. Also, Augusto et al. (2014a) presented a stochastic method with ANN model for oil production forecast. Dynamic risks were not assessed in the work. Maschio et al. (2014) used MCMC model for oil production forecast. Dynamic risks were not investigated in the work. In fact, it is a stochastic approach, and not designed for production's dynamic risks analysis. Zhong et al. (2016) presented a hybrid model, which integrates ANN model with BN model. Similar to other previous works, dynamic risks and dynamic economic risks were not investigated in their work. Sun and Ertekin (2017a) developed a stochastic model for cyclic steam stimulation. The model is limited to cyclic steam stimulation enhanced oil recovery (EOR) scheme. Risks were not evaluated in the study. Wang et al. (2019) applied a deep neural network model on production forecasting in Bakken shale reservoir. Their model was mainly designed for production forecast. Hence, dynamic risks were not investigated in their work. Similarly, in the recent decade, some efforts were made in systems with installed production pumps. Samad & Nizamuddin (2013) presented a performance analysis of downhole production pumps used in oil wells. In their study, numerical modeling was conducted to analyze the flow behavior of the downhole pumps. Production predictions were not included in their work and risk analysis was not conducted. Khakimyanov et al. (2016) performed a research on production pumps efficiency analysis. Their research was not a risk-based study, and reservoir simulation was not conducted. Hence, dynamic risks assessment of the augmented downhole pressure system was not considered in their study. In fact, none of the reviewed smart methodologies is capable of dynamic risks predictions, monitoring, and dynamic economic risks assessment of the petroleum reservoir production systems. Hence, to the best of the authors' knowledge, risk analysis methodologies with in-built mechanisms for dynamic risks predictions, dynamic economic risk assessment and scenario/evidence-based production losses analysis are unreported in the literature. These weaknesses are addressed by implementing the proposed connectionist model in the current work.

The following findings summarize the knowledge gaps in the literature.

i. Inadequate risks assessments and production prediction models for reservoir production systems under natural drive.

ii. Lack of predictive models for production predictions and dynamic risk monitoring for reservoir production systems under pressure support.

iii. Deficiency in dynamic risk analysis approaches to model reservoir production systems with dual energy supports.

iv. Scarcity of methodologies for dynamic economic risk assessments of reservoir production systems.

v. Scarcity of dynamic risk-based models for reservoir production systems with pump systems.

These itemized five knowledge gaps in the literature are bridged in the current work as each of the defined five research objectives/tasks given in section 1.4 is designed to address each of these identified weaknesses.

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Chapter 3

Dynamic Risk Assessment of Reservoir Production Using Data-Driven Probabilistic Approach

Preface

A version of this chapter has been published in the ***Journal of Petroleum Science and Engineering 2020; 184:106486.*** *I produced the work alongside my co-authors; Faisal Khan, Sohrab Zendehboudi, and Sunday Adedigba. I am the main author. I conducted the literature review, formulated the concepts of the dynamic risk-based model and developed it for uncertainties and risk assessment for primary recovery processes. I prepared the first draft of the manuscript and subsequently revised the manuscript based on the co-authors' and peer review feedback. Co-author, Faisal Khan assisted in the development of concept, design of methodology, reviewing and editing the draft, and reviewing and revising the new version of the manuscript. Co-author, Sohrab Zendehboudi supported in the design of the methodology, reviewing and editing the draft, reviewing and revising the new version of the manuscript; this co-author also helped in the validation, review, and correction of the model and results. Co-author, Sunday Adedigba provided support in the development and implementation of the BN and ANN concepts.*

Abstract

Oil and gas companies use the reservoir simulation approach to history match and forecast reservoir production. While this strategy is easy and often effective, it has inherent setbacks, including a limited ability to capture temporal and spatial variability of the data, uncertainty in the data and reservoir models, and most importantly, impacts of these factors/parameters on the overall production risk profile. This research presents a hybrid method to forecast the production rate and risks attributed to oilfield development. The hybrid connectionist strategy integrates a data-driven model to capture variability with a probabilistic model to capture uncertainties and associated risks. The multilayer perceptron artificial neural network is built based on geological realizations and used as a substitute for the commercial simulator (e.g., CMG) to model reservoir production behaviour for the effective facilitation of the production prediction. The model has a generalization capability and captures the temporal-spatial dependency and non-linear complex relationships involved in isothermal reservoir flow behaviour. The Bayesian network model is developed to assess the production risks. It employs the concept of the early warning index system. The results show that the predicted oil production profile closely matches the history matched data from the simulator, and the assessed dynamic risks conform with the field reality. The hybrid modeling strategy leads to the minimum and average percentage errors of 0.02% and 5.28% respectively in the reservoir production forecast. The application of the proposed approach would assist in effective reservoir management decision making, enabling a risk-based optimal field performance of reservoir.

Keywords: Artificial neural network; Bayesian network; Oil production forecast; Reservoir simulation; Dynamic risk assessment

3.1 Introduction

The global demands for fossil fuel are still increasing. Thus, considerable advancement in various technologies to be employed, from the exploration stage to the production/recovery stage in the oil and gas industry, has attained higher performance in terms of technical, economic, environmental, and safety prospects. The most serious concern of the field operators for decision making and field development is to achieve some of their primary business objectives, which include accurate determination of recoverable reserves through production forecast and asset management to minimize risks. The industry goal is hence achievable through reservoir simulation and risk analysis. Reservoir simulation is the act of mimicking the behaviour of the reservoir system, where the variations of pressure and flow rate with respect to time and position are targeted. A sound knowledge of the state of reservoir depletion in terms of the remaining time and/or reserves is vital for proper asset management (Dalgleish et al., 2007; Khazaeni & Mohaghegh, 2011; Shahkarami et al., 2014). To obtain these important data/information, petroleum engineers typically utilize numerical models to simulate reservoir behaviour (with the aid of adequate adjustment) to match the observed field trends. This is a process termed history matching, wherein a model that is capable of mimicking the available historical data is developed (Costa et al., 2014). This procedure is time consuming, computationally expensive, and requires high processor capability. In addition, the development and implementation of such field-scale models can be highly financially demanding due to the required computational burden and human resources. These challenges become more pronounced in the remote harsh offshore environment where restricted access remains a posed issue. This highlights the need for the use of a data driven model to facilitate the simulation process for efficient oil production prediction.

In fact, analytical models are much simpler and less costly than the expensive numerical models. However, the analytical models are less representative of the actual reservoir model, due to several limitations occurring during the model development, which are associated with homogeneity, isotropy, fluid properties, flow regime, and production mechanisms. In addition, they do not require huge amounts of data and processor capability, though their applicability is very limited.

Yet, solely relying on the availability of huge resources and measurements for the field without a logical dynamic risk assessment is not always a realistic and proactive solution. Therefore, the commercial simulators may not always offer practical strategies/solutions in all scenarios. Also, the numerical and analytical methods might not be beneficial enough technically and economically for proper field development strategy and decision making. The data driven models enable engineers and researchers in the petroleum industries to conduct future field production performance analysis with limited data (Khazaeni & Mohaghegh, 2011). With smart modeling approaches such as an artificial neural network (ANN), an accurate prediction of process performance/behaviours is feasible if adequate data is provided and if the network is designed in an effective manner with the aid of process knowledge and statistical criteria. Implementation of such an approach can provide useful guidelines/tips for better design and operation as well as optimization of targeted processes or phenomena.

Artificial intelligence (AI) is a term used for virtual intelligence, computational intelligence, and/or soft computing in the literatures (Mohaghegh, 2000; Zendehboudi et al., 2018). It exhibits an impressive capability to learn and deal with complicated trends in various engineering and science cases. This technique is characterized by its potential to perform the attributes of reasoning such as generalization, discovery, organization, and perception (Mohaghegh, 2000; Zendehboudi et al., 2018). In this field of study, proper mathematical models are formulated to mimic human biological neural structure and thinking (Ma et al., 2018a). AI-based models have been extensively utilized to provide solutions to complex problems in petroleum engineering, especially in the exploration and appraisal phases (Dousari et al., 2016; Aleardi, 2015; Ali et al., 2013; Aminzadeh, 2005; Cranganu & Bautu, 2010; Gharbi, 2003; Gharbi et al., 1995; Gomez et al., 2009; Kalantari et al., 2009; Kazatchenko et al., 2006; Khazaeni & Mohaghegh, 2011; Maleki et al., 2014;

Mohaghegh et al., 2005; Mohaghegh, 2005; Mohaghegh, 2000; Nikravesh & Aminzadeh, 2003; Onalo et al., 2018; Rajabi & Tingay, 2013; Mojtaba et al., 2010; Rezaee et al., 2007; Tariq et al., 2016; Zendehboudi et al., 2018). However, there is a limited number of research works on the development and modification of conventional and hybrid connectionist tools (Ali Ahmadi et al., 2013; Aminzadeh, 2005; R. B. C. Gharbi, 2003; R. Gharbi et al., 1995; Kalantari Dahaghi & Mohaghegh, 2009; Khazaeni & Mohaghegh, 2011; Ma et al., 2018a; Mohaghegh, 2005; Mohaghegh, 2000; Nikravesh & Aminzadeh, 2003).

Providing a brief introduction to a few of the relevant works, Khazaeni & Mohaghegh (2011) presented intelligent production models where the production rate data and well log data were used as input data for a production forecast. They used single AI models, while we employ a hybrid model with dual functions in the current study. Maschio et al. (2014) introduced a system that combines a Markov Chain Monte Carlo (MCMC) with ANN for history matching. Their probabilistic approach is stochastic, deficient in logical reasoning and prohibitive due to the incorporation of MCMC. In another research work, Zhong et al. (2016) applied a combined system of ANN and BN on the historical data; however, they did not history match with the ANN-BN model to forecast the production and logically assess the corresponding risks. Augusto et al. (2014a) used the ANN approach to history match, while the risks were not studied. Similarly, Shahkarami et al. (2014) developed a surrogate model with ANN for an artificial intelligence assisted history match process. The literature reveals that there are no definite approaches for risk analysis in oilfield development risk. However, the method that adequately analyzes the development risk sounds most promising in the oil and gas field development phase and serves as a good choice for effective production related decision making.

Risk management has been extensively studied in the past decades. Interestingly, the research works have mostly aimed at tackling challenges associated with safety related risks to assure safety, and to ensure environmentally friendly processes in various chemical and energy industries such as offshore operating systems (Abimbola et al., 2015; Adedigba et al., 2016b, 2016a, 2017a, 2017b, 2018; Adedigba et al., 2018; Bhandari et al., 2015; Khakzad et al., 2014; Khakzad et al., 2013; Khakzad et al., 2014; Khan et al., 2016; Meng et al., 2019; Perez & Tan, 2018; Pui et al., 2017; Wu et al., 2016; Zhang et al., 2018). For instance, Khan et al. (2015) presented a comprehensive work on process safety and risk management methods where the past strategies, current status, and future trends of engineering and research activities in this area were highlighted. Based on their work, there are still significant gaps in the safety and risks field that motivate researchers to develop more systematic models. Despite the numerous efforts made in the chemical process facilities in terms of risk management, implementation of similar approaches for reservoir production systems seems very scarce in the literature. The risk analysis of reservoir production systems may pose theoretical and practical challenges due to a variety of geological complexities, the non-linear flow process, and different fluid behaviours. The common techniques to resolve the challenges are rarely cause and effect based but rather based on either stochastic or deterministic uncertainty quantification approaches. One of the most widely used techniques for uncertainties quantification among the stochastic methods is the Markov Chain Monte Carlo (MCMC) method, either as a stand-alone or in combination with other methods. (Efendiev et al., 2009; Hill, 2015; Li et al., 2017; Mohamed et al., 2011, 2012; Oghena, 2007; Olalotiti et al., 2015; Shams & Company, 2016; W. Sun, 2014). However, the method is computationally expensive as it requires generating a multiplicity of outcomes (reservoir models) in the process of risk assessment. This represents a huge pitfall. In this research, we employ an integrated system of logical and data driven models.

The main aim of this research is to develop a hybrid system (e.g., ANN-BN), which bridges the inherent gap in the traditional commercial simulators for production forecasting and associated risks assessment. The technique considers the temporal and spatial dependency of the variables as well as the uncertainty associated with models and variables. The artificial neural network (ANN) is used as a proxy model to map input and output variables and sequentially approximate the unknown rock and fluid flow properties with the model's synaptic weights to yield a representative reservoir production prediction model. The model is intended to capture the non-linear complex relationships of the reservoir flow properties in the flow process. The Bayesian network analyzes the dynamic risks associated with production forecasting. It provides the logical reasoning needed for identification of the sources of the risks encountered in the production process.

This research is structured as follows. Section 3.2 presents the theory and background and includes dynamic risk assessment using early warning as well as the basics/fundamentals of ANN and Bayesian network methods. Section 3.3 describes the hybrid methodology proposed in this work. The model field application is presented in Section 3.4. The results and discussion are given in Section 3.5. Lastly, the main remarking points/conclusions are listed in Section 3.6.

3.2 Theory and Background

3.2.1 Dynamic Risk Assessment Using Early Warning

Risk can be defined as the possibility of losing something of value. In other words, it is a state that causes loss or events to be in danger (Zhong et al., 2016). Relative to humans (not events), risk is generally categorized into two classifications in the chemical industries: individual risk and societal or group risk. While the former refers to the rate at which an individual could be exposed to suffer harm or injury from some identified hazards' occurrence, the latter deals with the relationship between the rate and the number of persons sustaining a specific degree of injury based on the occurrence of some known hazards. The principles of risk prediction and early warning incorporate the theories and techniques of risk identification and assessment. (Baca & Petersen, 2013; Horneret al., 2011; Zhong et al., 2016). To identify risk, the risk sources are the key basis of forecasting and early warning. The sources are normally categorized into two groups: 1) The first category corresponds to the intrinsic existence and is unregulated by humans, and 2) the influence of things or people gives rise to the second category (Zhong et al., 2016).

Normally, all risk indicators can be classified into three categories in the dynamic risk assessment of an oilfield in the development phase: the warning source index, warning sign index, and the warning situation index, (Zhong et al., 2016). The most well monitored and serious events in the field development phase such as liquid production, gas production, oil production, water production, and gas/oil ratio (GOR) can be considered as warning situation indexes. Warning sign indexes are directly related to the warning situation indexes and are straightforwardly measured. The causes of the risk are the indexes of warning source. The best way to manage the risk is commonly risk measurement. Thus, development of risk analysis in oilfields with the aid of risk measurement still needs further research studies. At present, the Markov Chain Monte Carlo (MCMC) technique, artificial neural network (ANN) method, Bayesian network (BN) approach, and other new stochastic and deterministic tools are utilized. We propose an integrated system that is made of ANN and BN for production and risk prediction purposes.

3.2.2 Artificial Neural Networks (ANNs)

The artificial neural network (ANN) could be generally considered as a robust computational tool or an information processing system characterized by performance synonymous with biological neural networks (Zendehboudi et al., 2018). It has the capability to relate input and output data in complex systems without detailed process knowledge. In a comprehensive review work, Zendehboudi et al. (2018) presented mathematical expressions for a single neuron signal processing system with *n* number of inputs, as given below:

$$z = \sum_{j=1}^{n} w_j x_j + b \tag{3.1}$$

$$y = f(z) \tag{3.2}$$

where z represents the sum of all inputs entering the neuron; w_j depicts the weight of the transmission channel (synapse) j; x_j denotes the input signal; b is the bias; y is the neuron output signal; and f stands for the activation function.

The ANN remains one of the paradigms of the artificial intelligent techniques. The discovery of the ANN dated back to 1943 when McCulloch and Pitts introduced the concept of the artificial neural network as the scientific peer of the human biological neural structures (Mohaghegh, 2000; Zendehboudi et al., 2018). The technique has been widely used in various science and engineering disciplines (Aïfa & Baddari, 2014; Augusto, 2014; Gholami et al., 2014; Hypothesis, 2014; Long et al., 2016; Ma et al., 2018b; Shahkarami et al., 2014; Shi et al., 2017; Sun & Ertekin, 2017; Van & Chon, 2017).

Artificial neural networks (ANNs) have different classifications based on the network characteristics. These categorizations may include application, connection type, topology, and learning method (Zendehboudi et al., 2018). Referring to the utilization prospect, the ANN categories include function evaluation, prediction, clustering, and classification. In terms of connection, feedforward and feedback are conceivable. This refers to the data feeding direction. Feedforward networks are the most common structures used in engineering applications. Information or signals are transferred from the input unit to the output unit in the forward direction and errors are propagated in the backward direction. In contrast, feedback networks transmit signals in both directions with the inbuilt loops. According to the network topology, the ANN could be grouped into self-organized structures, multi-layers, recurrent and one single layer. When the signal transmission in ANN with multiple layers goes from the input layer to the output layer (feedforward), it is referred to as the multi-layer perceptron (MLP), while a multilayer structure with feedback is regarded as a recurrent network. A group of artificial neural networks (ANN) of 2D grids with square or hexagonal neurons which are capable of reorganizing themselves during the learning period for espousal to the inputs is regarded as a self-organized network (Zendehboudi et al., 2018). Regarding the learning method, ANNs can be classified as supervised, unsupervised or hybrid processes. When both the inputs and targets are given as a guide during the training and the learning principles are applied, it is called supervised learning. In contrast, the target data are not required by the network to be trained in the unsupervised learning system. The hybrid learning employs both supervised and unsupervised learning mechanisms.

An ANN structure is composed of an input layer, hidden layer(s), and an output layer (Adedigba et al., 2017; Onalo et al., 2018; Zendehboudi et al., 2018). The multilayer perceptron (MLP) is typified by its ability to learn and form connections between the trajectories in input and output layers with the inbuilt interconnected neurons between all the layers.

Process modeling is first conducted by weights initialization and subsequent updating upon the completion of each of the iterations. Random selection of initial weight values is the first step of the cycle. After completing the iterations (epochs), the estimated errors are used to compute the minimum resultant error. The products of the selected weights and the signals are summed up and passed through the transfer functions, thereby yielding a process function which is dependent on the choice of the selected activation function. Upon the completion of the cycle, the errors are then calculated and propagated backward to update the weights, as presented in the methodology section. Details on activation functions are found in a review paper by Zendehboudi et al.(2018) where they presented the most commonly used transfer functions.

Employing the MLP approach in the proposed hybrid system, the production at time (t) is predicted using the following expressions (Adedigba et al., 2016b):

$$Q_{jk} = f_1\left(b_j + \sum_i W_{ij} I_{ik}\right) \tag{3.3}$$

$$Q_k = b + \sum_j W_j Q_{jk} \tag{3.4}$$

where Q_{jk} is the hidden layer neuron output; W_{ij} and W_j are the assigned weights; f_1 refers to the transfer function of the hidden layer neuron; b_j stands for the hidden layer bias; b is the output layer bias; I_{ik} represents an input vector; and Q_k is the output from the output layer (the predicted value).

Eqs. (3.3) and (3.4) are used to perform the forward pass while Eqs. (3.5) to (3.7) (Adedigba et al., 2016b), as listed below, are utilized to perform backpropagation (error computation and synaptic weights updating).

$$y_m = \frac{1}{1 + e^{-x_m}} \tag{3.5}$$

$$Error_{total} = \frac{1}{2}(target(t) - output_{1o})^2 \tag{3.6}$$

$$\Delta w_{k,lm} = -\eta \frac{\partial E_{total}}{\partial w_{k,lm}} \tag{3.7}$$

where y_m is the output from the neuron; x_m is the net input into the neuron; m denotes the neuron; and η symbolizes the learning rate, t is the target, $\Delta w_{k,lm}$ is the error gradient, ∂E_{total} is the change in the total error, $\partial w_{k,lm}$is the weight change and k, l and m are relative positions respectively.

3.2.3 Bayesian Networks

The Bayesian network (BN) is a product of a century's old effort. Bayes' network or the Bayesian network can be represented as a graphical tool which uses a directed acyclic graph to encrypt probabilistic bonds among random variables and their conditional dependence (Adedigba et al., 2016b). The theorem came into existence sometime in the 1740s. He developed the theorem by conducting a study on the theory of logic and inductive reasoning. The concept provides a mathematical foundation for relating the extent to which a new information (an observation) confirms the different hypothesized states of nature (cause). Bayes' mathematical work, which includes this logical theorem, was first published in 1763(Adedigba et al., 2016b), and later supported in 1774 by a more renowned scholar named Pierre Simon Laplace. He independently rediscovered Bayes' rule in words (without equations); he affirmed that the probability of a cause when the effect is observed is proportional to the probability of the effect given its cause. He continued to exploit, develop, clarify, and prove this new principle for a further period of forty years.

A Bayesian network (BN) is a representation of a joint probability distribution of a set of random variables with probabilistic dependencies, where X is the set of discrete random variable given by the following equation:

$$X = (X_1, X_2, \dots \dots .., X_n) \tag{3.8}$$

In Equation (3.8), *n* defines the infinity. The joint probability distribution for the set of discrete random variables, X, can be obtained by taking the product of all the priors and their conditional probability distributions. Mathematically, this distribution is defined as follows (Adedigba et al., 2016b):

$$P(x_1, x_2, \dots \dots .., x_n) = \prod_{i=1}^{n} P\left(x_i \middle| Pa_{(xi)}\right) \tag{3.9}$$

If the cause is given as X and the evidence is given as R, the Bayesian model can be mathematically described as follows:

$$P(X|R) = \frac{P(R|X)P(X)}{P(R)} = \frac{Likelihood \times P(prior)}{P(evidence)} \tag{3.10}$$

The main goal of the BN is to determine the posterior probability distribution of each of the possible unobserved causes when the observed evidence is given. Therefore, if $\mathrm{X}_1, \mathrm{X}_2 \dots \dots \dots \mathrm{X}_\mathrm{n}$ are discrete random variables of a set, X, R is an event (variable) with known conditional probability (likelihood) $P(R|X_i)$, and the prior probabilities $P(X_i)$ are known, the posterior probability $P(R|X_i)$ of any of the events X_i (when R is given) can be determined by the following equation (Oghena, 2007):

$$P(Z_i|R) = \frac{P(R|X_i)P(X_i)}{\sum_{i=1}^{N} P(R|X_i)P(X_i)} \tag{3.11}$$

The risk assessment is only achieved through learning (BN learning). Given training data built with the index system and expert knowledge of the possible causal relationship, the required learning steps are performed. These include structure learning and parameter learning. The former refers to the definition and identification of the structure, how the variables are related to each other (parent, children, neighbours, and spouses), while the latter refers to the determination of the probability distribution of the nodes in the BN.

Applying Bayes' rule would require adequate knowledge to perform structure learning and parameter learning. Structure learning involves how the variables are related to each other, while parameter learning refers to the determination of the probability distribution of each of the nodes in the BN. It will then be followed by the posterior probability distribution estimation.

3.3 Implemented Methodology

3.3.1 Main Procedure Steps

The key objectives of this study are to develop a hybrid system to bridge the inherent gap in the traditional commercial simulators in history matching and to conduct a dynamic risk assessment and the production estimation in the oilfield development phase. This type of work requires sound knowledge of the non-linear complex relationships of the isothermal reservoir flow processes and the early warning dynamic system of the oilfield development system. The data driven part of the proposed model is composed of an MLP-ANN while the logical part is the BN model built based on the concept of an oilfield development risk index system. The BN is selected for early warning analysis and risk prediction while the ANN is employed as a computational tool for prediction of the oil production rate as it facilitates history matching and captures the spatial and temporal variability of some of the reservoir production parameters. The outputs (oil production rate data) from the ANN are fed to the BN for risk assessment using early warning and the principles of risk prediction. The flow chart presented in Figure 3.1 illustrates the general procedure for development and implementation of the methodology proposed in this study.

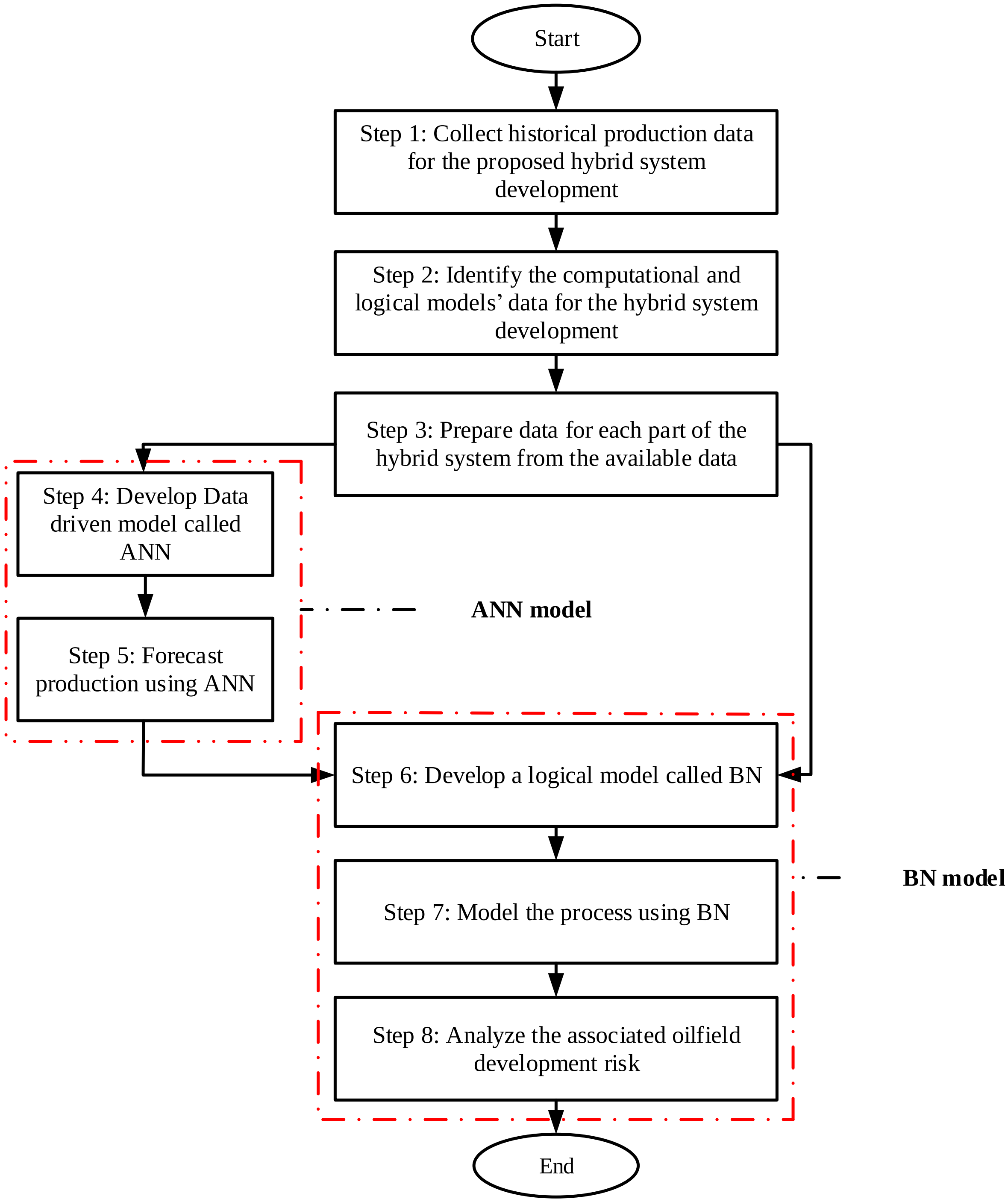

Figure 3.1: Proposed methodology- Data driven model integrated with a probabilistic model.

Figure 3.1 presents an overview of the main hybridization steps and components interactions while developing a hybrid model for prediction purposes. Steps 1 to 3 illustrate the field and probabilistic dataset collection and preparation. At step 3, partitioning of the data is performed based on the data type. Probabilistic data of the reservoir model's input parameters are directly transmitted to step 6 for the BN parameter learning. The computational data for history matching are also fed to the ANN at step 4 for the model development stages, namely, training, testing, and validation. The production data forecasted by the ANN (at step 5) are received as evidence by the BN at step 6 using the "3σ" rule mathematical concept and early warning index system to determine the possible states of the evidence (oil production rate). At step 7, the process modeling is initiated. The process risk assessment is eventually conducted at step 8.

The main steps involved in the development and implementation of the proposed methodology are further described in this section.

Spatial-temporal data set generation: This part of the methodology involves the following steps:

- Acquire and prepare data for reservoir model development.
- Develop a reservoir model from the geological data using a commercial simulator starting with the base case.
- Extract different static and dynamic data from the numerical simulation models to build the spatial-temporal database with which the ANN is trained.

Stand-in model development (data driven model): The following steps are needed in this phase:

- Identify and rank the influence of different reservoir properties on the reservoir performance.

- Use the ranked key rock and fluid flow properties as a guide to select ANN inputs, which are majorly affected by the reservoir modeling objective.

- Partition the temporal-spatial database into training, validating, and testing sets.

- Design the artificial neural network (ANN) architecture.

- Train, test, and validate the ANN.

- Validate the created ANN using a completely different realization of the reservoir.

- History match and predict oil production.

Oilfield development risk forecast (logical model): This phase deals with the following procedure:

- Build early warning development risk using the inputs and outputs from the developed data driven model based on adequate knowledge of the domain of interest (knowledge of the most vital elements of the physics of the isothermal reservoir flow processes).

- Compute the warning degree of the predicted warning situation indexes (oil production) from the data driven model using the "3σ" statistical principle.

- Use the prepared data and experts' knowledge for the BN structure and parameter learning.

- Enter the predicted outputs into the BN and compute the posterior probabilities with any new evidence (the observed production).

- Compare the prior and posterior probabilities of the risks of the warning sign indexes (the indicators that are related to fluid flow) and identify the sources of the risks that result in change of the degree of the warning situation index (change in production).

3.3.2 Data Selection

The preparation of data is the most difficult task in building a data driven model. The reservoir modeling objective strongly determines the choice of the needed input parameters (Shahkarami et al., 2014). Since the objective is to estimate the oil production rate, the reservoir properties that considerably affect the objective of study have a high degree of significance.

The spatial-temporal database comprises several types of data which include static and dynamic reservoir properties and functioning constraints. Static data refers to the reservoir parameters that do not change with time such as pay-zone thickness, porosity and permeability. However, the dynamic data are variable parameters that change with time, including oil production rate, bottom-hole pressure, and production time. Table 3.1 presents the selected dynamic and static data.

Table 3.1: Dynamic and static data for the reservoir system.

Data definition	**Parameter**
Static data	Pay-zone thickness, porosity, permeability, API gravity, transmissibility, and storativity
Dynamic data	Production time, bottom-hole flowing pressure, and production rate

3.3.3 ANN Model and Architecture

The type of ANN model to be developed is dependent on the type and characteristics of the problem (problem specifications). The ANN used for the reservoir production forecast in this research is a three-layered feedforward backpropagation ANN. It is made of an input layer, a hidden layer, and an output layer. The network receives signals through the input layer, the log sigmoid function is used in the hidden layer as the activation function, and the linear transfer function is utilized in the output layer due to the problem specification (desired target). Usually, an activation function is selected to meet the specifications of the problem being solved by the neuron. For instance, since production rates need to be computed, the values should be between zero and thousands. Hence, the linear transfer function would be the only proper option in the output layer. Otherwise, the network predictions would not be reliable. However, the sigmoid activation function is preferred for the hidden layer, not just because it remains the most common activation or transfer function used in a multi-layer neural network, but also because of the data transition it exercises. It takes the inputs (the values for which might be between plus or minus infinity) and considers the outputs within the range of 0 to 1. The log sigmoidal transfer function is close to 1 for large positive values, is 0.5 at zero, and very close to 0 for large negative values. This specific characteristic allows smooth modifications between the low and high outputs of the network neurons. Being differentiable is also one of the advantages of the log sigmoidal function. Ten biases are used in the ANN architecture that are determined by the network itself as a function of the hidden layer neuron. Bias is employed to make the network more powerful. For instance, when there are zero inputs, this ensures nonzero outputs. Bias is a weight of constant input of one (1). This is the basic difference between the bias and weight. The Levenberg-Marquardt function is used for the training phase, while mean square error (MSE) is selected as the performance function (Adedigba et al., 2017b). The choice of the Levenberg-Marquardt function as the optimization function is due to its high efficiency and fast rate of convergence (Adedigba et al., 2017a). The coefficient of determination (R^2) is the criterion used to end training. The expressions for MSE and R^2 are presented below (Adedigba et al., 2017b).

$$MSE = \frac{1}{n}\sum_{m=1}^{n}\left(Y_T - Y_{pred}\right)^2 \tag{3.12}$$

$$R^2 = 1 - \left\{\frac{\sum_j^n\left(Y_j^{Actual} - Y_j^{Predicted}\right)^2}{\sum_j^n\left(Y_j^{Actual} - \bar{Y}_j^{Actual}\right)^2}\right\} \tag{3.13}$$

where Y_j^{Actual} and $Y_j^{Predicted}$ introduce the actual and predicted values, respectively; $\bar{Y}_j^{Actual}$ represents the average of the actual value; the number of the actual values is *n*; *j* is the ordinal; and R^2 refers to the coefficient of determination.

Proper design of the ANN topology has been one of the most key issues in neural networks' applications to problems solving (Maschio et al., 2014). This refers to the identification of the number of neurons in the hidden layer, which is strongly dependent on the problem's specifications. Generally, this parameter is obtained by the trial and error approach by some researchers; however it has been an interesting area of research in the literature (Maschio et al., 2014; Vaferi et al. (2011). The optimum number of neurons in the hidden layer can be computed by an optimization procedure. In this research, we adopt the heuristic approach proposed by Vaferi et al. (2011) to determine this vital parameter.

ANN Learning Stage. One of the basic characteristics of the ANN is the ability to learn (Zendehboudi et al., 2018). The learning process is related to the ability of the network to update its structure and synaptic weights during the training stage when adequate data are provided. A cyclical process of computing or modifying the synaptic weights of the ANN to yield the desired output is referred to as training (Adedigba et al., 2017a). Therefore, allowing the model to find the optimal transformation arrangement of weights and their related input signals, which offer the nearest fit to the resultant target signal, remains the aim of training. After the training stage, the network can be used to perform targeted tasks due to its generalization capability. Supervised learning is used in the current research, as MLP uses the supervised training. Supervised learning is recognized as the most common type nowadays. During the training process, the feedforward propagation (forward activation) of the input data is followed by the implementation of the backpropagation algorithm to update (modify) the weight as a function of the computed error gradient (Onalo et al., 2018). The input data contain the static and dynamic data, while the target data are the corresponding reservoir production rates. Then, the unknown rock and fluid flow properties are approximated by the data driven model with its synaptic weights for the process modeling. 70%, 15% and 15% of the input data are used for the training, testing, and validation of the network respectively. The detailed procedure for the training phase is encapsulated as follows (Adedigba et al., 2017a):

- Selection of network type (network architecture): This is mostly dependent on the type and nature of the problem of interest.

- Input and target data provision: The model is fed with the required input and target data.

- Random selection (initialization) of the assumed network weights and biases: The initial values of weights and biases are randomly chosen by the network and consequently adjusted with any new iteration.

- Forward pass calculation: The network output is computed by propagating the input data through the network.

- Mean squared error (MSE) computation: After completing the forward pass, the difference between the target value and the obtained output value is estimated.

- Back propagation of error term: After obtaining MSE, the error term is propagated backward through the network using the differentials (derivatives) of the transfer functions in each neuron to update the weights.

- Cyclical computation: The updated (modified) weights are used to initiate a new iteration process. They are fed back into the network system for the next iteration. This continues till the process is truncated by some criteria, such as the network output being moved significantly closer to the target (i.e., the error becomes reasonably insignificant or MSE is almost zero), limiting the maximum number of epochs (cycles), and/or constraining validation checks.

Generalization of the data driven model. The ANN models have strong generalization capabilities if they are trained with adequate dataset. The basic objective of generalization is to make the ANN model workable with the dataset with which the ANN model is not trained.

3.3.4 Probabilistic Model

The system of Early warning index of oilfield development risk: The petroleum reservoir production system is a complex model with serious challenges. The challenges are mainly either the observed negative events or their root causes which may sometimes be effects consequent to some other basic events. The worst-case scenarios in the petroleum reservoir production system are “no flow” (zero production) and extremely low production, which are the events seriously dreaded by oilfield operators. These events are consequences. Therefore, adequate understanding of the physics of fluid flow in porous media is key to the development of a template for oilfield risk forecasting. In order to properly identify, evaluate, and predict the risks involved in this complex process, the logical reasoning demonstrated in dynamic systems by Zhong et al. (2016) for oilfield development is adopted to build the early warning index of oilfield risk evaluation with BN. The first step is to identify the key flow parameters referred to as indexes (Zhong et al., 2016), followed by a proper analysis of the relationship among them in the defined block. The constructed index system includes 6 indexes, which are the oil production rate, index of warning situation ($IDSN$); bottom-hole flowing pressure, index of warning sign (IWS_1); drawdown, index of warning sign (IWS_2); transmissibility, index of warning sign (IWS_3); gravity, index of warning sign (IWS_4); and storativity, index of warning sign (IWS_5). As the reservoir system operates without pressure support, pressure maintenance is not considered in the current research. Oil production rate is the only index of warning situation among them, and others are the warning sign indexes.

Determination of the degree of oilfield development risk. After a successful history match, the “3σ” rule is applied on the output from the trained data driven model to determine the interval of warning degree, where σ is the standard deviation (Zhong et al., 2016). Based on the statistical principle, the probability value is based on the extent of deviation of the index from the mathematical expectation. The probability is set to be 31.74%, if the extent of the sample deviation from its mean (μ) is greater than one times σ. At a value of greater than two times the σ, the probability is only 5% and for a value of more than three times σ, the probability represents less than 1% which is normally referred to as a little event probability. Thus, we can compute the degree of the indexes of warning situation based on the computed intervals as listed below:

- Obtain the mean (μ) and standard deviation (σ) of the warning situation indexes predicted by the neural network.

- Partition the indexes of warning situation into the different classified intervals: the normal interval $[\mu-\sigma, \mu+\sigma]$, light abnormal intervals $[\mu-2\sigma, \mu-\sigma]$ and $[\mu+\sigma, \mu+2\sigma]$, and severe abnormal intervals $(-\infty, \mu-2\sigma]$ and $[\mu+2\sigma, +\infty)$ by "3σ" rule (Zhong et al., 2016).

- Determine the warning degrees of the outputs (warning situation indexes) of the ANN. Risk is not recorded only if the warning situation index predicted value falls in the normal interval. If the predicted value is within the light abnormal range, a smaller risk is recorded compared to when it appears within the range of the severe abnormal degree that implies a larger risk.

3.3.5 Risk and Index of Warning Situation Predictions

Some geological realizations are generated to prepare the input data (indexes of warning sign) for the ANN used as a surrogate model using the available data for prediction of the index of warning situation. The relationship among the production parameters is used to build the early warning production index system. The static and dynamic reservoir properties and functioning constraints used to build the index system include the oil production rate, bottom-hole flowing pressure, drawdown, transmissibility, gravity, and storativity. These selected five indexes of warning sign are considered to exhibit a direct effect on the production rate (index of warning situation), leading to an effective artificial intelligent assisted history matching. To conduct the risk assessment, the procedure involves the BN being fed with the predicted warning situation index and probabilistic data. In this approach, the BN structural learning, parameter learning, and interference need to be performed. The directed acyclic graph is first built, followed by the conditional probability distribution assignment in the child node. The number of the conditional probabilities in a node can be determined from Eq. (3.17). The predicted flow rate is received as an evidence by the BN in five states; low production heavy warning, low production light warning, normal, high production light warning, and high production heavy warning as presented in Table 3.5. The Bayesian interference is then initiated using Eq. (3.18). The Bayesian interference is utilized to calculate the updated (posterior) probabilities of the priors upon observing any evidence.

The index of warning situation and oilfield block development risk are estimated with the data as described:

- Deploy the steps in section 3.3.1 as presented.
- History match and predict the risk associated with the index of warning situation (oil production) using Eqs. (3.14), (3.15), (3.16) and (3.18).
- Estimate the updated probabilities of the indexes of warning signs with any new evidence using Eq. (3.18), compare their prior and updated probabilities, and determine the risk source that results in change of the degree of the warning situation index.
- Apply relevant changes during the development of strategies if necessary.

$$\text{Normal intervals} = [\mu - \sigma, \mu + \sigma] \tag{3.14}$$

$$\text{Light abnormal intervals} = [\mu - 2\sigma, \mu - \sigma] \text{ or } [\mu + \sigma, \mu + 2\sigma] \tag{3.15}$$

$$\text{Severe abnormal intervals} = (-\infty, \mu - 2\sigma] \text{ or } [\mu + 2\sigma, +\infty) \tag{3.16}$$

$$N = a^n \tag{3.17}$$

in which, N refers to the number of conditional probabilities in a child node (the node where the directed edge ends) and a is the number of states in which the parameter (the parent node) exists, and n stands for the number of parent nodes (the nodes from which the directed edges start).

Eq. (3.18) is utilized for the dynamic risk analysis in the Bayesian risk assessment, as shown below:

$$P((IWS)_i|IDSN) = \frac{P(IDSN|(IWS)_i)P((IWS)_i)}{\sum_{i=1}^{N} P(R|(IWS)_i)P((IWS)_i)} \tag{3.18}$$

where IWS represents the warning sign index; $IDSN$ is the predicted warning situation index with known likelihood $P(IDSN|(IWS)_i)$; $P((IWS)_i)$ are the known prior probabilities; and $P((IWS)_i|IDSN)$ introduces the posterior (updated) probability of the priors.

3.4 Application/Case Study

The proposed hybrid model is applied on the data taken from the Society of Petroleum Engineers (SPE) comparative solution projects to simulate an oil reservoir. The reservoir consists of three layers that are hydrodynamically connected and a single production well that produces at a maximum oil rate of 21000 STB/D. The well shut-in criteria are a minimum BHP of 1000 psi, a water-oil ratio (WOR) of 5 STB/STB, and a GOR of 12.5 MSCF/STB. The simulation is run for 10 years without pressure support. Tables 3.2 and 3.3 give the layers' characteristics and reservoir model data, respectively.

Table 3.2: The reservoir characterization data.

Layer	Thickness (ft)	Porosity (fraction)	Horizontal permeability (mD)	Vertical permeability (mD)
1	20	0.3	500	50
2	30	0.3	50	50
3	50	0.3	25	25

Table 3.3: The data of the reservoir system.

Parameter	**Value**
Grid dimension	$10 \times 10 \times 3$ ft
Water density	62.4 1b/ft^3
Oil density	51.8 1b/ft^3
Oil compressibility	$3 \times 10^{-6}\ psi^{-1}$
Reservoir temperature	200 °F
Initial reservoir pressure	4800 psia
Bubble point pressure	2300 psia
Reference depth	8400 ft
Initial water saturation	0.2
Initial oil saturation	0.8
Areal grid block dimensions	1000 ft $\times$ 1000 ft
Gas specific gravity	0.792

3.5 Results and Discussion

A hybrid system that integrates a data-driven model with a probabilistic model to capture uncertainty and associated risks is proposed in this study. Table 3.4 lists the characteristics of the proposed ANN.

Table 3.4: Main features of the ANN model.

ANN model	**Parameter**
Network architecture	Feedforward back propagation
Input data	Static and dynamic reservoir properties
Number of layers	3
Number of hidden neurons	10
Output data	Production rate
Training algorithm	Levenberg-Marquardt
Training function	Logsig-Purelin
Performance function	MSE

The Bayesian network model uses the concept of the early warning index system. After the index of warning situation has been successfully predicted, the method presented in the previous section is employed to evaluate the warning situation index (oil production) degree of the production scenario. The range of warning degree is tabulated in Table 3.5. Figure 3.2 shows the BN model of the considered scenario.

Table 3.5: Intervals of warning degrees.

Category	Warning degree	Production Range (STB/day)	
Low production heavy warning (LHW)	1	0	6008
Low production light warning (LLW)	2	6008	11148
Normal (NOR)	3	11148	21428
High production light warning (HLW)	4	21428	26568
High production heavy warning (HHW)	5	26568	$-\infty$

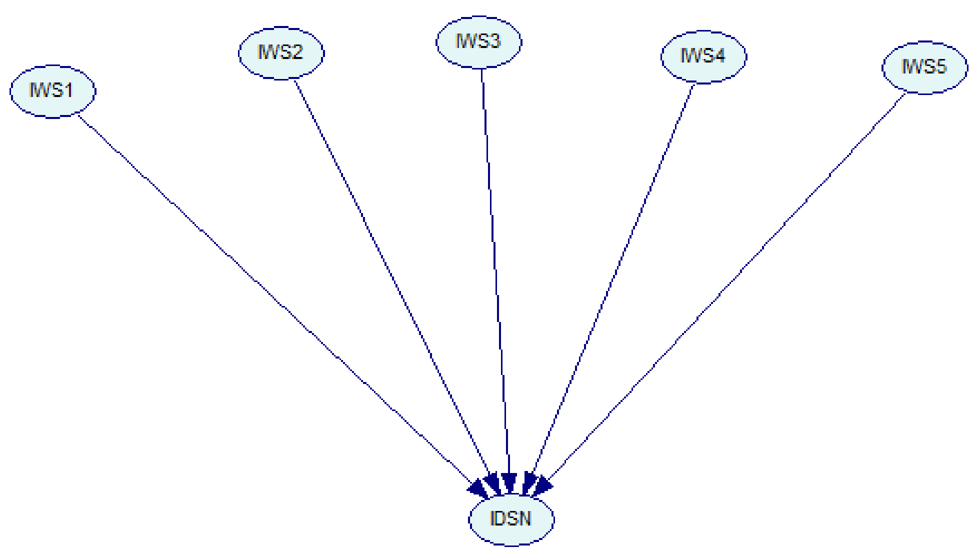

Figure 3.2: Bayesian network model suggested in the implemented methodology.

According to the results analysis, it is found that the predicted oil production profile closely matches the history matched data from the simulator. The assessed dynamic risks follow the field reality as presented in Figures 3.3, 3.5, 3.6, and 3.7. The use of the proposed approach would assist in effective reservoir management/decision making.

The risks, computational stress, huge time consumption, and other inherent challenges involved in the production forecast of the complex reservoir production system prompted the increasing efforts in this area of research in the last couple of decades, leading to advancement from single systems to hybrid systems, depending on the research objectives and the complexity of the problems. Stochastic and deterministic approaches have been applied by several researchers for providing efficacious solutions to these engineering problems; however, the former is confronted with computational challenges while the latter suffers from the lack of adequacy in process representation, even if used in the hybrid mode. The results obtained with the hybrid system proposed in this research work have demonstrated the need for a serious consideration of an integrated system of ANN and BN for reservoir production performance analysis.

The proposed methodology forecasts the oil production rate (index of warning situation) with the data driven part and the ANN output and other flow parameters are the inputs for the index system to construct the BN model, as shown in Figure 3.2. This hybrid system helps to analyze the associated risks in the field development when the oil production rate is precisely forecasted. The choice of the ANN structure in this research is based on its ability to model the process behaviour exclusively from relating the input and output data rather than from the process knowledge, irrespective of the extent of the dimensionality, non-linearity, and dynamics of the system, as depicted in Figure 3.3. This ANN potential has increased popularity in engineering applications.

They are the naturally inspired part of the artificial intelligence-based methods (Khazaeni & Mohaghegh, 2011). ANNs have been proven to be very effective in mathematical modeling and simulation for decades. However, what has always stood out as the innovation of the various developed methodologies has always been the problem of interest and the method of resolution. The cross-validation approach is employed in the current research to ensure that an appropriate number of validation checks is maintained to avoid the truncation of the training process while the network is still effectively learning. In addition, the limiting number of epochs is also considered with the network response to training. The model produces adequate results for production-related decision making. Figure 3.3 depicts the comparison between the results of the production rate obtained with the simulator and the hybrid model. The predicted oil production data closely match those from the simulator throughout the period of the forecast. To evaluate the predictive capability of deterministic models, there are some statistical criteria that consider the mean error values for showing the difference between the predictions and actual values. The statistical analysis helps to better understand the reliability and accurateness of the results presented in Figure 3.3. The mean absolute percentage error (MAPE) estimation yields minimum, average and maximum percentage errors of 0.02%, 5.28% and 15.85% respectively, given by Eq. (3.18). Table 6 shows the approximate mean errors of the results.

$$MAPE = \sum_{i=1}^{n} \left| \frac{\frac{Y_T - Y_{pred}}{Y_T}}{n} \right| \times 100 \tag{3.18}$$

where Y_T is the actual value; Y_{pred} is the predicted value; n represents the total amount of data

Table 3.6: Approximate mean value.

Statistical Method	**Mean value**
Mean absolute percentage error (MAPE)%	5.28
Root mean square error (RMSE)	797.70
Mean absolute deviation (MAD)	697.00

The results show that the hybrid system adequately models the non-linear complex dynamic isothermal reservoir flow processes. The profile generated by the model demonstrates how much it captures the temporal-spatial dependency of the process and is adequate for production-related decision making. There is a good agreement between the ANN predictions and simulator results during the infinite acting period of the reservoir production scenario, and after the end of the flow period. This indicates the accurate choice of the model input parameters and optimal structure design which does not necessarily have design criteria. However, it means that the flow properties are sufficient as input data while the unknown fluid and rock properties are approximated by the proposed model with its synaptic weights. Thus, adequate modeling of the non-linear complex relationships of the reservoir flow processes is guaranteed.

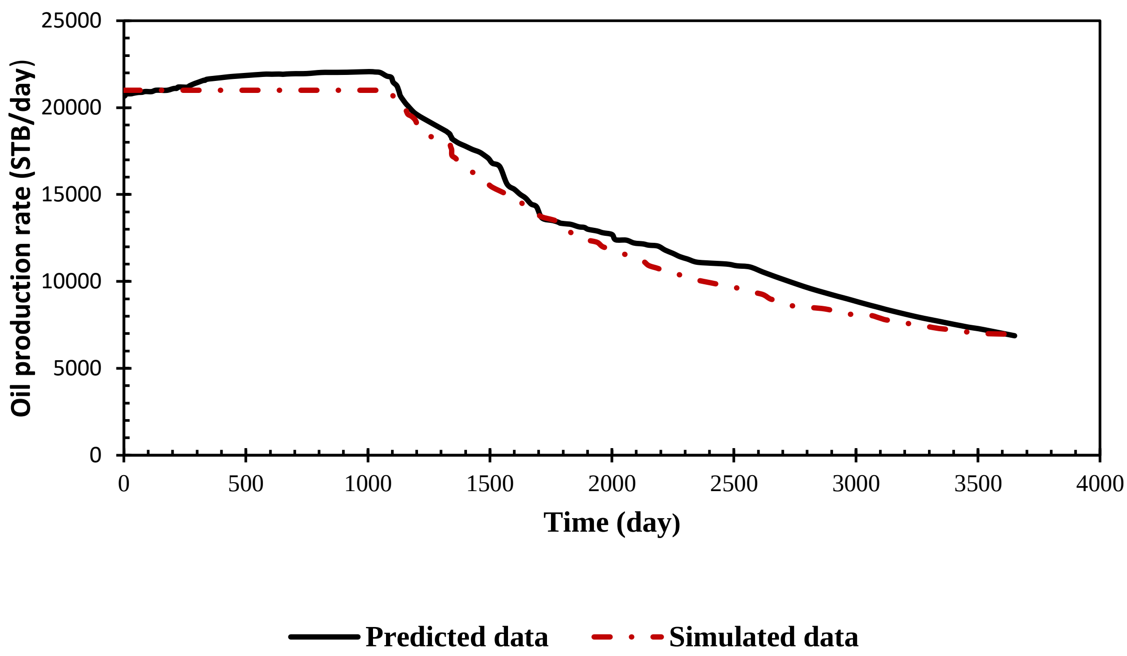

Figure 3.3: Comparison of production rate obtained with the simulator and the hybrid model.

After building the hybrid model, the BN part of the methodology performs a dynamic assessment of the risks associated with the production forecast in the oilfield development phase by evaluating the updated probability distribution of the indexes of warning sign (see Figures 3.4 to 3.7). There is a big risk only if the warning situation index predicted value is within the severe abnormal range and less risk would exist if the corresponding value were in the light abnormal interval. Risk ceases to exist only if the warning situation index predicted value is within the normal range. Oil production can have five possible states: low production heavy warning (LHW), low production light warning (LLW), Normal (NOR), high production light warning (HLW), and high production heavy warning (HHW). Figure 3.4 shows the parameter learning of the Bayesian network model of the proposed methodology, i.e., before observing any evidence. To analyze the risk, we start with observing normal production as depicted in Figure 3.5. This shows that the drawdown (IWS_2) must be 98% reliable (NO) to have normal production without interruption, maintaining a risk as low as only 2% (YES). This is better understood when compared to the learning state of the Bayesian network model of the proposed methodology as illustrated in Figure 3.4. Interestingly, this logical deduction is consistent with the field reality. However, if evidence of a severe low oil production state is observed, Figure 3.6 describes the possible causes in the updated probability distribution analysis of the Bayesian model. It is concluded that severe low production (including zero production) is only conceivable if the risk associated with the drawdown is 99% (e.g., a reliability of 1%). This implies that "no flow" or severe low production is a direct consequence of drawdown failure. This logical conclusion is in conformity with the principle of fluid flow in porous media and remains the biggest challenge in petroleum production engineering. Figure 3.7 demonstrates that the oil production rate value tends to shift or shifts from a severe low production state towards the normal oil production state when the risk associated with the drawdown (reservoir pressure drops) reduces. This is another milestone confirming the usefulness of the logical reasoning results from the proposed methodology. Part of the merits of the BN include: 1) Bayesian techniques can combine prior information, knowledge, and subject matter expertise without corresponding data; and 2) Bayesian techniques enable cause-effects interpretations rather than just correlations (Wang & Amrhein, 2018).

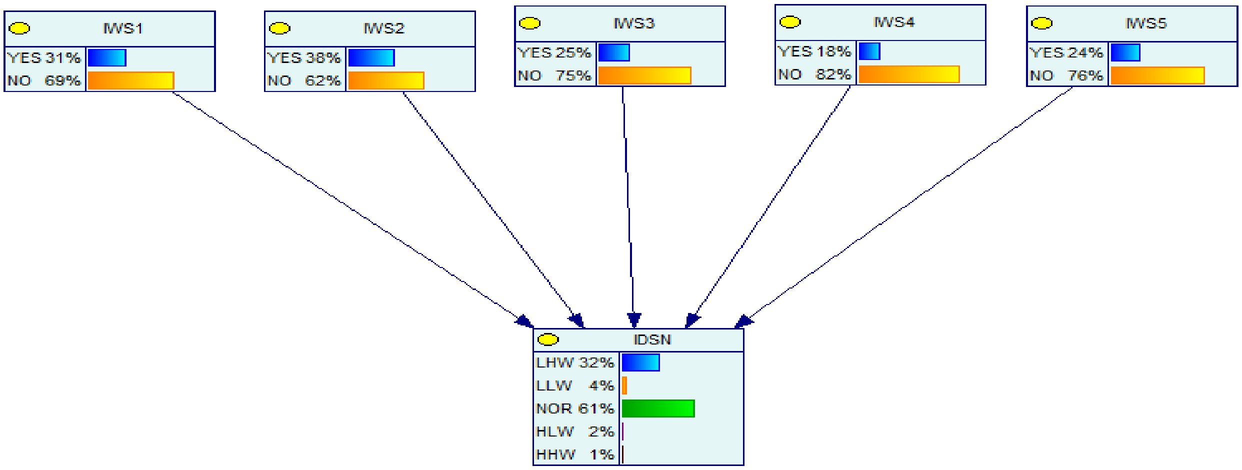

Figure 3.4: Bayesian network (BN) model's parameter learning of the proposed hybrid methodology.

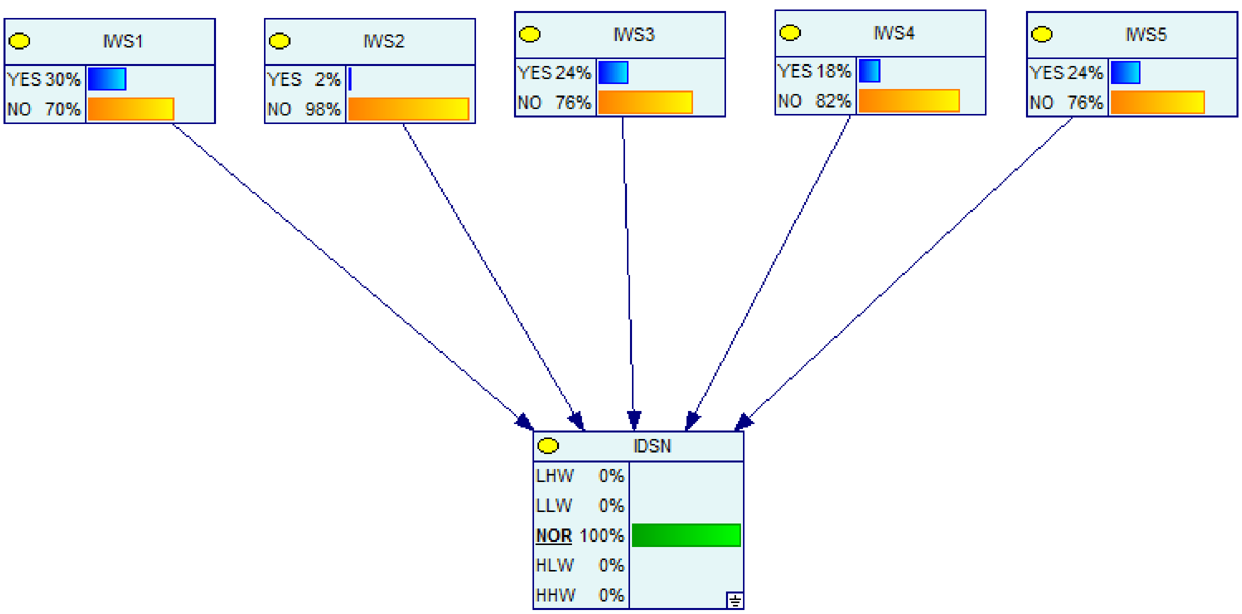

Figure 3.5: Posterior probability distribution of the logical model of the hybrid methodology with the evidence of a normal oil production state.

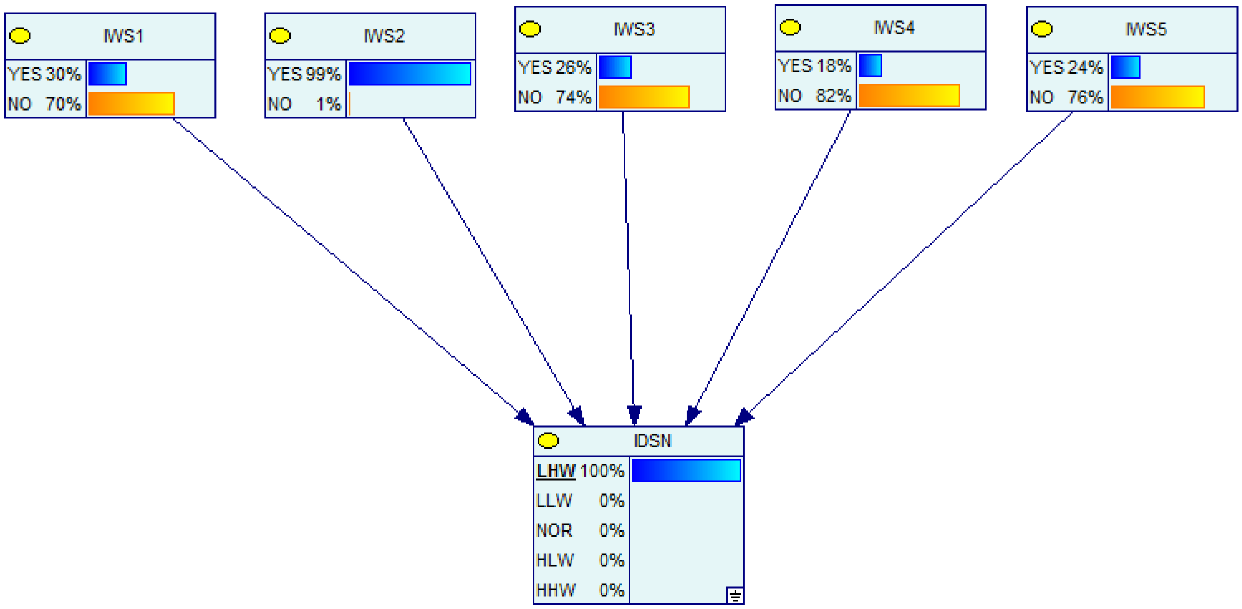

Figure 3.6: Updated probability distribution of the logical model of the hybrid methodology, considering the evidence of a severe low oil production state.

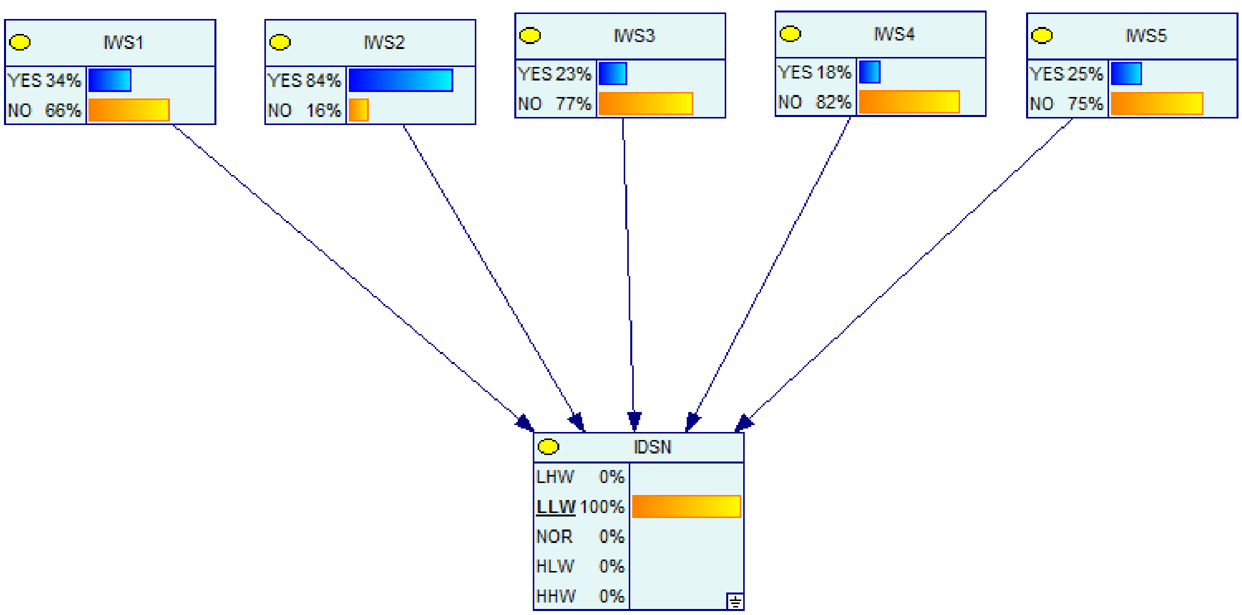

Figure 3.7: Updated probability distribution of the logical model of the hybrid methodology when the low oil production state is maintained.

A promising model has been proposed to bridge the gap inherent in the traditional commercial simulators in history matching and to conduct a dynamic risk assessment of the associated risk with the production forecast in the oilfield development phase. However, it is imperative to highlight basic drawbacks of the hybridized artificial based intelligent models. The performance and reproducibility of the ANN model strongly depend on the training process and the data which with the model is trained. One of the main challenges attributed to the ANN models is over fitting. Over fitting can hinder the generalization capability of the model and may also affect the prediction accuracy of the model (Onalo et al., 2018). In some cases, increasing the amount of data is reported not only to increase the computational time but also increase the possibility of over fitting (Onalo et al., 2018). Hence, better prediction is not always attained after increasing the amount of input data. Cross validation, regularization, and early stopping have been used to prevent the problem of over fitting (Adedigba et al., 2017a). ANNs have low extrapolation capabilities and process knowledge (Zendehboudi et al., 2018). Though the ANNs exhibit less computational burden, accurate determination of the model parameters and optimal structure design remains a major pitfall (Zendehboudi et al., 2018). The set criteria for optimal structure design of the ANN model to produce the best results do not exist (Onalo et al., 2018). The major setback of the BN is the subjectivity impact on the posterior estimates. This is because sometimes the subjective nature of the priors may substantially influence the posterior probability distribution.

Oil and gas industries have been presented with a template to reduce production forecast computational stress and to incorporate a dynamic risk assessment of the oilfield block development risk. This effectively reduces input data handling and the huge computational time required for history matching. In addition, it provides simultaneous monitoring of the effects of the production variables on the production rate and extent of the resultant risk upon observing any new production information. The proposed methodology also offers oil and gas industries an easier and cost-effective means to capture reservoir heterogeneities.

3.6 Conclusions

This research study presents a hybrid approach to forecast production and the risks associated with oilfield development. The current study only considers a production scenario without pressure support from which the results are reported. Therefore, the conclusions are drawn for this specific case of reservoir production system. The results show that some of the inherent drawbacks of the traditional commercial simulators such as a limited capability to capture temporal and spatial variability of the data, uncertainty in the data and reservoir models (and/or characteristics), and the influences of these factors on the overall production risk profile are addressed with the proposed hybrid system. In addition, the developed model yields best predictions at early and late time periods of production flow.

The proposed method combines the data-driven model with a logical model to capture variability, uncertainty, and associated risk. The application of the proposed approach would offer the field operators an efficient and effective reservoir management decision making strategy. According to the research results, the following conclusions can be drawn:

- A system that incorporates a Bayesian network with an artificial neural network can efficiently forecast oil production and provide means for dynamic risk updating.

- A Bayesian network can provide real time identification of risk sources. Hence, it can serve as an important tool for production risk management decisions.

- The artificial neural network is a promising predictive tool that offers reservoir engineers a proper approach for reduction of computational costs and simulation time.

- The artificial intelligence generates results that closely match the history matched data from the simulator, while the Bayesian network produces logical results consistent with the principles of fluid flow in porous media.

- The hybrid system yields minimum and average percentage errors of 0.02% and 5.28% respectively in the reservoir production forecast conducted in this research work.

Although a hybrid methodology to forecast production and conduct a dynamic risk assessment of the risks associated with the oilfield development phase is presented in this work, further complexities in terms of reservoir analysis and risk management are involved in our future research study, where pressure maintenance is considered.

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Chapter 4

A Hybrid Intelligent Model for Reservoir Production and Associated Dynamic Risks

Preface

A version of this chapter has been published in the ***Journal of Natural gas Science and Engineering 2020;18July:103512.*** *I delivered this work along with my co-authors; Faisal Khan, Sohrab Zendehboudi, and Sunday Adedigba. I am the main author. I conducted the literature review, formulated the concepts of the model and developed it for dynamic risk monitoring for secondary recovery processes. I prepared the first draft of the manuscript and subsequently revised the manuscript based on the co-authors' and peer review feedback. Co-author, Faisal Khan assisted in the development of concept, design of methodology, reviewing and editing the draft, and reviewing and revising the new version of the manuscript. Co-author, Sohrab Zendehboudi supported in the design of the methodology, reviewing and editing the draft, reviewing and revising the manuscript. This co-author also helped in the validation, review, and correction of the model and results. Co-author, Sunday Adedigba supported in the methodology concept development and implementation.*

Abstract

This research presents a hybrid model to predict oil production and to provide a dynamic risk profile of the production system. The introduced predictive approach combines a multilayer perceptron (MLP)-artificial neural network (ANN) model with a hybrid connectionist strategy (BN-DBN), which comprises a Bayesian network (BN) model and a dynamic Bayesian network

(DBN) model. The proposed hybrid methodology (MLP-BN-DBN) is designed to find the correlations between the input and output data to forecast the desired oil production rate. The MLP model captures the variabilities in the fluid and rock properties, model's uncertainties, and the effects of pressure maintenance on the production process. The BN model uses the 3σ mathematical rule to promptly signal the arrival of any production rate change and captures the pressure maintenance impact using the early warning source indexes. The DBN model provides a dynamic risk profile of the production system using the observed evidence and reservoir production hyperbolic decline concept.

The proposed methodology offers the field operators better opportunity to obtain real time estimate of the likelihood of impending production loss at any time during production operations. The model exhibits a high capability of oil production prediction with the minimum, averange, and maximum percentage errors of 0.01%, 6.57%, and 15.28%, respectively. The developed hybrid model serves as a risk monitoring system. The model is cost-effective and eases the computational burden of history matching processes and bridges the gaps in the existing systems for oilfield development dynamic risk forecast and production predictions. Hence, the proposed methodology serves as a multipurpose tool for dynamic risk assessment and for proper reservoir production optimization.

Keywords: Bayesian Network; Dynamic Risk Profile; Early Warning System; Multilayer Perceptron; Production Prediction; Pressure Maintenance

4.1 Introduction

Oil and gas production history and field experience have shown that the petroleum reservoir is a complex system composed of intrinsically uncertain data. The challenges of the dynamic risks associated with the dynamic data (production variables or indexes of warning situation) have become even more alarming, leading to production losses or avoidable production downtime, due to inadequate production risk analysis strategies (Mamudu et al., 2020). Interestingly, while efforts are being made to reduce the challenges associated with intrinsically uncertain data through history-matching, a computationally expensive process in petroleum reservoir engineering, the approaches used to resolve the dynamic risk remain scarce in the literature. History-matching is a process of determining a proper model's parameters so that the model's output data are as close as possible to the historical data (Mamudu et al., 2020; Subbey et al., 2003). This process aims to properly adjust the behaviour of the modeled system to simulate the behaviour of the actual case (Mamudu et al., 2020). Although artificial intelligence systems are being proposed to tackle the history-matching challenges in some research works, the literature has yet to report a dynamic risk profile of the production process of petroleum reservoirs. The dynamic predictive model analyzes and updates current and future production trends and forecasts the oilfield production dynamic risk, as proposed in this work. It uses real time and future early warning and risk prediction principles, hybridized with the concept of human biological neural structures exercised by a data-driven computational tool (information processing unit). In the current study, the main setbacks of history-matching and the challenges associated with a dynamic risk profile of the reservoir dynamic data are resolved using the proposed hybrid strategy. Reservoir simulation with the commercial numerical simulators is prohibitive because of the challenges associated with the variability of the model's input data, the model uncertainties, and the number of runs required to generate the geological realizations; this is relatively expensive in terms of CPU time (Subbey et al., 2003). On the other hand, analytical models suffer from a lack of adequate representation of the nonlinear complex behaviors and relationships of the reservoir system (Khazaeni & Mohaghegh, 2011; Mamudu et al., 2020).

There has been increasing interest in the applications of artificial intelligence models for solving complex and time-consuming engineering problems in the last two decades. Most interestingly, their applications in the development and production phases of oil field operations are relatively scarce in the literature. With proper implementation of these tools, the oil and gas industries would achieve some basic goals by applying cost-effective methodologies for simulation and projection of production behaviours and associated risks. Mamudu et al. (2020), in their work, presented a comprehensive review of the most recent efforts made in solving production-related challenges using predictive models. They identified the existing gaps in the literature and used their proposed innovative connectionist method to predict oil recovery and capture the uncertainties updating. However, their approach does not consider the pressure maintenance effect and dynamic risk profile of the reservoir production. Table A1 in the Appendix summarizes the identified pitfalls based on the literature review and highlights the differences between the current work and the previous related studies.

Advancement in the use of smart models in engineering problems has led to increasing research interests in the oil and gas industry in the last decade. In this work, we present an overview of the most relevant previous studies that deal with the application of smart models for hydrocarbons production prediction and uncertainty analysis. For instance, Subbey et al. (2003) used neighborhood algorithm (NA) for production prediction but the risks were not included in their study. Similarly, Nicotra et al. (2005) employed the same approach with the same setback. In addition, their models are stochastic, deficient in dynamic risk analysis, and expensive to be applied. They did not take into account the pressure maintenance influence and dynamic risk evaluation in their models. Lechner et al. (2005) implemented artificial neural network (ANN) model for production prediction; however, the risks were not investigated. The pressure maintenance and dynamic risk profiling were also not considered; their approach was stochastic. Khazaeni and Mohaghegh (2011) utilized artificial neural network (ANN) to forecast oil production. Like others, the risks analysis was not included in their model. Shahkarami et al. (2014) effectively used an ANN model for production forecast. However, the risks were not studied in their work. Similarly, Augusto et al. (2014a) developed a stochastic approach with ANN model to predict oil production. The dynamic risks were not studied in their work. In addition, they did not incorporate pressure maintenance in their developed model for production forecast. Maschio et al. (2014) applied the Markov Chain Monte Carlo (MCMC) to predict oil production. Their model does not capture dynamic risk profiling, and pressure maintenance. In fact, their approach is stochastic, prohibitive, and inadequate for dynamic risk analysis. Zhong et al. (2016) developed an integrated model, which combines ANN with Bayesian network (BN). Similar to other previous studies, their model does not consider the dynamic risk profiling. Sun and Ertekin (2017a) presented a stochastic model for cyclic steam stimulation. Their model does not capture dynamic risk analysis. Moreover, it is limited to cyclic steam stimulation processes. Their model does not consider dynamic risk profiling. Like Zhong et al. (2016)'s work, Mamudu et al. (2020) introduced an advanced connectionist approach that combines the ANN and BN for process analysis. The dynamic risk profiling, and downhole pressure maintenance were not considered in their work. In summary, this review has shown that the available modeling smart methodologies do not capture the dynamic risk profiling of the production system as well as the effects of downhole pressure maintenance processes on the overall dynamic risk profile of the production system. Thus, to the best of the authors' knowledge, none of the current intelligent models can perform dynamic risk assessment of the reservoir production systems with pressure support. These knowledge gaps are bridged in the current study.

The main objective of this research work is to develop a hybrid model to overcome the drawbacks of the model presented by Mamudu et al. (2020). The proposed model considers the nonlinearity behaviours of the process flow variables and their interactions. The model is built to incorporate the pressure maintenance condition and provide a dynamic risk analysis. This study includes contour plots to predict the transition time and state from a higher production rate to a lower production rate. This helps in monitoring the production trends and variations to avoid unnecessary production downtime. In addition, the proposed hybrid model offers a proper dynamic risk monitoring system for field operators.

This work is structured as follows. After the introduction section, the theory and background are presented in Section 4.2. In this section, the concepts of Bayesian network (BN) and the dynamic Bayesian network (DBN) are discussed. Artificial neural networks (ANN) concept is also briefly explained in the section. Section 4.3 describes the proposed research methodology. It presents the details of the steps involved in the proposed procedure to investigate the three important aspects of the hybrid model: 1) temporal and spatial data set building, 2) surrogate model development for oil flow rate forecast, and 3) dynamic risk analysis during oilfield development and production, using an early warning system. Section 4.4 includes the field application of the introduced model.

Section 4.5 contains the study results and discussions. Section 4.6 presents the research conclusions.

4.2 Background and Theory

Risk can be broadly described as a measure of economic loss. This refers to both the likelihood of an invent and the extent of the loss. Thus, risk analysis has become highly expedient in huge investments such as oilfield development and production. The dynamic risk assessment conducted with the BN model in the hybrid strategy (employed in the current study) uses the principles of early warning and risk prediction. The early warning index incorporates the concepts and procedures of risk assessment (Mamudu et al., 2020; Baca & Petersen, 2013; Horneret al., 2011). Typically, the indicators of risk can be grouped into three broad categories for risk analysis in the development and production phases of oil and gas operations: the warning situation index, index of the warning source, and warning sign (Mamudu et al., 2020; Zhong et al., 2016). Water production, oil production, and gas/oil ratio (GOR), gas production that are measurable are considered as the indexes of warning situation. They are the commonly observed variables in the field development and production stages. The indexes of warning sign have direct relationships with the situation indexes. The warning source indexes are the causes of the risk; for instance, they are the basic variables such as transmissibility, storativity, and injection rates 1, 2, 3, and 4. Further information on the early warning concept can be found in open sources (Mamudu et al., 2020).

ANN is usually referred to as a computational tool originating from the logics/concepts of the human biological neural systems (Mamudu et al., 2020). ANN is characterized by its potential to perform input - output mapping in complex processes without the underlying process knowledge and irrespective of the process dimensionality and nonlinearity (Mamudu et al., 2020;

Mohaghegh, 2005; Noureldien & El-banbi, 2015; Onalo et al., 2018; Mojtaba et al., 2010; Rezaee et al., 2007; Shahkarami et al., 2014; Sun & Ertekin, 2017; Tariq, Elkatatny etb al., 2016; Tavassoli et al., 2004; Zendehboudi et al., 2018; Zhao et al., 2012). It is one of the archetypes of artificial intelligence (AI) method (Mamudu et al., 2020). The ANN approach has been employed in numerous disciplines (Adedigba et al., 2016, 2017; Aminzadeh, 2005; Augusto et al., 2014; Foroud et al., 2014; Kalantari et al., 2009; Khazaeni & Mohaghegh, 2011; Long et al., 2016; Ma et al., 2018b, 2018a; Maleki et al., 2014). In the exploration and appraisal phases of oilfield development, many researchers and industry professionals have used artificial intelligence-based models to solve challenges associated with temporal-spatial dependency and non-linear complex relationships involved in isothermal reservoir flow behaviour encountered in petroleum industries.(Ali et al., 2013; Kalantari et al., 2009; Mamudu et al., 2020). However, less efforts have been made in the development and production phases of hydrocarbon reserves (Mamudu et al., 2020; Mohaghegh, 2005; Nikravesh & Aminzadeh, 2003). The most relevant and advanced proposed AI-based models are reviewed in the current work (see Table 4.A1) to clearly show the existing knowledge gaps in the literature and contribution of our research work. Thus, we propose a hybrid model for effective advancement and modification of the existing traditional and hybrid connectionist methodologies.

The ANN model adopted in this research is the multilayer perceptron (MLP). In this approach, the data propagation in the multiple layers normally starts from the input layer and ends at the output layer (i.e., in the forward direction). Further details on the ANN fundamentals, classification, topology, applications, learning methods, and connection types are given in the literature (Mamudu et al., 2020). ANN assembly is primarily made up of an input, hidden and output layer(s) (Adedigba et al., 2017). The MLP is characterized by its capability to receive signals and form networks between the routes in the model's layers, using the intrinsic unified network's neurons. Details of the process modelling, which begins with weights' random selection and successive adjustment, are found in the comprehensive work of Mamudu et al. (2020). Some detailed review documents reported in the literature provide useful information and descriptions of weight initialization and updating, and the activation or transfer functions commonly used in ANN systems (Zendehboudi et al., 2018). The MLP approach in the proposed hybrid system uses Eqs. (4.1) and (4.2) to predict the production at any time (t) (Mamudu et al., 2020):

$$Q_{jk} = f_1\left(b_j + \sum_i W_{ij} I_{ik}\right) \tag{4.1}$$

$$Q_k = b + \sum_i W_j Q_{jk} \tag{4.2}$$

where Q_{jk} represents the hidden layer neuron output; W_{ij} and W_j denote the synaptic weights; f_1 introduces the hidden layer neuron transfer function; b_j is the bias of the hidden layer; b symbolizes the bias of the output layer; I_{ik} refers to the input vector; and Q_k is the output (dynamic data) from the neuron in the output layer.

The BN system is a product of Bayes' rule. It can be defined as a graphical tool that encodes probabilistic relationships among random variables and their conditional dependencies by utilizing a directed acyclic graph (Mamudu et al., 2020). Bayes' rule describes how to update the probabilities of hypothesis, given an evidence. Mamudu et al. (2020) presented the general form of Bayes' rule given in Eq. (4.3) for risk updating. If there exists a set of discrete random variables (Y) , the joint probability distribution is mathematically expressed by Eq. (4.4) (Adedigba et al., 2016b; Bhandari et al., 2015):

$$PP(Y_i|Q) = \frac{P(Q|Y_i)P(Y_i)}{\sum_{i=1}^{N} P(Q|Y_i)P(Y_i)} \tag{4.3}$$

$$(y_1, y_2, \dots \dots .., y_n) = \prod_{i=1}^{n} P\big(y_i \big| Pa_{(xi)}\big) \tag{4.4}$$

in which, $\mathrm{Y}_1, \mathrm{Y}_2 \dots, \mathrm{Y}_\mathrm{n}$ represent the variables of the set, *Y*; Q is a variable of a known $P(Q|X_i)$; $P(Y_i)$ introduces the prior probabilities; and $P(Q|Y_i)$ is the posterior probability of any variable Y_i, given Q.

The Bayesian network model can only be used for prior probabilities' updating to analyze the risk sources among the input variables during parameter learning, having any observed evidence. Thus, the main objective of the Bayesian network (BN) is to compute the updated probabilities of probable causes, given an evidence. This updating process can be performed at any discrete time interval with the BN model. This is because it deals with discrete functions. To reflect the dynamic effect of observed evidence at a discrete time interval in the entire production period, a dynamic form of the BN is required, since the production rate is a continuous function. This implies that a hybridized system of the Bayesian network (BN) model and a dynamic Bayesian network (DBN) model are needed to capture the effects of each observed change in the dynamic variable (change in the warning situation category) of the production profile, as proposed in this research. In other words, the DBNs are the Bayes' networks for dynamic processes. In fact, the BN introduces appropriate temporal dependencies to model the random variables' dynamic behaviours. DBNs are established to cope with systems having complex dynamics (Zhang et al., 2018). Therefore, the DBN can adequately simulate the dynamics of the complex nonlinear reservoir production system. The joint probability distribution of a DBN model with the total time steps, T, is obtained by Eq. (4.5) (Zhang et al., 2018).

$$P(Y_{1:T}^{1:N}) = \prod_{i=1}^{N} P_{B1}\left(x_1^i \middle| Pa(Y_1^i)\right) \times \prod_{t=2}^{T}\prod_{i=1}^{N} P_{B\rightarrow}\left((Y_t^i) \middle| Pa(Y_t^i)\right) \tag{4.5}$$

In Eq. (5), Y_t^i represents i^{th} in the time-step t; $Pa(Y_1^i)$ is the parent Y_t^i that is either in the prior time-step$(1-t)$ or the same/equivalent time-step t; N denotes the random variables' number in Y_t^i; and T refers to the number of time-steps. A detailed theory of the DBN model is found in the work of Zhang et al. (2018).

4.3 Proposed Methodology

This section systematically describes the method employed in this research study.

4.3.1 Main Procedure Steps

Figure 4.1 depicts the steps involved in the procedure implemented to investigate the three important aspects of the hybrid model: 1) temporal and spatial data set building, 2) surrogate model development for oil flow rate forecast, and 3) dynamic risk analysis during oilfield development and production, using an early warning system. Referring to steps 1 and 2, data collection and processing are performed. At this phase, the dataset is prepared for the reservoir model development using geological data taken from a case study available in a commercial simulator. Also, the probabilistic data are prepared at this stage. At step 3, the data classification is conducted to transmit the probabilistic data to the BN model through the early warning index system (steps 5, 6, and 7). The non-probabilistic data are transferred to the ANN model for surrogate model development and implementation at step 4. The MLP model is utilized at step 4 to forecast the oil production rate. The predicted oil production rates are transmitted and received at step 5 as the indexes of warning situation. The early warning index system (EWIS) of oilfield development block is activated at step 5 for the index concept initiation. Thus, at step 5, a complete early warning system is built. The implementation of the statistical "3σ" rule is performed at step 6 to introduce the probabilistic concept for the warning intervals' determination. At step 7, the intervals of warning degrees are determined, and the EWIS output data are transmitted to the BN model. At step 8, the BN model is activated for structural and parameter learning. The flooding pattern (e.g., five-spot flooding pattern) is selected for the BN learning; the effects of both the injection and production wells are incorporated. Identification of evidence of any change in the production rate occurs at step 9. At step 10, a decision is taken upon observing any evidence of change in the dynamic data. If a change in the warning degree is not observed, step 10 is repeated until there is an observable variation in reservoir production. If a change is observed, the prior probabilities are updated at step 11, and the evidence is directly transmitted to the DBN model for dynamic risk profiling of the production system, to capture the dynamic impact of the change on the well production life. At step 12, the DBN model recognizes the observed evidence transmitted from the BN model and propagates it to step 13, where it is analyzed through implementing the hyperbolic decline rate concept, a variable from a range of values between two extremes: the harmonic and exponential decline rates. The dynamic risk profiles are developed at step 14 for risk monitoring.

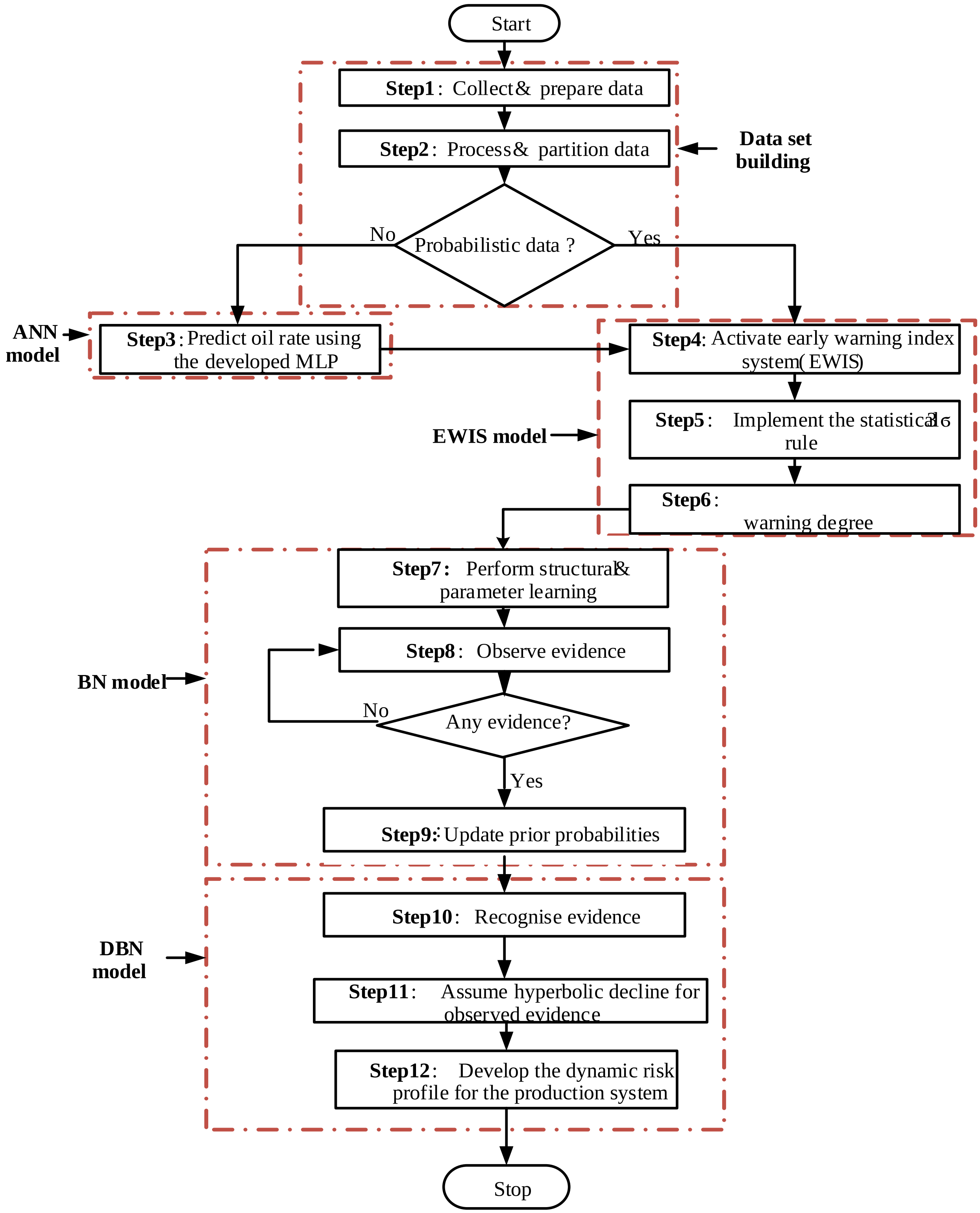


Figure 4.1: Proposed hybrid connectionist methodology (MLP-BN-DBN).

4.3.2 Data Collection/Preparation

The data required for the development and implementation of the hybrid connectionist model are mainly influenced by the function of each interconnected component of the proposed deterministic strategy. Therefore, the aim of modeling work strictly regulates the selection of input parameters/variables for the ANN model used in the proposed methodology (Mamudu et al., 2020; Shahkarami et al., 2014). Appropriate data selection remains the most vital and challenging task in data driven model development. Therefore, the reservoir flow properties that considerably affect the oil production rate and its associated dynamic risk quantification are given a high priority. The processed data comprise both probabilistic and non-probabilistic data. The non-probabilistic data are built with the temporal-spatial dataset, which includes the static and dynamic reservoir properties as well as the operational constraints. The static data are the reservoir variables, such as absolute permeability, transmissibility, storativity, porosity, and pay zone thickness. The dynamic variables/parameters include the bottom-hole flowing pressure, oil production rate, and production time. Table 4.1 lists the variables considered for the BN and DBN models.

Table 4.1: Early warning index system data for BN and DBN models.

No.	Early warning system index	Parameter
1	Index of warning source	Injection rates 1, 2, 3, and 4
2	Index of warning sign	Drawdown, reservoir pressure, bottom-hole flowing pressure, storativity, and transmissibility
3	Index of warning situation	Oil production rate

4.3.3 Artificial Neural Network Model (ANN)

The ANN model implemented in this research is the MLP type. The ANN is an algorithm that has been originated from the motivation of developing a machine, which can mimic human brain behaviour and neurons' interconnections (Kim et al., 2019; Shahkarami et al., 2014). The model basically utilizes a group of artificial interconnected neurons to achieve its basic functions (Elkatatny et at., 2018; Elkatatny et al., 2019; Elkatatny et al., 2018; Moussa., 2018; Ossai, 2020; Pakzad et al., 2020; Tariq et al., 2017b, 2017a). The functions include evaluation, prediction, clustering, and classification (Mamudu et al., 2020; Zendehboudi et al., 2018). The function required in this study is prediction. According to the MLP model, the signal communication in the ANN with multilayers moves from the input layer to the output layer, and the errors are propagated backwards. MLP is the most commonly training approach used in various engineering disciplines. The AI model receives information in the input layer, transmits it through the hidden layer(s), and forecasts the expected output at the output layer. The hidden layer's neurons use the log sigmoid transfer function, while the output layer neuron uses the linear activation function to meet the requirements of the expected target.

There are ten biases used in the MLP model architecture, which are randomly selected by the network. The used training algorithm is the Levenberg-Marquardt function. The network uses mean square error (MSE) for the performance criterion during training. The Levenberg-Marquardt training algorithm is selected because of its efficiency. The coefficient of determination (R^2) is another important criterion applied to end the training phase. The formulas for MSE and R^2 are given as follows (Mamudu et al., 2020):

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(Y_T - Y_{pred}\right)^2 \tag{3.6}$$

$$R^2 = 1 - \left\{\frac{\sum_j^n\left(Y_j^{Actual} - Y_j^{Predicted}\right)^2}{\sum_j^n\left(Y_j^{Actual} - \bar{Y}_j^{Actual}\right)^2}\right\} \tag{3.7}$$

where Y_j^{Actual} and $Y_j^{Predicted}$ denote the actual and predicted values, respectively; $\bar{Y}_j^{Actual}$ refers to the mean of the actual data; *n* stands for the number of the actual data ; *j* resembles the position vector; R^2 introduces the coefficient of determination; and i represents the position.

Mamudu et al. (2020) reported that effective ANN topology design is one of the most difficult tasks in ANNs' development and applications (Maschio et al., 2014). The challenge lies in the identification/determination of the best possible number of the hidden layer neurons (Maschio et al., 2014). According to Mamudu et al. (2020), it is firmly reliant on the desired target's requirements. Based on the work of Maschio et al. (2014) , this parameter can be obtained by the trial and error procedure. Determination of this parameter through more reliable and accurate methods has been an interesting research topic (Maschio et al., 2014; Vaferi et al., 2011). The approach used by Mamudu et al. (2020) and Vaferi et al. (2011) to offset the challenges associated with determination of the optimum number of neurons is adopted in this research work; this basically involves an iterative process. The error convergence with a definite change in the number of hidden layer neurons in a particular order is monitored. Once the optimum value is obtained, the process stops. Otherwise, the order is changed.

The ANN is generally characterized and recognized by its ability to learn the corresponding operation and/or phenomenon. This process enables the model to adjust its synaptic weights and structure in the training process. However, suitable data should be supplied in the training phase. An iterative procedure of modifying the MLP synaptic weights to forecast the desired target is known as training (Adedigba et al., 2017a). The network can be used to perform targeted tasks after the training stage because of its generalization capability. In fact, the data-driven models have robust generalization capabilities when trained with an adequate number of data points. The main aim of model generalization is to enable the MLP model to perform efficiently including more data than the training data. The MLP utilizes supervised learning; hence, the supervised learning scheme is also chosen in this study. 15%, 15%, and 70% of the input data are selected for the testing, validation, and training of the network, respectively. A comprehensive procedure for this learning phase is provided in the literature (Mamudu et al., 2020).

4.3.4 Probabilistic BN and DBN Models

Both BN and the DBN models are the graphical tools, known for dynamic risk (probabilities) updating and dynamic risk profiling, respectively. The BN can be utilized for prior probabilities updating to analyze the risk sources. This process works for the risk identification of the process at any time; it is suitable for a discrete function. The DBN should be introduced to conduct dynamic risk evaluation over time if it is a continuous variable, noting that the DBNs are appropriate for dynamic processes. The DBN model is a BN system that establishes adequate temporal dependencies to model the random parameters' dynamic behaviours. Thus, it can handle systems with complex dynamics such as nonlinear reservoir production cases (Zhang et al., 2018). One of the most difficult tasks in the Bayes' networks' construction is the learning. The structural and parameter learnings are conducted using experts' knowledge and prepared data. The parameter learning is more challenging, owing to the required information of the conditional probabilities table (CPT). To perform the learning process of this logical hybrid model (BN and DBN), the EWIS is employed. Mamudu et al. (2020) presented a comprehensive precedure for this phase in their work. It requires adequate knowledge of the underling fluid flow behaviour of porous system to develop the model for the oilfield's dynamic risk prediction. The logic of the index systems was well demonstrated by Mamudu et al. (2020) and Zhong et al. (2016). The hybridized logical models are structured so that the BN relies on the data forecasted from the ANN, using the index system to perform the probabilities updating for risk sources identification among the input data, upon observing a change in the reservoir production rate. To capture the effect of rate change over the entire production period of the well, a dynamic form (DBN) of the traditional BN is built. Thus, the DBN is fed with the evidence from the BN, and it reflects the impact of such a dynamic change. The number of states of the output variable is determined by the principles implemented in the early warning index system.

4.3.5 Early Warning Indexes for Dynamic Risk Assessment

One of the key objectives of the EWIS is to enable the BN model to receive the predicted oil flow rates (non-probabilistic data) from the ANN model and implement them during the learning stage. This step establishes the production warning intervals for risk monitoring. The early warning index system interprets the predicted oil rates in a probabilistic form using the 3σ mathematical rule. The details of the early warning index are found in the literature (Mamudu et al. 2020; Zhong et al., 2016). It should be noted that BN models are designed to only receive probabilistic input data. Thus, the prior probabilities can be updated upon any observed change in the production operation. Then, the propagated effects of the production change in the reservoir can be predicted using the DBN model. Figure 4.1 presents the steps to implement the EWIS on the oil field development risk block. In fact, it is initiated at step 5 and ends at step 7. This early warning index system is built to properly represent the interactions among the vital flow variables, using sound reservoir production knowledge. The probabilistic approach implemented in the index systems is discussed in the studies conducted by Mamudu et al. (2020) and Zhong et al. (2016). The key reservoir flow parameters and other operational variables/constraints (described as indexes) are firstly identified, followed by an evaluation of the variables' relationships in the developed early warning oilfield block system. The built index system in the proposed methodology comprises 10 indexes: 4 indexes of warning source, 5 indexes of warning sign, and 1 index of warning situation, as reported in Table 4.1. The next step is to determine the degree of oilfield development risk. When a successful production prediction is achieved with ANN, the possible range of production is specified, which normally varies from 0 to $+\infty$; the plus infinity($+\infty$) might be regarded as the theoretical q_{max} or the absolute open flow (AOF). This is the production rate range, assumed by the statistical "3σ" rule utilized by the oilfield development early warning index system (Mamudu et al. 2020). The standard deviation is denoted by σ. The mathematical principle assumes probability values based on the degree of the eccentricity of the index from the statistical average (mean). For an outcome above 3σ, the chance is set at a value below 1%, which typically indicates a small occurrence probability. If there is a value of greater than 2σ, the occurrence chance is set to be 5%. However, a probability of 31.74% is considered if the degree of the sample variation from its μ is more than σ. These intervals enable us to evaluate the indexes of warning situation degrees as follows (step 7 in Figure 4.1): Taking μ and σ of the production forecasted by the MLP model; dividing the production into various categorized ranges, including the light abnormal intervals $[\mu-2\sigma, \mu-\sigma]$ and $[\mu+\sigma, \mu+2\sigma]$, the normal interval $[\mu-\sigma, \mu+\sigma]$, and severe abnormal intervals $(-\infty, \mu-2\sigma]$ and $[\mu+2\sigma, +\infty)$ using the statistical " 3σ " rule (Mamudu et al. 2020); using the EWIS to evaluate the warning degrees predicted by the data-driven model; and then analyzing the sources of risk among the independent variables. Based on this procedure, risk is not observed if the forecasted production data falls in the normal range, as compared to when it falls in the severe abnormal interval, implying that a large risk exists. If the estimated data are in the light abnormal range, there is a relatively less significant risk (Mamudu et al. 2020).

4.4 Case Study and Model Development

4.4.1 Data Collection and Analysis

The hybrid connectionist model proposed in this research is implemented using some comparative project data available in the literature (Odeh, 1981). A petroleum reservoir under pressure support is simulated. The reservoir is made up of three hydrodynamically connected layers; a 5-spot flooding pattern is employed in the active gas injection flooding process. In this case study, there is a production well with a maximum flow capacity of 10,000 bbl/day and four injection wells at the four edges (boundaries) of the reservoir. A minimum bottom hole pressure (BHP) of 820 psi and/or a minimum oil production rate of 1,000 bbl/day are set as stopping criteria. The simulation study is scheduled to run for 9 years (3287 days). Tables 4.2 and 4.3 present the reservoir data/information and the characteristics of the reservoir layers, respectively.

Table 4.2: Reservoir rock and fluid properties.

Reservoir/fluid parameter	**Value**
Dimension of the grid	$10 \times 10 \times 3$ ft
Density of water	62.4 1b/ft^3
Density of oil	49.0 1b/ft^3
Compressibility of oil	$3 \times 10^{-6}\ psi^{-1}$
Temperature	200 °F
Initial pressure	3800 psia
Bubble point pressure	2100 psia
Depth	7500 ft
Initial water saturation	0.2
Initial oil saturation	0.8

Table 4.3: Reservoir heterogeneity data.

Formation layer	Pay zone thickness (ft)	Porosity (fraction)	Permeability in the horizontal direction (mD)	Permeability in vertical direction (mD)
1	20	0.2	500	50
2	30	0.2	50	50
3	50	0.2	25	25

4.4.2 Model Development and Application

In this section, we briefly summarize the applied hybrid connectionist model principles using the presented data (Odeh, 1981). The ANN model provides the required oil production predictions using forward pass and backpropagation for signal processing and error minimization, respectively. Eqs. (4.2) and (4.1) are used to complete the feed forward process for generating the target data, while Eqs. (4.8) to (4.10) are needed to implement the backpropagation stage to bring the predicted outputs as close to the target values as possible. All these processes are performed at step 4 of Figure 4.1. Eq. (14.11) is employed to generate the CPT, a process accomplished at step 9 of Figure 4.1. Table 4.4 presents the features of the ANN strategy implemented in this study. In the forward pass and backpropagation, the synaptic weights are modified, and a new iterative process is begun upon the cycle completion. This step is repeated until the stopping criteria are met. The early warning principle is used to categorize the production into intervals and classify them into degrees as presented in steps 5 to 7 of Figure 4.1. The BN model relies solely on the probabilistic data and the data forecasted by the ANN. The BN part of the hybrid model updates the probabilities to identify risk for any loss in the production rate. This can be visualized from steps 9 to 11 in the methodology flowchart, as depicted in Figure 4.1. The DBN predicts the impact of such a loss in the well production period (see Figure 4.1). Eqs. (4.8) to (4.10) are used to perform a forward pass (wherein the error is estimated), and to conduct backpropagation for the synaptic weights adjustment as given below:

$$y_m = \frac{1}{1 + e^{-x_m}} \tag{4.8}$$

$$E_{total} = \frac{1}{2}(target - output)^2 \tag{4.9}$$

$$\Delta w_{k,lm} = -\eta \frac{\partial E_{total}}{\partial w_{k,lm}} \tag{4.10}$$

where y_m denotes the neuron output; x_m resembles the neuron net input; m is the neuron; η is the learning rate; $\Delta w_{k,lm}$ refers to the error gradient; ∂E_{total} is the total error change; $\partial w_{k,lm}$represents the change in the weight; and k, l, and m are the positions.

The first step in the logical model building is structural learning, as depicted in Figure 4.2. It then follows the parameter learning, using Eqs. (4.11) and (4.12) for the conditional probability table (CPT) and dynamic risk evaluation, respectively.

$$N = a^n \tag{4.11}$$

$$P(Y|Q) = \frac{P(Q|Y)P(Y)}{P(Q)} \tag{4.12}$$

in which, N is the number of conditional probabilities in the child node; a represents the states of the parent node(s); n denotes the number of the nodes where the directed edges begin; Q introduces the dynamic reservoir data (production); and Y is either an operational constraint or variable.

To evaluate the developed hybrid methodology prediction capability, the mean absolute percentage error is obtained as follows (Mamudu et al., 2020).

$$MAPE = \sum_{i=1}^{N} \left| \frac{T_P - Q}{T_P} \Big/ N_T \right| \times 100 \tag{13}$$

where MAPE stands for the mean absolute percentage error; N_T refers to the total number of predictions; Q is the predicted oil production rate; T_P symbolizes the target production value; and i represents the data point index.

Table 4.4: The hybrid connectionist MLP model features.

ANN model	**Parameter**
Model architecture	Feedforward-backpropagation
Input	Dynamic and static data
Number of layers	3
Number of hidden neurons	10
Output	Oil production rate
Performance function	Mean square error
Training function	Log sigmoid - Pure linear
Training algorithm	Levenberg-Marquardt

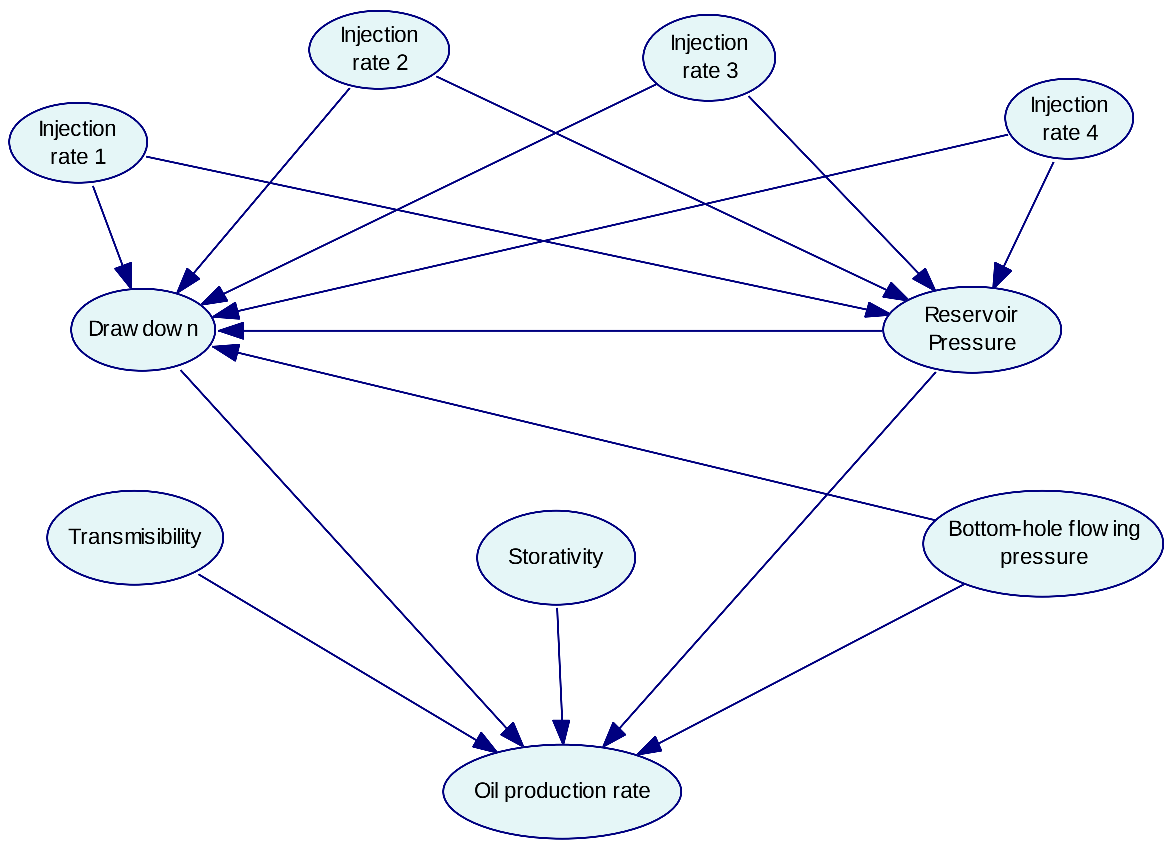


Figure 4.2: Schematic of structural learning approach of the BN in the hybrid connectionist model.

4.5 Results and Discussion

The main contributions of this research work are to develop a hybrid connectionist strategy that captures uncertainties, to forecast oil production, to update prior probabilities (risks), and to perform a dynamic risk assessment of the production system. The hybrid model can be a multipurpose tool for petroleum production related decision-making strategies. The developed system incorporates the effects of pressure maintenance and quantifies the dynamic risks of the probable production losses. The results obtained from the proposed hybrid approach are presented in Figures 4.3 to 4.13. Figure 4.3 shows the oil flow rate predictions using the MLP-ANN model.

The residual errors are illustrated in Figure 4.4. The outputs of the BN approach are shown in Figures 4.5 to 4.10. The DBN results are reported in Figures 4.11 to 4.13.

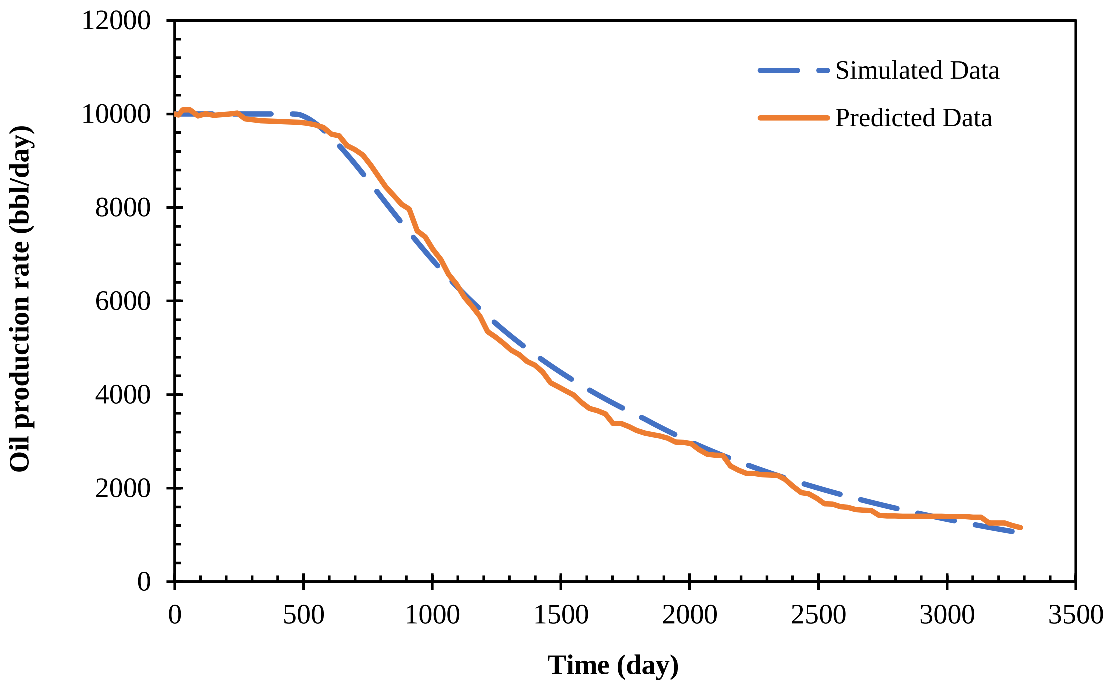


Figure 4.3: Predicted and simulated data for production rate.

According to Figure 4.3 , there is a very good match between the simulated and predicted production rates. Based on the statistical analysis in the form of distributed residual errors (see Figure 4.4), no particular pattern is observed in the graph of residual error versus predicted data, implying that a proper determistic tool has been developed. In addition, the minimum, average, and maximum percentage errors are 0.01%, 6.57%, and 15.28%, respectively, demonstrating the fitness of the proposed model.

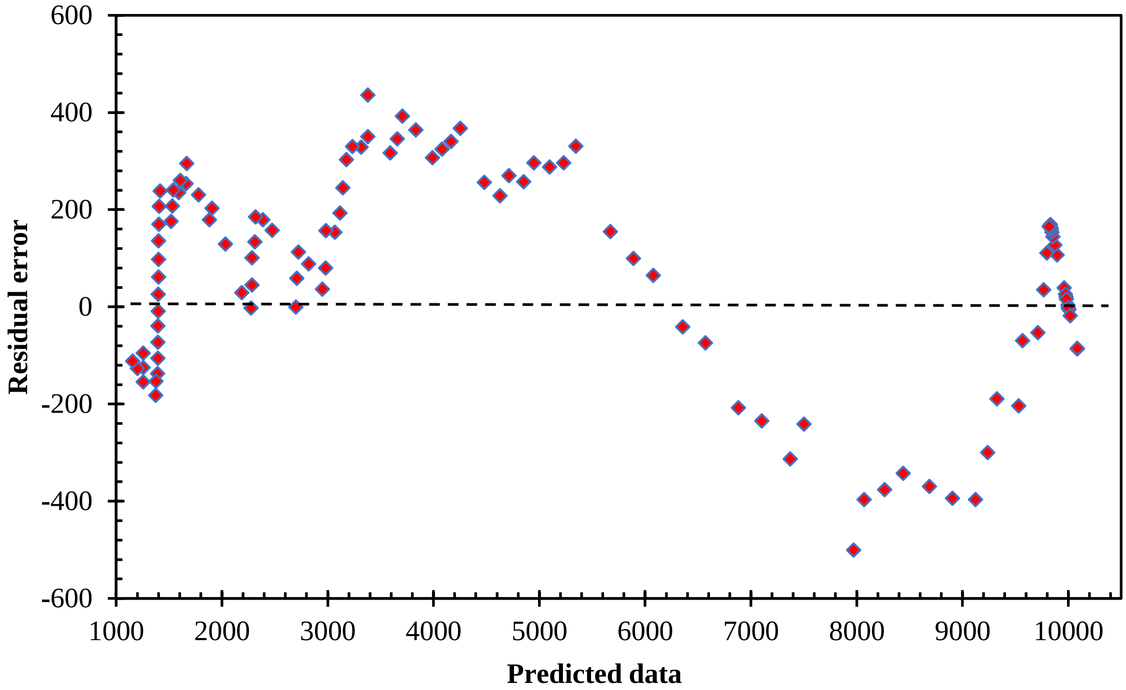


Figure 4.4: Residual error plot for predicted production rate.

Table 4.5 shows the outputs (e.g., warning classes and production rate ranges) obtained from the MLP-ANN model included in the connectionist approach.

Table 4.5: Warning classes and degrees of the predicted production rate.

Warning class	Degree	Production range (bbl/day)	
Heavy warning low production (HLP)	1	0	2005
Light warning low production (LLP)	2	2005	4716
Average or normal (AVG)	3	4716	5365
Light warning high production (LHP)	4	5365	8077
Heavy warning high production (HHP)	5	8077	+∞

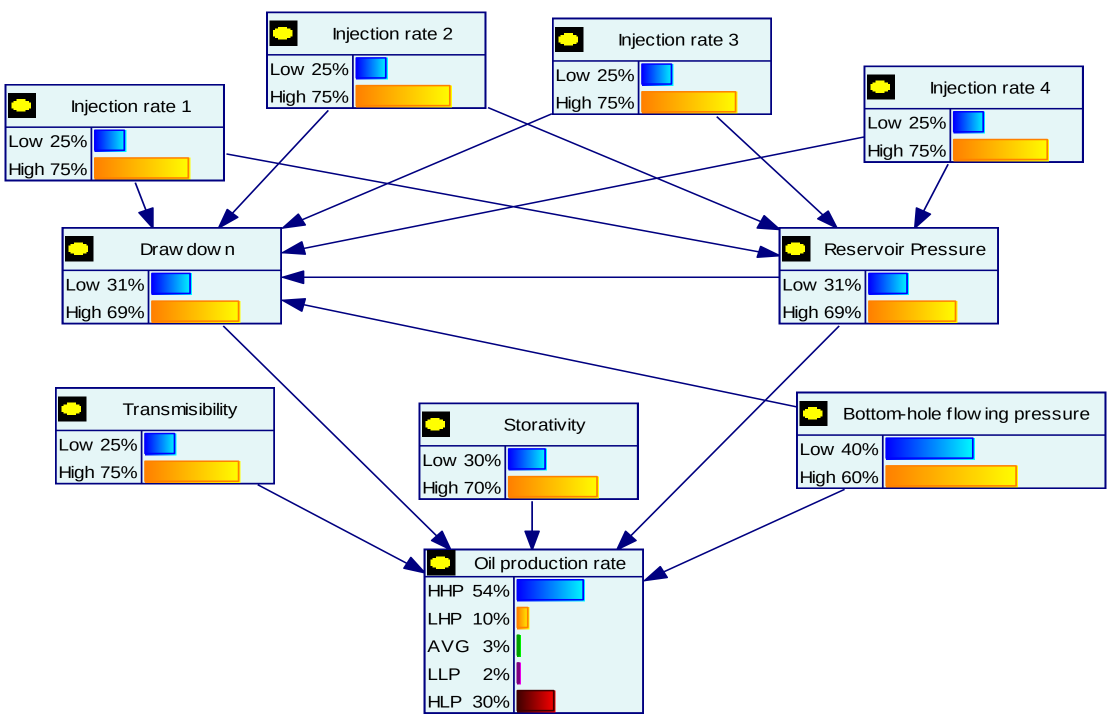


Figure 4.5: Parameter learning of the BN component of the model.

Figure 4.5 shows the parameter learning of the constructed oilfield dynamic risk system of the hybrid connectionist model. The parameter reliability is a function of the adequacy of the structural learning and expert knowledge. The results in Figure 4.5 are obtained before encountering any production abnormality or losses. Once a change in the production operation is observed (that is, a 100% probability of occurrence of any practically possible production loss), the effect of such an evidence is analyzed by updating the prior probabilities of the model's input variables to identify the real risk sources among the input parameters. Based on Figure 4.5, it is concluded that all the injection wells are equally effective for reservoir pressure maintenance; this is planned in the reservoir flooding design. However, such an assumption can only be affirmed if the posterior probabilities are estimated, and a comparative analysis is conducted using this proposed methodology. The analysis offered by the proposed methodology can identify the injection wells with probable less effective injection rates. Thus, the production strategy might be correspondingly adjusted to optimize the production rate.

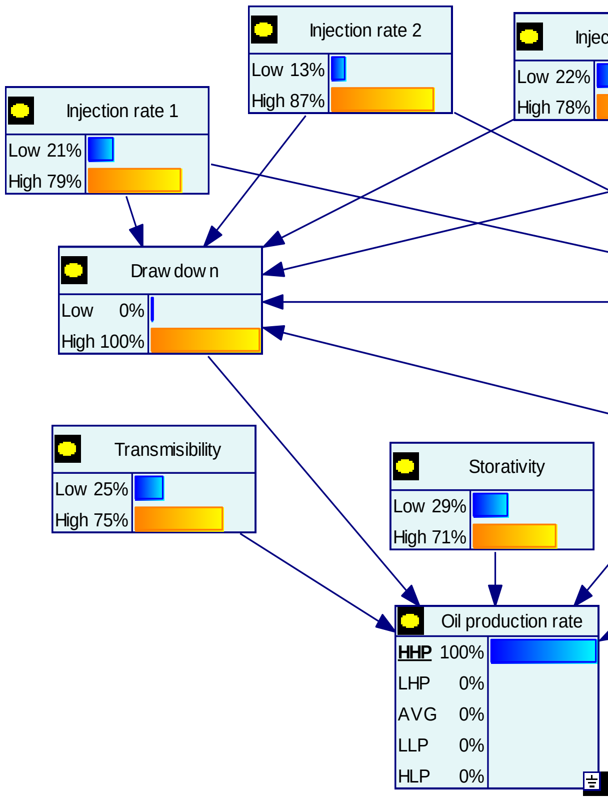


Figure 4.6: Implementation of the BN involved in the hybrid connectionist model during evidence of heavy warning- high production.

Figure 4.6 presents the outputs of the connectionist strategy during evidence of a heavy warning-high production state. It shows that for a production rate of 8077 bbl/day and above (up to the theoretical q_{max} or $+\infty$), the drawdown should be 100% high, and the chance of being low is theoretically zero. This finding agrees with the theoretical and field reality for obtaining q_{max}, where the reservoir flow assumption of q_{max} corresponds to a theoretical zero value of p_{wf}. It implies that the drawdown (pressure differential) is the most important parameter for reservoir fluid flow. This again confirms the usefulness of the proposed connectionist strategy. Investigation of the effect of the flooding system demonstrates that some injection wells are more reliable than others. This might be due to the chance of occurrence of viscous fingering and/or the extent of reservoir layering or heterogeneities. For instance, the associated uncertainties/risks expected in the design phase of the flooding scheme at 25% for each injection rate appear to be 26%, 14%, 25%, and 23% for well 1, well 2, well 3, and well 4, respectively, when the normal production becomes evident. This demonstrates that injection well 2 is the most reliable well when normal production is maintained at operating conditions. If a change in the production strategy is intended, there should be more focus on well 1, well 3, and well 4, accordingly. This shows that the proposed methodology captures the impact of the injected gas on the pressure maintenance and on the overall recovery process, as depicted in Figure 4.3. Thus, reinjection of the produced gas for flooding is encouraged in a similar case study. A flooding scheme was also emphasized by Umar et al. (2019).

According to Figures 4.5 to 4.10, the risk of having low reservoir drawdown should be minimized to maintain a steady production. It is known that a lower reservoir drawdown results in a lower production rate. This is consistent with the fundamentals/physical concept of Darcy's law; the fluid flow rate is directly proportional to the pressure gradient. According to Figure 4.6, the risk associated with drawdown (ΔP) would be zero to produce at AOF, which is the flow rate at a P_{wf} of zero. Thus, the risk associated with the drawdown increases with decreasing production rate. This agrees with the results reported in Figures 4.7 to 4.10; the risks associated with the drawdown are in an increasing order of 2%, 13%, 27%, and 96% for the light warning-high production (LHP), normal production, light warning-low production (LLP), and heavy warning-low production (HLP), respectively. This shows that oil production would fail totally (zero production rate) at a 96% probability of the drawdown failure. Furthermore, a workover job and/or production strategy adjustment are recommended when the probability of failure (associated risk) of the drawdown exceeds 27%, to avoid production losses. Figures 4.5 to 4.10 also demonstrate that the proposed methodology properly captures the relationship between the drawdown and the bottom-hole flowing pressure (P_{wf}). For instance, the probabilistic interpretations of the risks associated with P_{wf} and ΔP depicted in Figures 4.5 to 4.10 reveal that the drawdown decreases with increasing P_{wf} and increases with decreasing P_{wf}.

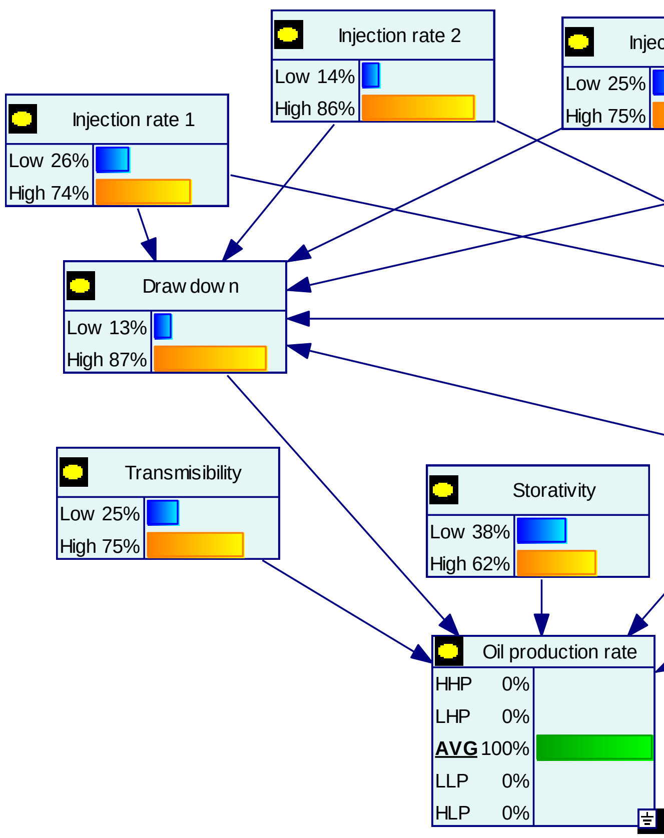


Figure 4.7: Evidence of normal production based on the results of the BN model.

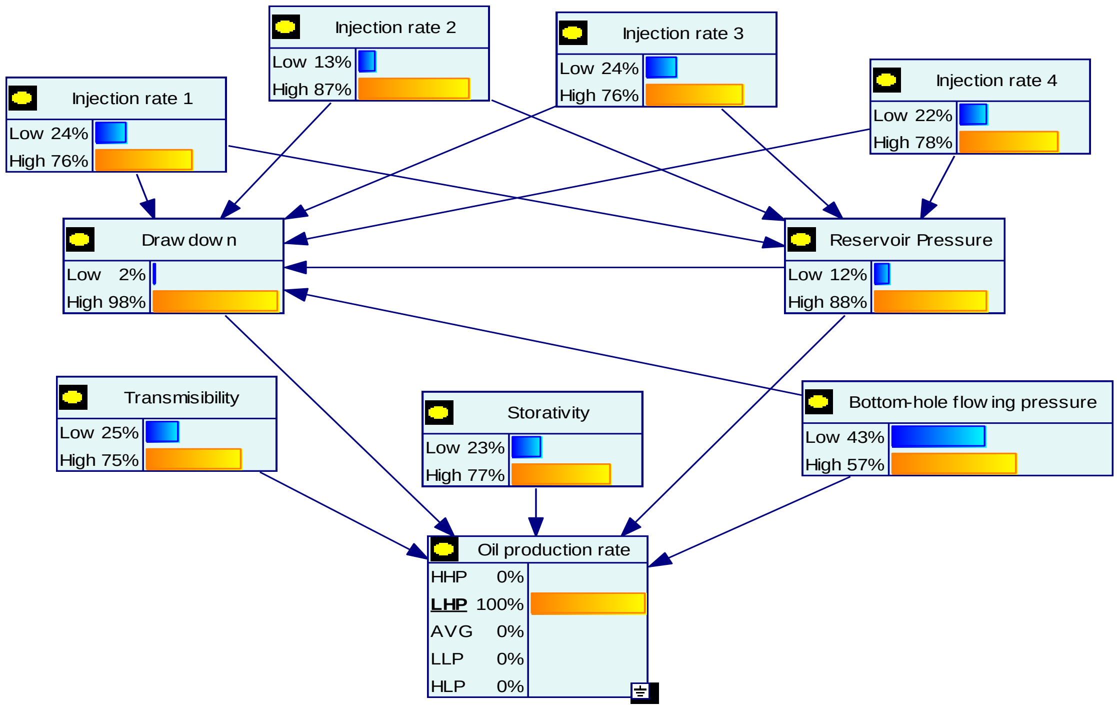


Figure 4.8: Schematic of light warning-high production evidence.

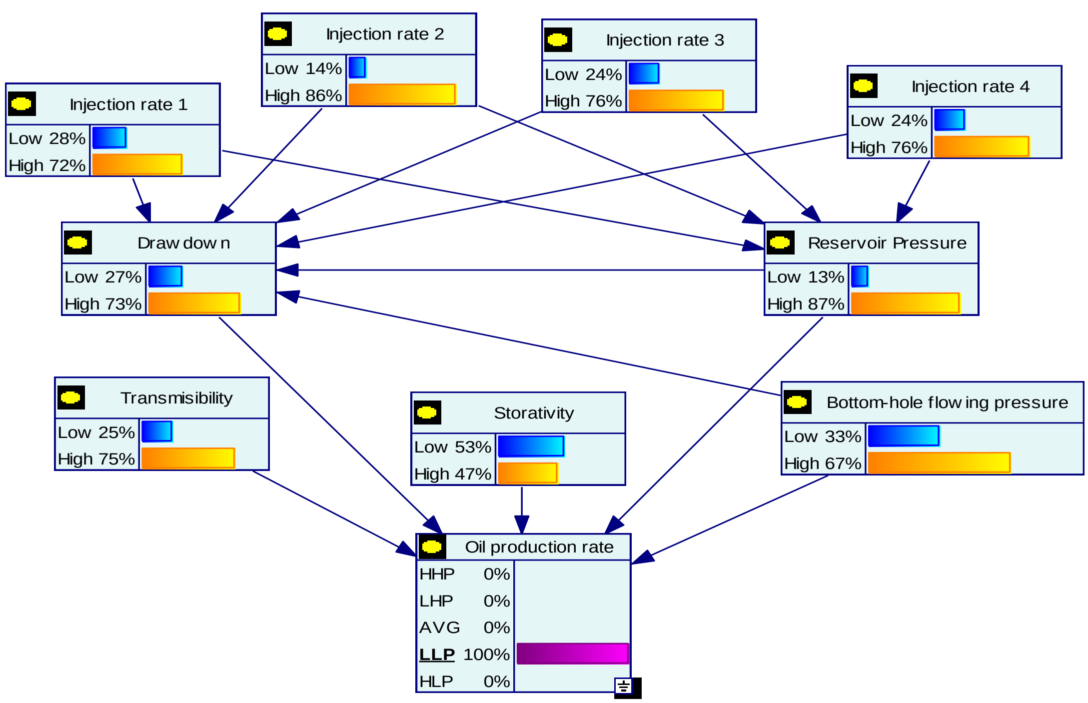


Figure 4.9: Results of light warning-low production evidence.

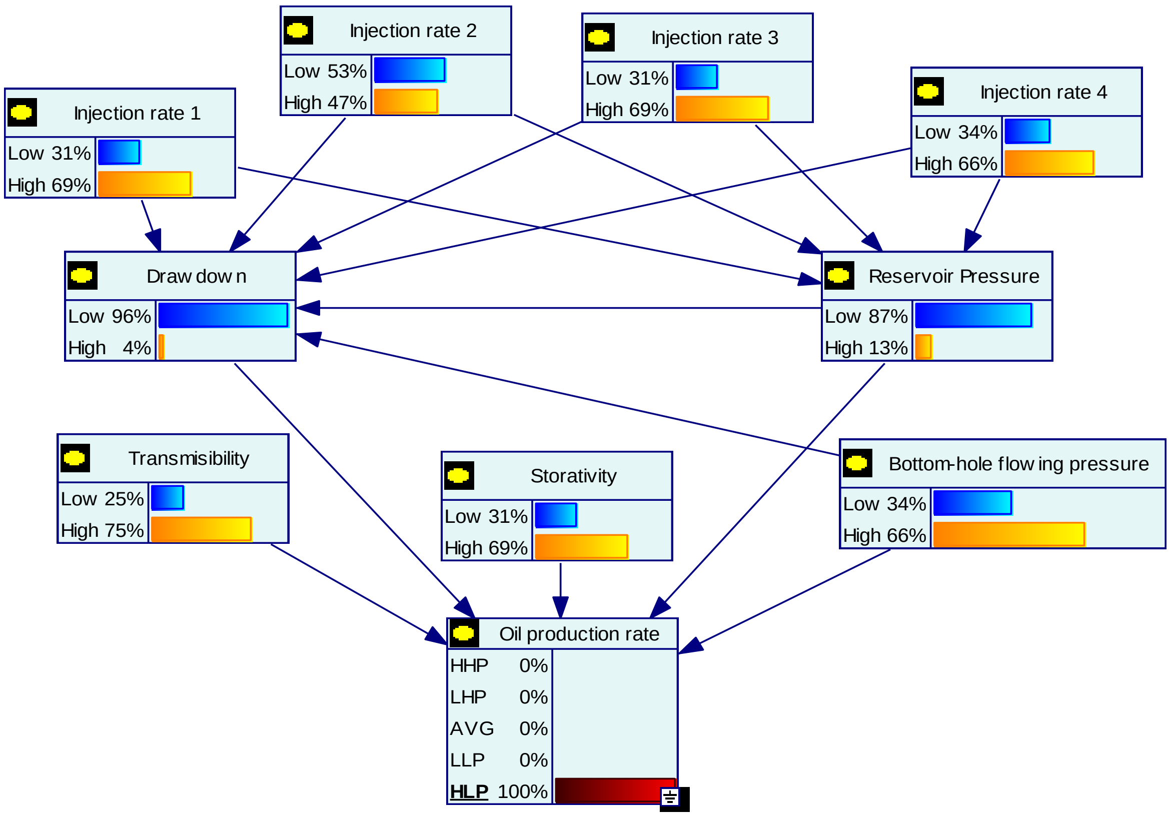


Figure 4.10: Simple graphical demonstration of heavy warning-low production evidence.

Figures 4.11 and 4.12 illustrate the developed dynamic risk profiles for the reservoir production system. The results present the dynamic effect obtained from the data reported in Figures 4.5 to 4.10. Thus, the risk profiles attained from the DBN phase are the direct products of the BN outputs. Figure 4.11 presents the comparative risk analysis plots for different possible scenarios during production losses. The generated risk profiles belong to the heavy-warning-high production (HHP) state, light warning-high production (LHP) state, normal production (AVG) state, and heavy warning-low production (HLP) state. The light warning-low production (LLP) state is the condition where zero (0) production rate can be recorded. Hence, one of the stopping criteria is met at this production interval (see the data reported in Section 4.4.1). Referring to Figure 4.11, if the well produces at a maximum capacity (8077 bbl/day or above), there is a 60% chance that the well will flow after nine years. Similarly, if the plan is to maintain a rate of 8077 bbl/day $>$ $q_o \geq$ 5365 bbl/day (LHP) for the next nine years, there will be a 72% chance for the well to flow. In addition, if an average flow rate, between 4761 bbl/day and 5365 bbl/day, is maintained, the well will have a 91% chance of continuous production after nine years. A 100% chance is guaranteed after nine years if the production rate is set between 2005 bbl/day and 4761 bbl/day (LLP). In fact, the probabilistic risk analysis reveals that the chances of production failure increase with decreasing reserves, which is also confirmed by the convectional reservoir production principles. This strategy offers useful guidelines to the field operators to optimize the production scheme at any time t, in the production life of the well. Generally, this can assist in efficient reservoir analysis and production related decision making.

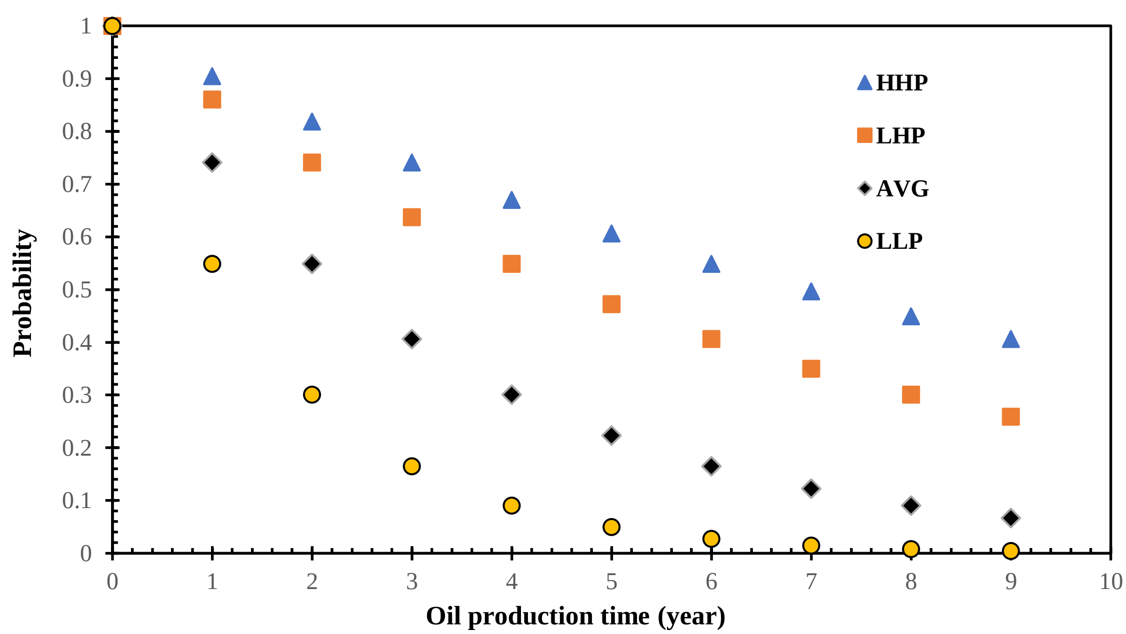
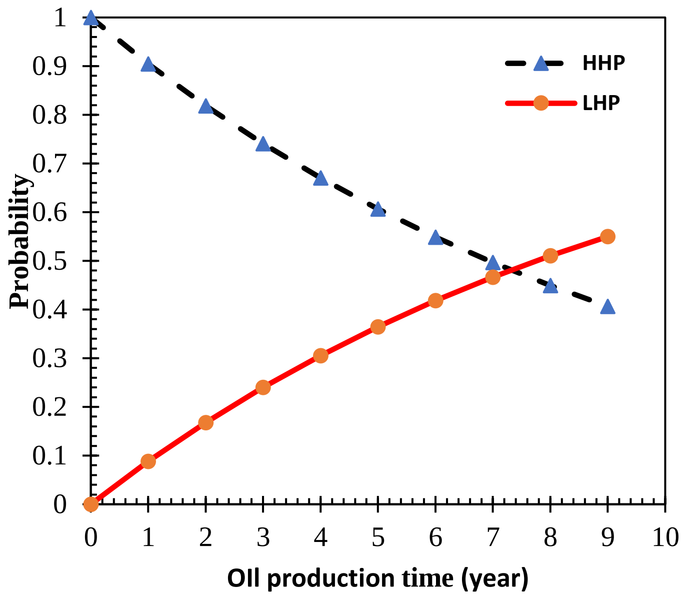
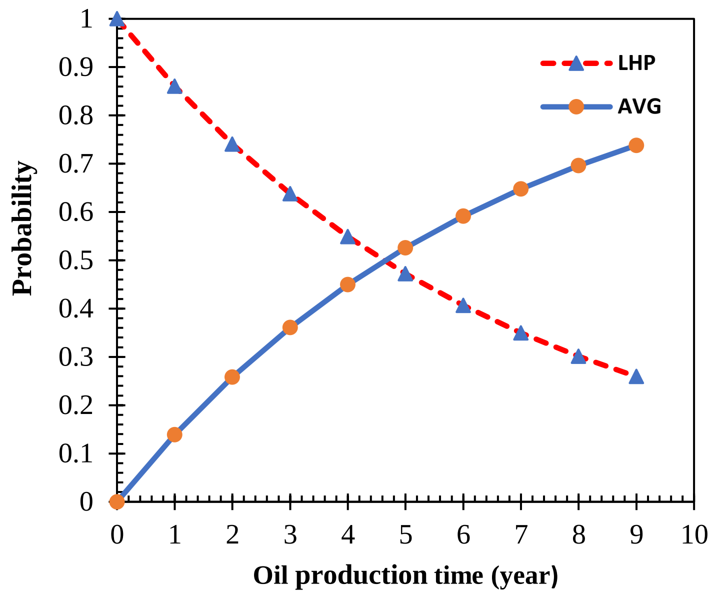


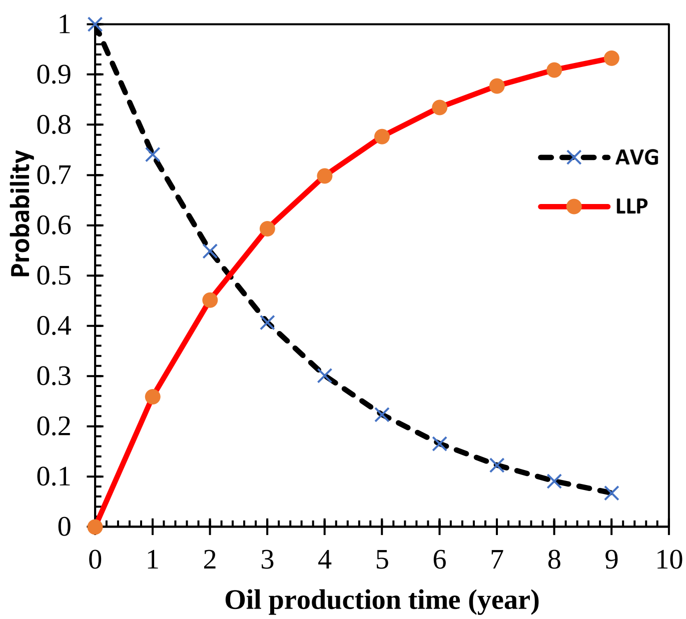
Figure 4.11: Risk comparative analysis curves generated by the DBN model.



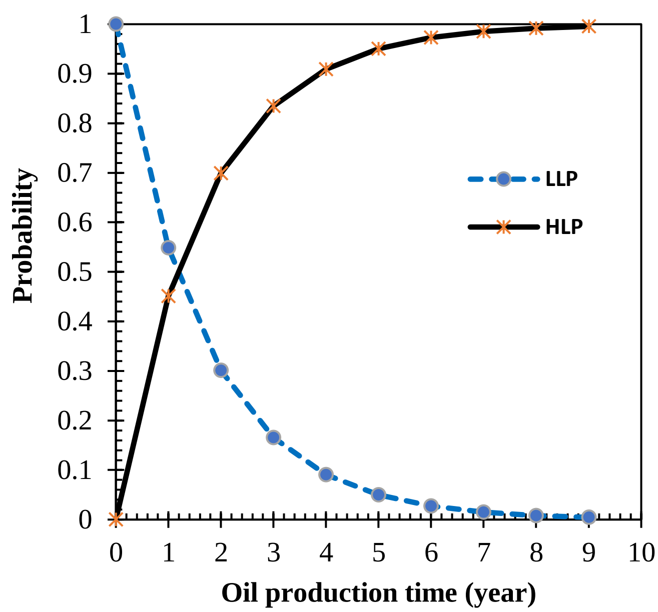
a. Plots of HHP-LHP.



b. Plots of LHP-AVG.



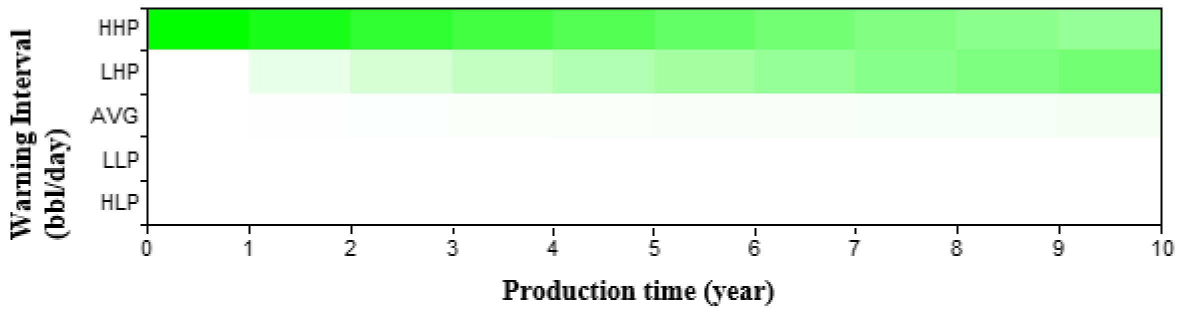
c. Plots of LLP-AVG.



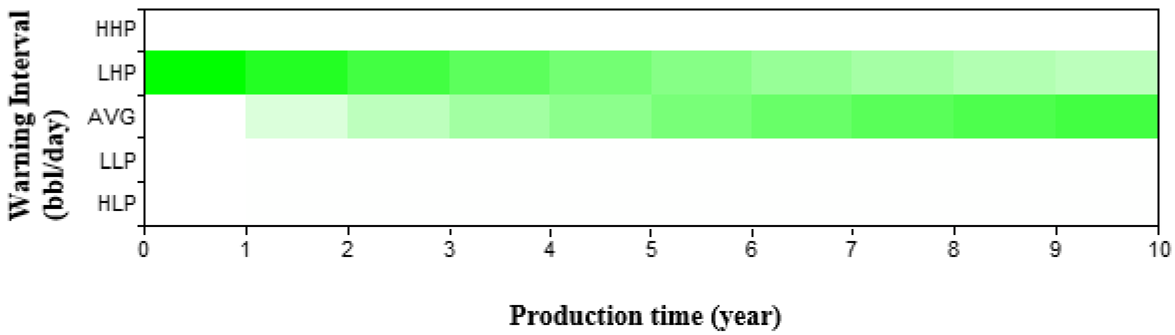
d. Plots of LLP-HLP

Figure 4.12. Risk monitoring system plots resulted from the DBN implementation.

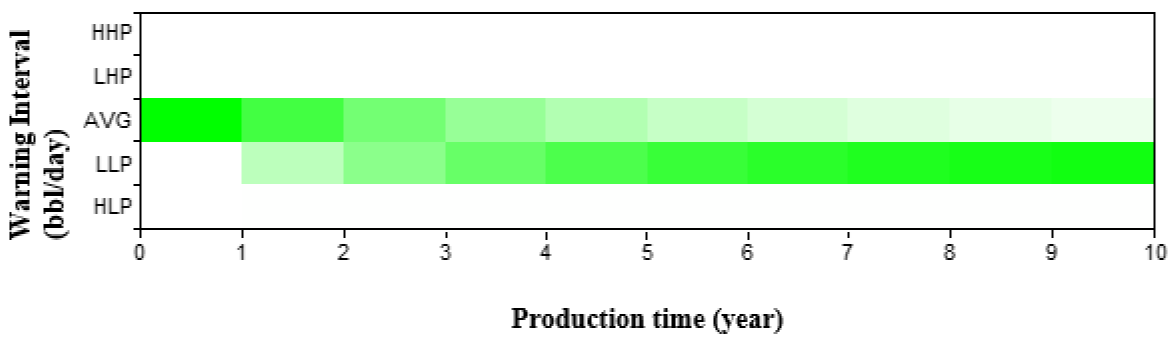
Based on Figure 4.12a, if a production rate is maintained at the HHP level, it will take 7 years before the well produces at less than 8077 bbl/day. Figure 4.12b depicts that once the well starts producing at less than 8077 bbl/day, it does not take more than five years before the daily production drops to the average (AVG) warning interval. This risk monitoring system shows a similar trend for subsequent production declines experienced in the well. For instance, according to Figure 4.12c, when the well starts producing at 4763 bbl/day, this daily production can not be sustained for more than one and a half years. Similarly, Figure 4.12d demonstrates that if the oil production rate becomes 2005 bbl/day, the production system would fail in less than a year from the time when this low flow rate is recorded. To avoid production losses as a worst-case scenario (based on the DBN results), P_{wf} should be optimized or the production enhancement approach should be modified. It can be concluded that the dynamic risk analysis/monitoring system (DBN) of the proposed hybrid strategy is as efficacious as other parts/phases of the proposed methodology, because it produces dynamic risk curves that can be useful for optimizing production strategies.



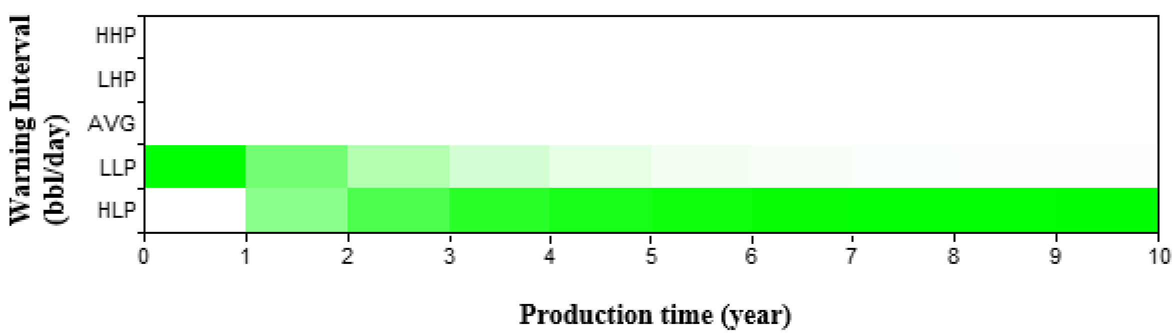
a. Contour plots of HHP-LHP



b. Contour plots of LHP-AVG



c. Contour plots of AVG-LLP



d. Contour plots of LLP-HLP

Figure 4.13: Risk contour plots of warning intervals versus production time for dynamic risk monitoring.

Figures 4.13 demonstrates the contour plots of the dynamic reservoir system. The profiles present the warning intervals-production time graphs. The horizontal axis represents the production time, while the vertical axis signifies the warning intervals developed by the EWIS. The plots show the overlapping periods and transitions that occur during production losses. In fact, the plots reveal that a lower flow rate takes precedence or prevails as a previously maintained higher flow rate is lost, due to the risks associated with the dynamics of the complex nonlinear production system. The results from Figure 4.13 show that the overlapping effects of the higher production rate decrease as those of the lower production increase. This intrinsically defines the decline in the recovery rate (Mamudu & Olafuyi, 2016; Mamudu, 2016; Olafuyi & Mamudu, 2015). Thus, there is an urgent need for a change in the production strategies to forestall future production losses or downtime.

Petroleum industries can benefit from the multipurpose hybrid model developed in this study for reservoir production forecasting, production dynamic risk prediction, and real time monitoring. The introduced approach overcomes the weaknesses in the existing intelligence models used for reservoir production prediction and risk analysis. The hybrid model uses prediction and monitoring systems to analyze the dynamic risks associated with the production predictions in the operating phases. The proposed model offers the oil and gas industry a cost-effective and easier approach to capture reservoir heterogeneities' effects. It also produces dynamic risk profiles and logical reasoning which facilitate the bottom-hole flowing pressure optimization.

The proposed methodology has been applied only to a gas (or only water) drive reservoir under pressure support, to forecast the production rate and provide associated dynamic risk profiles. Thus, it can be a good risk analysis approach for gas and oil reservoirs. It explores the nonlinearity of the process flow variables' interactions, considering the effect of the pressure maintenance. Note that the presented model is not primarily designed for reservoirs with a combination of drive mechanisms. It is not applicable to artificial lift systems; the model does not incorporate economic analysis; and it does not capture the effects of artificial lift mechanisms on the bottom-hole flowing pressure. Thus, it is recommended that representative risk and recovery prediction models are developed for the reservoirs with active combination drives. In addition, the effects of an artificial lift mechanism should be incorporated in the dynamic risk analysis of the production system, to analyze its impacts on the bottom-hole flowing pressure failure analysis. Another important aspect is the economic analysis to be conducted for the dynamic risk assesment of the reservoir production systems.

4.6 Conclusions

This research work presents a hybrid model that incorporates a data driven model with an integrated logical model (MLP-BN-DBN). The proposed approach is made of three interconnected models, concurrently. The MLP-ANN model of the connectionist strategy exhibits a robust predictive capability by mapping between the input and output data for a precise oil production forecast. It captures the uncertainties in the fluid and rock properties and the model's uncertainties when the pressure maintenance effect in the reservoir analysis is considered. The BN model captures the pressure maintenance effects using the early warning source indexes and implements the 3σ mathematical rule to promptly signal the arrival of any production rate variation (dynamic data). The DBN model generates dynamic risk profile over the production period for each dynamic effect/change in the production. The proposed connectionist model presents an effective risk monitoring system for field operators and engineers. In summary, the following key findings are obtained in the current research work:

- The proposed methodology serves as an effective tool for dynamic risk assessment and production method optimization of petroleum reservoirs.
- The model offers the field operators a good opportunity to develop dynamic risk profiles. It also gives a real time estimate of the likelihood (chance) of any impending production loss during the production operations. Thus, it can provide the oil and gas industry with a cost-effective and straight- forward approach to capture petroleum reservoir model and data uncertainties.
- The hybrid system produces logical reasoning that helps in the failure analysis of the bottom-hole flowing pressure.
- The MLP-ANN included in the proposed hybrid method provides the required history-matching process and captures the temporal and spatial dependencies of the important flow parameters. It yields precise oil production rate predictions; the minimum, averange, and maximum percentage errors are obtained as 0.01%, 6.57%, and 15.28%, respectively.
- The hybridized model utilizes a probabilistic risk analysis that facilitates the optimization of production schemes to prevent production losses.
- The model predicts the transition time between the successive early-warned production levels necessary for a change in the production strategy to avoid production downtime.

The developed model can be improved by considering the following vital aspects: a) Economic analysis of the dynamic risk profile of the reservoir production system; b) Representative risk and recovery prediction models for combining various production drives in petroleum reservoirs; and

c) Integration of an artificial lift set-up with a production strategy definition in the dynamic risk analysis of the production system.

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Appendix 4.A

Table 4.A1: A summary of previous production performance models and knowledge gaps.

No.	Author(s)	Model	Knowledge Gap	Result
1	Subbey et al. (2003)	Neighborhood Algorithm (NA)	i. The system is stochastic, deficient in dynamic risk analysis, and expensive. ii. The risks are not studied. iii. It does not incorporate the pressure maintenance effect and dynamic risk assessment.	Oil production
2	Nicotra et al. (2005)	Neighborhood Algorithm (NA)	i. The system is stochastic, deficient in dynamic risk analysis, and expensive. ii. The risks are not studied. iii. It does not incorporate the pressure maintenance influence and dynamic risk evaluation.	Oil production
3	Lechner et al. (2005)	ANN	i. The risks are not investigated. ii. It does not include the pressure maintenance effect and dynamic risk profile. iii. It is stochastic.	Oil production
4	Khazaeni & Mohaghegh (2011)	ANN	i. The risks are not included. ii. The system does not incorporate history matching. iii. It does not consider the pressure maintenance impact and dynamic risk analysis.	Oil production
5	Shahkarami et al. (2014)	ANN	i. The risks are not studied. ii. It does not incorporate the pressure maintenance impact and dynamic risk analysis.	Oil production
6	Augusto et al. (2014a)	ANN	i. The risks are not studied, and the used method is stochastic. ii. It does not incorporate the pressure maintenance effect and dynamic risk assessment.	Oil production
7	Maschio et al. (2014)	Markov Chain Monte Carlo (MCMC)	i. The system is stochastic, deficient in dynamic risk analysis, and expensive. ii. The risks are not studied. iii. The system does not incorporate history matching. iv. It does not capture the pressure maintenance effect and dynamic risk profiling.	Oil production
8	Zhong et al. (2016)	ANN & BN	i. The system does not incorporate history matching. ii. The model does not capture the pressure maintenance effect and dynamic risk evaluation.	Oil production
9	Sun & Ertekin (2017a)	ANN	i. The system is stochastic, deficient in dynamic risk analysis, and expensive. ii. It is only limited to cyclic steam stimulation. iii. The employed model does not consider the pressure maintenance effect and dynamic risk profiling.	Oil production
10	Mamudu et al. (2020)	ANN & BN	i. The hybrid model does not consider the pressure maintenance effect and dynamic risk profiling.	Oil production
11	Current work	MLP, BN, and DBN		- Oil production - Dynamic risk profile

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Chapter 5

Dynamic risk modeling of complex hydrocarbon production systems

Preface

A version of this chapter has been published in the ***Process Safety and Environmental Protection 2021; 151:71-84.*** *I produced the work alongside my co-authors; Faisal Khan, Sohrab Zendehboudi, and Sunday Adedigba. I am the main author. I conducted the literature review, formulated the concepts of the dynamic risk assessment model and developed it for the risk assessment of dual energy support-systems. I prepared the first draft of the manuscript and subsequently revised the manuscript based on the co-authors' and peer review feedback. Co-author, Faisal Khan provided guidance in the development of concept, design of methodology, reviewing and editing the draft, and reviewing and revising the new version of the manuscript. Co-author, Sohrab Zendehboudi supported in reviewing and editing the draft, reviewing and revising the new version of the manuscript. This co-author helped in the review, and correction of the model and results as well. Co-author, Sunday Adedigba supported in the review of the BN and ANN concepts.*

Abstract

This study presents a dynamic risk modeling strategy for a hydrocarbon sub-surface production system under a gas lift mechanism. A data-driven probabilistic methodology is employed to conduct a risk analysis. The integrated approach comprises a multilayer perceptron (MLP) – artificial neural network (ANN) model and a Bayesian network (BN) technique. The MLP-ANN

model performs the production forecast, and the BN model analyzes dynamic risks (the production response) and evaluates the impact of the sand face pressure on risks. The introduced model offers an effective strategy to avoid production failure and to monitor dynamic risks. The dynamic risk analysis yields predictive outcomes at any production time in the well's production life. It offers field operators an early warning system based on the Bayesian model with prognostic capabilities. The proposed strategy effectively manages production risks and assists in production decision-making, especially in complex production systems.

Keywords: Bayesian network; Bottom-hole flowing pressure; Dynamic risk; Dual-energy system; Gas lift; Multilayer perceptron

5.1 Introduction

Insufficient reservoir energy to push the reservoir fluids to the surface at economic rates necessitates effective production enhancement techniques. Lifting the well/hydrocarbons artificially (by gas lift) is a viable option if water or gas injection is not economically or technically feasible (Guo et al., 2007). Thus, the downhole production system becomes a reservoir case with dual-energy support. The energy produced by the injected gas supplements the inadequate reservoir energy by reducing the sand face pressure at the well bottom (Umar et al. 2019). The gas lift process implemented for the downhole pressure maintenance increases the system complexity in terms of production uncertainties measured as risks. The risk assessment is of great importance in this situation. Also, the history matching challenges such as technical and financial difficulties of production predictions have attracted researchers' attention in the past decades. This study presents a predictive production tool and a dynamic risk analysis approach to model a reservoir production system with dual-energy support.

Some research studies in the literature focus on production predictions and risk analysis of hydrocarbon production systems. For instance, Khazaeni & Mohaghegh (2011) used an artificial neural network (ANN) to predict oil production. The risk analysis is not included in their model. Their study did not account for the impact of injected gas variables (injected rate and working gas-liquid ratio, GLR) on the sand face pressure and dynamic risks. Shahkarami et al. (2014) successfully employed an ANN model for assisted history matching and production forecasting. However, the risk was not considered in their study. Their model does not consider the gas lift's response analysis, bottom-hole pressure's response, and their impact on production. Augusto et al. (2014) also used an ANN model and a stochastic approach to predict oil production. The risks and dynamic risk assessments were not studied in their work. They did not incorporate the lift system and bottom-hole pressure in their developed model for the production forecast. Maschio et al. (2014) employed the Markov Chain Monte Carlo (MCMC) to forecast production. The model was a stand-alone model. Their model does not capture dynamic risk profiling and the gas lift system's impact on sand face pressure. Their approach is stochastic, prohibitive, and inadequate for dynamic risk analysis. Zhong et al. (2016) presented an integrated model for production and uncertainties evaluations. Their model considers uncertainties quantifications but not dynamic profiling. They did not incorporate the gas lift system's impact on sand face pressure study. Like other previous studies, the model has a dynamic risk assessment deficiency. The modeling tool does not capture the downhole pressure maintenance effect. Sun and Ertekin (2017a) introduced a stochastic tool for cyclic steam stimulation. Their developed model does not incorporate a dynamic risk assessment. Besides, it is only limited to the cyclic steam stimulation process. The model does not consider the gas lift system's effect on the downhole production system and dynamic risk profiling. Similar to Zhong et al. (2016)'s work, Mamudu et al. (2020a) presented an advanced connectionist approach that was an integration of the ANN and BN. Although the production predictive component is a part of their hybrid model, the dynamic risk profiling, lift system's impact on the downhole production system, and the bottom-hole pressure's response were not considered. To the best of the authors' knowledge, none of the existing smart models can handle the dynamic risk assessment of reservoir production systems with a dual downhole energy support. The methodology proposed in this research bridges these identified knowledge gaps. The model considers production prediction process, dynamic risk profiling, downhole pressure maintenance effect, and the gas lift system impact on sand face pressure and consequently potential risks.

This study's main objective is to develop a modeling tool for a reservoir production system with dual-energy support. The model is designed for production forecasts and dynamic risk analysis. The introduced data-driven probabilistic methodology offers a means to predict oil production and analyze the associated risks (failure chances). The model has an adequate predictive capability for risk prediction. The proposed approach conducts a real-time assessment of the dynamic risk resulting from the production state and the bottom-hole flowing pressure (p_{wf})'s response. It also captures the codependency of the production system on the two independent energy systems (lift mechanism and downhole pressure system).

This work is organized as follows. Section 5.2 introduces the background and theory of the proposed technique. A simple schematic of a production system is also introduced in this section to demonstrate the lift concept. The proposed methodology is presented in Section 5.3. Section 5.4 includes a case study. The proposed model's field implementation is described in detailed steps in this section as well. The results and discussion are given in Section 5.5. Finally, Section 5.6 encapsulates the main findings of this research work.

5.2 Background Study

This section provides a brief description of the gas lift technique and machine learning tools (and their applications).

5.2.1 Gas Lift Technique

Gas lift is a known method to improve the oil production rate by injecting compressed gas into the lower segment of the tubing through the tubing-casing annulus and an operating valve installed on the tubing string. As the injected gas enters the tubing, the production rate increases due to two mechanisms (Guo et al., 2007): 1) the gas mixes with the oil; thus, the resultant density of the aerated oil reduces, and its movement to the surface becomes more manageable, and 2) the oil is transferred to the wellhead by expansion. Figure 5.1 presents a simplified schematic of the gas lift strategy.

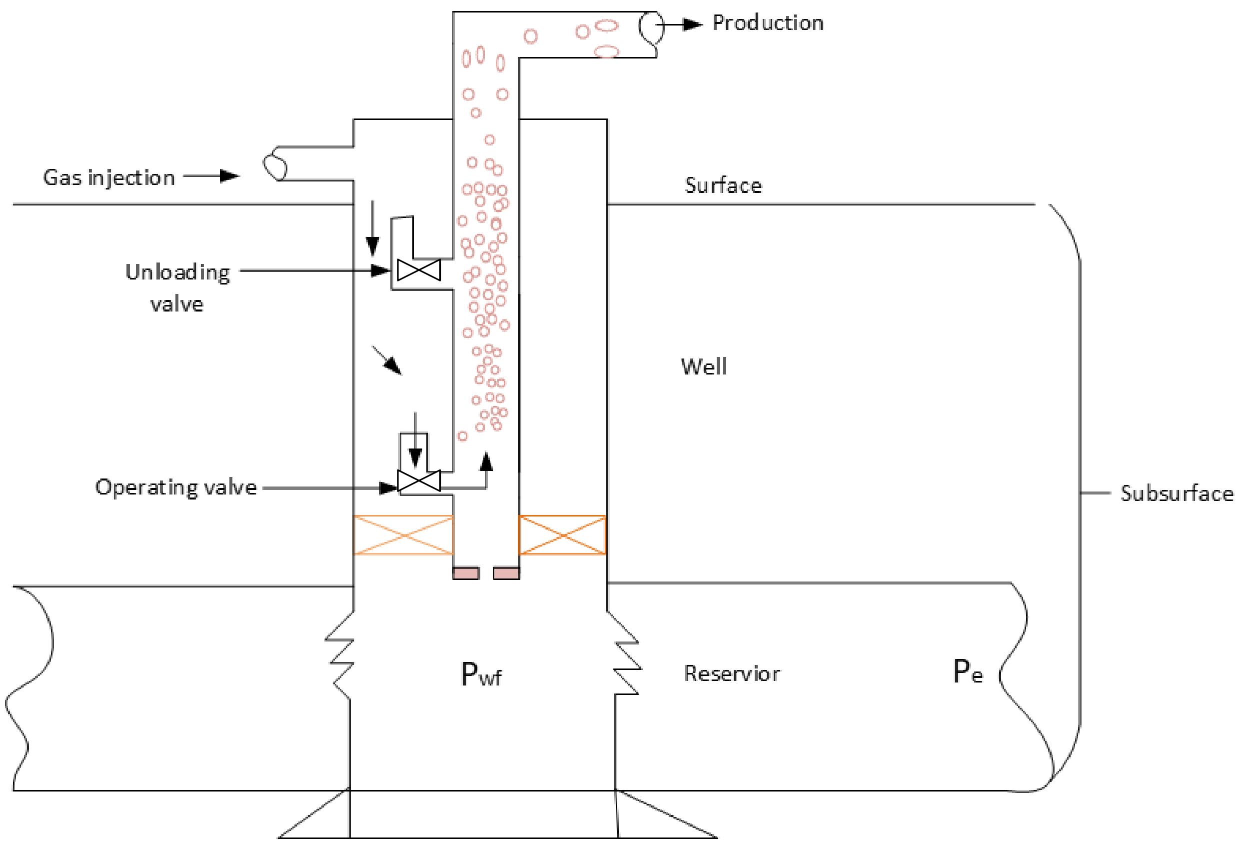


Figure 5.1: A schematic of a typical gas-lift well and reservoir system.

It is significant to mention that the risk assessment conducted by the logical component of the proposed methodology focuses specifically on the downhole production (subsurface production system) and the gas flow parameters such as working gas-liquid ratio (GLR) and injected gas rate. Thus, the risk assessment conducted using the hybrid model involves the gas lift's complex effects on the production operation. The subsurface production system contains various components and parameters such as the wellbore, bottom-hole pressure response, reservoir pressure, reservoir, and gas lift system. The gas lift is a type of artificial lift, which is considered in a production system where the reservoir pressure (P_e) is not enough to direct the reservoir fluid to the surface at adequate rates in terms of economic prospects. The bottom-hole flowing pressure (P_{wf}) is reduced to increase the drawdown energy required for acceptable production rates. Equations (5.1) and (5.3) express the relationship between the reservoir pressure and the bottom-hole flowing pressure (BHP) and that between the BHP and the wellbore variables, respectively.

$$q_o \propto \Delta p \tag{5.1}$$

where

$$\Delta p = p_e - p_{wf} \tag{5.2}$$

in which p_e is the reservoir pressure; p_{wf} refers to the bottom-hole flowing pressure; and q_o stands for the oil production rate. The BHP is given by Eq. (5.3):

$$p_{wf} = p_{tf} + \left({}^{dp}/_{dz}\right) H \tag{5.3}$$

where p_{tf} is the tubing head flowing pressure; H introduces the reference depth; and $\left({}^{dp}/_{dz}\right)$ represents the pressure gradient.

5.2.2 Machine Learning Approach

The application of Artificial intelligence has demonstrated the importance of machine learning in various academic disciplines. The recorded successes and its efficiency have led to its increased applications in industries in recent decades. Production forecast is crucial in reserves estimate in today's complex oil and gas production operations. The quest to reduce the data and model uncertainties and improve the reliability of forecasted production data has led to smart tools (or ANN models)' uses in the various phases of oil and gas operations. The ANN models and corresponding procedures have been comprehensively explained in the literature, and many applications of these powerful tools have been reported (Adedigba et al., 2017; Kim et al., 2019; Kimaev et al., 2019; Sun and Ertekin, 2017b; Wang et al., 2019). For instance, Zendehboudi et al. (2018) discussed various ANN's applications in different engineering disciplines in a review paper. Risk analysis is a vital component of interest, whether in the industries or academia (Pui et al., 2017). Risk analysis has been extensively discussed in the literature (Adedigba et al., 2018; Khan et al., 2016; Khan et al., 2015; Meng et al., 2019; Zhang et al., 2018).

Artificial Neural Network (ANN) model has a remarkable/intrinsic capacity to mimic complex process behaviors and reproduce complicated behaviors in various engineering and science systems irrespective of non-linearity/dimensionality (Alsaffar et al., 2020; Li et al., 2020; Shahnazari, 2020). Typically, it connects input and output data for process modeling without the underlying process' knowledge (Hafeez et al., 2020). ANN models have mainly been classified based on network features/characteristics (Elkatatny et al., 2019; Mamudu et al., 2020b). These classes/categories comprise the learning method, application, connection type, and topology (Yupeng Li et al., 2020; Picos-Benítez et al., 2020; Saba & Elsheikh, 2020; Sharafati et al., 2020). The learning method describes ANNs as conventional (or hybrid), unsupervised, and supervised processes. The application of both the unsupervised and supervised learning methods during learning is named the hybrid process. In the unsupervised learning method/process, the target data are not supplied/fed to the training network. In contrast, the structure in which there is a provision of both the target and input data for training is called the supervised learning method. In the context of the application, ANN models are categorized into forecasting, clustering, classification, and function evaluation. The network connection type defines the data feeding direction/track. The feedback and feedforward are the only possible options here. The feedback models utilize in-built loops to send signals/data in both directions. The feedforward models conduct input-output signals transmission or forward direction with backpropagation for error transmission or backward direction. The feedforward models/networks are mostly used in engineering cases (Li et al., 2020; Mamudu et al., 2020a; Zhou et al., 2020). In terms of topology, the systems are classified into multilayers, single layer, self-organized structures, and recurrent. A multiple layer network model with a forward pass for signals transmission or input-to-output transfer of information is known as a multilayer perceptron (MLP). It is the network type deployed in the current research.

5.2.3 Dynamic Risk Assessment

Dynamic risk assessment is a method that updates the estimated risk of a failing/deteriorating process according to the performance of the control system, safety barriers, inspection and maintenance activities, the human factors, or procedure (Khan et al., 2016). Risk assessment models have been widely employed in engineering process modeling to ensure safety and system's reliability (Ahmadi et al., 2020; Hansen, 2020; Naghavi-Konjin et al., 2020). Bayesian network (BN) model and early warning index system (EWIS) of oilfield development risks block are the logical systems/models deployed in the current research to build the probabilistic component of the proposed dynamic risk-based analysis methodology to enable adequate dynamic risk assessment of the production variable/rate's abnormalities. The quest towards ensuring appropriate assets management makes process dynamic risk assessment an area of never-ending research. Numerous risk analysis methodologies have been proposed by several practitioners/researchers in different fields (Ahmadi et al., 2020; Chebila, 2020; Ghosh et al., 2020; Min Li et al., 2020; Yuntao Li et al., 2020; Naghavi-Konjin et al., 2020; Nhat et al., 2020; Wu et al., 2020). Like fault detection and diagnosis in complex engineering and science systems, the BN model is proposed in this work for risk sources detection and uncertainties analysis for the case study considered. Risk has been broadly described in the literature as a measure of loss or the product of the event's likelihood and the degree of the loss (Khan et al., 2016). The Bayesian network is a model that describes or demonstrates how hypotheses are updated, having observed new information (Naghavi-Konjin et al., 2020). The model can detect and analyze the risk sources that cause any reservoir production change. The model (BN)'s application is only feasible with probabilistic values. Hence, we build a connectionist model that comprises the EWIS model and the BN model for process data interpretations and modeling. EWIS of oilfield development risk block is mainly intended for 1) receiving predicted production data from the MLP model, 2) making the process data probabilistic interpretations, and 3) formulating the BN output states. The EWIS rules are based on risk detection/identification procedures and assessment (Horneret al., 2011). The reservoir flow parameters are classified as indexes in the built risk block (EWIS). The indexes or process system variables are categorized into three groups in the dynamic risk assessment process. These comprise the warning situation, warning sign, and warning source indexes. Gas-liquid ratio (GLR), liquid production, oil production, gas production, and water production represent the warning situation indexes. The warning sign indexes describe variables that are in direct contact with the warning situation indexes. The warning source indexes are the risks' causes.

5.3 Proposed Methodology

This section presents the details of the proposed methodology.

5.3.1 Proposed Model Development Steps

The following steps summarize the proposed hybrid strategy's modeling procedure: 1) building the temporal and spatial data set, 2) proxy model development for production estimation, and 3) developing the early warning system, enabled-Bayesian model. These three steps involve many sub-steps as mentioned below:

- Obtain and prepare the dataset for reservoir model building.
- Use geological data from a commercial simulator for creating a reservoir model, starting with the base case.
- Build the spatial-temporal database from the extracted data using the numerical simulation models to train the ANN.
- Classify and rank various reservoir properties based on their influence on reservoir production performance.
- Select ANN inputs, using the ranked fluid and rock properties as a guide.
- Divide the spatial-temporal dataset into training data, validation data, and test dataset.
- Select and build the ANN architecture.
- Conduct the training, testing, and validation phases of the ANN model. The results of the training process error statistical analysis are presented in Table A1 (Appendix A). Figure A1 presents the MSE plot obtained during the training phase.
- Validate the developed ANN model using different geologic data (realizations) of the reservoir model.
- Forecast oil production. This is presented in step 3 of Figure 5.2. (The obtained data are transmitted to the EWIS-assisted Bayesian model through step 4, as seen in Figure 5.2).
- Identify the lift mechanism variables and prepare data for BN structural learning.
- Construct an early warning oilfield risk index system using the probabilistic data and the outputs from the developed MLP-ANN model.

- Calculate the warning degree of forecasted oil production.
- Perform the BN structural and parameter learning using the experts' knowledge and prepared data.
- With the outputs predicted from the BN (parameter learning), update the prior probabilities given any new evidence (e.g., change in the oil production rate).
- Find the causes of the risks that lead to the change in the production rate (dynamic data). Relate the posterior and prior probabilities of the warning sign or source indexes as the case may apply.
- Assume hyperbolic decline rate (a variable from a range of values between two extremes, namely, harmonic and exponential decline rates).
- Assess the dynamic risk associated with the production, which results from production energy losses.

The flowchart depicted in Figure 5.2 presents the steps involved in the hybrid modeling development and implementation. The data are first collected and partitioned based on steps 1 to 2 (in Figure 5.2). After this stage, the probabilistic data are separated from the computational data used for flow rate prediction. The probabilistic data are transmitted directly to step 5 in the early warning system; the rest is fed to step 3 for production prediction. The forecasted data are sent to the early warning system in step 4 for evaluations and probabilistic interpretations. The warning intervals and degrees evaluated at step 4 are transferred to step 5 to obtain the early warning system's required outcomes. The logical model receives the results of step 5 at step 6 to develop the early warning-enabled (EWIS) BN model. At this stage, the structural and parameter learning process is performed. A change in the production is evaluated at step 7. If any evidence is observed, the prior probabilities are updated, and the dynamic risk assessment due to production energy response is conducted at step 8. This process in step 8 ends the dynamic risk assessment process. Else, step 7 is repeated.

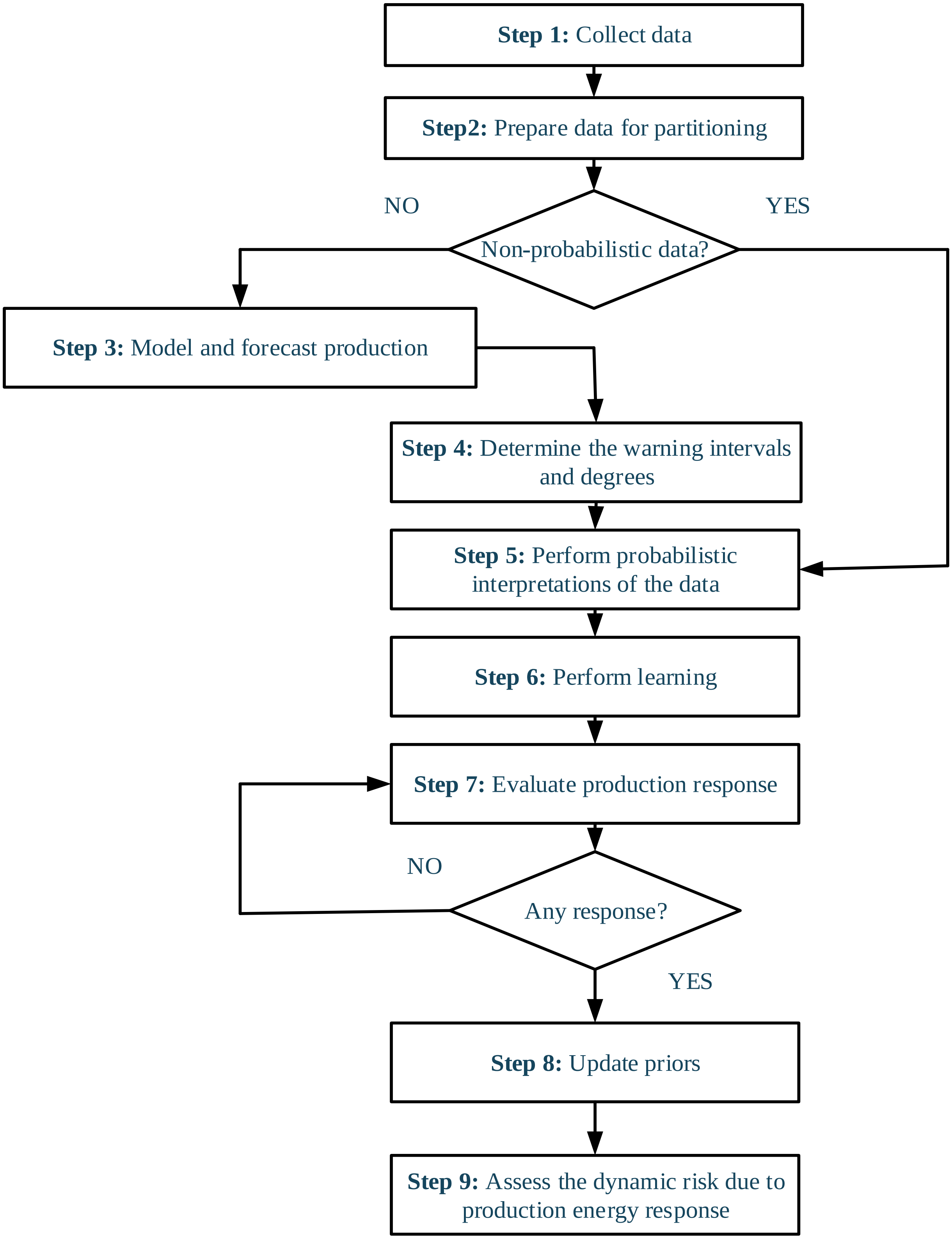


Figure 5.2: A simplified flowchart to show the key elements in the integrated methodology.

5.3.2 Parameter (Data) Selection

The implementation of the proposed methodology requires probabilistic and non-probabilistic data. The non-probabilistic data are the production data that include the reservoir parameters (e.g., pressure, porosity, permeability, transmissibility, storativity, and pay zone thickness), operational constraints (e.g., production rate and limiting GLR), and fluids properties (e.g., density and viscosity). These data are provided for developing, testing, and validating the proposed approach's ANN component. The probabilistic data are the variables that represent the failure chances or uncertainties in the selected production data, and the gas lift mechanism variables such as working GLR and injected gas rate. The data selection is based on the work's objectives as the data's quality and quantity are key to successful modeling. To meet the purposes of the current study, which are flow rate prediction and production dynamic risk assessment, the parameters selected for the hybrid approach are the reservoir drawdown (Δp), reservoir pressure (p_e), bottom-hole flowing pressure (p_{wf}), transmissibility, storativity, injected gas rate, gas-liquid ratio (GLR), production rate (q_o), and the operating valve open state. For instance, the data selected for the MLP-ANN model include the reservoir drawdown (Δp), reservoir pressure (p_e), bottom-hole flowing pressure (p_{wf}), transmissibility, storativity, and production rate (q_o). The oil flow rate is the target data, while other parameters are the input data. The data used in the EWIS-enabled Bayesian model are assigned probabilistic values of the injected gas rate, gas-liquid ratio (GLR), operating valve, reservoir drawdown (Δp), reservoir pressure (p_e), bottom-hole flowing pressure (p_{wf}), production rate (q_o), transmissibility, and storativity. Details of the built EWIS-based BN model are presented in Figure 5.6. Section 5.4.2 presents the detailed steps of the EWIS-based BN model's implementation.

5.3.3 Specifications of Smart Tools

The ANN tool used in the current study is the multilayer layer perceptron (MLP). A detailed description of this ANN type is reported in numerous published articles (Onalo et al., 2018; Shahnazari, 2020). An MLP model is a multilayer ANN model that uses supervised learning in the training process (Kim et al., 2019). Information/signals are typically transmitted from the input to the output layer with a reverse process for the error propagation. Mojiri et al. (2020) presented a compressive review of this process. The steps involved in the MLP-ANN modeling process (information transmission and error propagations) are : 1) network architecture selection (this is problem specification dependent) and input and target data selection, 2) initialization of biases and weights, 3) propagation of the input data through the network (forward pass process), 4) error estimation using the mean squared error (MSE), 5) propagating the error term backward through the network (this is backpropagation of error term), and 6) the continuous iterative process till the error term is minimized. The input data selected for the MLP-ANN model are Δp, p_e, p_{wf}, transmissibility, and storativity. The target is the production rate (q_o) to be fed to the EWIS-enabled Bayesian model. The model architecture selected in this study is the feedforward-backpropagation. The number of layers and number of hidden neurons are 3 and 10, respectively. Log sigmoid-Pure linear and Levenberg-Marquardt are the training function and training algorithm, respectively, in this study.

The linear activation function is employed in the output layer in the current work due to the problem characteristics (target variable). Typically, the output layer transfer function is selected to meet the attributes of the problem (prediction of process variable) being solved by the output layer neuron. For example, since flow rates are the target variables, the values should be in the range of zero and thousands. Thus, the linear activation function should be a viable option in the output layer to guarantee reliable predictions. In addition, the sigmoid activation function is preferred for the hidden layer, not just because it is the most common transfer function used in the multi-layer neural network, but because of the data transition it exercises. It basically accepts inputs (values which might be in a range of plus to minus infinity) and yields outputs within a range of 0 to 1. The log sigmoidal transfer function output is close to 1 for large positive values, is 0.5 at zero, and very close to 0 for large negative values. This special attribute allows smooth alterations between the low and high outputs of the network neurons. Differentiability is another key advantage of the log sigmoidal function in mathematical modeling.

Effective ANN topology construction is a challenging task in ANNs' development and implementations (Maschio et al., 2014). The step lies in the determination of the optimal number of neurons in the hidden layer (Maschio et al., 2014). This network parameter can be obtained by trial and error procedures (Maschio et al., 2014). Computation of this parameter through more dependable and relatively less time-consuming methods has also been presented in the literature (Maschio et al., 2014; Vaferi et al., 2011). The method employed by Vaferi et al. (2011) to overcome these challenges is used in the current work. The approach essentially involves an iterative procedure. Monitoring of the error convergence with a definite change in the number of hidden layer neurons in a particular order is initiated. Once the optimum value is obtained upon a substantial error convergence, the process is completed. Otherwise, the order is changed.

The early warning system uses the features of the EWIS and the Bayesian model for process modeling. This system facilitates probabilistic interpretations of the production rates, which typically range between zero and thousands of barrels per day. The required index of the oilfield development risk system is built using flow parameters such as warning situation indexes, sign, and source. The warning situation is the production rate (q_o) to be predicted, while the other index block variables are the warning signs and sources; injected gas rate, working GLR, operating valve, Δp, p_e, p_{wf}, transmissibility, and storativity. This procedure is summarized as follows: 1) find the standard deviation (σ) and statistical average (μ) of the production rates forecasted by the MLP-ANN model, 2) split the predicted production rates into distinct classified ranges, 3) ascertain the warning degrees of the outputs from the MLP-ANN component (of the proposed methodology) and correspondingly classify risk by utilizing the mathematical 3σ rule, and 4) identify the risk sources and evaluate the dynamic risks. The detailed application is presented in section 5.4.2.

5.4 Case Study

5.4.1 Field Data

The model proposed in the study is tested on the Society of Petroleum Engineers (SPE)'s project data. It is open-source data (Odeh, 1981). The case study involves a single well with a maximum daily capacity of 17,000 bbl/day. It is a well completed with installed gas lift facilities. The well is in a reservoir, which comprises three hydrodynamically connected layers. The stopping criterion is set at a minimum daily production of 3,000 bbl/day. The well is scheduled to flow for 3650 days using CMG commercial simulator. The processor and RAM of the employed computer/machine are 3.3GHz or faster and 8GB or more. The reservoir properties and operating conditions are an initial reservoir pressure of 4,000 psi, a temperature of 200 °F, a depth of 7,500 ft, and grid dimensions of $10 \times 10 \times 3$ ft. The fluid data include an oil density of 49.8 1b/ft^3, oil compressibility of $3 \times 10^{-6}\ psi^{-1}$, an initial oil saturation of 0.8, an initial water saturation of 0.2, and a water density of 62.4 1b/ft^3.

The case study data and the probabilistic data are collected and processed at steps 1 to 2, as depicted in Figure 5.2. The reservoir modeling is accomplished at step 4. The expected range of daily production is approximately between 3,000 bbl/day and 17,000 bbl/day. These production rates are fed to the EWIS model. The data processing and probabilistic interpretations are then performed. These interpretations enable the EWIS-assisted BN model to predict dynamic risks. The case study comprises a system with downhole pressure maintenance through the gas lift mechanism. The pressure enhancement process optimizes only BHP. The detailed analysis of this procedure summarized above is presented in section 5.4.2.

4.2 Description of Model Implementation

Steps 1 and 2 of Figure 5.2 presents the required data preparation and partitioning. The MLP model uses non-probabilistic data and is shown in step 3 of Figure 5.2. The flow rate is selected as the target data. The input data chosen to represent the geologic structure adequately are Δp, p_e, P_{wf}, transmissibility, and storativity. Storativity and transmissibility are the static system properties selected to enable efficient replication of the system's natural features. The other flow parameters are guessed by the ANN model using its synaptic weights during transmission. This process enhances the AI-based model performance and ensures reliable outputs. Eqs. (5.4) to (5.5) express the transmissibility and storativity, respectively.

$$Transmisibility = \frac{kh}{\mu} \tag{5.4}$$

$$Storativity = \emptyset C_t h \tag{5.5}$$

in which *k* is the average reservoir permeability; *h* represents the reservoir thickness; μ is the fluid viscosity; $\emptyset$ is the porosity; C_t symbolizes the total compressibility

70%, 15%, and 15% of the provided data/signals are used to train, test, and validate the model, respectively. The statistical characteristics of the dataset are provided in Table 5.1. ANN models are known for strong generalization capabilities when trained with an adequate dataset. This feature enables them to remain usable, even outside the training dataset. The essential fluid and rock flow properties are used as guidelines for the ANN's inputs selections to enable the desired targets' straightforward attainment. Having designed the architecture, the training, testing, and validation stages are conducted using the geologic realizations (data). The developed MLP model is validated with an entirely different geologic realization of the reservoir model and used for the production forecast, as shown in step 3 of Figure 5.2. The ANN model outputs, or the production predictions, are received by the EWIS of oilfield risks block and analyzed. This EWIS process is initiated at step 4 of Figure 5.2. EWIS of oilfield development risk block is designed to receive predicted production data from the MLP model, conduct the probabilistic data interpretations, and determine the BN output data states for dynamic risk assessment. The EWIS model uses "3σ" rule to compute the intervals and degrees. The estimated warning intervals are (1) low production heavy warning (LHW), (2) low production light warning (LLW), (3) average/normal production (NOR), (4) high production light warning (HLW), and (5) high production heavy warning (HHW). The interval classification process and degree determination occur upon receiving the predicted oil rate from the ANN model. Eqs. (5.6) to (5.8) give the different partitioned warning situations (flow rates) intervals. These represent the analytical relationships between the predicted parameters and their mean. The theory (mathematical "3σ" rule) assigns probability values to production rates based on the degree of their variances from the statistical average (μ). The failure probability increases with the increasing chance of the predicted flow rate's deviation from its means. Table

5.2 presents the details of the analytical values set by the “3σ” rule. σ represents the standard deviation of the predicted data.

Table 5.1: Statistical characteristics of the dataset.

	Flow parameter	**Mean**	**Standard deviation**
Input data	Drawdown	1173.66	126.808
	Bottom-hole flowing pressure	3626.34	126.808
	Transmissibility	65000	0
	Storativity	0.00009	0
	Reservoir pressure	4000	0
Target data	Flow rate	15043.11	3026.430

Eqs. (5.6) to (5.8) give the different partitioned warning situations (flow rates) intervals. (5.6) to (5.8).

Light abnormal periods/intervals = $[\mu - 2\sigma, \mu - \sigma]$ and $[\mu + \sigma, \mu + 2\sigma]$ (5.6)

Typical/normal interval or period = $[\mu - \sigma, \mu + \sigma]$ (5.7)

Serious/severe abnormal intervals or periods = $[-\infty, \mu - 2\sigma]$ and $[\mu + 2\sigma, +\infty]$ (5.8)

where σ represents the standard deviation of the predicted data, and μ is the mean.

Table 5.2: Data deviation extent and corresponding assigned probabilities by "3σ" rule

S/N	**Deviation Extent of Predicted Data from the Statistical Mean ($\boldsymbol{\mu}$)**	**Assigned Probability of Occurrence**
1	$> 3 \times \sigma$	31.74%
2	$> 2 \times \sigma$	5%
3	$> 1 \times \sigma$	1%

The following steps itemize the EWIS field implementation presented in steps 3 and 4 of Figure 5.2.

- Estimate the statistical mean (μ) and standard deviation (σ) of the flow rates (warning situation indexes) predicted by the developed neural network (MLP) model.
- Split the predicted production rates (indexes of warning situation) into distinct intervals/ranges using Eqs. (5.6) to (5.8).
- Evaluate the warning degrees of the distinct classified intervals of the warning situation indexes (predicted flow rates). The expected flow rate value in the normal/regular interval shows that no risk is observed. However, a little risk is observed if the predicted production variable falls in the light abnormal classified interval. Any production rate value in the severe abnormal classified interval implies a massive risk.

To construct the BN model begins with the structure learning and assigning the prior probabilities (parameter learning). The warning intervals represent the states of the EWIS-assisted BN model's outputs. The warning sign and source indexes represent the intermediate and parent nodes of the

EWIS -assisted BN model, respectively. Also, the child node or the BN model's output represents the warning situation index. The logical model (BN model) used in this study is the EWIS-based BN model. There are three basic tasks in the Bayesian model's applications for dynamic risks assessment: 1) Structure learning, 2) Parameter learning, and 3) Bayesian interference. These procedures are accomplished using Eqs. (5.9) to (5.11) (Bhandari et al., 2015; Mamudu et al., 2020b). These procedures are accomplished in steps 5 to 8 of Figure 5.2.

The posterior (updated) probability distribution or $P(H^b|E)$ is given as follows (Bhandari et al., 2015; Mamudu et al., 2020b):

$$P(H^b|E) = \frac{P(H^b)P(E|H^b)}{P(E)} = \frac{P(H^b, E)}{P(E)} \tag{5.9}$$

where $P(E)$ represents the probability of evidence or the normalization constant; $P(E|H^b)$ is the likelihood function, and E symbolizes the evidence. If the joint probability distribution of random variables is $X = (x_1, x_2, \dots \dots .., x_n)$, the Bayesian distribution can be mathematically expressed by Eq. (5.10) (Bhandari et al., 2015):

$$P(x|\theta_e, H^b) = \prod_{i=1}^{n} P(x_i|Pa_i, \theta_i, H^b) \tag{5.10}$$

Based on Eq. (5.10), H^b shows that the joint distribution of the network is decomposable; the random variable of the joint probability distribution of X is represented by $E = (X_1, X_2, \dots \dots .., X_n)$; Pa_i introduces the parent; θ_e denotes a parametric variable of the network; , θ_i is the vector form of θ_e and it represents its uncertainties; and $P(\theta_e, H^b)$ refers to a specified prior probability density function.

Assuming that a set of evidence variable is denoted by E, and that of query variable is represented by Q, the Bayesian inference needed to update the probability distribution of the query variable Q in $E = e$, is then given by Eq. (5.11) (Bhandari et al., 2015).

$$P(Q|E=e) = \sum_{X-E} P(x_1, x_2, \dots \dots .., x_n) = \sum_{X-E} \prod_{i=1}^{n} P(x_i|Pa_i) \qquad (5.11)$$

where Pa_i stands for the parent variable, x_i represents the state of the random variable, and n refers to the total number.

The following steps summarize the BN model field implementation presented in steps 6 to 9 of Figure 5.2.

- Select the required reservoir flow parameters (define the random variables) used in the constructed EWIS risk block.
- Conduct the structure learning of the EWIS-based model (See Figure 5.5).
- Perform the parameter learning: 1) assign the prior probabilities, and 2) construct the conditional probability table (See Figure 5.6).
- Estimate the posterior or updated probabilities and compare the prior and posterior probabilities of the flow parameters (route nodes) for risk detection/analysis (See Figure 5.10a and b).

5.5 Results and Discussion

Oil production forecasts and the associated risk predictions from a dual-energy support system are investigated in this study. The developed data-driven probabilistic model offers a means to predict oil production and analyze the associated risks (failure chances). It conducts a real-time assessment of the dynamic risk resulting from the production state and the bottom-hole flowing pressure (p_{wf})'s response. The model captures the codependency of the production system on the two independent energy systems (lift mechanism and downhole pressure system). Also, Predictive correlations are developed from the risk assessment conducted for the reservoir system (the case study). This enables dynamic risk predictions at any production time in the well's life considered in the case study. The deterministic models properly handle the two extreme risk cases (high or low risk), depending on the response of the downhole energy system. Figures 5.3 and 5.4 present the results obtained from the ANN component of the proposed methodology.

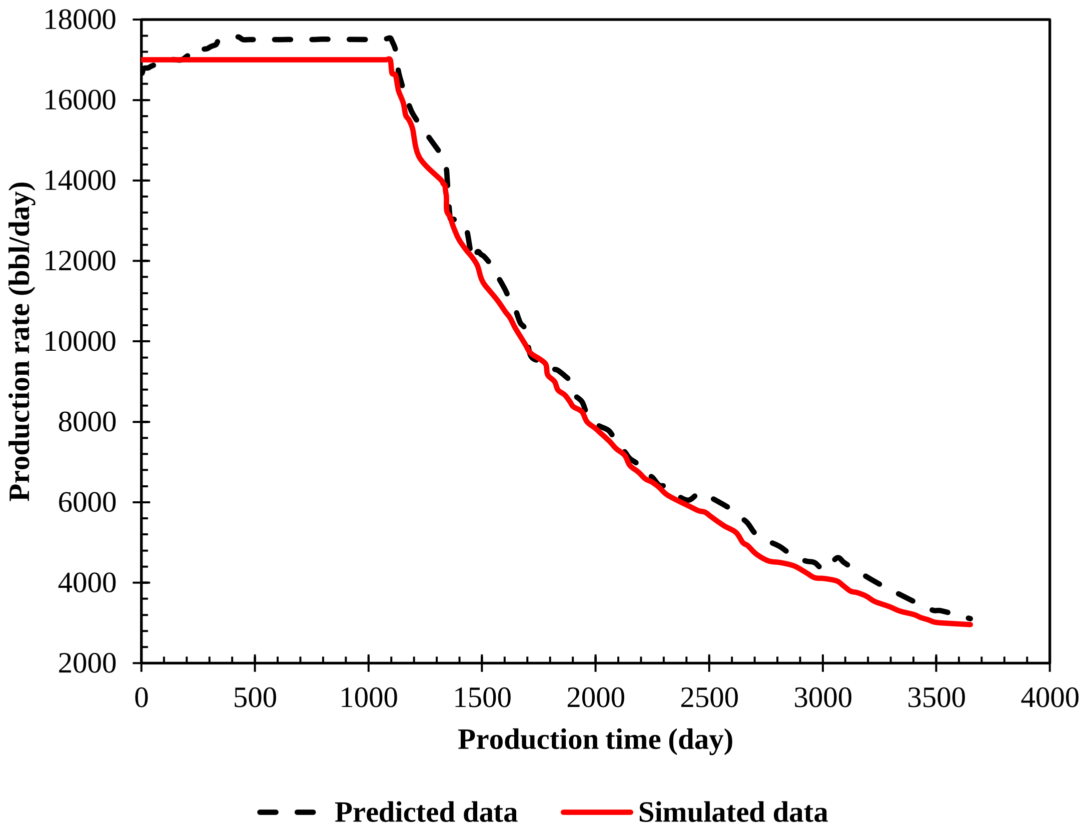


Figure 5.3: Predicted and actual data of production history.

Figure 5.3 shows the predicted and simulated production data versus time. According to Figure 5.3, the data-driven component (ANN) of the developed hybrid approach demonstrates efficient predictive capability. The model exhibits the best match within the production period of 1000 - 2500 days. Reasonable agreement between the predictions and real data is also noticed beyond the range of the best match. The transient flow period is well captured, and there is a good match in the late time. The mean absolute percentage error (MAPE) parameter is employed to examine the smart model's prediction precision statistically. The average and maximum percentage errors are reported to be 2.16%, and 9.04%, respectively. Figure 5.4 presents the residual plot, showing no specific pattern. This implies that an efficient predictive model has been developed. Figure 5.5 illustrates the proposed structural learning approach.

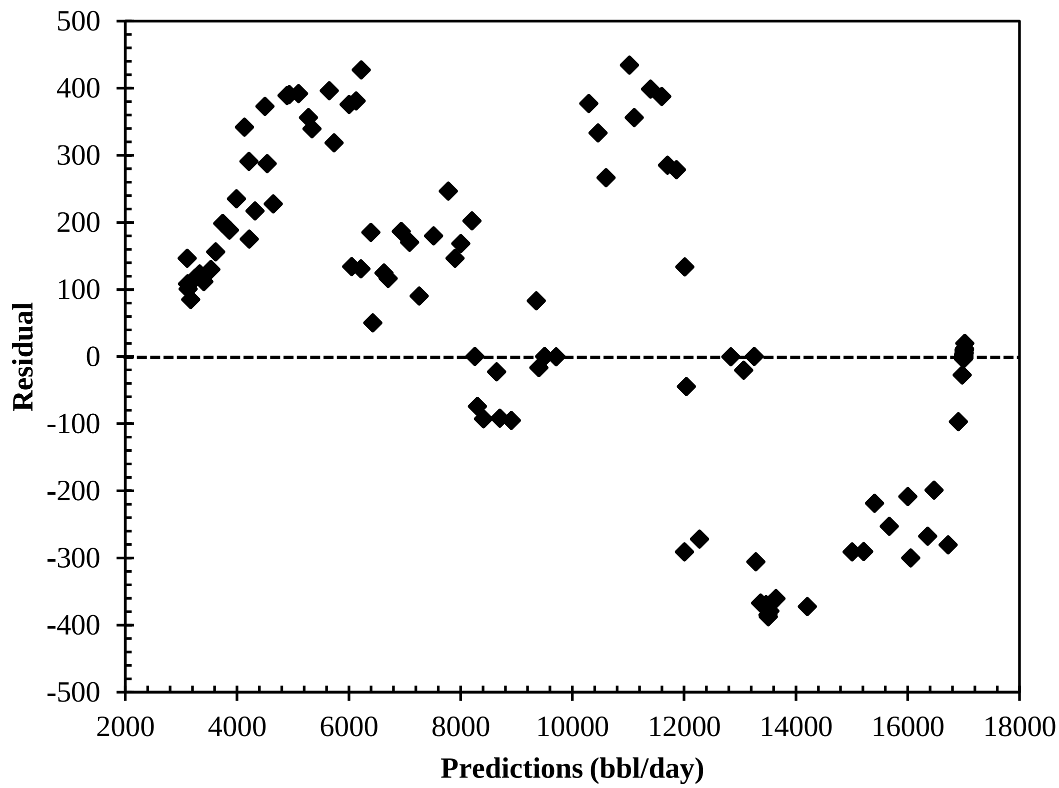


Figure 5.4: Residual errors versus predicted data.

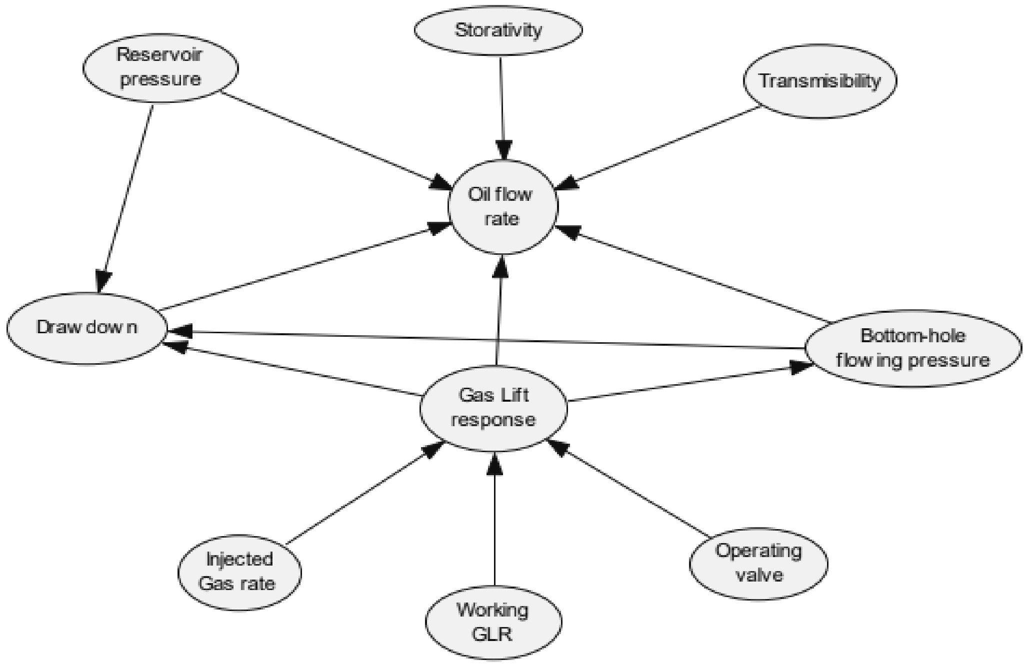


Figure 5.5: Proposed structural learning process.

In general, Figure 5.5 reveals the variables dependencies and their logical interactions. These interactions/dependencies show how the gas lift response is structurally connected to the working GLR, bottom-hole following pressure (p_{wf}), and drawdown (Δp). The gas lift response is shown to be dependent on the human error in estimating the GLR, injected gas flow rate, and the open state of the installed operating valve close to the sand face. These three parameters are the route nodes to the logical node, representing the lift. Figure 5.6 shows the parameter learning process of the model. Parameter learning is one of the most critical aspects as its sufficiency determines the accuracy of the BN model's predictions. The conditional probability table (CPT) should be appropriately constructed to yield good predictions for proper planning and minimize errors. Thus, it requires a sound knowledge of the underlying domain, such as reservoir fluid flow chemistry.

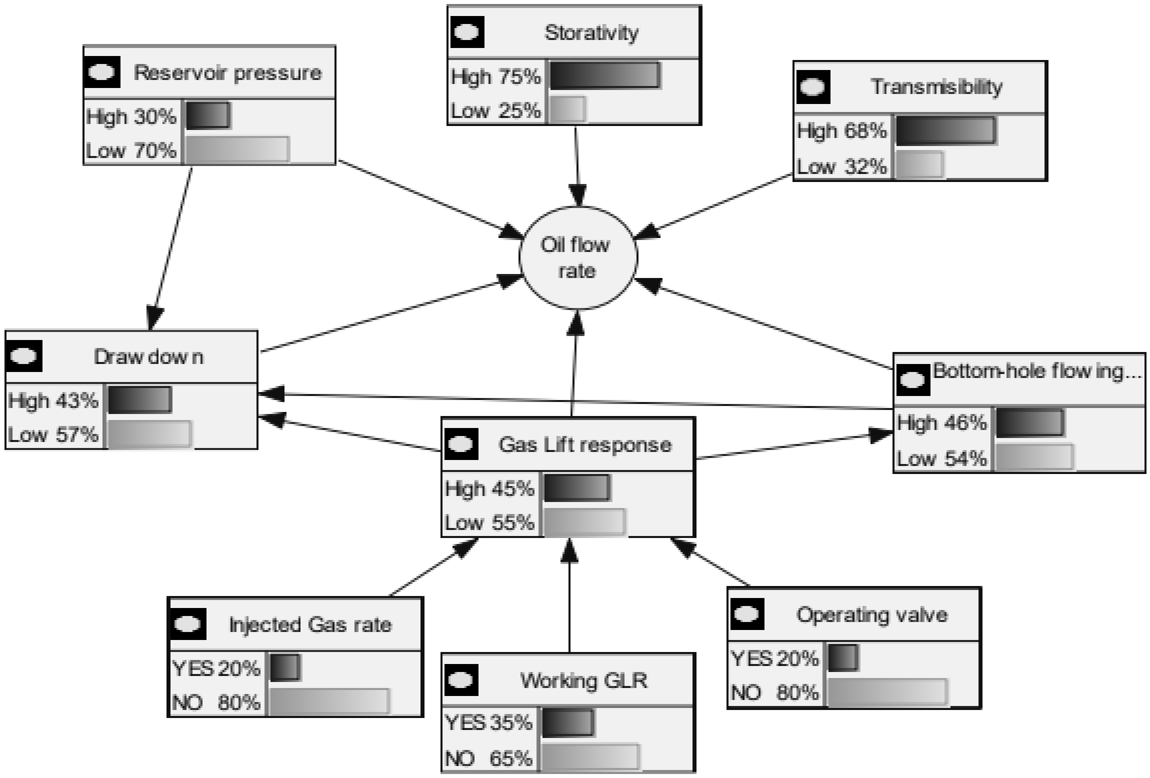


Figure 5.6: The proposed methodology for the parameter learning process.

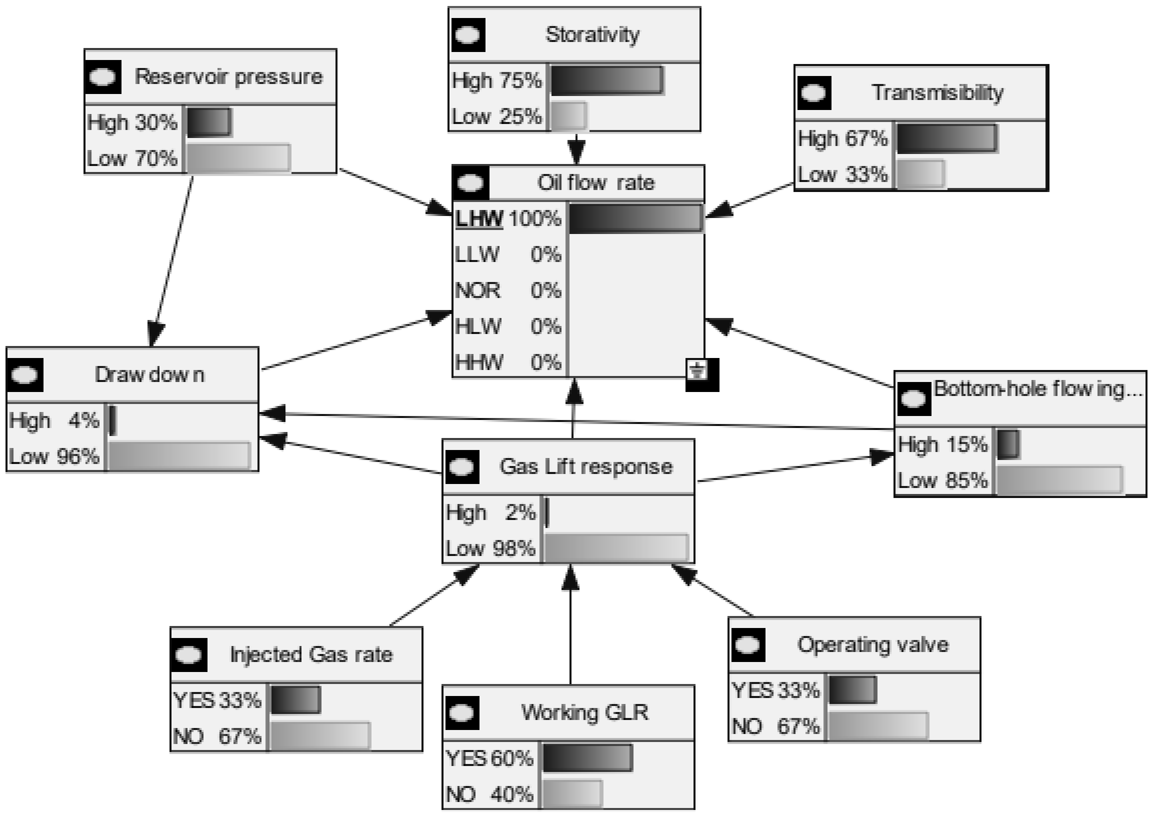


Figure 5.7: Posterior probability distribution from the evidence of low energy response (low production).

Figure 5.7 reports low production signals predicted by the early warning system-enabled BN model. This category is considered the extreme scenario of production losses. These results are attainable only when the production energy has failed critically. That is when both the gas lift and the reservoir energy are not responding sufficiently. In this scenario, the risk associated with the gas lift system response is as high as 98%, as depicted in Figure 5.7 against the prior probability of 55% recorded in Figure 5.6. Technically, this change is expected to have a direct numerical impact on the p_{wf} and the Δp responses. Thus, it follows that the risks of the p_{wf} and Δp are a posterior of 85% against a prior probability of 54%, and a posterior of 96% against a prior probability of 57% as recorded in Figures 5.7 and 5.6, respectively. This finding confirms the strong relationship between a gas lift's drive mechanisms and the bottom-hole flowing pressure. As the injected gas enters the tubing, the oil gets aerated by the gas. Thus, the resulting density of the hydrocarbons in the tubing becomes lower, and the pressure exerted by the hydrostatic head is reduced, which lowers the sand face pressure (bottom-hole flowing pressure). The reason for this behavior is that the p_{wf} is the summation of the tubing head pressure and the pressure applied by the fluid's hydrostatic head in the tubing. The extreme scenario shows that the bottom-hole flowing pressure does not positively impact the drawdown as the gas lift mechanism does not stimulate it. In summary, the system illustrated in Figure 5.7 shows the significant impact of dual-energy failure when the gas lift mechanism is less responding than expected.

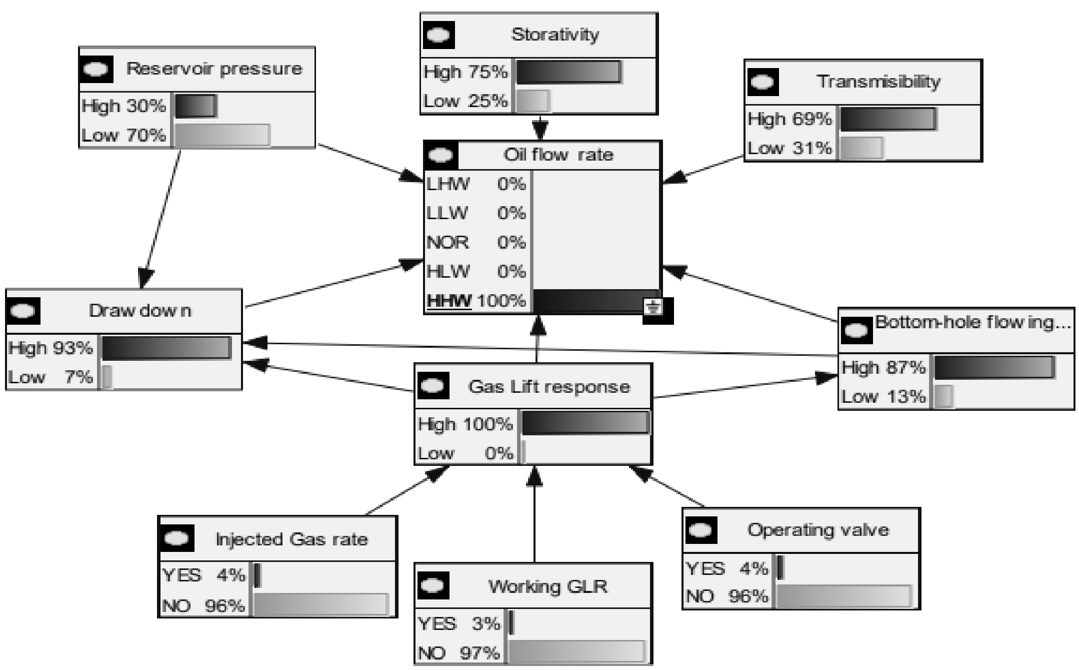


Figure 5.8: Posterior probability distribution from the evidence of sufficient energy (high production).

Figure 5.8 depicts the logical evidence of the high production case. According to Figure 5.8, increased production is a product of an efficient gas lift mechanism, provided the success state of the supplemented downhole pressure system is guaranteed. Firstly, the results show that the risks associated with the injected gas, the working GLR, and the operating valve should be minimized to have a successful gas lift operation. This applies to both onshore and offshore cases. Another important finding from this scenario is that a successful gas lift mechanism is independent of significant reservoir drawdown and bottom-hole pressure responses. All these findings validate the logical model's outputs. The human error in estimating the working GLR remains the most critical variable in the gas lift operation, with a posterior probability of 3%, as recorded in Figure 5.8, against a prior probability of 35% (as depicted in Figure 5.6). Therefore, the gas lift process can sustain an adequate production rate for a reasonable period only when the human error in estimating the GLR parameter is minimized. Thus, working GLR remains a key variable in the gas lift process. The injected gas inflow and the operating valve seem to show equal significance in the production system. This assertion demonstrates the proposed model's strength as it could be validated from a qualitative sense intuitively. On the other hand, the risk associated with reservoir pressure remains the same. Hence, once the oil production is augmented with the gas lift mechanism, it means that the reservoir energy has technically failed already (it is insufficient) as desired flow rates are not recorded at the surface. As a result, it does not contribute significantly to the drive mechanism required for production.

Figure 5.9 presents the dynamic risk profiles for the two possible cases (scenarios) that arise during the production process: 1) when the production is with minimal risk, and 2) when the production fails critically due to insufficient production energy. Thus, the gas lift impact is very low. The low-risk profile represents this event in Figure 5.9. According to the minimal risk scenario, the production failure chances increase with time; however, after 3650 days (10 years) of production, the possibility of failure remains below 55%. Unlike the maximum failure scenario, where the gas lift system has a low impact, the risk is higher. The failure probability increases drastically with time. After ten years of production, success is estimated to be lower than 10%, representing a staggering probability of failure of at least 90%, as shown by the high-risk profile plot in Figure 5.9.

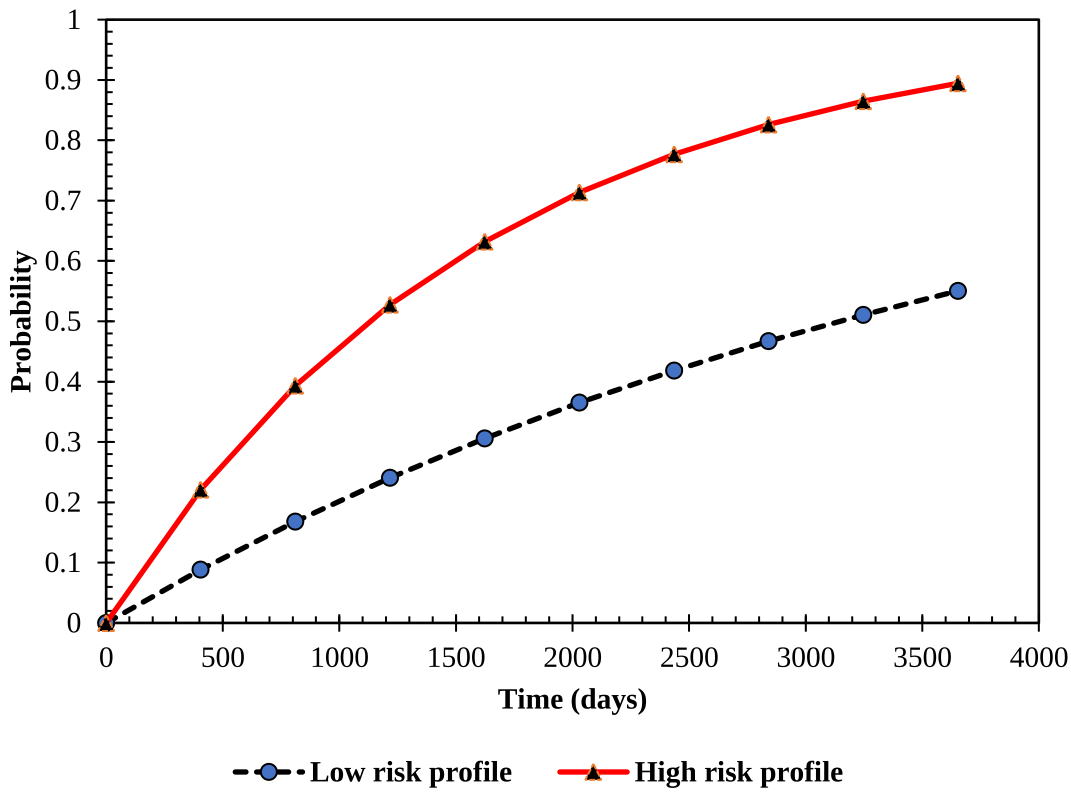


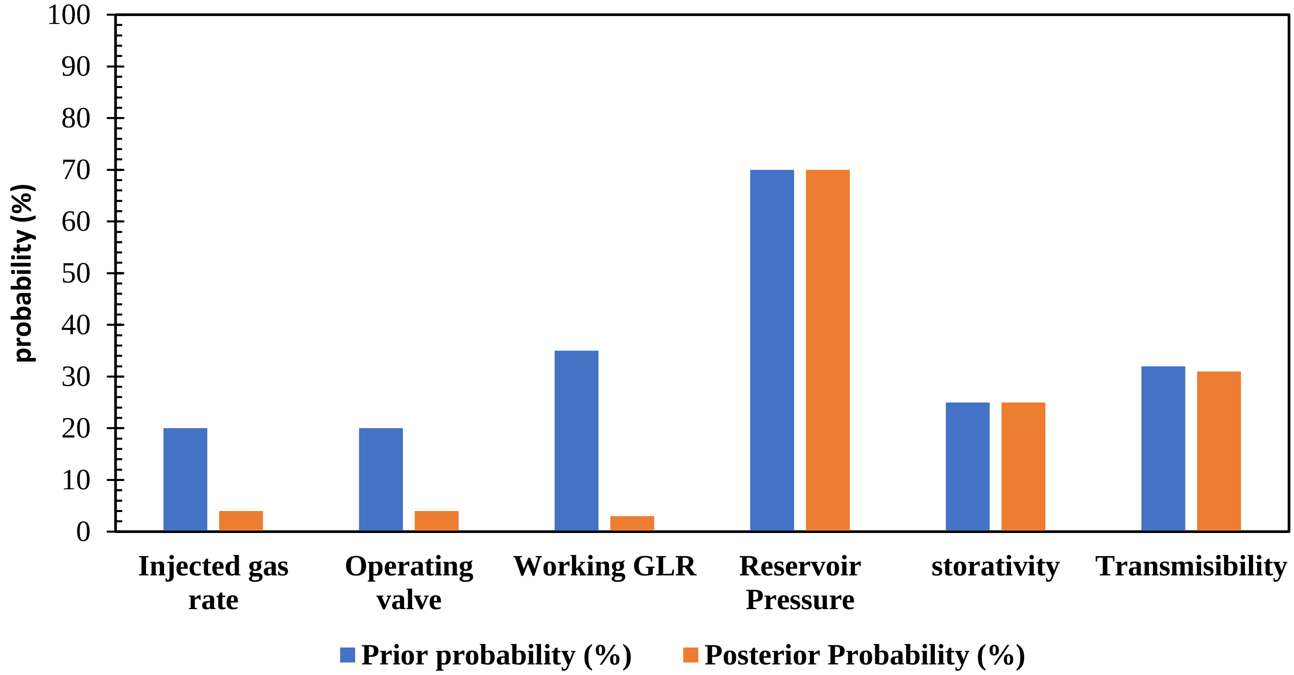
Figure 5.9: The probability curve for low and high-risk profiles.

Two correlations are developed for these two possible cases. The developed predictive correlations have a coefficient of determination (R^2) equal to 1. Thus, they are reliably applicable to risk predictions throughout the production life of the well. Eqs. (5.12) and (5.13) represent the forecasting correlations to estimate the high and low risks associated with the production system.

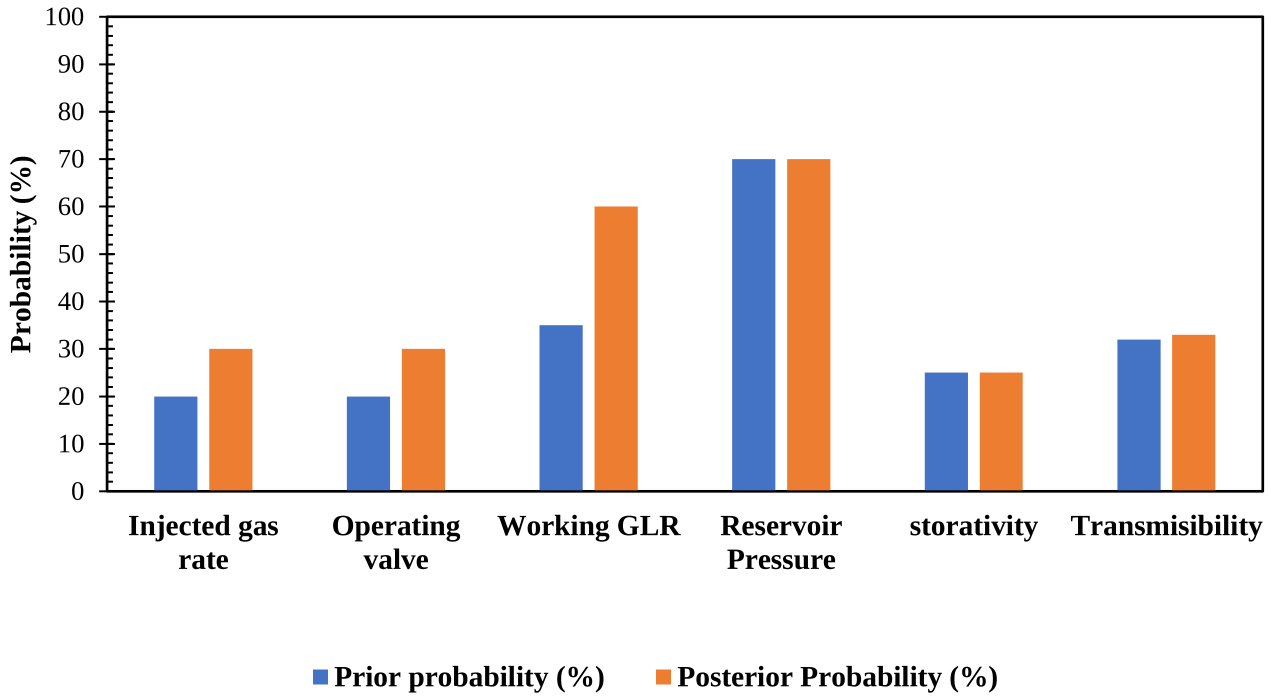
$$P_{(t)} = -2 \times 10^{-15} t^4 + 3 \times 10^{-11} t^3 - 2 \times 10^{-7} t^2 + 6 \times 10^{-4} t + 2 \times 10^{-4} \tag{5.12}$$

$$P_{(t)} = 1 \times 10^{-12} t^3 - 3 \times 10^{-8} t^2 + 2 \times 10^{-4} t + 1 \times 10^{-4} \tag{5.13}$$

where $P_{(t)}$ stands for the failure probability, and t is the production time



a) Probability data of low risk profile.



b) Probability data of high-risk profile.

Figure 5.10: Prior and posterior probabilities of the route nodes

Figure 5.10a shows the route nodes' prior and posterior probabilities for the low-risk scenario (evidence of sufficient energy corresponding to high production). At the same time, Figure 5.10b depicts the high-risk condition (evidence of low energy response or low production). The results from these Figures (5.10a and b) show that the reservoir has completely failed. Hence, the reservoir pressure remains constant (unchanged) with respect to the prior and posterior probabilities in the high and low-risk scenarios. Thus, the reservoir pressure is unaffected during gas lift operations. Regarding the transmissibility and storativity, the same applies as there is no considerable difference between the prior and posterior probabilities. These findings from the logical analysis conform to the field practice, implying that our parameter learning approach is reliable and adequate. Hence, the methodology would be useful in decision making for the scenario under study and other similar production systems.

According to Figure 5.10, the injected gas rate, working GLR, and operating valve failure state are the most vital process parameters. They record the most significant changes between the prior and posterior probabilities. They are the real contributing factors to the p_{wf} and Δp responses. In these results (5.10a and b), the validity and reliability of the logical component of the proposed methodology are demonstrated. According to Figure 5.10, drawdown and the bottom-hole flowing pressures should be the significant reservoir parameters of interest when optimizing production through the gas lift mechanism as the prior probabilities and posterior probabilities in both scenarios (low and high-risk) experience significant changes (See the intermediate nodes in Figures 5.7 and 5.8). Thus, logically, the drawdown and the bottom-hole flowing pressure should be considered essential flow parameters when optimizing production due to the gas lift mechanism. This finding technically validates the logical model results and ensures its reliability or efficiency as is both well-known and intuitively obvious in a qualitative/qualitative sense. Hence, the EWIS-based BN model could be adequately used to quantify established dependencies of the reservoir flow parameters to enable real-time optimization and adjustment of the parameters as the well is being produced. The model also offers a means to evaluate the risks involved in different production scenarios resulting from the variation of all the key parameters at the reservoir engineer's disposal.

The results depicted in Figures 5.7 to 5.10 demonstrate the specific findings of the conducted research. The comparative interpretations of Figure 5.10 (panels a and b) highlight the importance of the working GLR in the gas lift mechanism. It follows that adequate working gas-liquid ratio (GLR) ensures efficient production for a reasonable period, implying that the working GLR is a critical variable in the gas lift mechanism. The proposed methodology captures the effect of the gas lift mechanism on the p_{wf} and the production process. Hence, the proposed system would assist in production-related decision making.

This study provides a methodology for oil production prediction and the associated risk assessment under a dual-energy source. The proposed methodology investigates the impact of the gas lift mechanism on oil production rate as well as on p_{wf}. This study highlights the impact of the downhole pressure system and the interdependencies of the process variables. The proposed strategy enables adequate production prediction and mitigates data and model uncertainties. The models developed in this research can forecast risks within the case study duration adequately. The integrated methodology is reliable and recommended for academic and research centers and the related industries. However, there are some limitations to the proposed approach. For instance, the used data might only be adequate for the scenario under consideration; other systems need different data points to ensure the model's accuracy and reliability. It is recommended that effective hybrid methodologies are designed to incorporate economic losses evaluation. Besides, the current methodology can be improved and extended to production pump systems. Despite the numerous advantages of the ANN model in engineering applications, it is restricted by the lack of extrapolation capability. The BN model also faces the challenge of subjectivity. The key solution to improve the risk analysis model and data reliabilities is a sound knowledge of the domain of interest.

5.6 Conclusions

A hybrid methodology is proposed for the production forecast and dynamic risk modeling of a hydrocarbon production reservoir system. The data-driven probabilistic tool combines the ANN model and the BN model. The ANN component accurately forecasts the production rates and serves as the suitable candidate for uncertainties minimization. The BN component effectively assesses the dynamic risks in the production operations (or oilfield development risk block). The integrated model offers a proper approach to predict oil production rates and analyze the associated failure chances in the oilfield development systems with production energy challenges. The connectionist strategy is developed to generate deterministic correlations for the prediction of production risks. The model can capture the production system's codependency on the gas lift mechanism and reservoir energy (two independent energy sources). The real-time dynamic risk assessment is conducted based on the p_{wf}'s failure and production data. The following key conclusions are drawn from this study:

- A data-driven probabilistic model can be employed for efficient dynamic risk assessment in a dual energy-support production system. The proposed methodology captures the gas lift mechanism's effect on the bottom-hole flowing pressure and the production process.

- The ANN component of the hybrid connectionist strategy yields prediction precision with an average error of 2.16%.
- The gas lift mechanism can sustain an adequate production rate for a reasonable period only when the human error in estimating the working gas-liquid ratio (GLR) is minimized.
- The proposed strategy demonstrates that the working GLR is a critical variable in the gas lift mechanism as its adequacy ensures effective lift operations.
- The developed model offers field operators an early warning system-enabled Bayesian model that yields deterministic models with adequate risk monitoring capabilities. This enables dynamic risk prediction at any production time in the well's production life.
- The EWIS-based BN model offers the means to quantify the reservoir flow parameters' dependencies to enable real-time optimization and adjustment of the uncertain parameters as the well is being produced.
- The model would enable the operators to evaluate the risks involved in the different production scenarios resulting from the variation of all the key reservoir flow parameters at reservoir engineers' disposal during operations.

It is recommended to design proper deterministic strategies to incorporate economic losses in the modeling framework. Furthermore, the proposed methodology can be extended to production systems with pump schemes.

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Appendix 5.A

This appendix reports some statistical information for the training phase.

Table 5.A1: The statistical analysis of the training process.

Mean type	**Standard deviation**	**Mean**
MAE	0.000769	0.003675
MSE	1792.315	5250.681

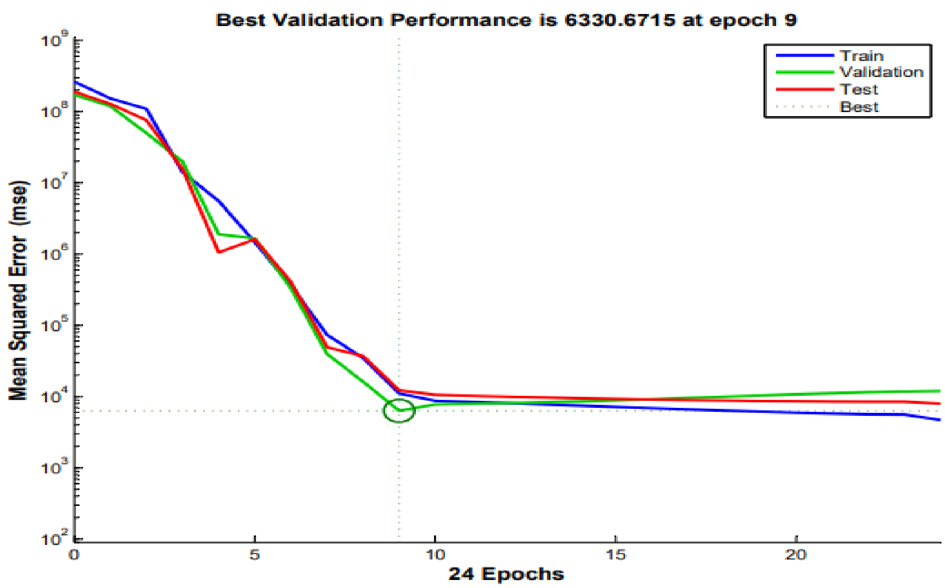

Figure 5.A1: MSE plot of the training process.

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Chapter 6

A connectionist model for dynamic economic risk analysis of hydrocarbons production systems

Preface

A version of this chapter has been accepted for publication in the ***Journal of Risk Analysis****. I delivered this work together with my co-authors; Faisal Khan, Sohrab Zendehboudi, and Sunday Adedigba. I am the main author. I conducted the literature review, formulated the concepts of the economic risk assessment model and developed it for dynamic economic risks assessment of petroleum reservoir production systems. I prepared the first draft of the manuscript and subsequently revised the manuscript based on the co-authors' and peer review feedback. Co-author, Faisal Khan assisted in the review of the developed concept and methodology, reviewing and editing the draft, and reviewing and revising the new version of the manuscript. Co-author, Sohrab Zendehboudi supported in the review of the developed concept and methodology, reviewing and editing the draft, and reviewing and revising the new version of the manuscript. Co-author, Sunday Adedigba assisted in the review of the developed concept and methodology.*

Abstract

This study presents a connectionist model for dynamic economic risk evaluation of reservoir production systems. The proposed dynamic economic risk modelling strategy combines evidence-based outcomes from a Bayesian network (BN) model with the dynamic risks-based results produced from an adaptive loss function model for reservoir production losses/dynamic economic risks assessments. The methodology employs a multilayer-perceptron (MLP) model, a loss function model; it integrates an early warning index system (EWIS) of oilfield block with a BN model for process modeling. The model evaluates the evidence-based economic consequences of the production losses and analyzes the statistical disparities of production predictions using an early warning index system (EWIS)-assisted BN model and the loss function model at the same time. The proposed methodology introduces an innovative approach that effectively minimizes the potential for dynamic economic risks. The model predicts real time daily production/dynamic economic losses. The connectionist model yields an encouraging overall predictive performance with average errors of 1.954% and 1.957% for the two case studies: cases 1 and 2, respectively. The model determines transitional/threshold production values for adequate reservoir management toward minimal losses. The results show minimum average daily dynamic economic losses of $267,463 and $146,770 for cases 1 and 2, respectively. It is a multipurpose tool that can be recommended for the field operators in petroleum reservoir production management related decision-making.

Keywords: Connectionist model; Dynamic economic risk; Economic loss; Loss function model; Reservoir production

6.1 Introduction

Petroleum reservoirs are complex process systems defined by intrinsically uncertain data and a distinct pressure gradient. The upstream sector's assets include huge uncertainties/high risks (Asheim, 1988; Bittencourt & Horne, 1997; Khazaeni & Mohaghegh, 2011; Wang et al., 2019; Zhao et al., 2012). Hence, the investments in these complex underground systems often suffer significant economic risks due to the process complex dynamics, environmental factors, process data uncertainties, and human errors. Several oil and gas field development planning and optimization strategies have been employed to proffer solutions to these challenges (Wang et al., 2019). However, their use in petroleum economics has shown that these strategies lack the potency to handle dynamic economic risks assessments of the corresponding process as they are mainly developed to forecast production and/or quantify production uncertainties (and risks). Indeed, the reliable mechanisms to incorporate the production variables' dynamics are not considered in the existing methodologies. Petroleum economics is a core area of petroleum engineering and sciences. Field development models, petroleum production models, and reservoir management optimizations strategies are the key economic models in petroleum economics. While various methodologies have been used for reserves and production predictions, uncertainties quantification, and/or risks analysis over the past decades, to the best of the authors' knowledge, a strategy for dynamic economic risks assessment has not been reported in the literature. This motivates researchers to develop a multipurpose connectionist methodology for reservoir production forecast, evidence-based dynamic risks analysis, and dynamic economic risks assessment of the reservoir production systems. For instance, the complex dynamics of the production variables can be due to unforeseen severe production fluctuations, system failures, and/or abrupt well shut-in due to uncontrollable circumstances (environmental factors or governmental regulations).

Numerical and analytical models are commonly employed for field development. Numerical simulations are based on various numerical methods. The numerical models are only used for reserves and production predictions and uncertainties quantifications. In fact, the uncertainties quantifications conducted with the simulators are achieved by assuming ranges of values for the model's individual uncertain input parameter(s) and obtaining a corresponding model's output value for each of the assumed values of the input factors (Costa et al., 2014; Oghena, 2007). Thus, the approach is stochastic, prohibitive, and time consuming. In addition, it does not consider the process dynamic risks. The commonly used analytical models are the decline curves method. They are established models for reserve and production forecasts (Rahuma et al., 2013). Some operators have utilized this method for decades (Rahuma et al., 2013). However, the models lack adequate process representation due to several assumptions made during their development such as system homogeneity, isotropy, flow regime, boundary conditions, and geologic structural shape limitations. In addition, the decline curve models are built to yield/define fixed production curves. Therefore, the models have no potentials to handle/capture dynamic risks or evidence-based production abnormality such as abrupt well shut-in or sever abnormal production losses. In this work, we propose a connectionist modeling strategy to address the identified challenges of dynamic economic assessment. The proposed dynamic economic risk modelling approach combines evidence-based outcomes from a Bayesian network (BN) model with dynamic risks-based analyzed deviations predicted from a loss function model for reservoir production losses/dynamic economic risks predictions. It employs an MLP model, a loss function model, and integrates an early warning index system (EWIS) of oilfield block with a BN model for process modeling.

In the recent decades, there have been huge advances in smart models' applications in the oil and gas industries. A brief review of the relevant previous research studies is presented in this work. Bittencourt and Horne (1997) presented a hybrid generic algorithm (GA) for economic analysis and production simulation of a reservoir system. Similarly, Subbey et al. (2003) used a neighborhood algorithm (NA) in their study to predict production rate. Nicotra et al. (2005) implemented a similar method with an in-built stochastic feature. Some other researchers employed artificial neural network (ANN) models to forecast the amount of production (Augusto et al., 2014a; Khazaeni and Mohaghegh, 2011; Lechner et al., 2005; Shahkarami et al., 2014; Wang et al., 2019; Zhao et al., 2012). Maschio et al. (2014) used Markov Chain Monte Carlo (MCMC) for oil production prediction. In addition, Sun and Ertekin (2017a) developed a stochastic model for simulation of cyclic steam stimulation processes. The model is limited to cyclic steam stimulation enhanced oil recovery (EOR) schemes. Zhong et al. (2016) presented a hybrid model, which integrates an ANN model with a BN model for process modeling. Also, Mamudu et al. (2020b) combined an ANN approach with a BN model for reservoir production modeling. Although the models mentioned above were successfully implemented for production forecast, the dynamic economic risks were not assessed in their works as the models were not primarily designed for such tasks. In summary, the reviewed smart methodologies cannot conduct dynamic economic risks assessment. To the best of the authors' knowledge, risk analysis methodologies with in-built features for dynamic economic risks evaluation and evidence-based production losses analysis have not been reported in the literature. The current work is intended to fill this identified knowledge gap.

The main objective of this research is to develop a dynamic economic risk modelling strategy that combines evidence-based outcomes from a Bayesian network (BN) model with analyzed deviations predicted from an adaptive loss function model for reservoir production losses/dynamic economic risk prediction. The proposed model independently links a data-driven model to a loss function model for assessment of predictions deviations. It links an early warning index system block to a BN model to enable evaluation of evidence-based production losses. The evaluated evidence-based production losses due to the dynamic risks are further modeled with the loss function model for economic analysis/reservoir production management decision-making. Thus, the proposed connectionist model assesses production losses/dynamic economic risks due to the observed evidence from the BN model and the outputs predicted from the loss function model.

This work is structured as follows. Section 6.2 presents the theory and background. The concepts of the individual component models that form the proposed connectionist methodology are also presented in this section. Section 6.3 describes the proposed methodology. The steps involved in the implementation of the proposed connectionist model are briefly given in this section. The two case studies are presented in Section 6.4. Section 6.5 includes the results and discussion. Lastly, Section 6.6 summarizes the main findings of this research work.

6.2 Theory and Background

This section presents a brief description of the concepts of the individual component systems/models that create the proposed connectionist approach.

6.2.1 Artificial Neural Network (ANN) Model

ANN is an artificial intelligent (AI) model developed with the idea of having a mathematical representation of the human biological neural schemes (Zendehboudi et al., 2018). Artificial intelligence is described in the literatures as a computational intelligence, soft computing, and/or virtual intelligence (Mohaghegh, 2000). ANN is the most used AI approach in engineering applications (Li et al., 2020; Shahnazari, 2020). The ANN model has an intrinsic/remarkable ability to mimic complex system behaviors and replicate complicated process behaviors in various engineering and science systems irrespective of the process dimensionality and non-linearity natures. The black-box model is characterized by its intrinsic potency of reasoning attributes such as perception, discovery, grouping, and generalization (Aleardi, 2015; Cranganu & Bautu, 2010;

Gharbi, 2003; Kalantari et al., 2009; Khazaeni & Mohaghegh, 2011; Maleki et al., 2014; Mohaghegh, 2000; Onalo et al., 2018; Mojtaba et al., 2010; Zendehboudi et al., 2018). Zendehboudi et al. (2018) described ANN as a strong mathematical black-box model/tool characterized by functions identical to the human neural systems. Typically, it relates input and output data for process systems modeling without process knowledge. For a single neuron's signal processing unit with n number of inputs, Zendehboudi et al. (2018) mentioned the expressions presented in Eqs (6.1) and (6.2) as the synaptic weights, biases, input and output data relationships.

$$z = \sum_{j=1}^{n} w_j x_j + b \tag{6.1}$$

$$y = f(z) \tag{6.2}$$

in which, z denotes the sum of all inputs entering the neuron; b introduces the bias; y represents the neuron output signal; w_j describes the transmission channel synaptic weight; j is the synapse ; x_j refers to the input signal; and f is the transfer/activation function (a linear activation function).

ANNs have been broadly classified based on the network characteristics (Elkatatny et at., 2018; Elkatatny et al., 2019; Elkatatny et al., 2018; Mamudu et al. 2020b; Moussa., 2018; Ossai, 2020; Pakzad et al., 2020; Tariq et al., 2017b, 2017a). These categories include learning method, application, connection type, and topology. Based on learning method, ANNs are categorized as conventional (and/or hybrid), unsupervised, and supervised processes. The use of both the unsupervised and supervised learning methods during learning is termed the hybrid process. In the unsupervised learning process, the target data are not fed to the network. On the other hand, the system in which there is a provision of both the target and input data for training is called the supervised learning method. In the context of application, ANNs are classified into prediction, clustering, classification, and function evaluation. The network connection type describes the data feeding route/direction. This only includes feedback and feedforward. The feedback models use in-built loops to send signals/information in both directions. However, the feedforward models/networks send signals from the input to the output component (forward direction) with backpropagation for errors transmission (backward direction). The feedforward models/networks are mainly used in engineering cases (Mamudu et al., 2020a). In terms of topology, the networks are classified into multi-layers, single layer, self-organized structures, and recurrent. A multiple layer network model with a forward pass for signals transmission (input to output transfer of information) is known as a multi-layer perceptron (MLP); this approach is employed in the current research. Further information on ANNs classifications is provided in the literature (Adedigba et al., 2017; Onalo et al., 2018; Zendehboudi et al., 2018).

6.2.2 Bayesian Network (BN) Model and EWIS Oilfield Development Risks Block

The pursuit towards ensuring proper assets management makes process risk analysis an area of endless research efforts. Several risk analysis methodologies have been proposed by several researchers. Similar to fault detection and diagnosis in complex engineering systems, the use of BN model has been proposed for risks sources detection and uncertainties analysis in the recent years (Mamudu et al., 2020b; Zhong et al., 2016). It was found that the dynamics of the production variable is adequately captured by the dynamic model (BN model). Risk has been broadly described in the literature as a measure of loss (the product of the event's likelihood and the degree of the economic loss). The Bayesian theorem is a model that describes how the hypotheses (priors) are updated having observed evidence (Adumene et al., 2020; Adumene et al., 2021; Adumene et al., 2021; Adumene et al., 2020; Mamudu et al., 2021). Thus, the model analyzes the risk sources for any reservoir production change (evidence). The detailed analytical procedure for the model's implementation is presented in section 3.3; it is feasible with probabilistic values. Hence, it seems essential to develop a connectionist model through integration of EWIS model with the BN model for process data interpretations and modeling. EWIS of oilfield development risk block is primarily designed for 1) receiving predicted production data from the MLP model, 2) processing probabilistic data interpretations, and 3) establishing the BN output data states for dynamic risk analysis. The detailed procedure is given in section 6.3.3. The EWIS principles are based on the procedures of risk identification and assessment (Horneret al., 2011; Zhong et al., 2016).

The indexes (or process system variables) are categorized into three classes in the assessment process. These include the warning situation, warning sign, and warning source indexes. Gas-liquid ratio (GLR), liquid production, oil production, gas production, and water production represent the warning situation indexes. The warning sign indexes are the variables that are in direct contact with the warning situation indexes, while the warning source indexes are the risks causes (Zhong et al., 2016).

6.2.3 Loss Function Model

Loss function generally measures the extent of deviation of an estimated variable (value) of a quantity from the true variable (optimal value). The loss function model required for a given process is process-data dependent (whether they are classification or regression losses). In the recent years, loss function models have been widely accepted among quality assurance practitioners and researchers due to the inherent features of Taguchi method as it yields adequate quality improvement strategies (Adedigba et al., 2018). There are several types of loss function models reported in the literature (Adedigba et al., 2018). These include: 1) quadratic loss function, 2) quartic loss function, 3) inverted normal loss function, 4) modified inverted normal loss function, 5) inverted beta loss function, 6) inverted gamma loss function, 7) pseudo-Huber loss function, 8) Cauchy loss function, 9) German-McClure loss function, 10) Welsh loss function, and 11) generic adaptive algorithm loss function. The details of the generic adaptive loss function model employed in the current research are presented in section 6.3.3.

6.3 Methodology

Figure 6.1 depicts the flowchart of the proposed connectionist model for dynamic economic risks assessment of petroleum reservoir production systems. The main aim of the introduced model is to provide field operators/researchers with a methodology to adequately evaluate dynamic economic risks at any time in the production life of a well or reservoir. The model uses an ANN model for production forecast, an early warning system- assisted BN model for dynamic risks predictions, and an adaptive loss function model for evidence-based dynamic economic losses analysis.

Steps 1 and 2 of the methodology present the dataset building and segregation for sub-models' development. The hydrocarbons production forecast is conducted at step 3. The adequacy of the predictions is assessed at step 4 using the loss function evaluation technique. The early warning system is activated at step 5 to feed the BN model at step 6. The structural learning of the early warning system- assisted BN model is constructed at step 6. The parameter learning is also accomplished at this step. The monitoring of production losses or dynamic risks takes place at step 7. If any evidence of production loss is observed, signals are sent to step 8 for adequate evidence-based outcomes analysis. On the other hand, if no evidence is noticed, production monitoring continues at step 7. The analyzed deviations from step 4, and the evidence-based outcomes from step 8 are received at step 9 for the dynamic economic risk/losses' assessment. The evidence-based production losses evaluated based on the dynamic risks from step 8 are further assessed using the adaptive loss function model at step 9. The results from step 9 determine the necessary decision strategy for implementation.

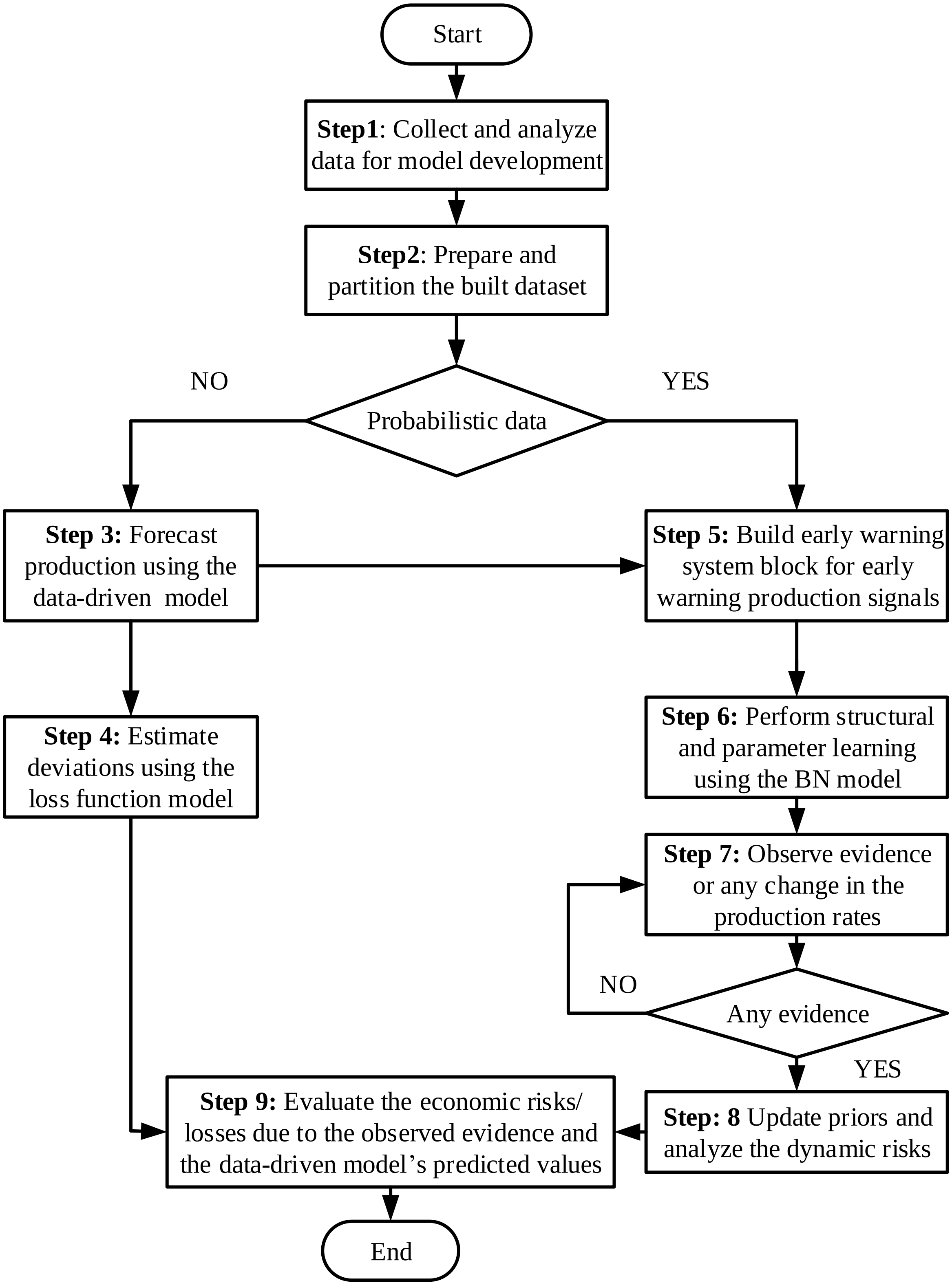


Figure 6.1: The flowchart of the proposed connectionist model.

6.3.1 Data Selection

The key objective of the current study is dynamic economic risks assessment of the reservoir production systems. The data preparation/selection is majorly influenced by the goal of the studies (Shahkarami et al., 2014). Hence, adequate dataset preparation is imperative for proper process system representation as well as simulation success. The proposed mathematical modeling considers space and time dependency (spatial-temporal process dependencies) of the reservoir production system with the intrinsic characteristics of the MLP model and BN model. The selected process data in the current work are non-probabilistic and probabilistic process data. The probabilistic process data are used by the BN model. The ANN model uses the non-probabilistic process data. The information/data consists of operational constraints (pressures, and injection and production rates), and rock and fluid properties such as compressibility, pay-zone thickness (reservoir thickness), viscosity, porosity, permeability, specific gravity, transmissibility, storativity, and API gravity. More information about the used data is presented in sections 6.4.1.1 and 6.4.1.2. The process modeling involves: 1) reservoir production predictions using the built temporal-spatial dataset and the developed MLP model, and 2) dynamic economic risks assessment using EWIS model, EWIS-assisted BN model, and the adaptive loss function model. The field application of the proposed approach is provided in section 6.4.2.

6.3.2 Reservoir Production Predictions

The data building is followed by the production predictions, which is the first stage of the two-stage modeling scheme. The predicted reservoir production data are obtained with the developed MLP model. The steps involved in the modeling process are as follows:

1. Obtain temporal-spatial dataset for reservoir model building.

2. Using geological data from a simulator to build a reservoir model starting with the base case.
3. Building the spatial-temporal database from the extracted static and dynamic data using the trained ANN as explained in section 6.3.2.1.
4. Determining and categorizing the influence of various reservoir flow properties on the reservoir production performance.
5. Using the ranked rock and fluid properties to select ANN inputs.
6. Dividing the temporal-spatial dataset into training, validating, and testing data sets.
7. Choosing and constructing the ANN architecture.
8. Training, testing, and validating the ANN model as presented in sections 6.3.2.1 and 6.4.2.
9. Validating the developed ANN through using separate geological realizations of the reservoir.
10. Estimating reservoir production with the adequately built model.

The ANN model selected in the current study is the multilayer perceptron (MLP) due to its robustness and network characteristics to meet the research objective as well as problem specifications. It has an input layer, one hidden layer, and an output layer (Shahkarami et al., 2014). The model is implemented at step 4 shown in Figure 6.1. The transfer/activation function used in the hidden layer is the sigmoid function given by Eq. (6.3) (Zhong et al., 2016). Eq. (6.4) introduces the considered linear activation function model (Zendehboudi et al., 2018). The performance function used in the model's learning is the mean square error (MSE). The Levenberg-Marquardt function is utilized for the network training as it has a fast convergence rate and high efficiency as an optimization function. The determination coefficient (R^2) and MSE are used to ensure appropriateness and reliability of the model developed in the training. The statistical parameters are expressed by Eqs. (6.5) and (6.6) (Adedigba et al., 2017b). Applications of ANN models in different engineering cases are well-documented in the literature (Adedigba et al., 2017a ; Kim et al., 2019; Kimaev et al., 2019; Zendehboudi et al., 2018 ; Zhong et al., 2016).

$$f(x) = \frac{1}{1 + e^{-x}} \tag{6.3}$$

in which, f stands for the activation function and x represents a variable.

$$f(x) = x \tag{6.4}$$

$$MSE = \frac{1}{n}\sum_{m=1}^{n}\left(Y_T - Y_{pred}\right)^2 \tag{6.5}$$

$$R^2 = 1 - \left\{\frac{\sum_j^n\left(Y_j^{Actual} - Y_j^{Predicted}\right)^2}{\sum_j^n\left(Y_j^{Actual} - \bar{Y}_j^{Actual}\right)^2}\right\} \tag{6.6}$$

In Eqs. (6.4) to (6.6), $Y_j^{Predicted}$ and Y_j^{Actual} symbolize the predicted variable, and actual variable respectively; $\bar{Y}_j^{Actual}$ denotes the numerical average of the actual variable; *n* is the number of the actual data; *j* refers to the ordinal; and R^2 represents the determination coefficient.

6.3.2.1 ANN Training.

One of the key attributes of the ANN is its capability to learn during training. In this section, we present an illustrative example to enable technical readers to better understand the theoretical background of the MLP and its black-Box nature. The learning manner is characterized by the network's ability to update its synaptic weights and structure. A repeated process of computation/modification of the MLP synaptic weights to produce the known outputs is regarded as training. Hence, the key objective of training is to enable the model to obtain the best possible arrangement or assembly of the synaptic weights and their connected input signals that would yield the nearest fit to the targeted signal. The log sigmoid function is utilized in the hidden layer, while the linear activation function is used in the output layer due to the problem specification/required target. Typically, a transfer function is carefully chosen to handle the problem being solved by the neurons. For example, since production rates need to be computed, the predicted values should be in the range of zero and thousands. Thus, the linear activation function is the only viable option in the output layer. Otherwise, the MSE obtained based on the output layer neuron would never converge. The sigmoid transfer function is chosen for the hidden layer, not just for being the most used activation function in an MLP case, but because of the data transition it employs. It accepts inputs and yields outputs within a range of 0 to 1 irrespective of how large the input data are. This special attribute enables smooth modifications between any low and high outputs of the network neurons. Upon training completion, the model can be employed to accomplish targeted tasks due to its generalization potential. Supervised learning is utilized in this work, since MLP includes the supervised learning algorithm. In the training, the forward activation of the input data is followed by the backpropagation of errors to update the synaptic weights. The input data include the static and dynamic data as presented in sections 6.3.1 and 6.4.2. The target data are the corresponding reservoir production rates. The data driven model approximates the unknown flow parameters with its synaptic weights for the system modeling. 70%, 15%, and 15% of the data are used for the training, testing, and validation of the model, respectively. Ten neurons are used in the hidden layer. The model is set to stop upon six successive epochs/iterations without a substantial increase in the minimal error. The detailed procedure for the training is summarized as follows:

1. Selection of network type/network architecture: This is problem specification dependent. Hence, it depends on the nature and type of problem of interest.

2. Selection of dataset (or input) and target data: The network is provided with the adequate input and target data.

3. Initialization or random selection of the assumed network synaptic weights and biases: The initial weights and biases' values are randomly selected by the network and subsequently modified with repeated iterations.

4. Forward activation or forward pass computation: The network output is calculated by transmitting the input data through the synaptic transmission lines of the network.

5. MSE computation: Following the completion of the forward pass, the difference between the target value and the prediction value is estimated using Eq. (6.5), known as MSE.

6. Back propagation: Upon estimating the MSE, the error term is propagated backward through the synaptic transmission lines of the network using the differentials of the activation functions in each neuron to update the synaptic weights.

7. Repeated iterations or cyclical computation: A new iteration process is initiated with the updated/modified synaptic weights. The input data and updated weights are fed back into the model for the next iteration. This iteration process continues till it is ended/truncated by some criteria, such as the maximum number of epochs (cycles), and/or validation checks or the network output being moved significantly closer to the target (i.e., the error becomes reasonably insignificant or MSE is almost zero).

To facilitate better understanding of the concept of the MLP, an illustrative example is given in this section to demonstrate the presented procedure or show how the MLP is used for reservoir production prediction.

Example 6.1. Given a scenario where the reservoir drawdown (Δp) and oil viscosity are given as 190 psi and 0.78 cp, respectively. A fractional oil recovery $\left({}^{N_p}/_{N}\right)$ or FOR of 0.24 is reported. An MLP can predict the fractional oil recovery when only pressure drop data and oil viscosity are the available data.

The oil production rate for a production system with a constant pressure at the outer boundary during the steady state flow condition is determined by the following equation (Bourdet, 2002):

$$q_o = \frac{kh\left(P_e - P_{wf}\right)}{141.2 B_o \mu_o \left[ln\left(\frac{r_e}{r_w} + S\right)\right]} \tag{6.7}$$

where q_o introduces the oil production rate; k refers to the rock permeability; h denotes the reservoir thickness; P_e is the initial reservoir pressure; P_{wf} represents the bottom-hole flowing pressure; B_o stands for the oil formation volume factor; μ_o is the oil viscosity; and S symbolizes the skin factor.

Figure 6.2 depicts the schematic of the MLP architecture for Example 6.1. Table 6.1 comprises the inputs, target, assumed weights, and biases.

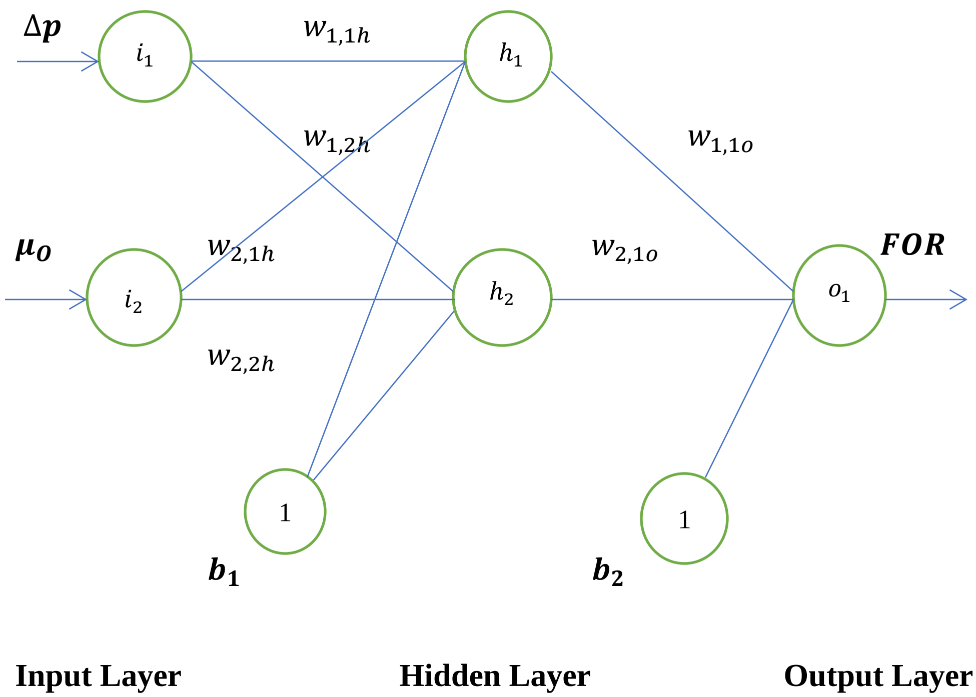


Figure 6.2: Schematic of the ANN architecture used in Example 6.1.

Table 6.1: The magnitudes of inputs, target parameters, assumed synaptic weights, and biases.

Input values		**Target**	**Assumed synaptic weights**						**Biases**	
i_1	i_2		$w_{1,1h}$	$w_{2,1h}$	$w_{1,2h}$	$w_{2,2h}$	$w_{1,1o}$	$w_{2,1o}$	b_1	b_2
190	0.7800	**0.2400**	0.60	0.50	1.20	1.20	0.25	-1.50	0.80	0.50

Figure 6.3 presents the results obtained for the sample example. This figure shows the strength of the ANN in predictive modeling; it also reveals how the error is minimized with each repeated iteration or cycle during training. The detailed procedure and computations involved in the forward pass and backpropagation are given in Appendix 6**A**.

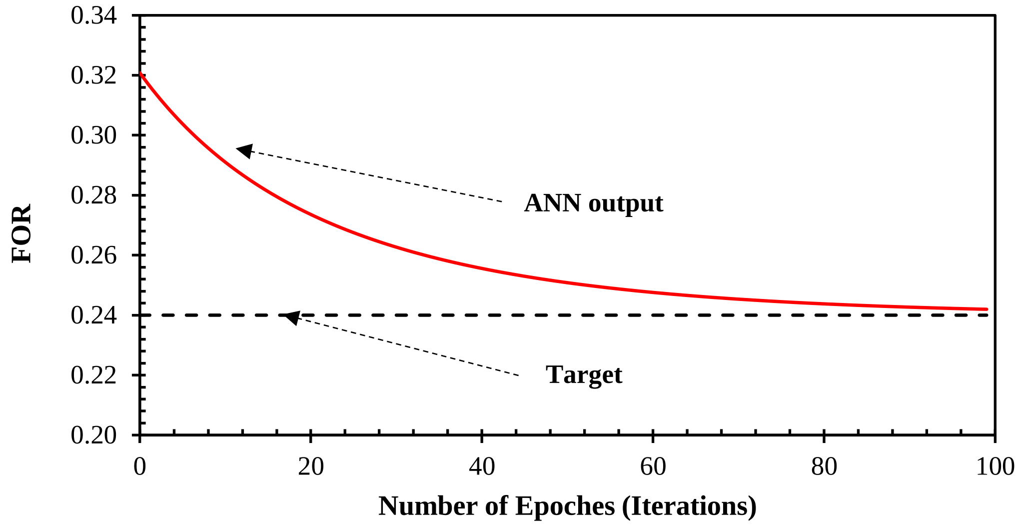


Figure 6.3: Results of the data driven model from 1st to 99th iteration.

6.3.3 Dynamic Economic Risks Assessment

The main objective of the current study is dynamic economic risk analysis of the petroleum reservoir production systems as any dynamic change/loss observed in the production variable (or rate) implies a direct dynamic economic loss per lost barrel of crude oil. The analyzed dynamic risk is space- and time-dependent to replicate the reservoir flow system. It is a complex, porous, permeable, and saturated sub-surface geologic structure/entrapment with hydrocarbons under a distinct pressure gradient (Mamudu & Olafuyi, 2016; Mamudu, 2016; Olafuyi & Mamudu, 2015; Umar et al. 2019). The economic risks/losses assessment is evidence-based. Thus, it represents the real time dynamic economic risks associated with the production operations. This assessment process is the second stage of the proposed modeling methodology. It involves the production losses predictions stage. The procedure is provided as follows:

1. Choose and prepare data for dynamic economic risks assessment.

2. Construct the EWIS oilfield development risks block using the prepared probabilistic data and the production forecasts from the developed MLP model.
3. Classify production rates' levels into warning intervals using "3σ" rule, depending on the severity of loss as presented in Table 1.
4. Specify the standard warning intervals as low production heavy warning (LPHW), low production light warning (LPLW), normal production (NORP), high production light warning (HPLW), and high production heavy warning (HPHW) as shown in Table 6.2.
5. Evaluate the warning degree of the classified production rate's ranges from the predictive model.
6. Conduct the logical model's structure development and parametric learnings.
7. Update the prior probabilities given any evidence of production rate change or loss using the logical model's predicted reservoir production variable (output), and then analyze the dynamic risks.
8. Develop the dynamic risks profiles of the production systems.
9. Initiate the evidence-based assessment of dynamic economic risks with NORP as the desired operating production level.
10. Assume West Texas Intermediate (WTI) crude oil price of $39.82USD per barrel (Month Front, July 01, 2020) to predict losses associated with the evaluated dynamic risks.
11. Evaluate the dynamic economic risks associated with the production losses using the NORP as the reference and assess the impact of the daily losses on the continuous production, considering the severity of the varying production warning categories.

12. Employ the adaptive loss function model to capture the effect of the observed evidence/production changes and the severity of the varying abnormal production classes on the dynamic risks profile of the process system in the specified operating period.
13. Assess the predicted dynamic economic risks for reservoir production management decision-making.

Generally, the risk indicators can be grouped into three categories in the dynamic risk assessment of an oilfield in the development phase: the warning source index, warning sign index, and warning situation index (Zhong et al., 2016). The most monitored events in the field development phase such as water production, oil production, gas production, and gas/oil ratio (GOR) are considered as the warning situation indexes. Warning sign indexes are directly related to the warning situation indexes and are easily measured. The risk causes are the indexes of warning source. In this work, the index of warning source includes injection rates 1, 2, 3, and 4. The index of warning sign comprises the drawdown, reservoir pressure, bottom-hole flowing pressure, gravity, storativity, and transmissibility. Oil production rate is the index of warning situation. These indexes are the nodes of the developed EWIS-assisted BN model. The child node classification includes low production heavy warning (LPHW), low production light warning (LPLW), normal production (NORP), high production light warning (HPLW), and high production heavy warning (HPHW) using "3σ" rule. High and Low are the parent and intermediate nodes' states classifications.

The petroleum production system is a complex underground system with critical challenges. The challenges are majorly the observed undesired events or their root causes. "No flow" is the worst-case scenario in the petroleum reservoir production system, which gives oilfield operators serious concerns. Most of these events are consequences. Hence, adequate knowledge of the physics of fluid flow in porous media is essential for formulating a template for the oilfield risk assessment. To appropriately detect, assess, and predict the risks involved in this complex process, the logical reasoning used in dynamic systems by Zhong et al. (2016) is implemented to develop an EWIS-assisted BN model. The first step is to identify the key flow parameters (Zhong et al., 2016), followed by finding an appropriate relationships among the vital flow variables in the defined block. This necessitates sound knowledge of the underling domain (expert's knowledge), which refers to oilfield development experience and in-depth knowledge of production history. Hence, it does not necessarily require a questionnaire. To prove or ensure the objectiveness of the model, the logical model's output should conform with Darcy's law. Otherwise, the predictions are not reliable. This is achieved with our current connectionist model. Zhong et al. (2016) also achieved a similar outcome in their work. One of the key tasks in the development of the logical model is the construction of the conditional probabilities table (CPT). This is unraveled in the current research with Darcy's law as the guide. The conditional probabilities are carefully assumed using the Darcy's law to develop a representative logical model that could replicate the petroleum reservoir production flow system. Darcy's law is the fundamental law of fluid flow in porous media. It clearly states the relationship among the vital reservoir flow variables. The radial form of the Darcy's law could be represented by Eq. (6.7). The reasonable assumptions are justified as the research outputs conform with the Darcy's law.

The EWIS of oilfield risk block is primarily designed to receive production, classify them using the statistical "3σ" rule and form the BN model's output states. This process ensures the probabilistic interpretations of the numerical production rate values by the BN model. The oilfield block is built to adequately reflect the interactions among the system variables. Zhong et al. (2016) presented a comprehensive procedure of the EWIS of oilfield development risk block in their work.

The logical model (BN model) employed in this research is the EWIS-assisted BN model. There are three basic tasks in the Bayesian model's applications for dynamic risks assessment: 1) Structure learning, 2) Parameter learning, and 3) Bayesian interference. These procedures are accomplished using Eqs.(7) to (9) (Bhandari et al., 2015; Mamudu et al., 2020b).

The posterior (updated) probability distribution or $P(H^b|E)$ is given as follows (Bhandari et al., 2015; Mamudu et al., 2020b):

$$P(H^b|E) = \frac{P(H^b)P(E|H^b)}{P(E)} = \frac{P(H^b, E)}{P(E)} \tag{6.8}$$

where $P(E)$ represents the probability of evidence or the normalization constant; $P(E|H^b)$ is the likelihood function; and E symbolizes the evidence. If the joint probability distribution of random variables is $X = (x_1, x_2, \dots \dots .., x_n)$, the Bayesian distribution can be mathematically expressed by Eq. (6.9) (Zhong et al., 2016):

$$P(x|\theta_e, H^b) = \prod_{i=1}^{n} P(x_i|Pa_i, \theta_i, H^b) \tag{6.9}$$

Based on Eq. (6.9), H^b shows that the joint distribution of the network is decomposable; the random variable of the joint probability distribution of X is represented by $E = (X_1, X_2, \dots \dots .., X_n)$; Pa_i introduces the parent; θ_e denotes a parametric variable of the network; , θ_i resembles the vector form of θ_e and it represents its uncertainties; and $P(\theta_e, H^b)$ refers to a specified prior probability density function.

Assuming that a set of evidence variable is denoted by E, and that of query variable is represented by Q, the Bayesian inference needed to update the probability distribution of the query variable Q in E = e, is then given by Eq. (6.10) (Zhong et al., 2016).

$$P(Q|E=e) = \sum_{X-E} P(x_1, x_2, \dots \dots \dots, x_n) = \sum_{X-E} \prod_{i=1}^{n} P(x_i|Pa_i) \qquad (6.10)$$

where Pa_i stands for the parent variable; x_i represents the state of the random variable; and n refers to the total number.

The loss function model used in this research is the generic adaptive algorithm model given by Eq. (6.11) (Liu et al., 2020; Yarom et al., 2015):

$$\rho(x,\alpha) = \frac{|2-\alpha|}{\alpha}\left[\left(\frac{x^2}{|2-\alpha|}+1\right)^{\alpha/2} - 1\right] \qquad (6.11)$$

In Eq. (6.11), ρ represents the loss; α is the shape parameter/parametric constant; and x introduces the process parameter.

The model has an adaptive function that can be applied in various statistical problems irrespective of the loss type/category. Loss function models are broadly categorized into two: regression and classification losses. The categorization is basically dependent on the problem specification (specific tasks). In this research, we deal with regression losses. The parametric constant or shape parameter (α) determines the intrinsic characteristic of the generic adaptive model. It ranges from 2 to $-\infty$. When α is 2, $\rho(x,\alpha)$ represents L_2/quadratic loss. It represents the pseudo-Huber loss when α is set at 1, and Cauchy loss when it is equal to 0. When it is set at -2, it represents German-McClure loss. It becomes Welsh loss when it approaches $-\infty$. This reveals some of the advantages of this adaptive model. In this research, we set the shape parameter (α) at approximately 2 to best reflect our process data characteristics. The model ($\rho(x, \alpha)$) is used to statistically analyze the evidence-based outcomes from the EWIS-assisted BN model at step 9. At step 4, the model is employed for statistical evaluation of the ANN's output. These outcomes are fed to step 9 for decision-making. An extensive review of loss function models is reported by Adedigba et al. (2018).

6.4 Case Study

6.4.1 Data

The proposed connectionist model is applied on two case studies. The case studies are from the open source comparative solutions projects conducted by the Society of Petroleum Engineering (SPE) (Odeh, 1981).

6.4.1.1 Case Study 1

The data presented in this scenario are collected from a previous study to simulate a layered oil reservoir. The layers are hydrodynamically connected with a single producing well under natural flow driving force. The well's maximum production capacity is set at 15000 bbl/day. The stopping criterion is 1000 bbl/day. The production is scheduled to run for 3462 days. The horizontal permeabilities of the hydrodynamically connected layers are given as 500 mD, 50 mD, and 25 mD. Also, 50 mD, 50 mD, and 25 mD are the vertical permeabilities. The layers' thicknesses are 20 ft, 30 ft, and 50 ft. The other information includes a reservoir temperature of 200 °F, an initial reservoir pressure of 4,800 psi, a bubble point pressure of 3,200 psi, an oil density of 51.8 1b/ft^3, a water density of 62.4 1b/ft^3, an initial water saturation of 0.2, an initial oil saturation of 0.8, a specific gravity of 0.792, a porosity of 0.3, and an oil compressibility of $3 \times 10^{-6}\ psi^{-1}$. Other important modeling data are the grid dimensions of $10 \times 10 \times 3$ ft, areal grid block dimensions of 1000 ft × 1000 ft, and reference depth of 8400 ft.

6.4.1.2 Case Study 2

The data in this case study are from a simulation study conducted on a layered reservoir under pressure support. The layered system includes three layers that are hydrodynamically connected. The case has a producing well with a maximum initial flow capacity of 15000 bbl/day with injection wells at the four reservoir boundaries. The shut-in criteria are set as a minimum BHP of 1000 psi or a GOR of 12.5 MSCF/STB. A period of 3285 days is set as the simulation duration. The layers' characteristics of the reservoir are the horizontal permeabilities of 500 mD, 50 mD, and 25 mD, vertical permeabilities of 50 mD, 50 mD, and 25 mD, and thicknesses of 20 ft, 30 ft, and 50 ft with a constant porosity of 0.3. The other reservoir information are the initial reservoir pressure of 3800 psia, bubble point pressure of 2100 psia, reservoir temperature of 200 °F, oil density of 49.0 1b/ft^3, water density of 62.4 1b/ft^3, initial water saturation of 0.2, initial oil saturation of 0.8, oil compressibility of $3 \times 10^{-6}\ psi^{-1}$, grid dimensions of $10 \times 10 \times 3$ ft, areal grid block dimensions of 1000 ft × 1000 ft, and reservoir depth of 7500 ft.

6.4.2 Model Implementation

Data building is the first stage of the model implementation. This occurs at steps 1 and 2 (see Figure 6.1). The non-probabilistic data are used to build the MLP model. The data selected to adequately represent the geologic structure in building the MLP model are the production rate (model output), and input data such as bottom-hole flowing pressure, drawdown, transmissibility, storativity, and API gravity. Transmissibility, storativity and API gravity are the static system properties selected to enable replication of the system's intrinsic characteristics. This enhances the AI-based model performance and ensures reliable outputs. Eqs. (6.12) to (6.14) express the transmissibility, storativity and API gravity of the system, respectively.

$$Transmisibility = \frac{kh}{\mu} \tag{6.12}$$

$$Storativity = \emptyset C_t h \tag{6.13}$$

$$API\ gravity = \frac{141.5}{\gamma_o} - 131.5 \tag{6.14}$$

in which, k is the average reservoir permeability; h represents the reservoir thickness; μ is the fluid viscosity; $\emptyset$ is the porosity; C_t symbolizes the total compressibility; and γ_o denotes the specific gravity.

The vital fluid and rock flow properties are used as guidelines for the ANN's inputs selections to enable easy attainment of the desired targets. The temporal-spatial dataset is portioned into training, validating, and testing sets for the MLP model development. Then, an ANN architecture is designed. The training, testing, and validation stages are conducted using the geologic realizations (data). The developed MLP model is validated with an entirely different geologic realization of the reservoir model and used for production forecast, as shown at step 3 of Figure 6.1. The statistical deviations of the outputs are analyzed with Eq. (10) at step 4 (see Figure 1). The MLP model outputs (the production predictions) for the two scenarios are received by the EWIS of oilfield risks block and analyzed (refer to Table 6.2). This is shown at step 5 of Figure 6.1. These warning intervals established by the EWIS of oilfield risks block using "3σ" rule are the low production heavy warning (LPHW), low production light warning (LPLW), normal production (NORP), high production light warning (HPLW), and high production heavy warning (HPHW).

Table 6.2: Warning intervals and degrees based on "3σ" rule.

	Case 1			Case 2		
Production (Category)	**Degree**	**Warning Interval (bbl/day)**		**Degree**	**Warning Interval (bbl/day)**	
LPHW	1	0	284	1	0	3322
LPLW	2	284	4842	2	3322	6656
NORP	3	4842	15094	3	6656	13324
HPLW	4	15094	20220	4	13324	16658
HPHW	5	20220	$+\infty$	5	16656	$+\infty$

The warning intervals represent the states of the EWIS-assisted BN model's outputs. The indexes of warning source and sign represent the parent and intermediate nodes of the EWIS -assisted BN model, respectively. Also, the child node/BN model's output represents the warning situation index. Figures 6.4 and 6.5 depict the structure learning of the EWIS-assisted BN component of the proposed methodology applied on the reservoir production systems for cases 1 and 2, respectively. This process modeling is depicted at step 6 of Figure 6.1.

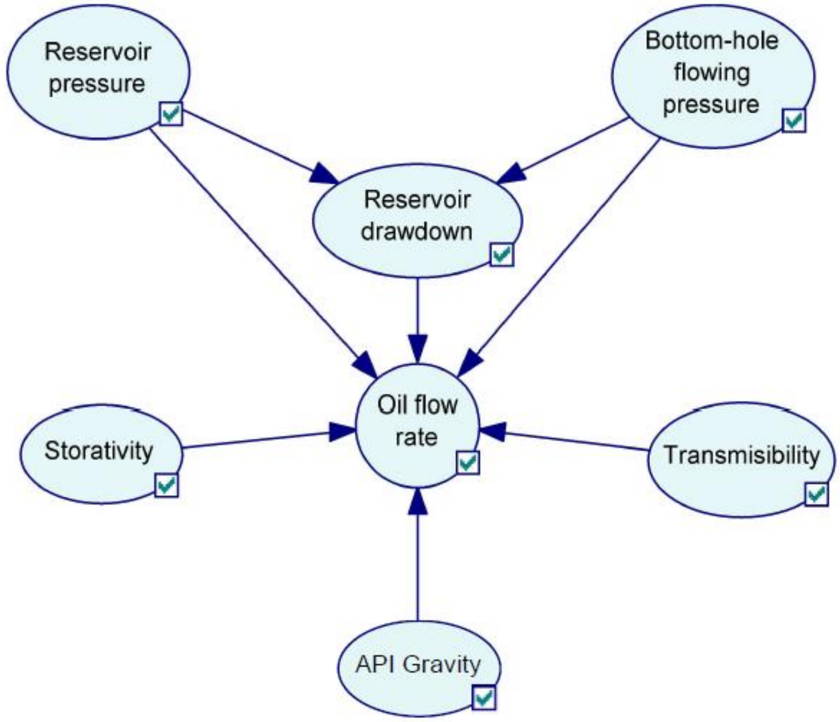


Figure 6.4: EWIS-assisted BN model's structure learning for scenario (case) 1.

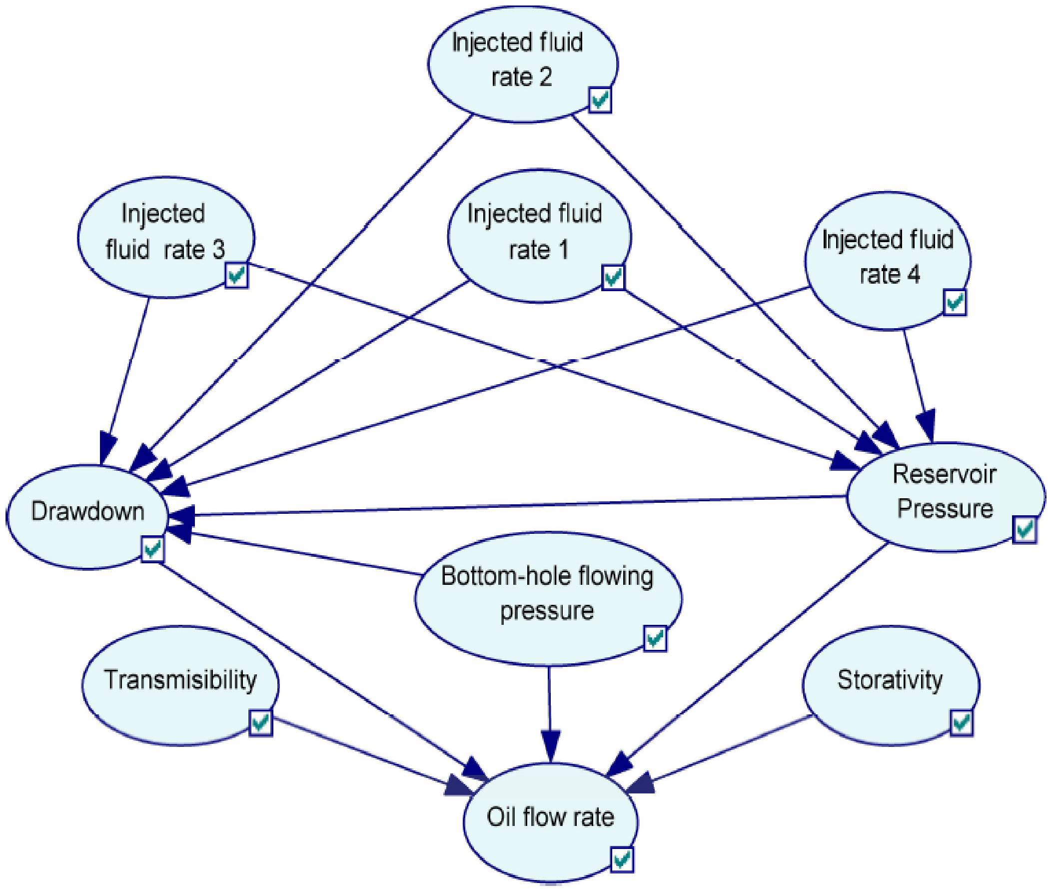


Figure 6.5: EWIS-assisted BN model's structure learning for scenario (case) 2.

The stage presented by Figures 6.4 and 6.5 is followed by parameter learning using the prepared process data and experts' knowledge. Upon any production rate change, the updated probabilities are then computed and compared with the priors to ascertain the risks sources. Any evidence of observed production rate outside the classified normal production warning interval causes dynamic economic losses. Hence, the economic consequences are predicted using the proposed loss function model utilized in the proposed connectionist methodology (see Eq. 6.11). This enables adequate production strategies and proper reservoir management decision-making. In fact, it is designed to ensure optimal outcomes even in the event of severe production uncertainties or worst-case scenarios.

6.5 Results and Discussion

The results obtained from the proposed connectionist methodology for the case studies are highlighted in this section. Figures 6.6 and 6.8 show the model's production forecasts. Figures 6.7 and 6.9 represent the residual plots. Figures 6.10 and 6.11 illustrate the predicted production loss profiles due to MLP model's predictions deviations. Figures 16.12 and 6.13 represent the parameter learnings of case 1 and case 2, respectively. Figures 6.14 and 6.15 show evidence-based results from the logical model. Panels a and b of Figure 6.16 include the dynamic risks. Figures 6.17a and b show the evidence-based dynamic economic risks profiles of case 1. Panels a and b of Figure 6.18 depict the evidence-based dynamic economic risks profiles of case 2. Table 6.3 lists the evidence-based average economic losses per day for both cases.

The key objective of this study is to design a dynamic economic risk modelling strategy for dynamic economic risks/evidence-based production losses assessments for the field operators. To ensure the achievement of this overall modeling objective, we require proper effective interlinks among the selected sub models of the hybrid model. The evidence-based losses analysis is strongly dependent on the dynamic risks predicted by the BN model. The BN model is based on EWIS of oilfield risks block. The building of the EWIS of oilfield development risks block is influenced by the established production constraints or output from the MLP model. The analyzed dynamic economic losses/loss profiles generated by the loss function model are suitable for management decision-making.

Figure 6.6 is obtained based on the data for case 1. According to Figure 6.6, the proposed methodology yields perfect match in the first 300 days; this also reveals a statistically reasonable match in a further period of 1000 days. Hence, it gives an excellent performance in the early time or transient flow period. Similarly, the overall performance in the production period seems encouraging with the minimum, average, and maximum percentage errors of 0.023%, 1.954% and 14.025% respectively. Figure 6.7 shows the residual plot. It follows that the proposed connectionist methodology exhibits effective prognostic capacity. The residual error range is in hundreds, while the predicted production rate range is in thousands. The essential information required from the residual error plot is the distribution pattern/shape of the residual errors. The pattern of the distributed residual errors reveals whether or not a proper determistic tool has been developed. According to the residual plots, no particular pattern is observed, implying that the determistic tool is reliable.

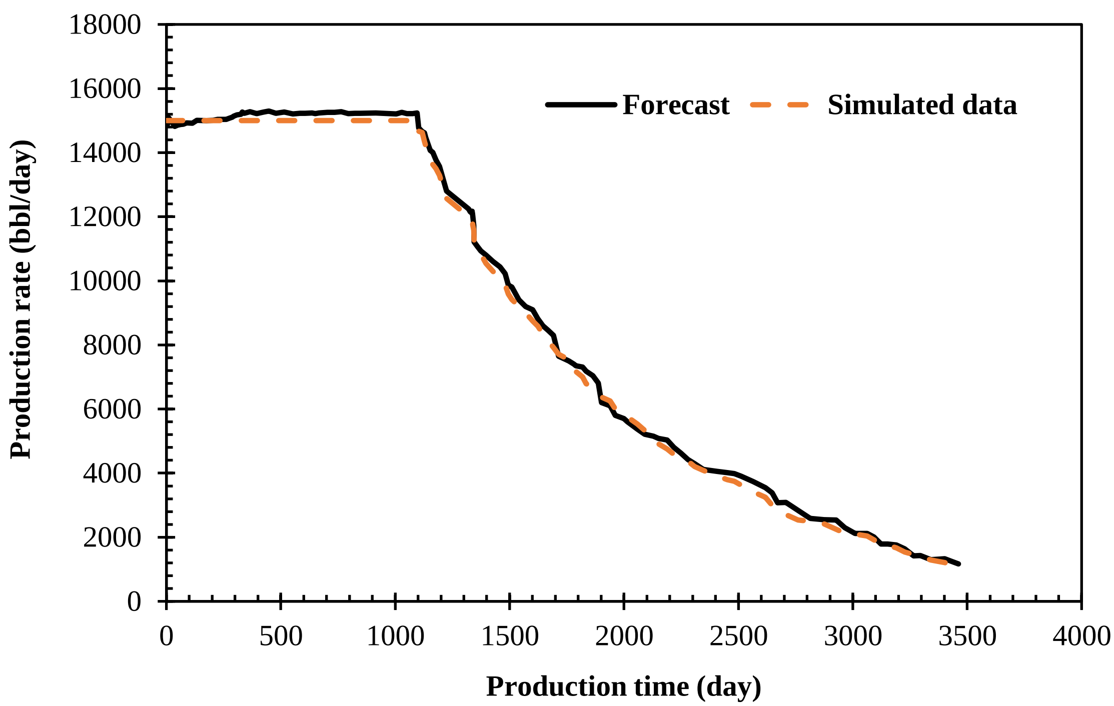


Figure 6.6: Forecasted and simulated production data of case 1.

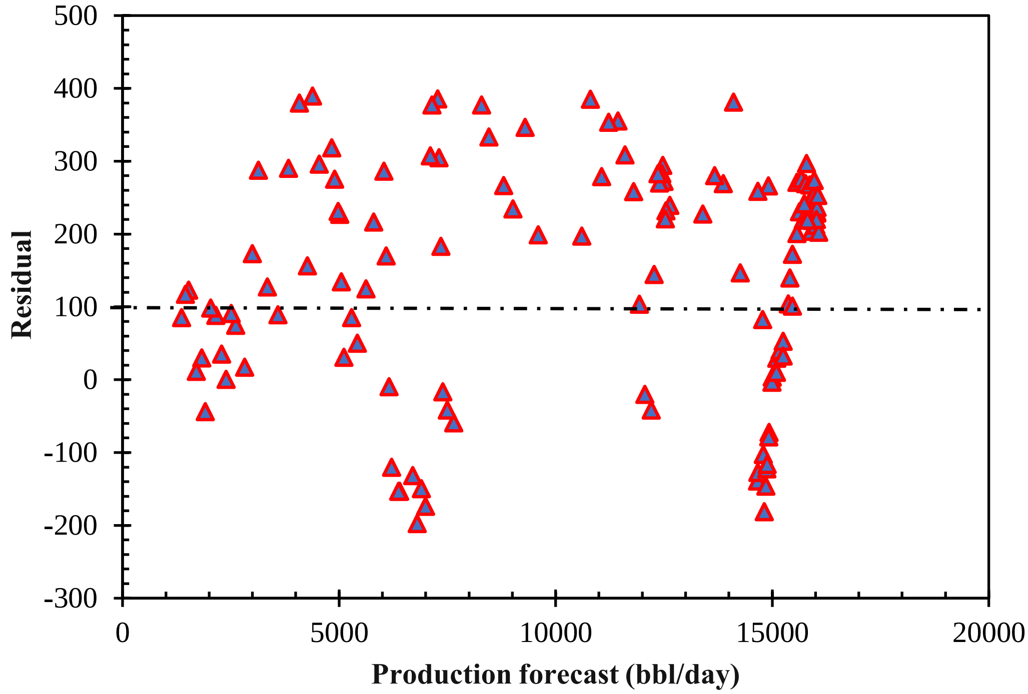


Figure 6.7: Residual plot of the forecasted and simulated production data of case 1.

Figure 6.8 depicts the forecasted and simulated data of case 2. According to Figure 6.8, the developed connectionist strategy demonstrates an effective predictive capability. Reasonable agreement between the predictions and simulated data is also noticed within the intermediate production periods. The mean absolute percentage error (MAPE) is employed to examine the prediction precision of the smart model. The minimum, average, and maximum percentage errors are reported to be 0.002%, 1.957%, and 4.943.88%, respectively. According to Figure 6.9 as a residual plot, no specific pattern is observed. Thus, an efficient predictive model has been developed.

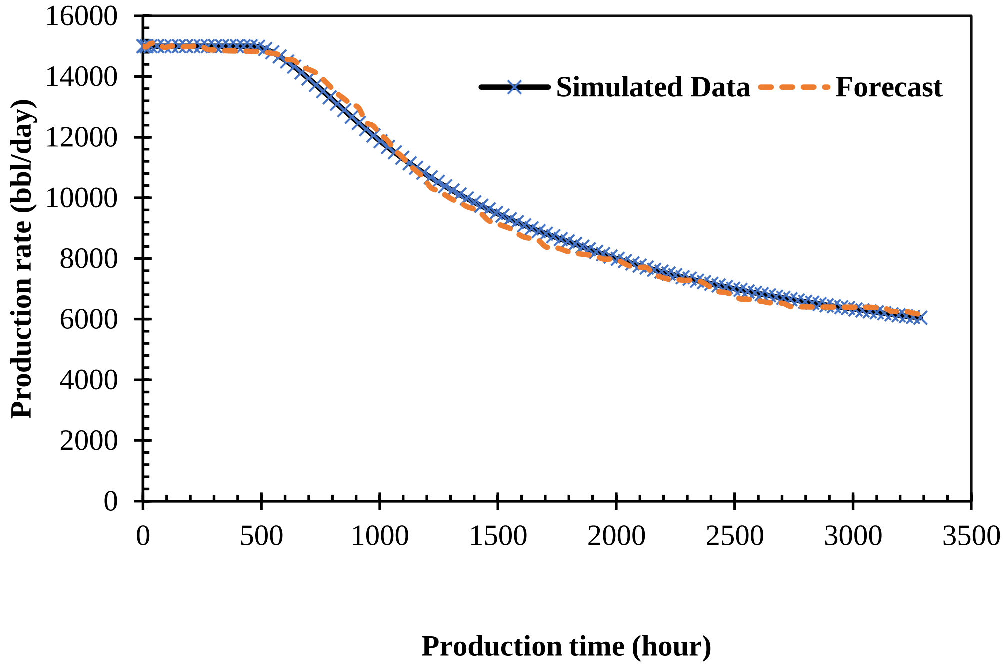


Figure 6.8: Forecast and simulated production data of case 2.

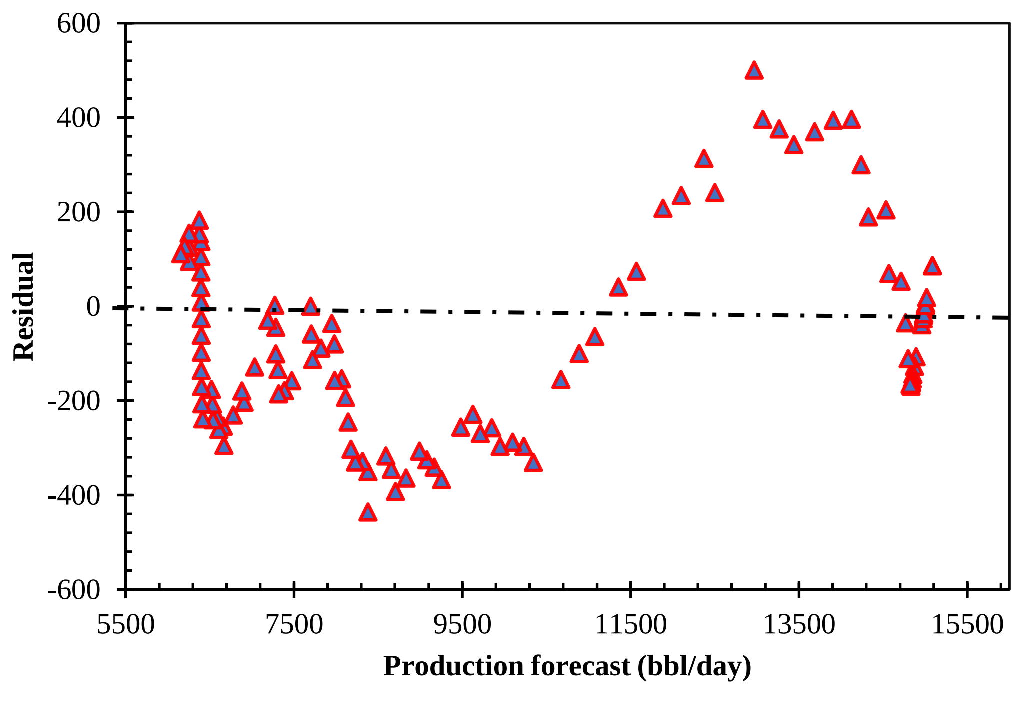


Figure 6.9: Residual plot of the forecasted and simulated production data of case 2.

The model displays the best match in the early and late times of the production period. Late and early times are the two most important/major flow periods in reservoir flow regimes. The early time is mainly characterized by radial flow, spherical flow, and unsteady state conditions, while the late time is normally characterized by linear flow typically encountered at the reservoir external boundaries. Being able to adequately predict production in these flow periods guarantees a representative reservoir model. Figures 6.7 and 6.9 clearly confirm the precision and reliability of our proposed connectionist model. Late time is defined as any time in the production life of a well after the effect of the outer boundary of the reservoir is felt by the "pressure transient" (pressure wave propagation) or any time greater than or equal to the end of the semi-steady state flow period. However, early time is defined as the unsteady state flow period in the production life of a well or the period where the effect of the external boundary has not been felt by the "pressure transient" (pressure wave propagation).

Figures 6.10 and 6.11 show the loss profiles of the analyzed predictions deviations using the loss function model for cases 1 and 2. According to Figures 6.10 and 6.11, the loss function is strongly dependent on the selected data (process data). The adaptive algorithm loss function perfectly defines a graphical feature of the quadratic loss function at zero loss, a typical characteristic of the adaptive algorithm loss function at $\alpha = 2$. The loss function model gives some reasonable statistical values; this is also confirmed by the residual plots in Figures 6.7 and 6.9, implying an excellent performance of the model. According to Figure 6.10, a maximum deviation of 380 bbl/day is recorded. In addition, the statistical disparity could yield a maximum adaptive algorithm loss of about 40000 bbl/day in the scheduled production period of about nine and half years. Figure 6.11 shows a similar behavior of the case/scenario 2 with a maximum deviation of about 450 bbl/day.

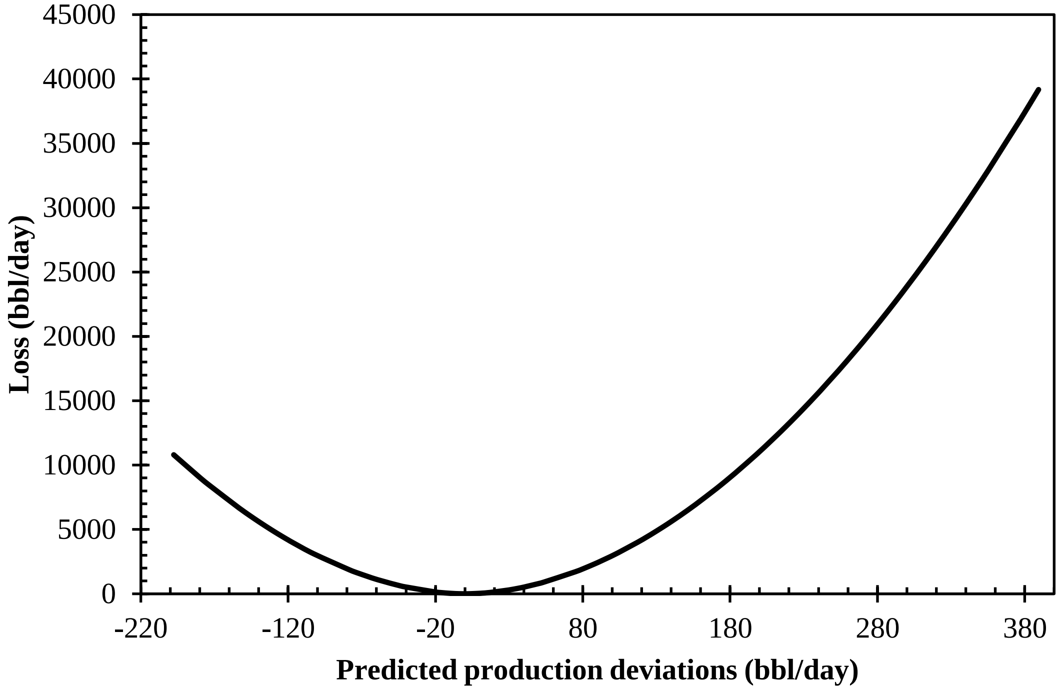


Figure 6.10: Analyzed predictions losses using the loss function model (case 1).

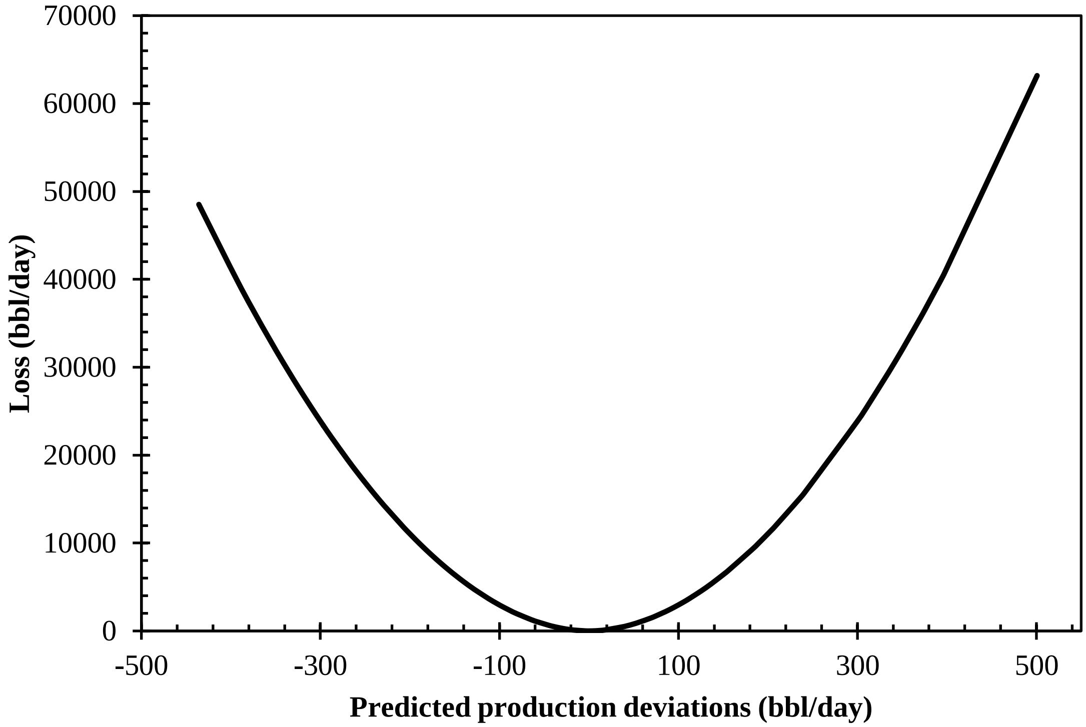


Figure 6.11: Analyzed predictions losses using the loss function model (case 2).

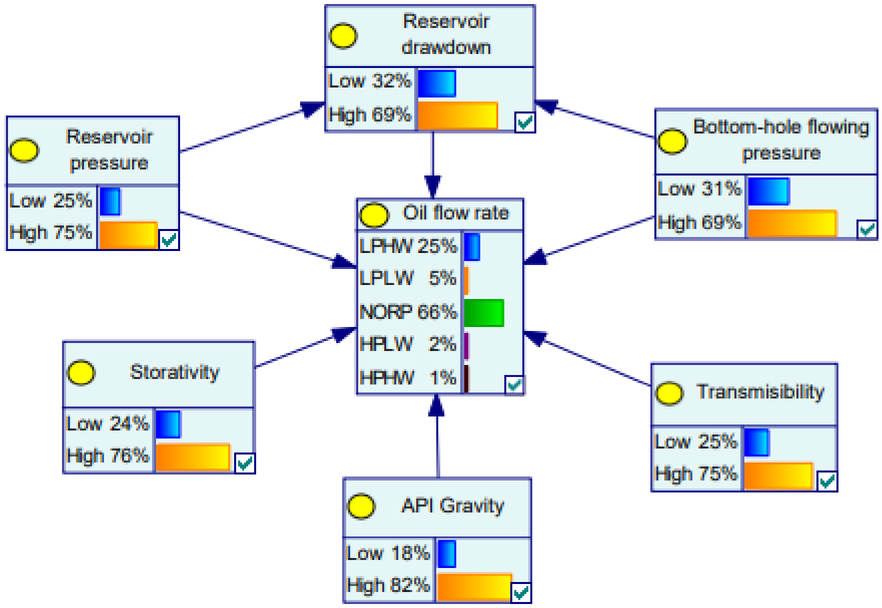


Figure 6.12: Parameter learning of the BN component of the connectionist model (Case 1).

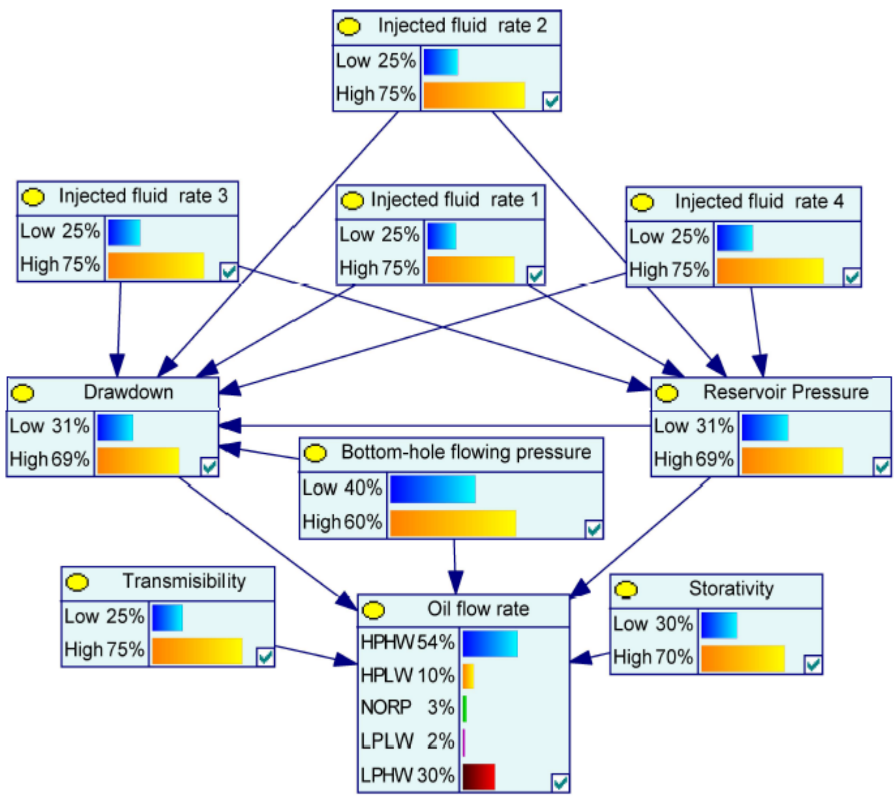


Figure 6.13: Parameter learning of the BN component of the connectionist model (Case 2).

Figures 6.12 and 6.13 report the parameter learnings from the EWIS-assisted BN model deployed in the connectionist strategy for the two case studies. The dependencies/logical process interactions among the process variables under natural drive mechanism (without pressure support) are shown in Figure 6.12. According to the constructed EWIS-assisted BN model, under this production scenario, the drawdown, reservoir pressure, and bottom-hole flowing pressure are the major flow factors. This parameter learning represents a stage in the process modeling when no evidence has been observed. It is shown at step 6 of Figure 6.1. It is used as a basis/reference for evidence observations employed for the dynamic economic risks' assessments. Hence, the economic losses presented in this study are real time evidenced-based losses. Evidence of low production heavy warning (LPHW) is regarded as the worst-case scenario where zero production ($q_o = 0$) is possible. This is the most dreaded scenario as it is attributed to a very expensive condition. Total production failure or governmental regulations (or environmental factors) are often direct causes of this event. Another risky production category is the low production light warning (LPLW). Unlike the LPHW scenario, the LPLW category is expected to have a less economic impact on the financial losses associated with the overall production losses. The NORP class is maintained without losses. Hence, no risk is associated with this scenario. Figure 6.13 reveals the dependencies/logical process interactions among process system variables under pressure support. In this scenario, the reservoir pressure is supported such that the pressure at the outer boundary is intentionally kept constant to maintain a sufficient reservoir drawdown to push the hydrocarbons to the surface at adequate economic rates. Hence, the reservoir pressure and the drawdown (pressure differential, Δp) are the two process variables, which are directly impacted by the injected fluid rates at the sand face of the injection wells, as depicted in Figure 6.13.

Figures 6.14 and 6.15 depict the results of the EWIS-assisted BN model under the evidence of normal production. According to these results, normal production is only guaranteed (100% assurance or occurrence probability) if both the reservoir drawdown and pressure are reasonably high. Figure 6.14 shows 90 % chance of having high reservoir pressure against a prior probability of 75% depicted in Figure 6.12 and 98% chance of the occurrence of high reservoir drawdown against a prior probability of occurrence of 68%. This implies that the drawdown is directly proportional to the flow rate and reservoir pressure. This is intuitively correct as it conforms with field reality. In addition, it is a confirmation of the findings from Darcy's law. The results of case study 2 also confirm the logical models' outputs validity as they present similar trends as those of case study 1. For instance, Figure 6.15 shows 87 % and 86% probabilities of occurrence of high reservoir drawdown and pressure, respectively against prior probabilities of 69% each for the same flow variables as displayed in Figure 6.13. These findings validate the developed EWIS-assisted BN model and demonstrate its objectivity.

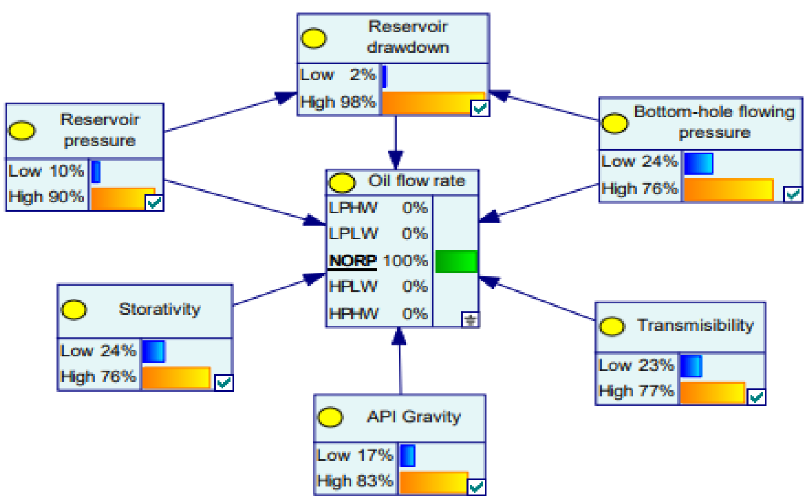


Figure 6.14: EWIS-assisted BN model during evidence of normal production (Case 1)

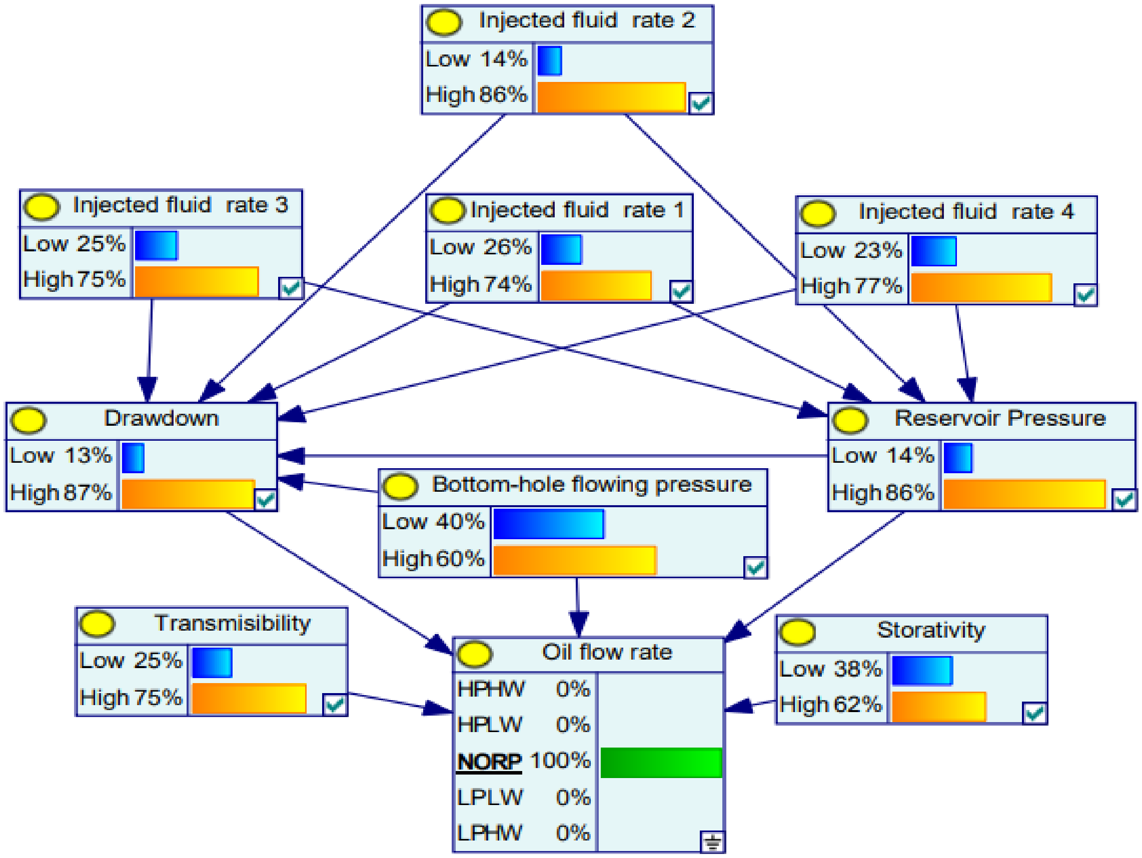
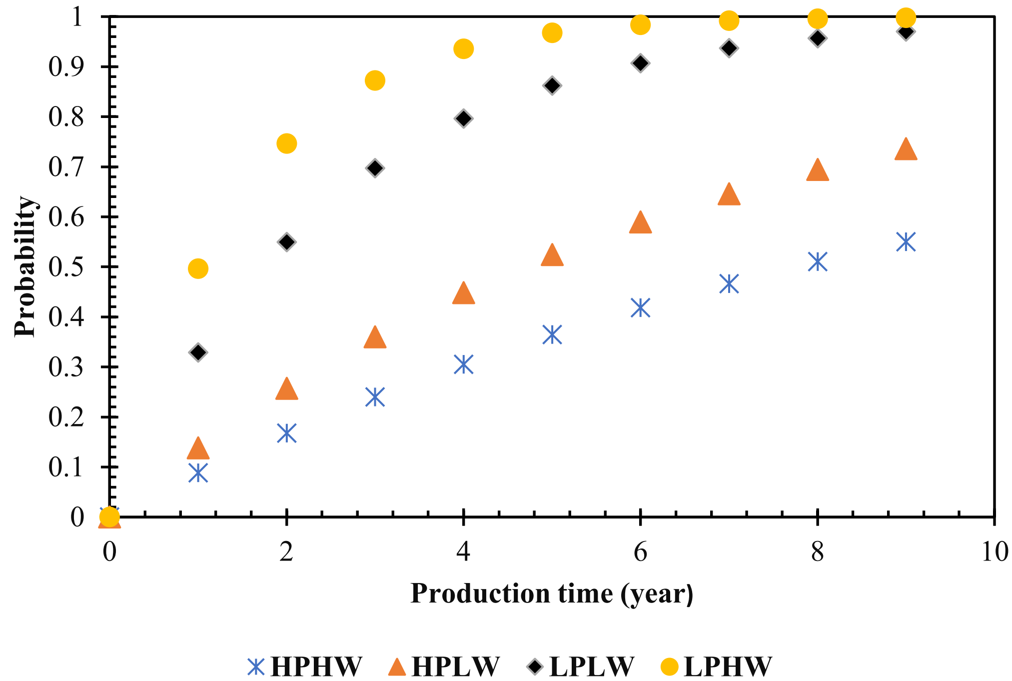
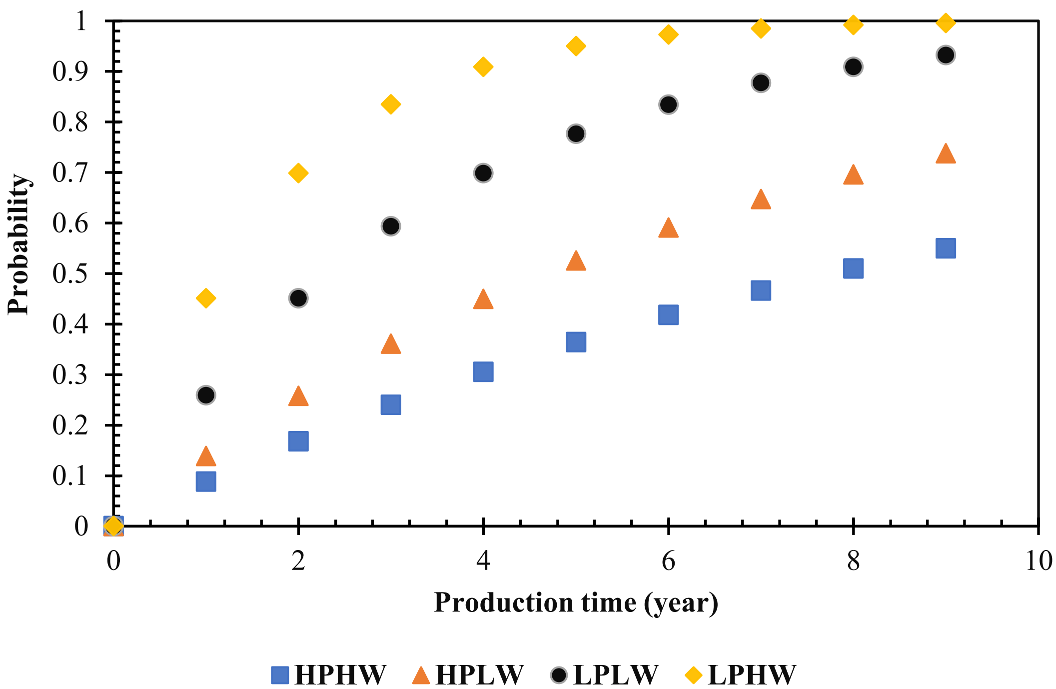


Figure 6.15: EWIS-assisted BN model during evidence of normal production (Case 2)"



(a) Associated dynamic risk profiles with production abnormalities (Case 1)

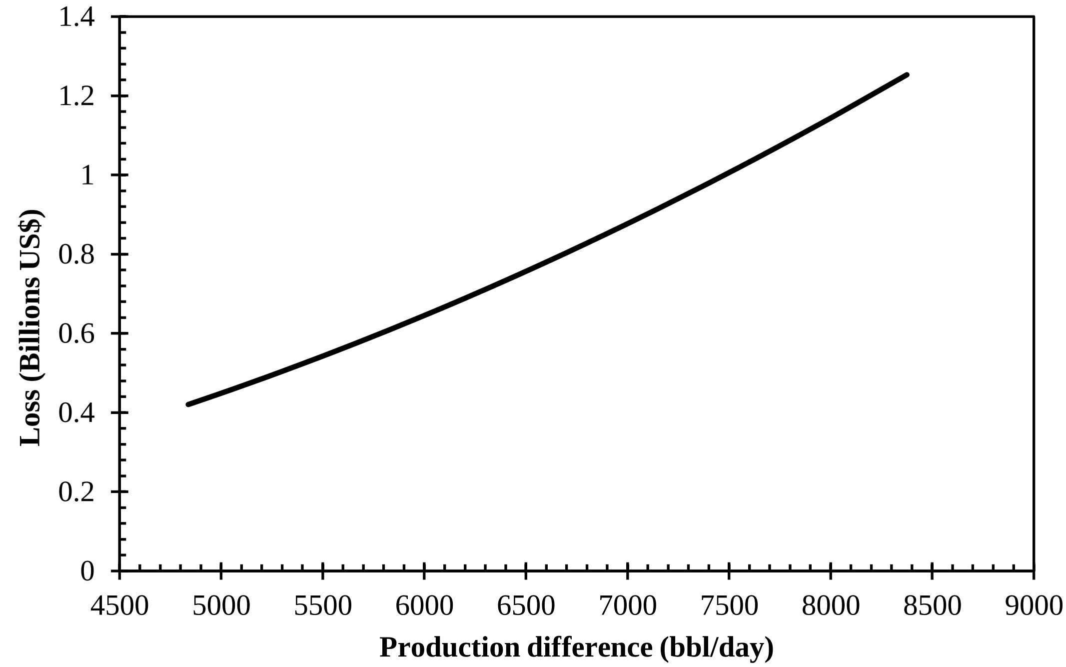


(b) Associated dynamic risk profiles with production abnormalities (Case 2)

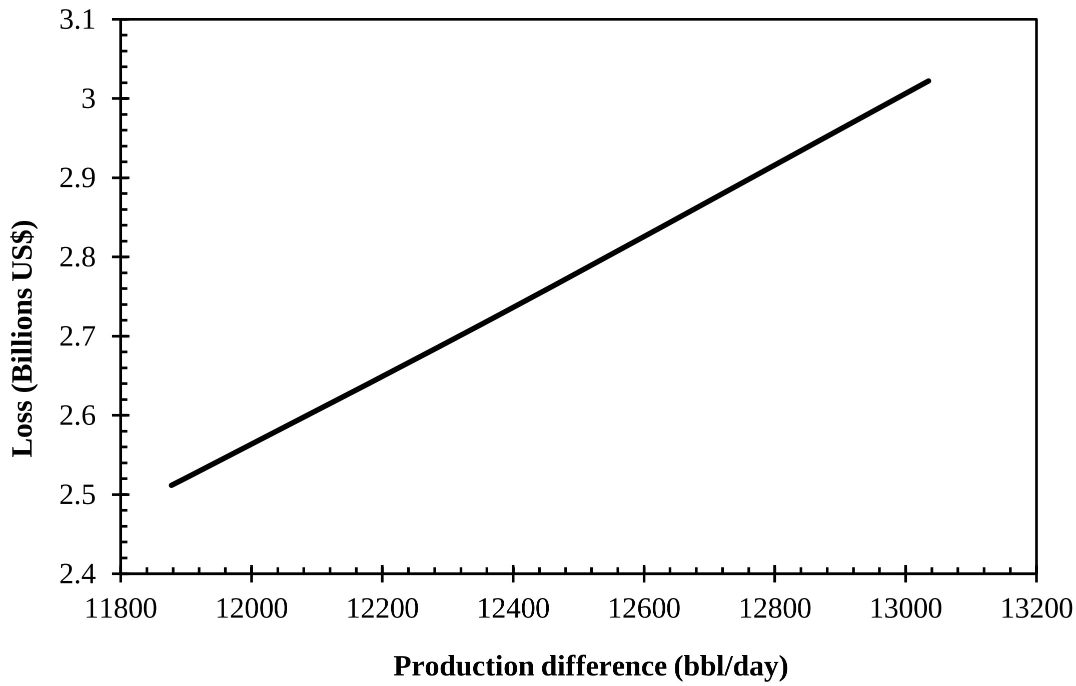
Figure 6.16: Dynamic risk curves associated with the different production abnormalities

Figure 6.16 depicts the profiles of the dynamic risks associated with the different production categorized abnormalities/classes. The encountered real time production losses are mainly due to these evaluated dynamic risks. The estimated/predicted production losses are shown in Figures 6.17 and 18, and Table 6.3. Figure 6.16 demonstrates that there are increasing dynamic risks with increasing severity of the production abnormality. According to Figure 6.16a, if low production light warning (LPLW) scenario is observed at the beginning of production, there is a 99% chance that a no-flow event would be experienced in the sixth year of production. On the contrary, if high production high warning (HPHW) is the recorded production scenario, a reliable production performance is expected even after the 9^{th} year of production with less than 50% chance of production failure. Hence, it is evident that the associated dynamic risks increase in the creasing order of the degree of severity of the classified abnormal production scenarios as failure probabilities of approximately 50%, 70%, 96% and 100% are expected at the ninth year of operations for HPHW, HPLW, LPLW, and LPHW categories, respectively.

Figure 6,16b confirms the finding obtained from Figure 6.16a; similar trends are depicted with dissimilar production abnormalities severities, which are statistically reasonable as the dynamic risks results are process data- and system-dependent. The resultant economic losses from the analyzed dynamic risks (Figures 6.16a and b) are presented in Figures 6.17 and 6.18 as well as in Table 6.3. Any observed evidence of abnormal production change has a direct impact on the overall risks profile of the process system as well as the economic losses. The resultant average daily losses and the cumulative outcomes are also presented in Table 6.3 and Figures 6.17 and 6.18, respectively. The results reveal the usefulness of the proposed model for reservoir production analysis irrespective of the process system complexities.



(a) Under evidence of low production light warning (LPLW)

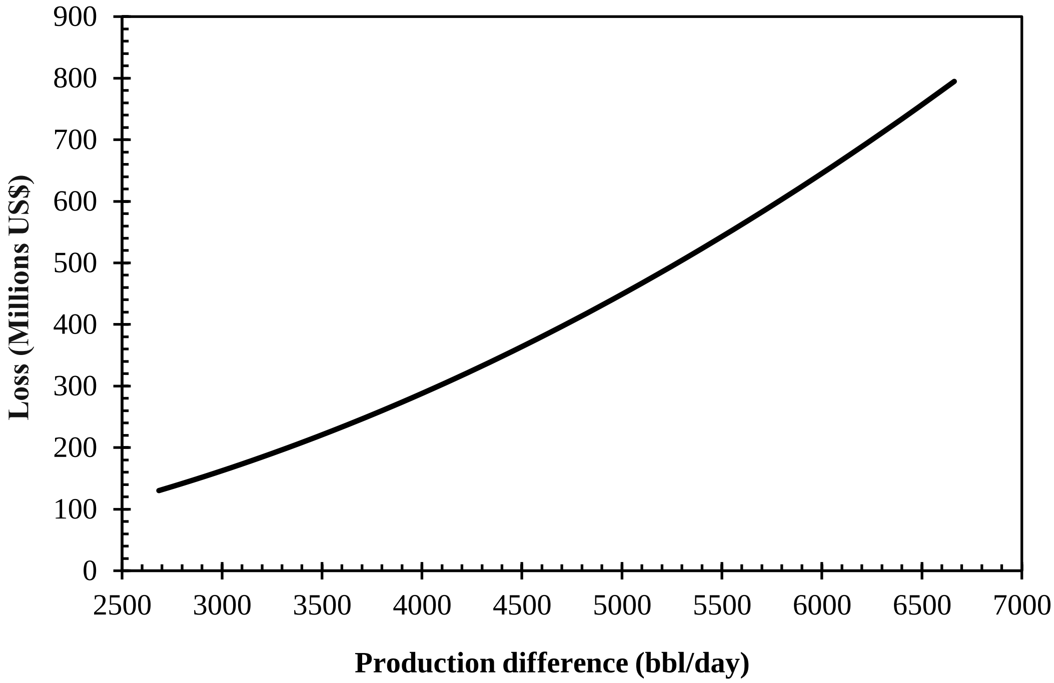


(b) Under evidence of low production heavy warning (LPHW)

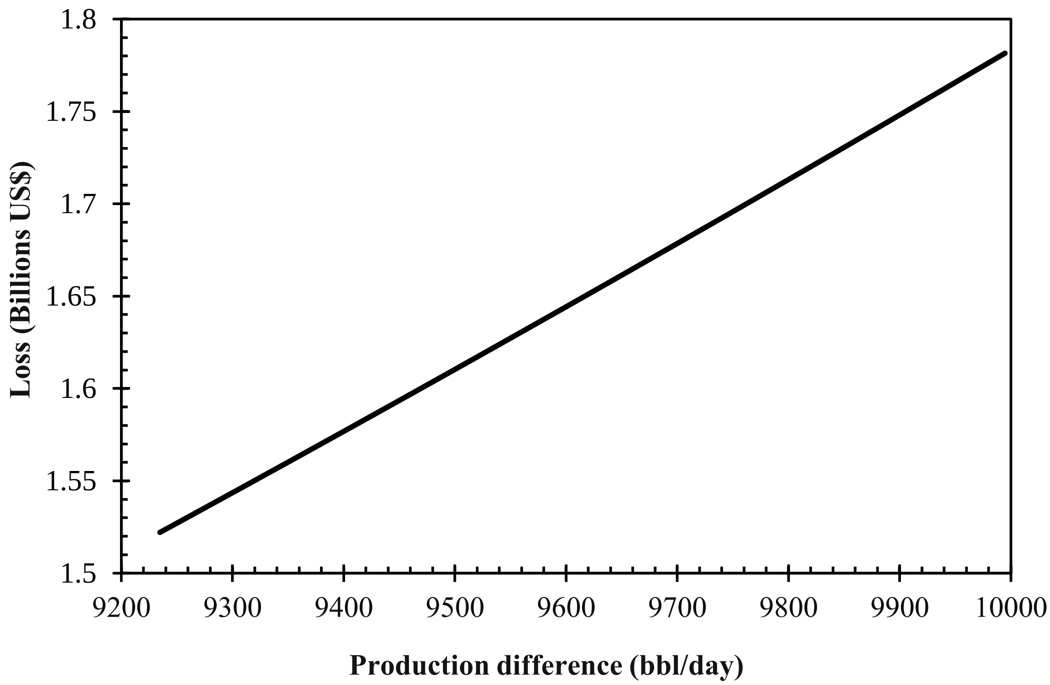
Figure 6.17: Evidence-based dynamic economic risks/loss profiles (case 1)

Figures 6.17a and 6.17b present the evidence-based dynamic economic risks profiles obtained for case 1. Figure 6.17a shows the results obtained under the evidence of low production light warning (LPLW). It demonstrates the possibility of a maximum economic loss of about $1.25 billion (USD) in the scheduled production period of 3462 days. A minimum dynamic economic loss of $420 million (USD) is expected. The data represent the less severe scenario for case 1 as they are events under LPLW category. This profile shows that the adaptive loss function model's loss increases with increasing daily production losses. This confirms the strength or excellent performance of the proposed methodology for evidence-based economic risks assessment. Another vital observation is the quadratic feature of the profile depicted in Figure 6.17a, compared to the linear relationship defined by Figure 6.17b at higher daily production losses. This is an expected characteristic of a proper (well-built) loss prediction model. This is because as losses tend to zero, a well-defined curvy shape is depicted by the process trend. On the other hand, the higher the daily losses, the more pronounced the linear relationship as shown by Figures 6.17a and 6.17b. Also, an excellent adaptive loss function model is expected to precisely yield these profiles at $\alpha = 2$ or 1.99. It is a loss-dependent characteristic of the model. According to the results from Figure 6.14a, it is concluded that the minimum and maximum daily production losses of about 4700bbl/day and 8300bbl/day are expected if the optimization and/or change of production strategies are not made. Figure 6.17b presents the dynamic economic losses associated with the worst case-scenario (LPHW) from case 1. This scenario involves severe production fluctuations (variations), total production failures (zero production, $q_o = 0$) or well shut-in that might be due to governmental regulations or other environmental factors. Hence, the proposed methodology captures the outcomes of these severe events, their direct causes, and their impact on the overall dynamic economic risks profiles of the reservoir production system (refer to Table 6.3). It is worth noting that all losses (dynamic economic risks) are calculated based on the deviations from the expected/scheduled productions and WTI crude oil price of $39.82USD per barrel (Month Front, July 01, 2020). According to Figure 6.16b, the minimum and maximum daily production losses of about 11840bbl/day and 13000bbl/day are expected. A minimum economic loss of about $2.52billion (USD) is expected in LPHW category in the scheduled operation period of 9 years. These values indicate the severity of the LPHW scenario relative to LPLW category where about 4700bbl/day and 8300bbl/day are the forecasted losses. The dynamic risks data demonstrate the need for evidence-based methodology applications in petroleum economics as the models' economic analysis considers the economic impacts of the production variables dynamics. Hence, the proposed connectionist methodology is strongly recommended for petroleum reservoir economics.

According to Figures 6.17 and 6.18, the higher the daily production losses, the more likely the evidence of a more severe scenario. If the daily production losses exceed 11840 bbl/day, LPHW production scenario set in as the designed process production threshold is exceeded (see Figure 6.17). Figure 6.18 also confirms the effectiveness of the proposed connectionist model. When the daily reservoir production losses are more than 9220 bbl/day, the threshold is exceeded. Thus, the abnormal production state results in LPHW production event, a scenario that should be prevented to avoid unnecessary production economic crisis. These transitional (threshold) production values yield analytical results that could be very useful in reservoir production management as well as decision- making. Therefore, the proposed deterministic tool provides the field operators with the means to assess real time economic consequences and impact of dynamic economic risks on the overall reservoir production losses or process systems risk profiles.



(a) Under evidence of low production light warning (LPLW)



(b) Under evidence of low production heavy warning (LPHW)

Figure 6.18: Evidence-based dynamic economic risks/loss profiles (case 2)

Figure 6.18a presents the dynamic economic risk profile under evidence of low production light warning (LPLW). This evidence-based dynamic economic risk profile describes the loss trend of case 2 with less severe production variables deviations (LPHW) from normal. According to Figure 6.18a, this abnormal situation indicates a maximum probable daily production loss of about 6700 bbl/day, while a minimum of 2600 bbl/day is recorded. The loss function model yields a profile with lower and upper loss limit values of about 110 million (USD) and 780 million (USD) in the scheduled production time (t). This implies that economic losses between 110 million (USD) and 780 million (USD) are expected if the production strategy is not optimized to prevent the abnormal situation occurrence. The reduction in the adaptive model loss (USD) as a function of the decreasing level of severity of the abnormal production situation confirms the efficiency/potency of the proposed connectionist methodology (see Figures 6.17 and 18); the effective production management to the handle production variable losses per day is imperative to minimize loss function model's outputs and/or dynamic economic losses.

According to Figure 6.18b, the evidence of low production heavy warning (LPHW) indicates the most severe events, compared to a less severe case presented by Figure 6.18a. If this abnormal situation (LPHW) is not avoided, the expected daily minimum production variable loss is more than the maximum encountered when a less severe scenario (LPLW) is observed (see Figure 6.18a). For instance, Figure 6.18b shows that the minimum and maximum production daily losses of 9220 bbl/day and 9995 bbl/day can be experienced as against the minimum and maximum daily losses of 4700 bbl/day and 8300 bbl/day shown in Figure 6.18a, respectively. Based on Figure 6.18b, the evidence of low production heavy warning (LPHW) defines a worst-scenario in which operations in the scheduled production period of more than 9 years could maintain losses of more than $1.75 billion (USD). This is the most feared scenario due to its financial consequences.

Extremely low production, abrupt well's shut-in, and/or total production failure fall in this category (LPHW). These analyzed outcomes could offer the operators with proper events planning that would be very handy in reservoir production analysis even in the event of worst economic crisis.

Table 6.3: Daily evidenced-based dynamic economic losses for cases 1 and 2.

	Case 1	**Case 2**
Production (Category)	**Average Loss Per Day (USD)**	**Average Loss Per Day (USD)**
Normal Production (NORP)	$0	$0
Light Loss (LPLW)	$267,463	$146,770
Severe or Heavy Loss (LPHW)	$486,596	$369,208

Table 6.3 lists the evidenced based daily economic losses for cases 1 and 2. The considered categories are the normal (NORP), LPLW or light Loss, and severe/heavy loss or LPHW categories. The definitions of warning classes are presented in Table 6.2. Based on the system design, losses only occur when normal production is not maintained. The normal production is used as the criterion or reference for deviations measures. The deviations from normal are called abnormal events. They are mainly caused by production abrupt fluctuations due to unforeseen circumstances. The NORP scenario (reference for deviations measure) leads to a daily loss of $0 USD for either case. For case 1, a daily economic loss of $267,463 USD is recorded under evidence low production light warning (LPLW). However, for a more severe scenario (LPHW), a production rate that varies between 0 bbl/day and 284 bbl/day, is a possibility as presented in Table 6.2. According to Table 6.3, an average daily economic loss of $486,596 USD is expected. This represents a loss increase of about 55% from the less severe category (LPHW). This shows the economic consequence of the impact of dynamic economic risks on the production economic losses as well as the use of inadequate production strategies for reservoir management and

production decision-making. Under evidence of low production light warning (LPLW), case 2 experiences a daily average economic loss of $146,770 USD, compared to a daily average economic loss of $369,208 USD for a more severe case, under evidence of low production heavy warning (LPHW). This represents a direct loss increase of 40%. The dynamic economic loss profiles depicted in Figures 6.17 and 6.18 also confirm the economic implications for not preventing losses with proper reservoir production economic analysis models and adequate production optimization strategies.

It is imperative to emphasize that based on the design, the normal production is utilized as the reference for deviations measurements/evaluations. Hence, losses are not recorded if normal production is maintained. The divergences from the normal (NORP) are termed the undesired/abnormal events. Thus, the NORP scenario suffers/experiences a daily loss of $0 USD for either case. In addition, all losses are computed based on these deviations from the expected NORP and WTI crude oil price of $39.82USD per barrel (Month Front, July 01, 2020). The results demonstrate that the proposed model is designed to provide the field operators with adequate means to assess real time dynamic economic risks and their impact on the overall process systems risk profiles during production operations. Thus, it is a novel model for dynamic economic risk predictions. The model yields transitional (threshold) production values usable in effective reservoir management to minimize losses. It adequately predicts the losses associated with the overall dynamic risk profiles. The risks analysis employed bridges the gaps in the existing risks analysis methodologies as they lack the potency to incorporate dynamic economic risks. The connectionist model predicts real time daily production economic losses resulting from the dynamic risks. It predicts the production, analyzes the dynamic risks, and assesses the associated production economic losses. The model has an overall prognostic performance with average errors of 1.954% and 1.957% for the two case studies considered in the present work: cases 1 and 2, respectively. Under the operating conditions, the minimum daily average economic losses of $267,463 and $146,770 are expected in cases 1 and 2, respectively. However, this could be minimized with adequate production management strategies. The model could be very handy in facilitating adequate production strategies for reservoir management and production decision-making. It evaluates the evidence-based production losses and analyzes the production predictions statistical disparities using EWIS-assisted BN model and the loss function model, simultaneously. It is a multipurpose tool for field implementation in production related management decision-making.

In this research, we propose a connectionist methodology for dynamic economic risks analysis of petroleum reservoir production systems. This is an efficient evidence-based dynamic economic risks analysis strategy for oilfield development planning and reservoir production management. This study introduces a multiple purpose connectionist model as it forecasts productions, predicts dynamic risks, and assesses the economic consequences. There are some drawbacks with the introduced model. For instance, the parameter and structure learnings of the BM model are subjective and mainly knowledge-base. The MLP model suffers extrapolation capability limitations and overfitting flaws. One of the key challenges of the ANN models is over fitting. The generalization capability and prediction accuracy of the model might be affected by over fitting as it hinders the ability to learn or memorize events. In fact, in some occasions, increasing the amount of training data has been reported not only to increase the computational time but also the likelihood of over fitting (Onalo et al., 2018). Therefore, improved prediction is not always achieved by increasing the amount of input data. Cross validation, regularization, and early stopping have been used to avoid the problem of over fitting. These criteria/features are considered in the current study. The proposed methodology can be improved by extending its design to incorporate reservoir production systems with 1) bottom-hole flowing pressure (P_{wf}) optimization scheme, and 2) enhanced oil recovery (EOR) operations.

6.6 Conclusions

This study presents a connectionist model for dynamic economic risk assessment of reservoir production systems (with or without pressure maintenance). The dynamic economic risk model combines evidence-based outcomes from a Bayesian network (BN) model with analyzed deviations predicted from an adaptive loss function model for reservoir production losses/dynamic economic risk predictions. The connectionist strategy links a data-driven model to a loss function model for prediction deviations assessment and integrates an early warning index system of oilfield development risks block to a BN model to enable evidence-based production losses evaluation. The model's outputs are employed for dynamic economic risks analysis and reservoir production management decision-making. The following conclusions are drawn from the current research work:

- The proposed connectionist model provides the field operators with the means to assess real time dynamic economic risks and their impact on the overall process systems risk profiles.
- The hybrid model forecasts production, assesses the dynamic risks, and evaluates the associated production economic losses.
- The proposed model yields transitional (threshold) production values for effective reservoir management to minimize production losses.

- A novel evidence-based model for dynamic economic risk predictions is proposed in this research.
- The connectionist model evaluates real time average daily production economic losses.
- The hybrid model yields an encouraging overall predictive performance with average errors of 1.954% and 1.957% for the two case studies considered in this research: cases 1 and 2, respectively.
- The proposed model enables the filed operators to facilitate adequate production strategies for reservoir management and production decision-making.
- The proposed model evaluates the evidence-based production losses and analyzes the production predictions statistical disparities using EWIS-assisted BN model and the loss function model simultaneously.
- The developed approach can be a recommended multipurpose tool for use by the field operators in reservoir production management.
- The proposed risks analysis model bridges the gaps in the existing risks analysis methodologies as they lack the potency to incorporate dynamic economic risks.

It is strongly recommended that the proposed methodology is extended to reservoir production systems: 1) with bottom-hole pressure optimization scheme, and 2) under enhanced oil recovery (EOR) operations. The former includes pump systems and gas lift setup, while the later can include chemical and thermal EOR methods.

Acknowledgements

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Appendix 6A

Solution to Example 6.1

Backpropagation Algorithm Procedure

- *Forward activation or forward Pass Procedure*

The inputs, target values, and the assumed weights and biases are presented in Table 1.

Computation of the net inputs to each hidden layer neuron and their respective outputs:

Computing the net input of the first neuron in hidden layer, h_1, gives:

$$Net\ input_{h1} = w_{1,1h} \times i_1 + w_{2,1h} \times i_2 + b_1 \times 1 \qquad (A1)$$

$$Net\ input_{h1} = 151.1900$$

The sigmoid function yields the following output of the hidden neuron, h_1:

$$Output_{h1} = \frac{1}{1 + e^{-Net\ Input_{h1}}} = \frac{1}{1 + e^{-151.1900}} = 1.0000 \qquad (A2)$$

Estimating the net input of the second neuron in the hidden layer, h_2, gives:

$$Net\ input_{h2} = w_{1,2h} \times i_1 + w_{2,2h} \times i_2 + b_1 \times 1 \qquad (A3)$$

$$Net\ input_{h2} = 229.7360$$

$$Output_{h2} = \frac{1}{1 + e^{-Net\ Input_{h2}}} = \frac{1}{1 + e^{-229.74}} = 1.0000 \qquad (A4)$$

Estimation of the output layer net input and output.

$$Net\ input_{o1} = w_{1,1o} \times Output_{h1} + w_{2,1o} \times Output_{h2} + b_2 \times 1 \qquad (A5)$$

$$Net\ input_{o1} = -0.7500$$

$$Output_{o1} = \frac{1}{1 + e^{-Net\ Input_{o1}}} = \frac{1}{1 + e^{-0.7500}} = 0.3208 \qquad (A6)$$

Total error computation

To calculate the total error, the squared error function is used, as follows:

$$Error_{total} = \frac{1}{2}(target(T) - output_{1o})^2 \qquad (A7)$$

$$Error_{total} = \frac{1}{2}(0.2400 - 0.3208)^2 = 3.27 \times 10^{-3}$$

The output (results) of the first forward pass is provided in Table A1

- *Back propagation or backward pass procedure*

The main goal of the backward pass is to adjust or update the weights so that the error would be minimized. The size of the adjustment would depend on the learning rate, η, and on the contribution of the weight to the error in the function. If the weight considerably contributes to the error, the adjustment will be greater than if it contributes to a smaller amount. Eq. (A8) is used until we find appropriate weights (the error is minimal). The derivative of the sigmoid function is presented in this section.

$$\Delta w_{k,lm} = -\eta \frac{\partial E_{total}}{\partial w_{k,lm}} \qquad (A8)$$

The derivative of the log sigmoid function

Suppose the log sigmoid function is y_m:

$$y_m = \frac{1}{1 + e^{-x_m}} \qquad (A9)$$

$$\frac{dy_m}{dx_m} = \frac{d}{dx_m}\left(\frac{1}{1 + e^{-x_m}}\right) \qquad (A10)$$

Applying function of a function (chain) rule gives:

$$\frac{dy_m}{dx_m} = (1 + e^{-x_m})^{-1} = \ -(1 + e^{-x_m})^{-2}(-e^{-x_m})$$

$$= \frac{e^{-x_m}}{(1 + e^{-x_m})^2} = \frac{1}{1 + e^{-x_m}} \times \frac{e^{-x_m}}{1 + e^{-x_m}} \qquad (A11)$$

Adding and subtracting one from the right-hand side of Eq. (A11) gives:

$$= \frac{1}{1 + e^{-x_m}} \times \frac{(1 + e^{-x_m}) - 1}{1 + e^{-x_m}} \qquad (A12)$$

$$= \frac{1}{1 + e^{-x_m}} \times \left(\frac{1 + e^{-x_m}}{1 + e^{-x_m}} - \frac{1}{1 + e^{-x_m}}\right)$$

$$= \frac{1}{1 + e^{-x_m}} \times \left(1 - \frac{1}{1 + e^{-x_m}}\right) \qquad (A13)$$

Substituting Eq. (A9) into Eq. (A13) results in:

$$= y_m \times (1 - y_m)$$

Therefore, Eq. (A10) equals:

$$\frac{dy_m}{dx_m} = y_m \times (1 - y_m) \qquad (A14)$$

That is, for a given function (log sigmoid function):

$$y_m = \frac{1}{1 + e^{-x_m}}$$

The derivative is:

$$\frac{dy_m}{dx_m} = y_m \times (1 - y_m)$$

Output Layer error computation

Estimating the change in the total error with respect to $w_{1,1o}$, function of a function (chain) rule is applicable.

$$\frac{\partial E_{total}}{\partial w_{1,1o}} = \frac{\partial E_{total}}{\partial output_{1o}} \times \frac{\partial output_{1o}}{\partial net\ input_{1o}} \times \frac{\partial net\ input_{1o}}{\partial w_{1,1o}} \qquad (A15)$$

Recall from Eq. (A14)

$$\frac{\partial E_{total}}{\partial output_{1o}} = output_{1o} - target(T) \qquad (A16)$$

$$\frac{\partial E_{total}}{\partial output_{1o}} = 0.0808$$

Estimating the change in $output_{1o}$ with respect to net input from Eq. (A9) leads to:

$$\frac{\partial output_{1o}}{\partial net\ input_{1o}} = output_{1o}(1 - output_{1o}) \qquad (A17)$$

$$\frac{\partial output_{1o}}{\partial net\ input_{1o}} = 0.2179$$

Estimating the change in $net\ input_{1o}$ with respect to $\partial w_{1,1o}$ from Eq. (A5) gives:

$$\frac{\partial net\ input_{1o}}{\partial w_{1,1o}} = Output_{h1} = 1.000 \qquad (A18)$$

Change in the total error with respect to $\partial w_{1,1o}$ from Eq. (A15) leads to:

$$\frac{\partial E_{total}}{\partial w_{1,1o}} = 0.0808 \times 0.2179 \times 1.000 = 1.76 \times 10^{-2}$$

Assuming a learning rate of $\eta = 0.5$, the updated value of $\partial w_{1,1o}$ would be:

$$\partial w_{1,1o}^{+} = \partial w_{1,1o} - \eta \frac{\partial E_{total}}{\partial w_{k,lm}} \qquad (A19)$$

$$\partial w_{1,1o}^{+} = \mathbf{0.2412}$$

Estimating the change in $net\ input_{1o}$ with respect to $\partial w_{2,1o}$ from Eqs. (A5) gives:

$$\frac{\partial E_{total}}{\partial w_{1,1o}} = \frac{\partial E_{total}}{\partial output_{1o}} \times \frac{\partial output_{1o}}{\partial net\ input_{1o}} \times \frac{\partial net\ input_{1o}}{\partial w_{2,1o}} \qquad (A20)$$

$$\frac{\partial net\ input_{1o}}{\partial w_{2,1o}} = Output_{h2} = 1.0000 \qquad (A21)$$

$$\frac{\partial E_{total}}{\partial w_{1,1o}} = 1.76 \times 10^{-2}$$

The updated value of $\partial w_{2,1o}$ becomes:

$$w_{2,1o}^{+} = \partial w_{2,1o} - \eta \frac{\partial E_{total}}{\partial w_{k,lm}} \qquad (A22)$$

$$\partial w_{2,1o}^{+} = \mathbf{-1.5088}$$

Hidden Layer error computation

In this section, $w_{1,1h}, w_{2,1h}, w_{1,2h}, and\ w_{2,2h}$ are updated.

The first neuron, h_1 in the hidden layer

Estimating change in total error with respect $w_{1,1h}$ results in:

$$\frac{\partial E_{total}}{\partial w_{1,1h}} = \frac{\partial E_{total}}{\partial output_{h1}} \times \frac{\partial output_{h1}}{\partial net\ input_{h1}} \times \frac{\partial net\ input_{h1}}{\partial w_{1,1h}} \qquad (A23)$$

Estimating change in total error with respect h_1 gives:

$$\frac{\partial E_{total}}{\partial w_{1,1h}} = \frac{\partial Error_{o1}}{\partial output_{h1}} \qquad (A24)$$

$$\frac{\partial Error_{o1}}{\partial output_{h1}} = \frac{\partial Error_{o1}}{\partial Net\ inputo_1} \times \frac{\partial Net\ inputo_1}{\partial output_{h1}} \qquad (A25)$$

Based on Eq. (A16) and (A17), we have:

$$\frac{\partial Error_{o1}}{\partial Net\ inputo_1} = \frac{\partial Error_{o1}}{\partial output_{o1}} \times \frac{\partial output_{o1}}{\partial Net\ inputo_1} \qquad (A26)$$

$$\frac{\partial Error_{o1}}{\partial Net\ inputo_1} = 1.76 \times 10^{-2}$$

Estimating the change in total net input with respect $\partial output_{1h}$ given by Eq. (A5) results in:

$$\frac{\partial Net\ inputo_1}{\partial output_{h1}} = w_{1,1o} = 0.25 \qquad (A27)$$

Substituting Eqs. (A26) and (A27) into Eq. (A25) gives:

$$\frac{\partial Error_{o1}}{\partial output_{h1}} = 1.76 \times 10^{-2} \times 0.25 = 4.40 \times 10^{-3} \qquad (A28)$$

From Eq. (A5)

$$\frac{\partial output_{h1}}{\partial net\ input_{h1}} = output_{h1}(1 - output_{h1}) = 0 \qquad (A29)$$

$$\frac{\partial net\ input_{h1}}{\partial w_{1,1h}}\ could\ be\ avaluated\ from\ Eq.(A1)$$

$$\frac{\partial net\ input_{h1}}{\partial w_{1,1h}} = i_1 = 190 \qquad (A30)$$

Substituting solutions to Eqs. (A28), (A29), and (A30) into Eq. (A23) gives:

$$\frac{\partial E_{total}}{\partial w_{1,1h}} = 4.40 \times 10^{-3} \times 0 \times 190 = 0$$

The updated value of $\partial w_{1,1h}$ becomes:

$$w_{1,1h}^{+} = \partial w_{1,1h} - \eta \frac{\partial E_{total}}{\partial w_{k,lm}} \qquad (A31)$$

$$\partial w_{1,1h}^{+} = 0.6 - 0 = \mathbf{0.6}$$

For $w_{2,1h}$, we have:

$$\frac{\partial E_{total}}{\partial w_{2,1h}} = \frac{\partial E_{total}}{\partial output_{h1}} \times \frac{\partial output_{h1}}{\partial net\ input_{1h}} \times \frac{\partial net\ input_{h1}}{\partial w_{2,1h}} \qquad (A32)$$

$$\frac{\partial net\ input_{h1}}{\partial w_{2,1h}} = i_2 = 0.78$$

Therefore, Eq. (A32) becomes:

$$\frac{\partial E_{total}}{\partial w_{2,1h}} = 4.40 \times 10^{-3} \times 0 \times 0.78 = 0$$

The updated value of $\partial w_{2,1h}$ becomes:

$$w_{2,1h}^{+} = \partial w_{2,1h} - \eta \frac{\partial E_{total}}{\partial w_{k,lm}} \qquad (A33)$$

$$\partial w_{2,1h}^{+} = 0.5 - 0 = \mathbf{0.5}$$

The second neuron, h_2 *in the hidden layer*

Estimating the change in total error with respect $w_{1,2h}$ gives:

$$\frac{\partial E_{total}}{\partial w_{1,2h}} = \frac{\partial E_{total}}{\partial output_{h2}} \times \frac{\partial output_{h2}}{\partial net\ input_{h2}} \times \frac{\partial net\ input_{h2}}{\partial w_{1,2h}} \qquad (A34)$$

$$\frac{\partial E_{total}}{\partial w_{1,2h}} = \frac{\partial Error_{o1}}{\partial output_{h2}} \qquad (A35)$$

$$\frac{\partial Error_{o1}}{\partial output_{h2}} = \frac{\partial Error_{o1}}{\partial Net\ inputo_1} \times \frac{\partial Net\ inputo_1}{\partial output_{h2}} \qquad (A36)$$

Estimating change in net input to the output layer with respect to $\partial output_{h2}$ leads to:

$$\frac{\partial Net\ inputo_1}{\partial output_{h2}} = w_{2,1o} = -1.5 \qquad (A37)$$

Solving Eq. (A36) by substituting Eqs. (A35) and (A26) gives:

$$\frac{\partial Error_{o1}}{\partial output_{h2}} = -1.5 \times 1.76 \times 10^{-2} = -2.64 \times 10^{-2}$$

Using Eq. (A4), we can obtain Eq. (A38):

$$\frac{\partial output_{h2}}{\partial net\ input_{h2}} = output_{h2}(1 - output_{h2}) = 0 \qquad (A38)$$

$\frac{\partial net\ input_{h2}}{\partial w_{1,2h}}$ could be avaluated from $Eq.(A3)$

$$\frac{\partial net\ input_{h2}}{\partial w_{1,2h}} = i_1 = 190 \qquad (A39)$$

Substituting solutions of Eqs. (A35), (A38), and (A39) into Eq. (A34) gives:

$$\frac{\partial E_{total}}{\partial w_{1,2h}} = -1.76 \times 10^{-2} \times 0 \times 190 = 0 \qquad (A40)$$

The updated value of $\partial w_{1,2h}$ becomes:

$$w_{1,2h}^{+} = \partial w_{1,2h} - \eta \frac{\partial E_{total}}{\partial w_{k,lm}} \qquad (A41)$$

$$\partial w_{1,2h}^{+} = 1.2 - 0 = \mathbf{1.2}$$

For $w_{2,2h}$, we have:

$$\frac{\partial E_{total}}{\partial w_{2,2h}} = \frac{\partial E_{total}}{\partial output_{h2}} \times \frac{\partial output_{h2}}{\partial net\ input_{h2}} \times \frac{\partial net\ input_{h2}}{\partial w_{2,2h}} \qquad (A42)$$

$$\frac{\partial net\ input_{h2}}{\partial w_{2,2h}} = i_2 = 0.78 \qquad (A43)$$

Substituting solutions of Eqs. (A33), (A38), and (A43) into Eq. (A42) gives:

$$\frac{\partial E_{total}}{\partial w_{2,2h}} = -1.76 \times 10^{-2} \times 0 \times 190 = 0$$

The updated value of $\partial w_{2,2h}$ becomes:

$$w_{2,2h}^{+} = \partial w_{1,1h} - \eta \frac{\partial E_{total}}{\partial w_{k,lm}} \qquad (A44)$$

$$\partial w_{2,2h}^{+} = 0.5 - 0 = \mathbf{0.5}$$

Currently, all the randomly selected synaptic weights have been updated upon the completion of this first backpropagation and are fed back into the network system for the next iteration. This continues till the network output is significantly moved closer to the target as depicted in Table A2 and Figure 2 or the stopping criterion is reached.

Table 6.A1: The inputs, targets, assumed weights, and ANN output in the first forward pass

Input Values		Target	Output	Assumed weights						Biases	
i_1	i_2			$w_{1,1h}$	$w_{2,1h}$	$w_{1,2h}$	$w_{2,2h}$	$w_{1,1o}$	$w_{2,1o}$	b_1	b_2
190	0.7800	**0.2400**	**0.3208**	0.60	0.50	1.20	1.20	0.25	-1.50	0.80	0.50

Table 6.A2: 99th iteration results (as shown in Figure 5)

Input Values		Target	Output	Updated weights						Biases	
i_1	i_2			$w_{1,1h}$	$w_{2,1h}$	$w_{1,2h}$	$w_{2,2h}$	$w_{1,1o}$	$w_{2,1o}$	b_1	b_2
190	0.78	**0.2400**	**0.2420**	0.60	0.50	1.20	1.20	**0.05**	**-1.70**	0.80	0.50

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Chapter 7

Logic-Based Data-Driven Operational Risk Model for Petroleum Production Systems

Preface

This chapter has been completed and now being reviewed for submission to journals for publication. I and my co-authors; Faisal Khan, Sohrab Zendehboudi, and Sunday Adedigba produced the work. I am the main author. I conducted the literature review, formulated the concepts of the dynamic risk assessment model and developed it for dynamic risk assessment of pressure-augmented downhole petroleum production systems. I prepared the first draft of the manuscript and subsequently revised the manuscript based on the co-authors' and peer review feedback. Co-author, Faisal Khan provided guidance in the development of concept, design of methodology, reviewing and editing the draft, and reviewing and revising the new version of the manuscript. Co-author, Sohrab Zendehboudi supported in reviewing and editing the draft, reviewing and revising the manuscript, and also helped in the review, and correction of the model and results. Co-author, Sunday Adedigba aided in the review of the developed concept and methodology.

Abstract

This research presents an operational risk model for the dynamic risk analysis of pressure-augmented downhole petroleum production systems. The model is built through integrating multilayer perceptron (MLP) and early warning index system (EWIS) with Bayesian network (BN) for downhole pressure system analysis and production forecast. The introduced model employs its evidence-based dynamic risk features to monitor the operational risks associated with the interdependencies of downhole pump discharge pressure, downhole pump intake pressure, downhole pump pressure difference, drawdown, and bottom-hole pressure (BHP). The proposed operational risk model is used to assess the impacts of the progressive cavity pump (PCP) on the downhole pressure system. The evidence-based mechanism enables the proposed model to accurately predict the resultant real-time production risks as the wells are being produced from the reservoirs. Hence, the model facilitates management decisions to make operational adjustments to avert downtime or “no flow”. The model captures the temporal and spatial dependence of variables. The failure probabilities of the downhole pressure system are modelled as a function of time while using the evidence-based risk model. The results demonstrate downhole process system’s contribution to the overall risk and its vulnerability to the overall production scenarios. The proposed novel strategy can simulate the PCP impacts on reservoir systems during production. The introduced model serves an important tool for operational decision-making to manage risks of reservoir systems equipped with downhole pressure pumps for production.

Keywords: Augmented production system; Downhole pressure system; Dynamic risk; Oil production; Data-driven models

7.1 Introduction

The risk of failure scenarios increases with an increase in the system complexity and interdependency of the parameters. In petroleum production systems, the downhole pressure depletion influences the operational parameters. The need for downhole pressure enhancement/augmentation leads to the downhole pressure pump applications in the subsurface geologic systems (Guo et al., 2007). Downhole pumps are employed to increase pressure at the sand face (bottom of the tubing string) by an amount sufficient to transport the hydrocarbons to the surface (Guo et al., 2007). The force produced by the downhole pressure difference improves the reservoir drawdown by increasing the pressure at the sand face. Hence, inadequate reservoir driving force to transport the hydrocarbons to the wellhead at acceptable rates makes the applications of production enhancement methods very handy (Guo et al., 2007). The production pump system applied to the downhole reservoir pressure system increases the dynamic risks associated with the complex subsurface geologic pressure system. Hence, a real-time risk assessment of the process is necessary as the pressure depletion is a function of time. These production challenges are analyzed in the current study and proper solutions are proffered.

In recent decades, some researchers have presented/developed intelligent models for reservoir simulation and production analysis (Augusto et al., 2014a; Bittencourt and Horne, 1997; Khazaeni and Mohaghegh, 2011; Lechner et al., 2005; Maschio et al., 2014; Nicotra et al., 2005; Shahkarami et al., 2014; Sun and Ertekin, 2017a; Subbey et al., 2003; Wang et al., 2019; Zhao et al., 2012; Zhong et al., 2016). Although the introduced models were effectively applied to production evaluation; however downhole pressure pumps were not considered in their models. Thus, the performance analysis of downhole pressure pump parameters was not conducted in their studies. In addition, dynamic risks assessment of the augmented downhole pressure system was not conducted in the models.

Samad & Nizamuddin (2013) presented a performance analysis of downhole production pumps used in oil wells. In their study, numerical modeling was conducted to analyze the flow behavior of the downhole pumps. Production predictions were not included in their work and risk analysis was not conducted. Khakimyanov et al. (2016) carried out a research on production pumps efficiency analysis. Their research was not a risk-based study, and the reservoir simulation was not conducted. Hence, dynamic risks assessment of the augmented downhole pressure system was not considered in their study. Mamudu et al. (2020a) introduced a predictive model for production modeling. They did not consider the downhole pump pressure system and production pump mechanisms were not incorporated in the model. In fact, they only investigated gas flooding scheme and the risks associated with the system. Similarly, Mamudu et al. (2020b) presented an assisted history model. They only considered uncertainty quantification, and the dynamic risk profiling was not investigated in the work. They developed a methodology for a primary recovery process and did not consider augmented pressure systems or pump performance analysis. Mamudu et al. (2021) presented a risk-based production predictive model for gas lift performance/flow system reliability analysis. They did not consider production pumps in their analysis as their risk-based mechanistic procedure did not incorporate pump scheme.

The literature demonstrates the need for the development of an operational model for dynamic risk and performance analysis of augmented downhole distinct pressure gradient system with installed production pump systems. The review of previous studies highlights the knowledge gaps in the literature and the deficiency in the existing methods. This gap is bridged in the current work with the proposed operational risk model for conducting dynamic risk assessment of the risks associated with the pressure-augmented downhole reservoir system. To the best of the authors' knowledge, an operational risk analysis model for this system has not been reported in the literature.

The objective of this work is to develop a proper operational model for the dynamic risk analysis of pressure-augmented downhole petroleum production systems with pressure pump strategy. The analysis is space and time-dependent. The introduced tool is designed to model the production system and capture the sand face pressure enhancement impact on the reservoir. It predicts the chances of production failures as a function of time. It employs a procedure that integrates MLP and EWIS models with the BN model for risk-based production forecast.

This work is arranged as follows. Section 6.2 presents the theory and background of the study. Section 6.3 presents the methodology employed in the study. A flowchart to demonstrate the entire workflow along with the procedure for application of the proposed approach are also given in this section. The case study (and its characteristics) and implementation of the proposed model are described in section 6.4. Section 6.5 includes the results and analysis. Section 6.6 encapsulates the key findings of the study.

7.2 Theory and Background

***Bayesian Network* (*BN*)**. The BN models have been widely/successfully used in different engineering, science, and health domains as well as risk assessment decision support. The understandable visualization of the complicated relationships among the variables is one of the most appealing characteristics of a BN model, though its mystifying power lies in the ability to encode multivariate probabilistic distributions. The logical networks provide a clear and efficient way to model/visualize complex relationships between unobservable and observable variables. They can integrate data from diverse sources with contrasting degrees of uncertainty. Most interestingly, the BN approach enables the modeling of unique/different dynamic processes under a single and statistically robust framework. Risk assessment is an essential component of investment analysis, whether in academia or industries (Pui et al., 2017). It is one of the research areas mostly explored by multidisciplinary experts in engineering fields. In addition, it is widely reported in the literature (Abimbola et al., 2015; Adedigba et al., 2018; Khakzad et al., 2013;

Khakzad et al., 2014; Khan et al., 2016; Khan et al., 2015; Meng et al., 2019; Perez and Tan, 2018; Pui et al., 2017; Wu et al., 2016; Yang et al., 2017; Zhang et al., 2018).

***Artificial Neural Network* (*ANN*).** The ANN approach possesses an innate ability/feature to simulate complex processes and replicate complicated performances in numerous systems (Shahnazari, 2020). The data-driven black-box model is typified by its characteristic strength of reasoning attributes such as sensitivity, discovery, grouping, and generalization (Li et al., 2020; Zendehboudi et al., 2018). Li et al. (2020) demonstrated that ANN is one of the most advanced artificial intelligence (AI) models. ANNs are broadly categorized on characteristic basis (Hafeez et al., 2020). These classifications have been reported in several previous studies (Picos-Benítez et al., 2020; Sharafati et al., 2020). Further details on ANN categories are found in the work of Zendehboudi et al. (2018) where they presented an extensive review on ANN fundamentals, theory, and applications in various science and engineering cases. Multilayer perceptron (MLP) model is used in the current study. It is a robust tool which is mostly used in engineering systems (Alsaffar et al., 2020; Elkatatny et al., 2019; Zhou et al., 2020).

***Multilayer Perceptron* (*MLP*).** A review of the MLP (as a type of ANN model) has been given in the literature (Shahnazari, 2020). Data are normally transferred in the forward direction and the error transmission in the backward direction. The feedforward-backpropagation is the model architecture used in this work. The transfer/activation function used in the hidden layer is the log-sigmoid function, as presented in Eq. (7.1) (Zhong et al., 2016). The linear activation function model used in the output layer is given by Eq. (7.2). The mean square error (MSE) deployed as the performance function to evaluate the accuracy of the model's learning is given by Eq. (7.3). The optimization function employed during the network training is the Levenberg-Marquardt function as it exhibits a fast convergence rate and high efficiency. The stopping standard/criterion applied to end the network learning process is the determination coefficient (R^2). The statistical parameters are expressed by Eqs. (7.3) and (7.4) (Adedigba et al., 2017b). The use of the MLP in engineering cases is well-documented in the previous studies (Adedigba et al., 2017a; Kim et al., 2019; Kimaev et al., 2019; Zhong et al., 2016). In the current study, the MLP is hybridized with EWIS and BN for the risk-based modeling of the downhole pressure-augmented petroleum reservoir system.

$$f(x) = \frac{1}{1 + e^{-x}} \tag{7.1}$$

$$f(x) = x \tag{7.2}$$

$$MSE = \frac{1}{n}\sum_{m=1}^{n}\left(Y_T - Y_{pred}\right)^2 \tag{7.3}$$

$$R^2 = 1 - \left\{\frac{\sum_j^n\left(Y_j^{Actual} - Y_j^{Predicted}\right)^2}{\sum_j^n\left(Y_j^{Actual} - \bar{Y}_j^{Actual}\right)^2}\right\} \tag{7.4}$$

where the actual and predicted data are represented by Y_j^{Actual} and $Y_j^{Predicted}$, respectively; $\bar{Y}_j^{Actual}$ denotes the mean of the actual data; R^2 refers to the determination coefficient; the number of the actual data is symbolized by *n*; and *j* introduces the ordinal.

7.3 Proposed Operational Risk Model

Figure 7.1 depicts the flowchart of the proposed operational risk model. It shows the workflow from data collection to model implementation.

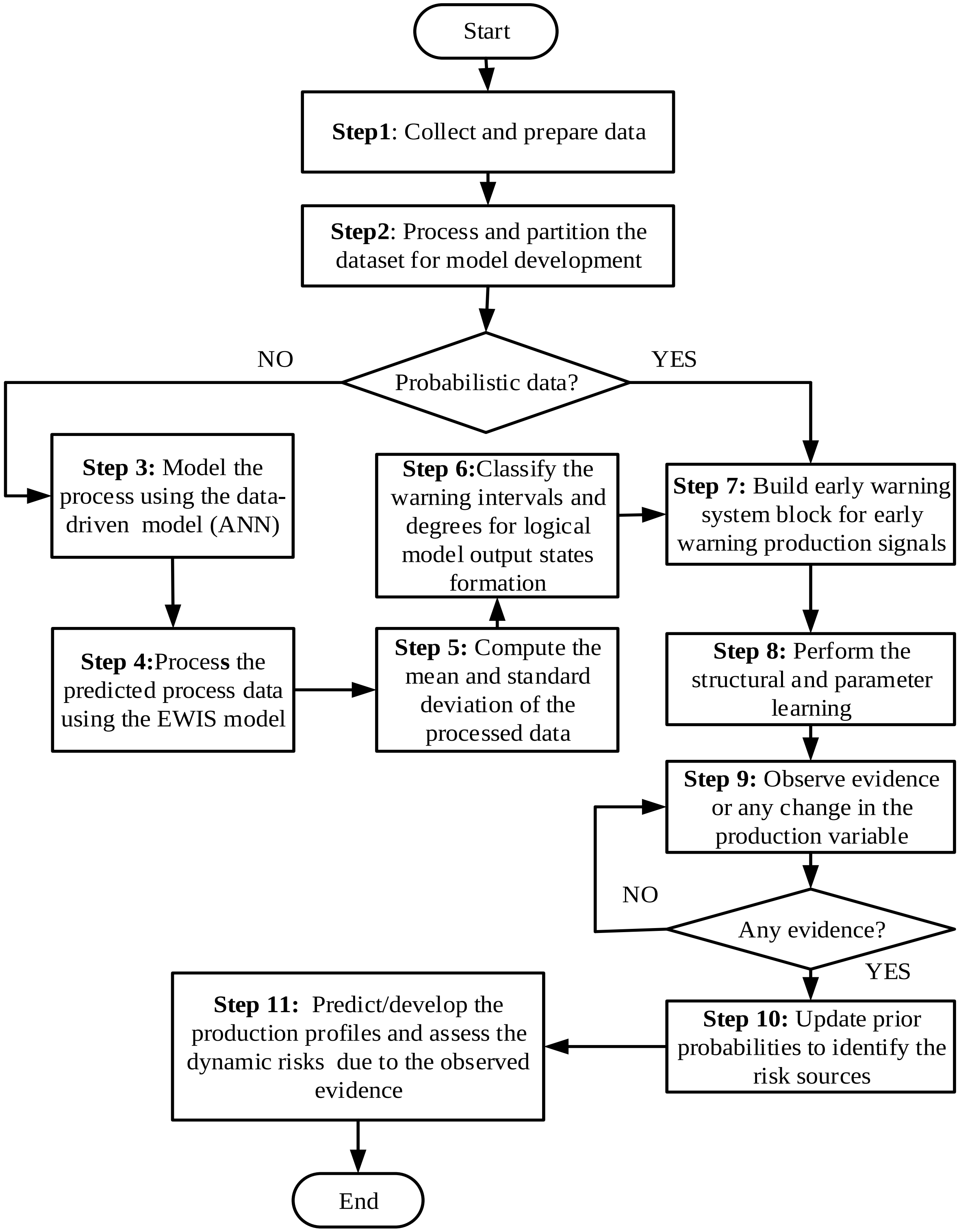

Figure 7.1: The Methodology of operational risk model development and implementation.

The dataset processing and categorization for the process modeling are conducted as seen in steps 1 and 2. The application of the MLP model to the hydrocarbons production system is described in step 3. The predictions obtained at step 3 are transmitted to the EWIS for modeling and interpretation. At step 4, the EWIS model is initiated and employed for the predicted data processing. The mean (μ) and standard deviation (σ) of the predicted data are evaluated in step 5 to ensure that optimal classified intervals are selected. The results from step 5 are used to classify the process production variables into distinct warning intervals in step 6. The number and type of states of the BN outputs are also determined in step 6. Then, the processed data are directed to step 7 where the risk block is built and activated for early warning production signal processing. At step 8, the outputs from the EWIS fed to the BN model are used for learning. The evidence is monitored at step 9. If there is no evidence of production abnormality, step 9 is repeated until there is an observable evidence of production fluctuations. However, if there are changes in the production levels or classified warning intervals, the prior probabilities are updated at step 10, and the dynamic risk profiles due to the observed evidence are generated. Finally, the predicted production profiles and the assessed dynamic risks due to the observed evidence are presented in step 11 for production analysis and decision making.

As discussed earlier, the proposed modeling strategy begins with data collection and processing as depicted in Figure 1, followed by production forecast and the associated dynamic risks assessment in the two-stage modeling system. The predicted reservoir production variables are obtained by the developed MLP model.

Production Forecast. This modeling phase begins by obtaining a temporal and spatial dataset for reservoir model building. Other steps include: 1) Using the prepared data to build a reservoir/geological model; 2) Constructing spatial and temporal database from the static and dynamic data using the developed MLP model; 3) Categorizing the influence of the flow characteristics on the production behavior/performance; 4) Using the analyzed flow properties to choose MLP model's inputs; 5) Splitting the temporal and spatial dataset into training, validating, and testing data sets; 6) Constructing the model architecture; 7) Training, testing, and validating the data-driven model; 8) Validating the developed ANN with different geological realizations of the reservoir; and 9) Forecasting the reservoir production using the built model.

The MLP approach is used in the current study due to its strength and network features (see step 4 in Figure 7.1). The brief procedure of the MLP modeling is as follows: 1) Network architecture design. This is determined by modeling objective and the provided input and target data; 2) Weights and biases initialization. This involves random selection of the synaptic weights and biases; 3) Forward propagation of the selected inputs through the synaptic transmission lines of the network; 4) Error evaluation using Eq. (7.3); 5) Transmitting the error term to update or adjust the randomly initially selected synaptic weights; and 6) Constant iterative procedure until the error value is substantially reduced. The model's inputs are storativity, drawdown (Δp), reservoir pressure (p_i), Bottom-hole flowing pressure ($BHP\ or\ p_{wf}$), and transmissibility. Production rate is the selected target, which is fed to the EWIS-based BN for processing. The numbers of hidden neurons and layers are 10 and 3 in the MLP network, respectively.

Dynamic Risk Analysis. The objective of this modeling study is to offer a template for analysis of the dynamic risks associated with any producing well located in a pressure-augmented downhole petroleum reservoir system. The analysis is evidence-based and space and time-dependent to adequately replicate the behavior (and performance) of the complex downhole pressure flow system. The logical model's outputs represent real-time dynamic risks associated with the production scenarios. This assessment follows the first stage of the proposed modeling strategy as summarized here: 1) Prepare the process data for risks assessment as depicted in steps 1 and 2 (see Figure 7.1); 2) Build the EWIS risks block with the prepared probabilistic and production data from the process model; 3) Using "3σ" rule, categorize the production rates' levels into standard warning intervals such as heavy warning low production (LHW), light warning low production (LLW), normal production (NOR), light warning high production (HLW), and heavy warning high production (HHW); 4) Assign the warning degrees to the evaluated warning intervals; 5) Perform structural and parametric learnings of the logical model as described in step 8 of Figure 7.1; 6) Analyze posterior events as stated in step 10 of Figure 7.1 to update the prior probabilities if any evidence of production rate change is observed in step 9, and then analyze the dynamic risks; and 7) Develop the dynamic risk profiles associated with continuously changing reservoir production variables.

The BN model only interprets the production variables/signals through the EWIS. As mentioned earlier, EWIS is principally intended to receive flow rates, classify them using the statistical "3σ" rule, and produce the BN's output states. The EWIS oilfield risk block is constructed to sufficiently replicate the interactions among the process variables. A review of the oilfield development risk block procedure can be found in the literature (Zhong et al. 2016). Also, Li et al (2020) provided a review on the BN model.

7.4 Application of the Proposed Model

The field data and model's application are given in this section. The data available in the literature, the Society of Petroleum Engineering (SPE), are used for implementation of the proposed methodology (Odeh, 1981).

Case Study. The field data used in this work are from a simulated layered oil reservoir. A single production well is drilled in the hydrodynamically connected layers under reservoir natural driving force with installed pressure support facilities. The maximum production capacity (initial flow rate) of the well is set at 12000 bbl/day. The stopping criterion is set at a pressure of 3200 psi. The production project is planned to run for 9 years. The layers' horizontal permeabilities are 500 mD, 50 mD, and 25 mD. The vertical permeabilities of the layers are equal to 50 mD, 50 mD, and 25 mD. The layers' thicknesses are 20 ft, 30 ft, and 50 ft. The other reservoir data include a reservoir temperature of 200 °F, initial reservoir pressure of 4,800 psi, bubble point pressure of 3,200 psi, oil density of 51.8 $1b/ft^3$, water density of 62.4 $1b/ft^3$, initial water saturation of 0.2, initial oil saturation of 0.8, a specific gravity of 0.792, porosity of 0.3, oil compressibility of $3 \times 10^{-6}\ psi^{-1}$, oil viscosity of 0.51 cp, water viscosity of 0.31 cp, gas gravity of 0.792, and water compressibility of $3.3 \times 10^{-6}\ psi^{-1}$. Other simulation information are the grid dimensions of $10 \times 10 \times 3$ ft, areal grid block dimensions of 1000 ft $\times$ 1000 ft, and reference depth of 8400 ft.

Model Implementation. This section presents a simple sketch of the pump system, discusses the steps for operational risk model implementation (as outlined in Figure 7.1). Figure 7.2 depicts the progressive cavity pump (PCP) system whose impacts on the downhole pressure of the reservoir are assessed. The interdependencies of the flow system contributing factors resulting from the applied pump system determine the complexities of the downhole pressure system. The extent of the uncertainties of the system dynamically increases as production proceeds. Hence, the need to develop the proposed approach for effective real-time operational dynamic risk management.

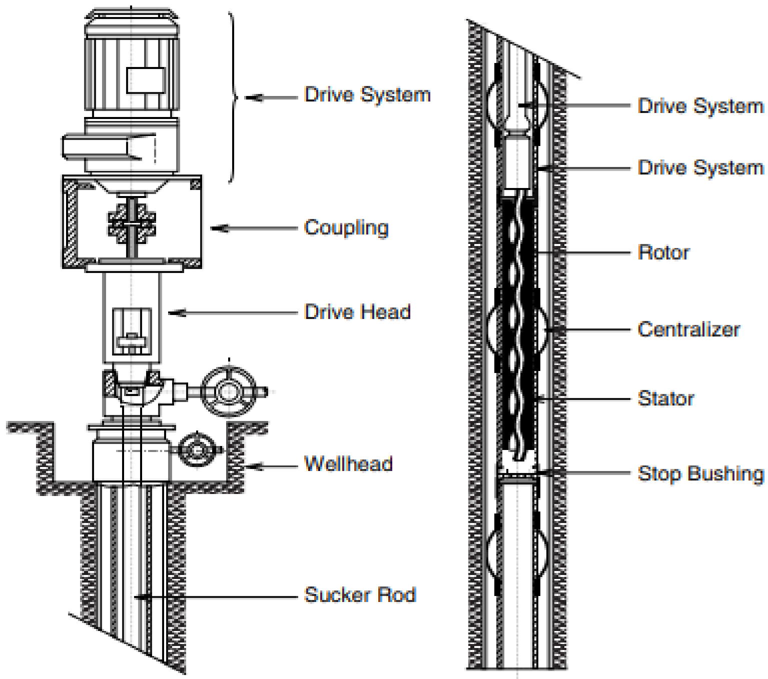

Figure7.2: PCP system on onshore location (Guo et al., 2007).

The field application of the proposed operational risk model for dynamic risk assessment begins with the generation of the production profiles (predicted production data). The built MLP component of the proposed model is used to accomplish this task as described in step 3 of Figure 7.1. There are five input parameters including Δp, p_i, p_{wf}, transmissibility, and storativity. The selected objective function is the flow rate.

EWIS-based BN model is constructed based on all the key variables of the pressure-augmented downhole petroleum reservoir system. Adequate real-time representation of the process would enable efficient assessment of the dynamic risks associated with the system. Steps 4 to 7 of Figure 7.1 demonstrate the implementation procedure. The selected contributing factors (flow parameters) are the risk block indexes. The indexes are mostly categorized in three types, which are the warning situation, warning sign, and warning source indexes. Production rate represents the index of warning situation. The warning sign indexes include, initial pressure, downhole pressure difference, pressure differential, transmissibility, sand face pressure, and storativity. Downhole pump intake pressure and downhole pump discharge pressure represent the warning source indexes. The selected indexes are the key contributing factors. Hence, they essentially determine the stability or failure of the continuously changing production variable (flow rate). The constructed EWIS-based logical model used for the dynamic risk assessment is displayed in Figure 7.3.

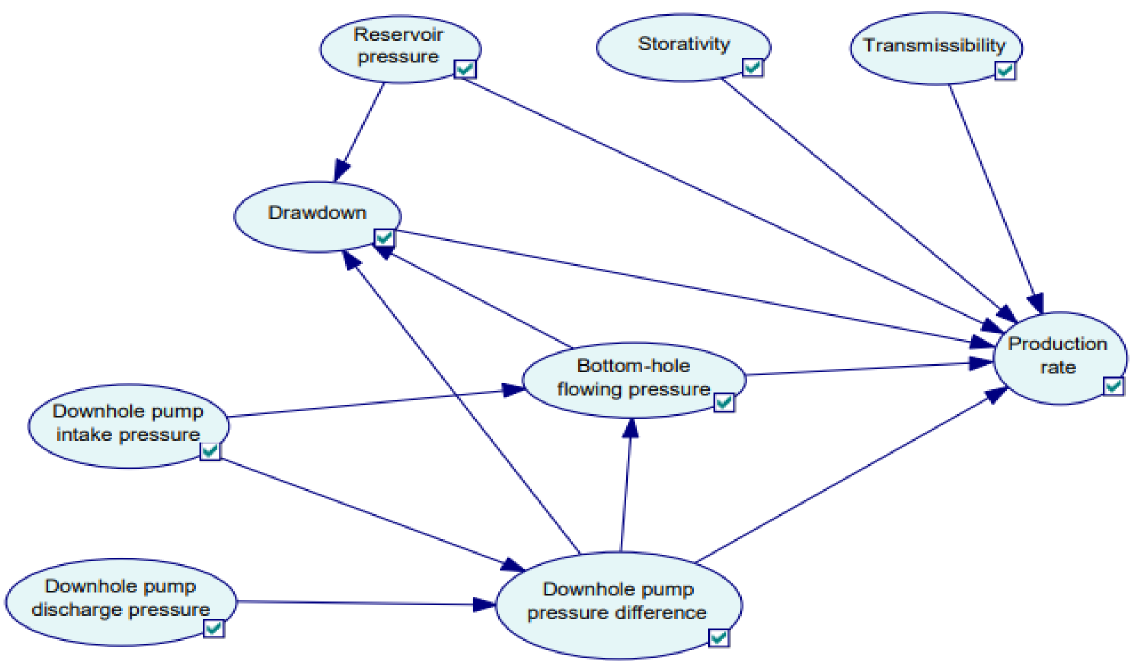

Figure 7.3: The introduced EWIS-based logical model.

Figure 7.3 is the product of the structural learning of the EWIS-based BN model implemented in step 8 of Figure 7.1. Monitoring of the production fluctuations/losses starts at step 9 of Figure 7.1. Substantial changes or losses of production are always momentarily captured as the well is being produced. Then, the prior probabilities of the contributing factors are updated for risk sources diagnosis/identification, and adjustments can be accordingly recommended as shown in step 10 of Figure 7.1. Finally, the dynamic risk profiles associated with the various classified warning intervals are generated for risk management, as described in step 11 of Figure 7.1.

7.5 Results and Discussion

The proposed dynamic risks-based operational strategy is primarily designed to model the production process, analyze the pressure-augmented process' impact on the reservoir production system, and predict the associated dynamic risks. The results from the MLP component of the model are depicted in Figure 7.4. EWIS model's results are provided in Table 7.1. The assessed dynamic risks are presented in Figures 7.5 to 7.11.

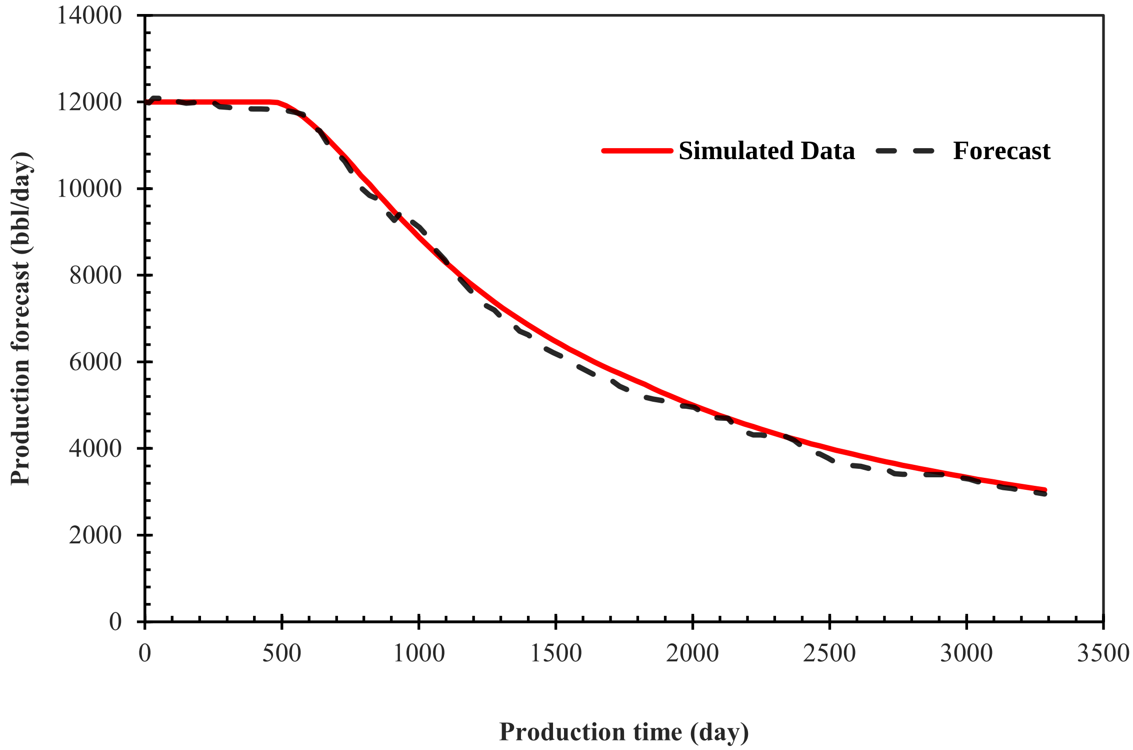

Figure 7.4: Production history based on the simulated data and forecast.

Figure 7.4 includes the production history of the well based on the simulated data and predictions. These data are supplied to the constructed EWIS model for risk analysis purpose. A very good match between the simulated and predicted production rates over the production operation is noticed. According to the statistical analysis, the minimum, mean, and maximum error percentages are 0.0037%, 1.58%, and 7.44%, respectively.

Table 7.1 presents the outputs from the implemented EWIS component of the developed model. Based on the results, any production rate (q_o) of less than 353 bbl/day represents the worst-case scenario and is regarded as the LHW warning class. This is a warning interval where "no flow" can occur, resulting in total production downtime. The LLW class refers to the critical production fluctuations or changes with respect to the normal state. The production abnormality captured in this warning class is less severe compared to the worst-case scenario accounted for by the LHW class. The normal (NOR) class is used as the reference or benchmark for production abnormality analysis. Any observable production rate change above the NOR is advantageous as it would be in either HLW or HHW warning class.

Table 7.1: Warning classes and scales/degrees of the reservoir flow variable.

Warning range	Scale/degree	Flow range (bbl/day)	
Heavy warning low production (LHW)	1	0	353
Light warning low production (LLW)	2	353	3657
Normal (NOR)	3	3657	6254
Light warning high production (HLW)	4	6254	9558
Heavy warning high production (HHW)	5	9558	+∞

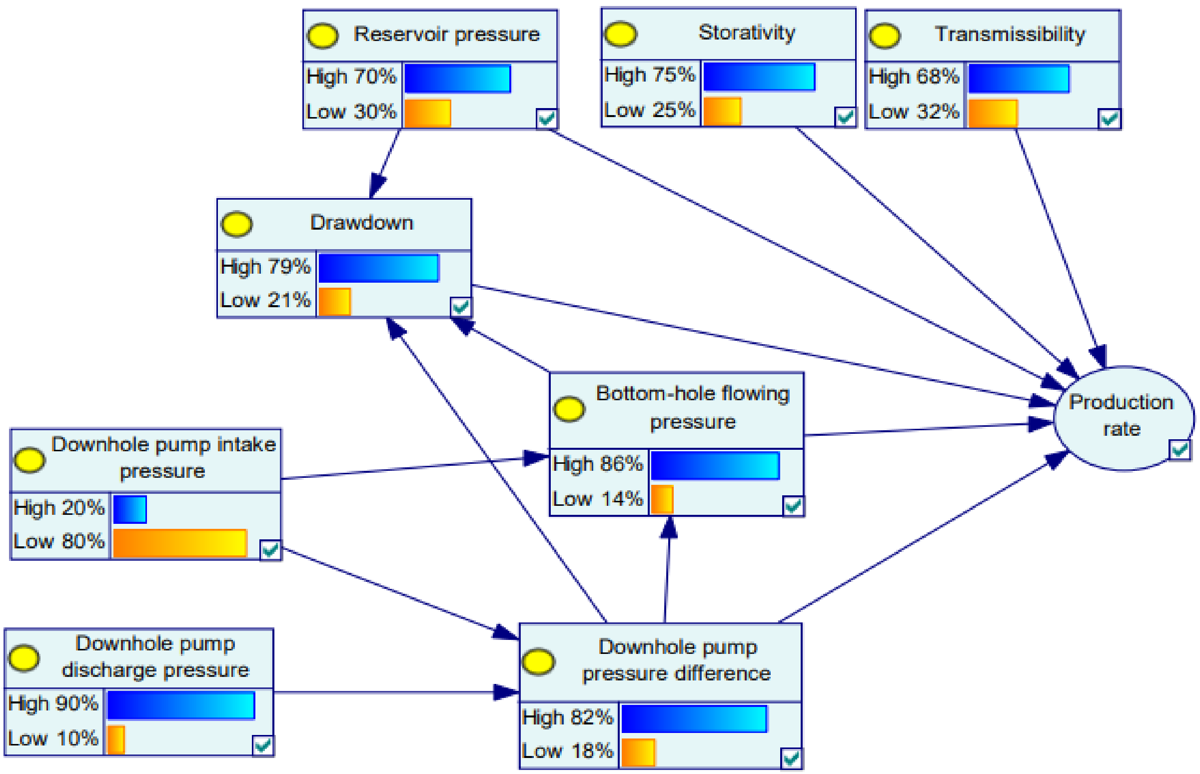

Figure 7.5: Parameter learning of the proposed model.

Figure 7.5 includes the prior probabilities data of the system that demonstrates the relationships among the system contributing factors (network variables). The data are the direct products of the constructed conditional probability table (CPT)/Bayesian interference. Figure 7.5 is employed as the benchmark for comparative analysis to detect risks upon posterior estimates. When production fluctuations are observed, the given prior probabilities of the key factors presented in Figure 7.5 are updated and the prior and posterior probabilities are compared to identify the risk sources.

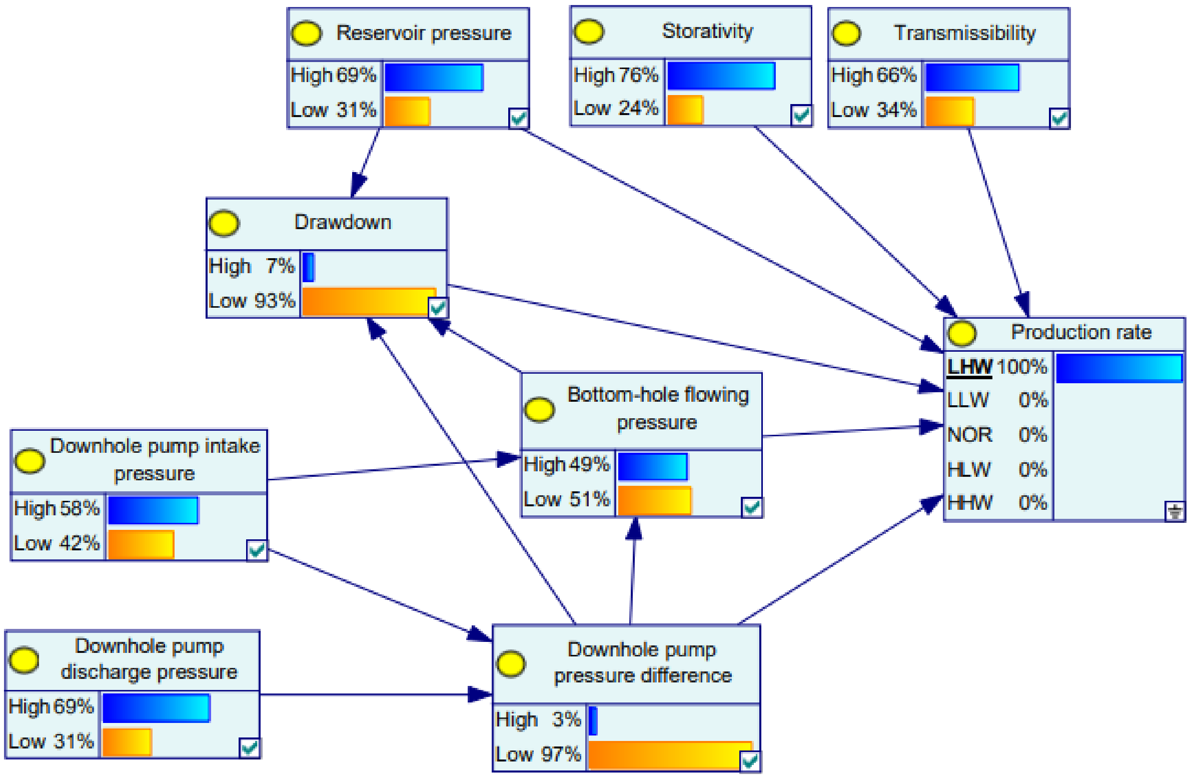

Figure 7.6: Updated probabilities during LHW warning class.

Figure 7.6 shows the results obtained when evidence of the LHW warning class is observed. This occurs during the worst-case scenario, where 0 bbl/day is conceivable. According to Figures 7.5 and 7.6, transmissibility and storativity do not influence the production output appreciably as the prior and posterior probabilities exhibit no significant difference. The same outcome is obtained for the reservoir pressure. This finding affirms that the failure is not associated with reservoir pressure during pressure-augmented downhole petroleum production operation that uses production pumps. On the other hand, a severely affected reservoir drawdown or critically low BHP coupled with a critically low downhole pump pressure difference seems to be the only practical reason for the observed LHW warning class. For instance, the chance of a high reservoir drawdown is 7% in Figure 7.6 as against the set benchmark of 79% in Figure 7.5. This drawdown outcome is after the failure of downhole pump pressure difference with a staggering failure probability of 97% seen in Figure 7.6 as against a set prior value of 18% in Figure 7.5. Also, the downhole pump pressure difference is observed to encounter a drastic increase in failure probability from a prior value of 18% to a posterior value of 97%. The relationships between the downhole pump pressure difference, and inlet and discharge pressures are also adequately monitored. The discharge pressure has a greater contribution to the production system stability. The outcomes demonstrate the efficacy of the proposed approach in the production system risk monitoring resulting from the contributing factors' impacts on the production. Figure 7.7 includes the results obtained during observable normal production. Based on the "3σ" statistical rule, any production rate observed in this warning class is normal as it is above the warning intervals where the substantial production losses are recorded.

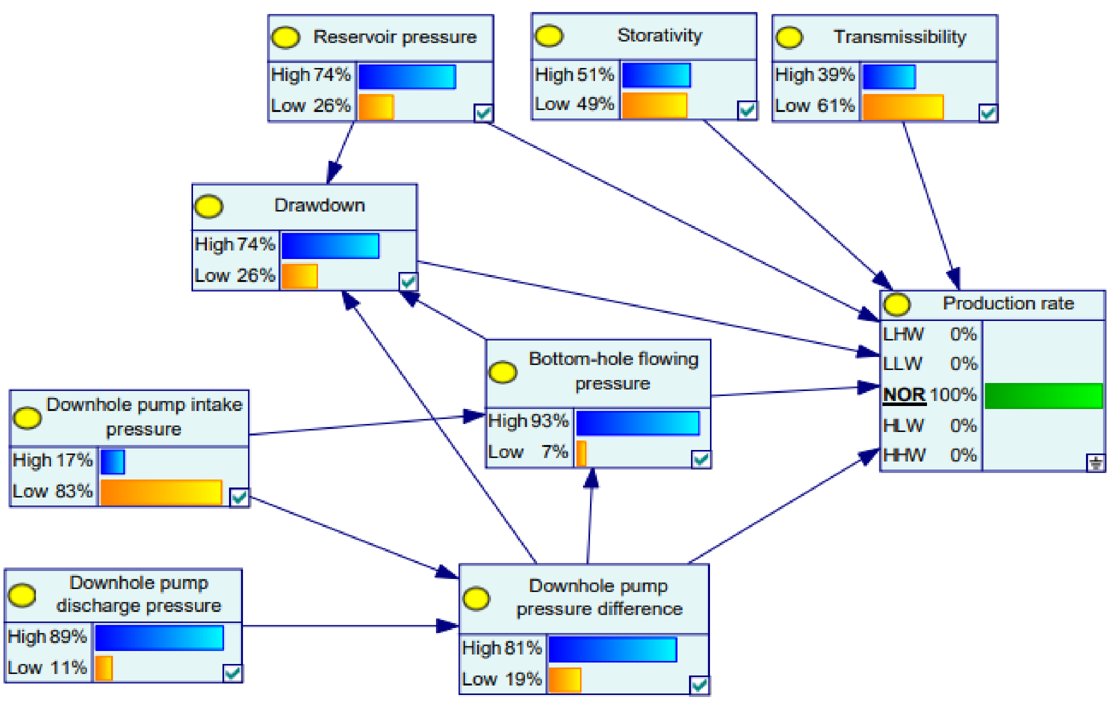

Figure 7.7: Updated probabilities during normal production.

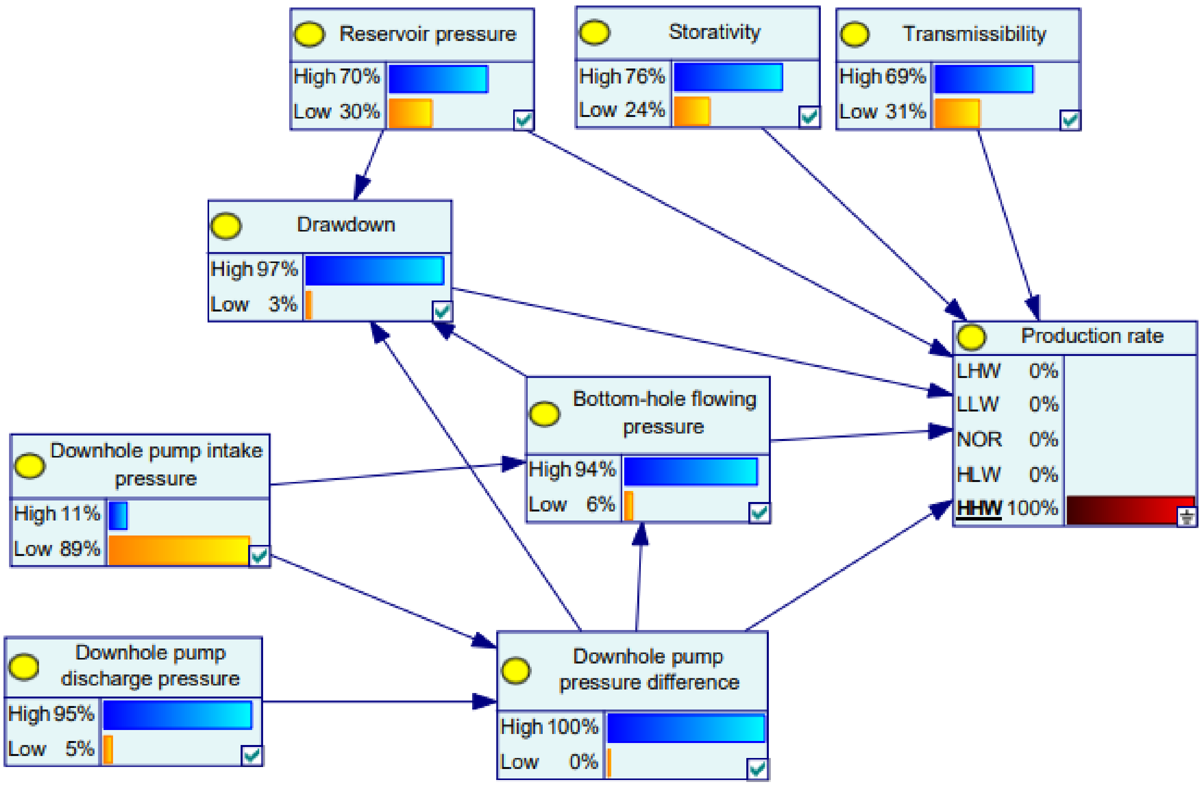

Figure 7.8: Updated probabilities during HHW warning class.

Figure 7.8 presents the outcome of the HHW class. It is found that at the highest production level, there is 100% assurance that the downhole pump pressure difference is high, which should result from low and high occurrence chances of the desired downhole pump intake pressure and downhole pump discharge pressure, respectively. For instance, when the probability of occurrence of high downhole pump pressure difference associated with HHW is 100%, that of the downhole pump discharge pressure is 95%. Intuitively, this relationship is expected as both contributing factors have a direct proportionality. The probability of having high downhole pump discharge pressure under this condition is expected to be low as this indicates the extent to which the augmented BHP was depleted. Hence, the chance of having a high BHP should be high (e.g., 94%) to sustain HHW as reported in Figure 7.8. This confirms that high BHP is one of the most important contributing factors when addressing production failure challenges resulting from high wellhead pressure. Hence, the proposed model can replicate the field scenario as the main objective of using downhole production pumps is to increase the sand face pressure/BHP to overcome the vertical flow performance challenges encountered due to high wellhead pressure. Once a sufficient reservoir drawdown is supplied by the additional downhole pump pressure difference, the vertical performance is improved. It implies that the proposed model offers the operators the logical platform to manage and analyze these production uncertainties/abnormalities.

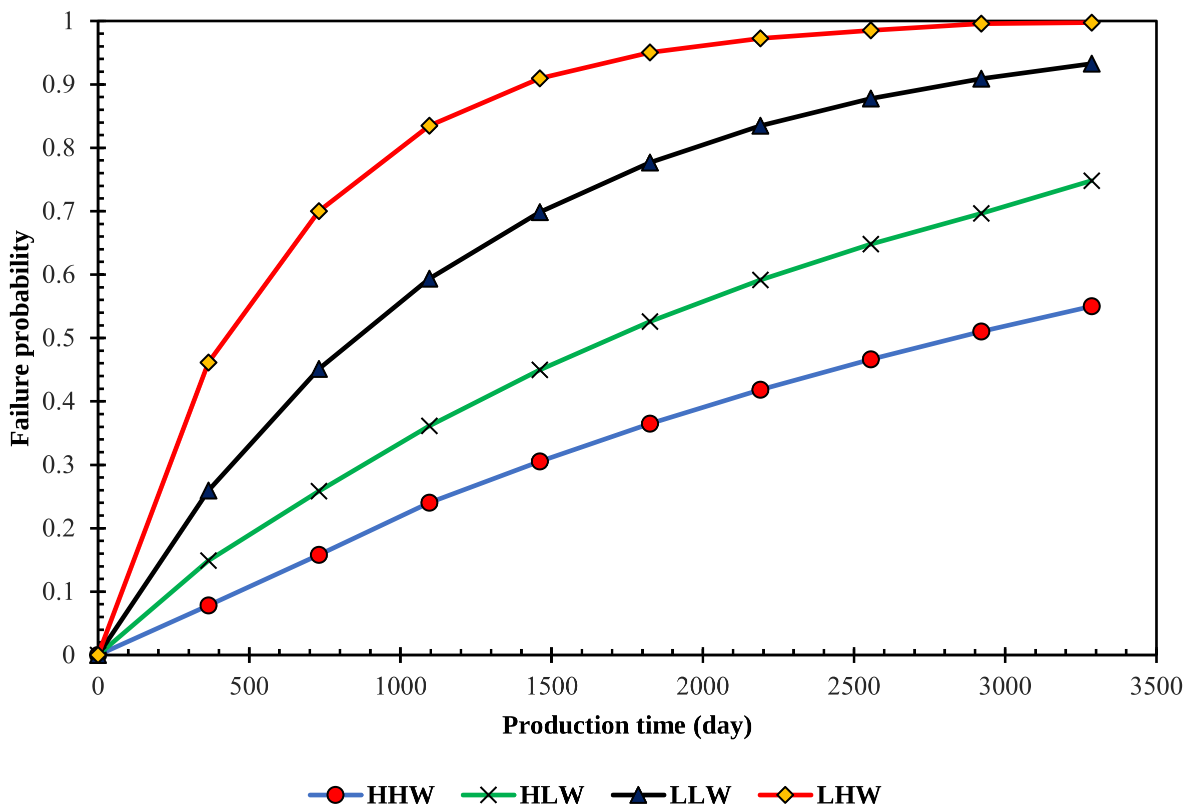

Figure 7.9: Dynamic risk curves of the pressure-augmented downhole petroleum system.

Figure 7.9 depicts the risk curves of the pressure-augmented petroleum reservoir system where the failure probabilities of the various abnormal production categories are represented as a function of time. Based on Figure 7.9, if HHW class is observed, there is about 50% assurance that the well would continue to flow even after producing for more than 9 years. For the HLW category, there is less guarantee for production after the same period as a risk of more than 70% is expected. If the well production rate falls in the LLW warning class, the probability that the well would experience “no flow” in the 9 years of production is 90%. In the event of the worst-case scenario in which the LHW category is observed, “no flow” is expected at any production time beyond 2500 days. Hence, it is strongly recommended to embark on adjustment strategy when LHW is observed. The risk profiles or failure probabilities as a function of time in the producing life of the well is an important outcome from the proposed risk monitoring approach.

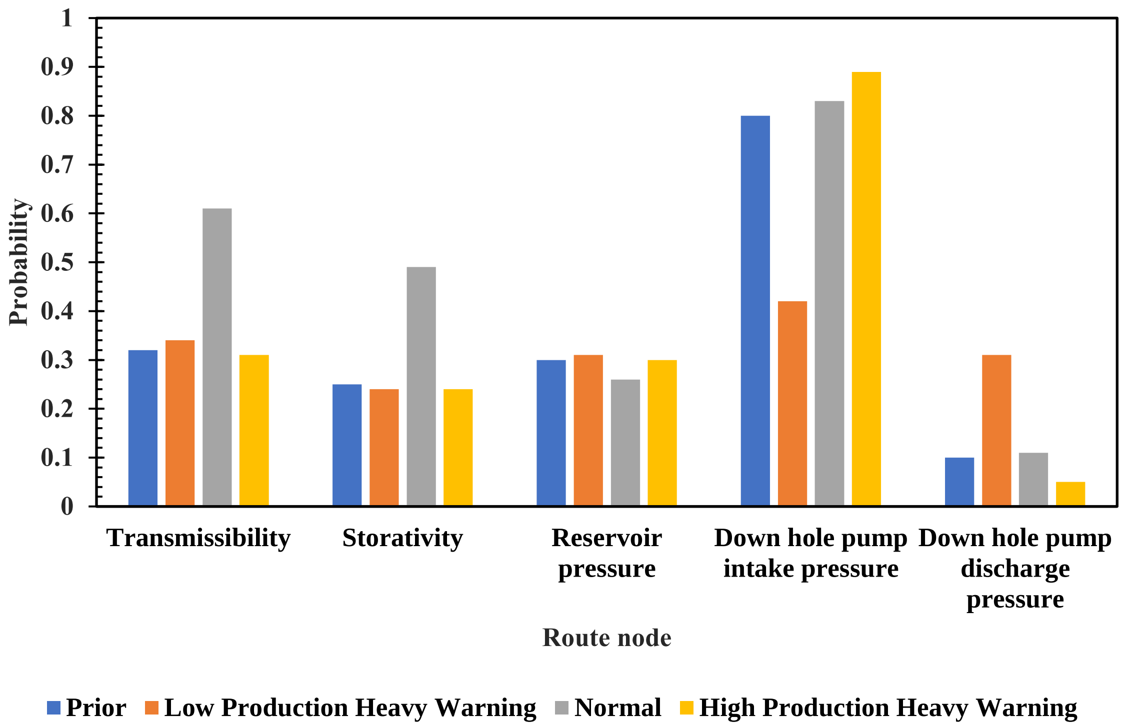

Figure 7.10: Prior and posterior probabilities under “low state”.

Figure 7.10 shows the probabilities of the route nodes of the network under the critical production scenarios. It is observed that the reservoir pressure does not contribute meaningfully to the failure of the production system to which the pump schemes are applied, but the BHP does. This finding is demonstrated by the downhole pump intake pressure prior and posterior data under the evidence of HHW and LHW. According to Figure 7.10, the transmissibility and storativity do not contribute to the production system output when vertical flow challenges due to high wellhead pressure are being offset.

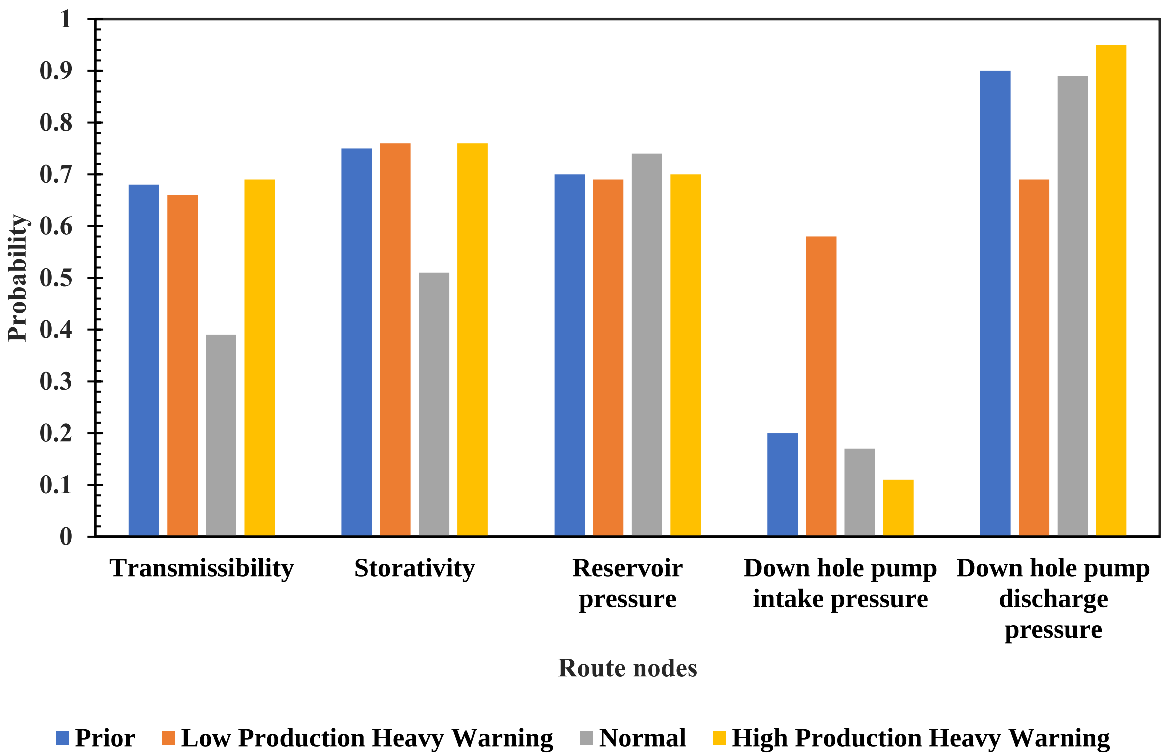

Figure 7.11: Prior and posterior probabilities under "High state".

The probabilities of the route nodes of the network under the contributing factors' high-performance condition ("high state") are reported in Figure 11. Like the finding from Figure 7.10, the reservoir pressure does not determine the success of the production pump scheme as the prior and posterior probabilities seem the same. It can be thus concluded that the downhole pump discharge pressure, downhole pump pressure difference, drawdown, and BHP are the vital flow parameters/indicators in a pressure-augmented downhole petroleum reservoir system. It implies that they should be adequately monitored to ensure process reliability. On the other hand, the transmissibility and storativity are not the main contributors as no significant changes in the posterior probabilities are recorded irrespective of the observed evidence/production abnormality category. This confirms that the reservoir pressure is not a crucial flow parameter when lifting the hydrocarbons with production pumps.

There are some weaknesses with the sub-models that constitute the risk-based AI methodology proposed in this study. The reproducibility of the MLP is greatly dependent on the network training and adequacy of the used dataset. Over fitting is one of the innate challenges associated with the ANN model. This pitfall generally affects the predictive performance as it systemically hinders the generalization potential of the model except with adequate training. A better prediction has been reported not to always increase the amount of input data as this strategy might increase the computational time and the possibility of overfitting. Early stopping, cross-validation, and regularization are used to overcome the over-fitting issue in the current work. ANNs impose less computational stress. However, optimum structure pattern and low extrapolation capacities are the common weaknesses of the ANN (Zendehboudi et al., 2018). The main flaws of the BN model are the subjectivity influence on the updated/posterior estimates and inadequacy of the CPT. The reliability of the logical model's predictions can be improved with sound knowledge of the research domain.

7.6 Conclusions

The dynamic risk assessment of the pressure-augmented downhole petroleum reservoir system with a PCP is covered in this work. The introduced risk model is space and time-dependent. The main goal of the proposed operational risk model is to offer the field operators a means to efficiently assess the dynamic risks associated with any pressure-augmented downhole petroleum reservoir system during the well's producing life. The model employs an MLP model for production forecast and a EWIS-based BN for risks assessment. The key outcomes of this research are given below:

- The proposed risk monitoring model analyzes the PCP's impacts on systems' failures during production and yields risk profiles and failure probabilities as a function of time over the production operation.
- Transmissibility and storativity have no significant contributions to the production system's flow rate when vertical flow challenges due to high wellhead pressure are being offset using production pumps.
- The operational risk model predicts productions and captures the dynamic risks associated with the pressure-augmented reservoir production system.
- The downhole pump discharge pressure, downhole pump pressure difference, drawdown, and BHP are the vital flow parameters/indicators in a PCP pressure-augmented downhole petroleum reservoir system.
- The introduced model demonstrates adequate downhole process system contributing factors' representations of the PCP system.
- The field operators are offered a proper tool for assessment of dynamic risk to ensure effective production management decision-making in pressure-augmented downhole systems.
- The reservoir pressure does not have a substantial contribution to the failure of the production system to which the pump schemes are applied, but the BHP does.

We believe that the proposed strategy can be extended to accommodate applications to chemical enhanced oil recovery processes.

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Chapter 8

Summary, Conclusions and Recommendations

8.1 Summary

The current research work demonstrates the use of artificial neural network model, Bayesian network model, dynamic Bayesian network model, and loss function model for dynamic risk-based assessment of petroleum reservoir production systems. Risks assessment models, deterministic predictive models, dynamic risks monitoring models, and dynamic economic risks assessment models are presented in the current work for different reservoir production scenarios to enable effective field development planning and adequate reservoir production management related decision-making strategies. Dynamic risks resulting from petroleum reservoir productions pose serious challenges in engineering operations in the upstream oil and gas sector as the existing traditional risks analysis models lack the potency to incorporate the process risks' dynamics. Hence, the presented hybrid model in the current work fills this knowledge gap.

The developed data-driven probabilistic models are applicable in both offshore and onshore geologic environments. The scientific contributions of this research work are summarized as follows: 1) A dynamic risks-based predictive model developed using an ANN and a BN is presented to forecast production, capture parameters variabilities, data's and model's uncertainties, and dynamic risks in primary recovery processes; 2) A novel hybrid model of ANN-BN-DBN template is introduced for dynamic risks monitoring/assessment and production forecast of secondary recovery processes; 3) A new approach is introduced to incorporate dual reservoir energy support mechanism in production predictions and associated dynamic risks forecast; 4) A dynamic economic risks analysis model is presented for real-time evidence-based economic risks assessment of the reservoir recovery processes; and 5) A dynamic risks-based model is introduced to capture sand face pressure enhancement influence on the reservoir production system with pump scheme. The research results show that the models capture temporal and spatial variability of the data, uncertainty in the data and reservoir models, and most importantly, the impacts of these factors/parameters on the overall production risk profile. The non-linear interactions of the vital flow parameters in the system are also adequately considered/captured with the presented models. The models adequately provide dynamic risks monitoring/assessment, assess dynamic economic risks, and predict real-time daily production economic losses.

8.2 Conclusions

8.2.1 Development of a Dynamic Risk Assessment Model for Primary Recovery Processes

This research presents a hybrid method to forecast reservoir production and the risks attributed to oilfield development. The hybrid connectionist strategy employs a data-driven probabilistic model to forecast production and capture the parameters' variabilities, data and model's uncertainties and dynamic risks of primary recovery processes. The model provides a cost-effective template for production risk assessment and eases the computational burden of history matching processes. The multilayer perceptron artificial neural network (ANN) is built with geological realizations to model the reservoir production behaviour for the effective facilitation of the production prediction. The model has a generalization capability and captures the temporal-spatial dependency and non-linear complex relationships involved in isothermal reservoir flow behaviour. The BN model assesses the production risks. It uses the concept of the early warning index system. The application of the proposed approach would assist in effective reservoir management decision making, enabling a risk-based optimal field performance of reservoir.

8.2.2 Development of a Hybrid Intelligent Model for Secondary Recovery Processes

This research presents a hybrid model to predict oil production and to provide a dynamic risk profile of the production systems with pressure support. The introduced predictive approach combines a multilayer perceptron (MLP)-artificial neural network (ANN) model with a hybrid connectionist strategy (BN-DBN), which comprises a Bayesian network (BN) model and a dynamic Bayesian network (DBN) model. The hybrid methodology (MLP-BN-DBN) establishes correlations between the input and output data to forecast the desired oil production. The MLP model captures the variabilities in the fluid and rock properties, and the effects of pressure maintenance on the production process. The BN model uses the 3σ mathematical rule to promptly signal the arrival of any production rate change and captures the pressure maintenance impact using the early warning source indexes. The BN-DBN model provides the desired dynamic risk monitoring of the process system. The proposed methodology offers the field operators better opportunity to obtain real-time estimate of the likelihood of impending production loss at any time during production operations. The developed hybrid model serves as a risk monitoring system. The model bridges the gaps in the existing models for oilfield development dynamic risk forecast and production predictions. Hence, the proposed methodology serves as a multipurpose tool for dynamic risk assessment and for proper reservoir production management.

8.2.3 Development of a Model for Production Systems with Gas Lift Mechanisms

This study presents a dynamic risk modeling strategy for a hydrocarbon sub-surface production system under gas lift mechanisms. The introduced novel model incorporates dual reservoir energy support mechanisms in production predictions and associated dynamic risks forecast. A data-driven probabilistic methodology is employed to conduct the risk analysis. The introduced model analyzes the production response and evaluates the impact of the sand face pressure on risks during production. The model offers an effective strategy to avoid production failure, monitor gas lift performance, and assess dynamic risks under lift mechanisms. The dynamic risk analysis yields predictive outcomes at any production time in the well's production life. It offers field operators an early warning system based on the Bayesian model with prognostic capabilities. The proposed strategy effectively manages production risks and assists in production decision-making, especially in complex production systems. The model offers a means to quantify the reservoir flow parameters' dependencies to enable real-time optimization and adjustment of the uncertain parameters as the well is being produced. The model would enable the operators to evaluate the risks involved in the different production scenarios resulting from the variation of all the key reservoir flow parameters at reservoir engineers' disposal during operations.

8.2.4 Development of a Connectionist Model for Dynamic Economic Risk Analysis

This study presents a connectionist model for dynamic economic risk evaluation of reservoir production systems. The proposed dynamic economic risk modelling strategy combines evidence-based outcomes from a Bayesian network (BN) model with the dynamic risks-based results produced from an adaptive loss function model for reservoir production losses/dynamic economic risks assessments. The methodology employs a multilayer-perceptron (MLP) model, a loss function model; it integrates an early warning index system (EWIS) of oilfield block with a BN model for process modeling. The model evaluates the evidence-based economic consequences of the production losses and predicts the statistical disparities of production predictions using an early warning index system (EWIS)-assisted BN model and the loss function model at the same time. The proposed methodology introduces an innovative approach that effectively minimizes the potential for dynamic economic risks. The model predicts real-time daily production/dynamic economic losses. The model employs loss function enabled-mechanisms to predict production deviations and ensuing losses. The model determines transitional/threshold production values for adequate reservoir management toward minimal losses. The developed model is a multipurpose tool that can be recommended to the field operators in petroleum reservoir production management related decision-making.

8.2.5 Development of a Logic-Based Data-Driven Operational Risk Model

This research presents a logic-based operational risk model for dynamic risk analysis of pressure-augmented downhole petroleum production systems. The introduced model employs its evidence-based dynamic risk features to monitor the operational risks associated with the interdependencies of downhole pump discharge pressure, downhole pump intake pressure, downhole pump pressure difference, drawdown, and bottom-hole pressure (BHP). The model assesses the impacts of the progressive cavity pump (PCP) on the downhole pressure system. The evidence-based mechanism enables the proposed model to accurately predict the resultant real-time production risks. Hence, the model facilitates management decisions for operational adjustments to avert downtime or “no flow”. It captures the temporal and spatial dependence of variables. Also, the model analyzes the

PCP's impacts on the systems' failures during production and yields risk profiles as a function of time as the production operation proceeds. The model demonstrates adequate downhole process system contributing factors' representations of the PCP system. Hence, the field operators are offered a proper tool for assessment of dynamic risks to ensure effective production management decision-making in pressure-augmented downhole systems.

8.3 Recommendations

This research work has been designed to present some novel concepts in risks assessment of the petroleum reservoir production systems. However, the scope of the current research can be extended by applying the introduced concepts to some other vital areas of petroleum production systems. These include, but not limited to:

- Development of smart models for dynamic risk-based assessment of enhanced oil recovery (EOR) processes.
- Development of risk analysis models for dynamic risk-based optimization of primary recovery processes.
- Development of dynamic risk analysis models for Dynamic risk-based optimization of secondary recovery processes.
- Design of methodologies for reservoir production model 's structure optimization.
- Development of smart models for dynamic risk analysis of leakages in offshore reservoirs
- Development of intelligent models for dynamic risk analysis of multiphase flow