

An Intelligence Approach for Porosity and Permeability Prediction of Oil Reservoirs using Seismic Data

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ABSTRACT

Nowadays the main challenge is to obtain a method for the estimation of key reservoir parameters with the lowest possible estimation error. Accurate reservoir characterization requires the integration of core and log data to understand the variation in hydraulic properties such as porosity, permeability and capillary pressure. Time-lapse seismic can be used as an important tool in reservoir characterization, monitoring and management. Reservoir parameters are converted to seismic parameters by using the rock physics models. This paper presents an analysis and explanation of an approach of developing rock physics model, and explains how the input data can be obtained to the model. And also this study presents an intelligence approach for the oil reservoir characterization by using seismic elastic properties and rock physics model together with minimum estimation error.

General Terms

Artificial Intelligence, Genetic Algorithm, Reservoir Characterization

Keywords

Artificial intelligence, Geophysics, Porosity, Permeability, Norne oil field, Reservoir characterizations

1. INTRODUCTION

In time-lapse or “4D” seismic projects, the objective is to infer fluid production from two or more seismic surveys recorded at different times in the reservoirs production life cycle. Rock physics modeling allows us to make these “time shifts” by changing saturation, pore pressure, and even porosity in the key reservoir intervals. Estimation of permeability and porosity using seismic data is a new challenge in the oil industry. Porosity and permeability are two of the most important parameters in most reservoir simulation models, and they have a large impact on reserve estimates, production forecasts and the economical evaluation of the reservoirs.

The process of oil or gas production causes variations in reservoir parameters such as fluid types, fluid saturation, pressure, temperature and viscosity, and thus changes seismic properties of saturated reservoir rock [1]. Converting saturations and pressure changes into seismic properties such as P-wave velocity, S-wave velocity and density changes requires information about the rock properties. The dependence between fluid saturation changes and the seismic parameters are described by rock physics models (RPMs).

Once these rock physics relationships are established for a given reservoir rock, the seismic forward modeling can be done. That means converting a given pressure and fluid saturation state for a given reservoir rock into a seismic section. Moreover, this procedure acts as a bridge that relates seismic parameter changes to reservoir parameter changes and vice versa. This means that rock physics is a key element in such a process. Several theories and empirical relations link seismic properties of reservoir rock to pore spaces, pore fluids, effective pressure and other reservoir parameters. For the developing of RPMs, elastic moduli and densities of fluid, grain and dry rock are input data and they can be computed using empirical or theoretical relations. Even relations from laboratory measurements of core samples are important in developing of RPMs, empirical relations work only for specific situations and theoretical models have limitations due to their assumptions [2]. This paper makes an analysis on method of constructing Duffy-Mindlin’s model for saturated reservoir rock and gives a brief introduction to the model.

This work aims at improving previous studies and presenting a robust, general and mathematically sound methodology for reservoir characterization. Our approach contains two new elements compared to the previous works:

- The use of rock physics models,
- The use of artificial intelligence for estimations.

In this paper we present an intelligence method for a joint estimation of porosity and permeability, which is generated by using field data from an oil field in Norway and using the rock physics models.

2. ROCK PHYSIC MODELS

A saturated porous reservoir rock contains of rock matrix and fluid, which can be considered as solid and fluid phases, respectively; when the pore has no fluid, the porous rock can be named as dry rock. Oil production from a reservoir makes alterations in fluid phase, while almost no changes in solid phase. Seismic wave velocities in a porous medium saturated with water depend on three constants, namely the bulk modulus (K), shear modulus (μ) and density (ρ). The bulk modulus or incompressibility of an isotropic rock is explained as the ratio of hydrostatic stress to volumetric strain. In other words, it knows us how difficult it is to compress the rock. The shear modulus or shear stiffness of the rock is explained as the ratio of shear stress to shear strain and in other words, how difficult it is to alter the shape of a rock sample. Han and

Batzle (2004) have indicated that the bulk modulus of dry and water-saturated rocks, which are symbolized as K_d and K_w , respectively, are more sensitive to the saturation of water than the P-wave velocity (V_p) under the same condition of pressure, further, the alteration in water saturation has little influences on the shear modulus since the shear modulus of fluid (μ_f) is zero. Since bulk modulus K is the most sensitive to the fluid saturation [2], Gassmann's model [3] calculates V_p and V_s of saturated rock by calculating K together with μ and ρ for saturated reservoir rocks, which are K_s , μ_s and ρ_s , respectively, in order to effectively reflect effects of fluid substitution. Duffy-Mindlin's model [4] believes V_p and V_s as functions of not only ρ_s , K_f , K_{gr} , μ_f , and μ_{gr} but also Young modulus (E) and Poisson ratio (γ). However, since E and γ are explained as functions of K_d and μ_d , all parameters that are necessary for the construction of RPM in Duffy-Mindlin model are the same with Gassmann's equation. Duffy and Mindlin [4][5] assumed array of identical spheres as a face-centered cubic to calculate Young modulus (E) and Poisson ratio (γ) as:

$$E = \frac{9K_d\mu_d}{3K_d + \mu_d} \quad (1)$$

$$\gamma = \frac{3K_d - 2\mu_d}{2(3K_d + \mu_d)} \quad (2)$$

Where K_d is bulk modulus of dry rock, and μ_d is shear modulus of dry rock. Derives seismic velocities as a function of E and γ , effective pressure (P_e) and base parameters as:

$$V_p^2 = \frac{\left[C_{11} + \frac{(1 - \frac{C_{11} + 2C_{12}}{3K_s})}{\frac{\phi}{K_f} + \frac{1-\phi}{K_s} + \frac{C_{11} + 2C_{12}}{3K_s^2}} \right]}{\rho_d} \quad (3)$$

$$V_s^2 = \frac{C_{11} + C_{12}}{2\rho_d} \quad (4)$$

Where K_s is bulk modulus of saturated rock, ρ_d is density of dry rock, ϕ is the effective porosity of the medium, K_f is bulk modulus of pore fluid that is calculated by using Wood's relation [6]:

$$\frac{1}{K_f} = \frac{S_o}{K_o} + \frac{S_g}{K_g} + \frac{S_w}{K_w} \quad (5)$$

Where K_o , K_g and K_w are bulk modulus of oil, gas and water respectively. And C_{11} and C_{12} are obtained, respectively, as:

$$C_{11} = \frac{4-3\gamma}{2-\gamma} \left\langle \frac{3E^2P_e}{8(1-\gamma^2)^2} \right\rangle^{\frac{1}{3}} \quad (6)$$

$$C_{12} = \frac{\gamma}{2(2-\gamma)} \left\langle \frac{3E^2P_e}{8(1-\gamma^2)^2} \right\rangle^{\frac{1}{3}} \quad (7)$$

With

$$P_e = P_{overburden} - P_{pore} \quad (8)$$

The bulk modulus of saturated rock can be calculated by using Gassmann's equation. It can be shown as the following equation [7]:

$$K_s = K_d + \frac{(1 - \frac{K_d}{K_{fr}})^2}{\frac{\phi}{K_f} + \frac{1-\phi}{K_{fr}} + \frac{K_d}{K_{fr}^2}} \quad (9)$$

Where K_{fr} is the bulk modulus of the solid frame work, ϕ is the effective porosity of the medium, K_f is bulk modulus of pore fluid that is determined by using Wood's relation. Duffy-Mindlin's model consists of most important effects such as porosity, lithology, and mechanical compaction and also for fluid because of presence of fluid bulk modulus, K_f . Furthermore, the model considers the presence and variations of effective pressure, P_e . Hence, in the presence of shale compaction, the model must be employed even though the model is more complex than Gassmann's equation. The advantages & disadvantages of Duffy-Mindlin's model are presented in Table1.

There are two ways of empirical relations and theoretical models for calculating μ_d and K_d . empirical relation can be best if we can obtain the values of K_d and μ_d from laboratory measurements of core samples. However, since core measurements are not always valid, we often calculate K_d and μ_d by using empirical relations such as Geertsma and Smith [8]. Here is the empirical relation that investigates the relation of dry moduli, grain moduli, porosity:

$$\frac{1}{A_d} = \frac{1}{A_{fr}} (1 + 50\phi) \quad (10)$$

Where A_d is either K_d or μ_d and ϕ is porosity.

Theoretical models which compute the effective elastic moduli based on assumptions of contact surfaces between grains such as Hertz-Mindlin [9]. The Hertz-Mindlin model is employed to explain seismic parameter alterations due to pressure changes. The model presents [10]:

$$K_d = \sqrt[n]{\frac{C^2(1-\phi)^2\mu^2P_e}{18\pi^2(1-\gamma)^2}} \quad (11)$$

$$\mu_d = \frac{5-4\gamma}{5(2-\gamma)} \left(\sqrt[n]{\frac{3C^2(1-\phi)^2\mu^2P_e}{2\pi^2(1-\gamma)^2}} \right) \quad (12)$$

Where P_e is the effective pressure, μ is the shear modulus of the solid phase, γ is poisson's ratio and n is the coordination number. In the original Hertz-Mindlin theory n is identical to 3. Some laboratory measurements of samples proposed a larger number for n . Vidal [11] discovered $n = 5.6$ for P-waves and $n = 3.8$ for shear waves for gas sands, while Landrø [12] employed $n = 5$ for oil sands. We use $n = 5$ in this study. C is the average number of contact points between the grains in a volume fraction, related with sorting, shape and packing of the grains, and porosity [13]. It is explained as:

$$C = 20 - 34\phi + 14\phi^2 \quad (13)$$

The effective pressure employed in Hertz-Mindlin theory is considered as the difference between the lithostatic P_{ext} and the hydrostatic pressure P [14]:

$$P_e = P_{ext} - \eta P \quad (14)$$

Where η is the coefficient of internal deformation that is commonly an unknown parameter. Table 2 presents the seismic elastic parameters of Norne oil field for this study.

3. CASE DESCRIPTION

The field to be studied is an oil reservoir in the Norne field. It is located in the blocks 6608/10 and 6508/10 on a horst block in the southern part of the Nordland II area in the Norwegian Sea. The rocks within the Norne reservoir are of late Triassic to middle Jurassic age. It was discovered in 1991, and oil production started in 1997. The Norne Field contains two separate oil compartments, the Norne Main Structure, Norne C-, D and E-segment, and the Northeast segment, Norne G-segment. In this study we use the Norne E-segment data (Figure 1). The present geological model contains five reservoir zones. They are Garn, Not, Ile, Tofte and Tilje. Oil is principally found in the Ile and Tofte Formations, and gas in the Garn formation. The sandstones are buried at a depth of 2500-2700 m. The porosity is in the range of 25-30 %, while permeability changes from 20 to 2500 mD [15].

4. PROPOSED METHODOLOGY

4.1 GENETIC ALGORITHM

The first step in GA method, like any other optimization algorithms is clarifying the objective function and its decision variables. Basic components of genetic algorithm are gene, chromosome and population. Genetic algorithm operates on a finite set of chromosomes (points) which are named population. The different populations are explained as gens. Population size, mutation probability and crossover probability are the control parameters that are used in genetic algorithm. Genetic algorithms are generally executed as follows:

- 1- Explain the problem as an objective function that shows the fitness, f_i , of each candidate solution, α_i , that is named chromosome.
- 2- Randomly initialize a population created by a certain number of chromosomes, with each chromosome representing a candidate solution to the problem.
- 3- Assign each chromosome a fitness score in accord with the objective function. If the chromosome population satiates the convergence tolerance, it is selected as the solution to the optimization problem. If not, the following steps are taken.
- 4- Produce a mating pool of the chromosomes from the existing population.
- 5- Create offsprings from the chromosomes in the mating pool by means of a crossover operator.
- 6- Change some of the chromosomes by the mutation operator.
- 7- Go back to step 3.

Figure 2 indicates general Genetic algorithm scheme. Genetic algorithm is applicable for optimizing the design parameters formed into a corporation into a specified fitness function to achieve a goal fitness quantity. The key characteristic of genetic algorithms and other similar algorithms is that they are derivative-free. In fact, the stochastic nature of the algorithm with dynamic evaluation of the fitness function changes it into a powerful systematic random search engine. This approach is an alternative to incapable derivative-based

methods. This extends its ability to a wide range of applications. Recently this approach has been employed to many different optimization problems including non-linear geophysical inversion [16].

4.2 MULTI AND SINGLE OBJECTIVE OPTIMIZATION

In single objective optimization we take into account minimizing or maximizing only one objective, without considering the effect of other criteria. Multi-objective optimization is delineated as the task of finding one or more optimum solutions when a problem contains more than one objective or goal. Unlike single objective that handles a single space (decision variable space), in multi-objective optimization, a new space is also taken into account which is named the objective function space. In a multi-objective optimization problem, the decision vector is symbolized by x and the decision space is shown by X . Similarly, the objective vector is symbolized by y and Y represents the objective space. The multi-objective optimization, in general form, can be explained as:

$$\begin{aligned} &\text{Maximize/Minimize } f_m(x), & m = 1, 2, 3, \dots, M \\ &\text{Subject to } g_l(x) \geq 0 & l = 1, 2, 3, \dots, L \\ &H_t = 0 & t = 1, 2, 3, \dots, T \end{aligned} \quad (15)$$

Where solution x is a decision vector of n variables, $x = (x_1, x_2, \dots, x_n)$. M is the number of objective functions in the problem which can be minimized or maximized: $f(x) = (f_1(x), f_2(x), \dots, f_M(x))$. The multi-objective optimization problem also may have constraint functions ($g_l(x)$ and H_t) which compute the set of feasible solutions. In any single objective optimization, the optimal solution is the one that presents maximum (or minimum) value of the objective function. However, in the context of a multi-objective optimization, the notion of optimality is different and we are curious in finding good compromises among the objectives that we hope to optimize.

Although multi-objective optimization algorithms have been widely employed in some engineering problems, their applications to petroleum engineering problems are still limited. Traditionally the oil industry employs some form of weighted sum approach for handling multiple objectives without considering the limits of this approach. Dal Moro and Pipan [17] employed multi-objective evolutionary algorithm for the joint inversion of seismic surface wave dispersion curves and reflection travel times. Boomer and Brazier [18] also suggested a new method to achieve velocity models from inversion of seismic data based on a non-dominated sorting genetic algorithm.

In this paper we use the multi-objective optimization and Genetic Algorithm for reservoir characterization with minimum errors by using seismic elastic properties.

5. RESULTS AND DISCUSSIONS

Two different rock physic models have been modified to determine bulk modulus of dry rock, namely Geertsma and Hertz-Mindlin models. The models have been modified by defining a set of coefficients to be adjusted by Genetic Algorithm (GA) optimization.

Multi-objective GA has been used to estimate the optimal coefficients so that V_p , V_s and ρ_s are estimated by the

Geertsma and Hertz-Mindlin models as close to measurements as possible. Measurements are presented in Table 2. Estimated values are shown in Table 3 and associated errors in Table 4. According to the results, the modified Hertz-Mindlin model is a considerably more accurate predictor, compared with the modified Geertsma model. For each run of Genetic Algorithm, Porosity and permeability of each formation were calculated using the Duffy-Mindlin's model and Hertz-Mindlin model, respectively presented in Tables 5 and 6. Corresponding horizontal permeability realizations were created by empirical porosity permeability relations that are presented in Table 7, and Table 8 illustrates the current reservoir zonation which is used in the simulation model [19].

6. CONCLUSION

Rock physics models explain crucial relations between reservoir parameters and seismic properties of reservoir rock and they are very important not only for a time-lapse seismic project but also for the reservoir characterization of one reservoir. In this work it was proved that the Duffy-Mindlin's model works properly at porous reservoir, especially in case of presence of shale compaction. In the case, we need to use not only empirical relations for constructing rock physics model but also a contact theoretical model for the calculation of dry moduli. Geertsma's empirical relation is often used due to its consistency to Duffy-Mindlin's model. Among theoretical models, Hertz-Mindlin's theoretical model is the most popular one, since the other theoretical models are based on the model of Hertz-Mindlin. This paper has shown the modified Hertz-Mindlin model is a considerably more accurate predictor, compared with the modified Geertsma model, and it is more suitable for calculation of dry moduli. Also it is proved that Genetic Algorithms are a feasible technique for generating reservoir characterization using time-lapse seismic data. The method is capable of handling many parameters, which is critical when dealing with large full-field reservoir simulation models. This paper has proved the application of a Genetic Algorithm to a realistic case, with respect to main issues of model's formulations for the reservoir characterizations.

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8. NOMENCLATURE

K: Bulk modulus
 K_d : Bulk modulus of dry rock
 K_w : Bulk modulus of water-saturated rock
 K_s : Bulk modulus of saturated rock
 K_{fr} : Bulk modulus of the solid framework
 K_f : Bulk modulus of pore fluid
 K_o : Bulk modulus of oil
 K_g : Bulk modulus of gas
 K_w : Bulk modulus of water
 V_p : P-wave velocity
 V_s : S-wave velocity

μ : Shear modulus
 μ_f : Shear modulus of pore fluid
 μ_s : Shear modulus of saturated rock
 μ_d : Shear modulus of dry rock
 ρ : Density
 ρ_d : Density of dry rock
 S_w : Water saturation
 S_g : Gas saturation
 P_e : Effective pressure
 S_o : Oil saturation
 ϕ : Porosity
 γ : Poisson's ratio
 P_{ext} : Lithostatic pressure
 P : Hydrostatic pressure
 E : Young modulus

Table 1. Advantages & Disadvantages for Duffy-Mindlin's model

Advantages	Disadvantages
Suitable for porous reservoir, especially in the case of presence of shale compaction	Fairly complex calculations
Take into account almost effects of reservoir parameters on seismic responses	Essentially need to obtain dry modulus
The estimation of the effects of fluid substitution would be well to make comparison between production stages	-----

Table 2. Seismic elastic parameters from Norne oil field [20]

Overburden	V_p V_s ρ_s	3350 1800 2450
Inside reservoir	V_p V_s ρ_s	3200 1600 2300
Under reservoir	V_p V_s ρ_s	3500 1900 2450
Garn formation	K_{fr} μ_{fr} K_{ma} ρ_{ma}	19 - 37 ϕ 12 - 21.5 ϕ 37 GPa 2650 kg/m ³
Ile, Tilje, Tofte formations	K_{fr} μ_{fr} K_{ma} ρ_{ma}	18.5 - 27.5 ϕ 11 - 13 ϕ 37 GPa 2650 kg/m ³
Bulk modulus of oil Bulk modulus of gas Bulk modulus of water Water density Gas density Oil density Salinity	K_o K_g K_w ρ_w ρ_g ρ_o SAL	1 GPa 0.1 GPa 2.7 GPa 1000 kg/m ³ 190 kg/m ³ 860 kg/m ³ 0.05 ppm

Table 3. Estimated values of V_p , V_s and ρ_s by the modified models

Geertsma Model	V_p	V_s	ρ_s	Hertz-Mindlin Model	V_p	V_s	ρ_s
Overburden	2713	2646	1813	Overburden	3149	1926	2254
Inside reservoir	2528	2416	1794	Inside reservoir	3072	1696	2093
Under reservoir	2905	2831	1862	Under reservoir	3290	1995	2327

Table 4. Estimation errors of the modified models in percent

Geertsma Model	V_p	V_s	ρ_s	Hertz-Mindlin Model	V_p	V_s	ρ_s
Overburden	19	47	26	Overburden	6	7	8
Inside reservoir	21	51	22	Inside reservoir	4	6	9
Under reservoir	17	49	24	Under reservoir	6	5	5

Table 5. The calculated porosity distribution of formations

Formations	Porosity
Garn formation	$0.23 \leq \phi \leq 0.34$
Ile and Tofte formation	$0.19 \leq \phi \leq 0.31$
Tilje formation	$0.18 \leq \phi \leq 0.29$

Table 6. The calculated permeability distribution of formations (mD)

Formations	Permeability
Garn formation	$36 \leq K \leq 1243$
Ile and Tofte formation	$24 \leq K \leq 1996$
Tilje formation	$51 \leq K \leq 2231$

Table 7. Porosity-Permeability relations for each layer

Layer number	Relation
1	$\text{Log}_{10}(K) = 7.2 \phi + 0.6$
2	$\text{Log}_{10}(K) = 31.4 \phi - 3$
3	$\text{Log}_{10}(K) = 23.5 \phi - 4$
5,6	$\text{Log}_{10}(K) = 16.8 \phi - 2$
7,8	$\text{Log}_{10}(K) = 18.2 \phi - 2.5$
9	$\text{Log}_{10}(K) = 22.5 \phi - 3.3$
10	$\text{Log}_{10}(K) = 13.96 \phi - 0.85$
11	$\text{Log}_{10}(K) = 17.1 \phi - 2.1$
12	$\text{Log}_{10}(K) = 17.3 \phi - 2.11$
13	$\text{Log}_{10}(K) = 13.3 \phi - 0.9$
14	$\text{Log}_{10}(K) = 20.32 \phi + 3$
15	$\text{Log}_{10}(K) = 15.83 \phi - 1.9$
16	$\text{Log}_{10}(K) = 12.7 \phi - 0.24$
17	$\text{Log}_{10}(K) = 19 \phi - 1.95$
18	$\text{Log}_{10}(K) = 14.1 \phi - 0.87$
19	$\text{Log}_{10}(K) = 21.7 \phi - 2.07$
20	$\text{Log}_{10}(K) = 15.1 \phi - 1.09$
21,22	$\text{Log}_{10}(K) = 23.98 \phi - 2.6$

Table 8. Reservoir zonation from the simulation model

Layer number	Formation name
1,2,3	Garn
5,6,7,8,9,10,11	Ile
12,13,14,15,16,17,18	Tofte
19,20,21,22	Tilje

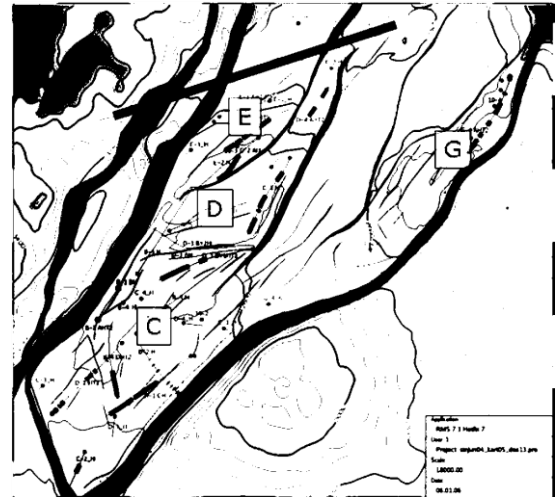


Figure 1. Top view of Norne field showing E-segment used in this study

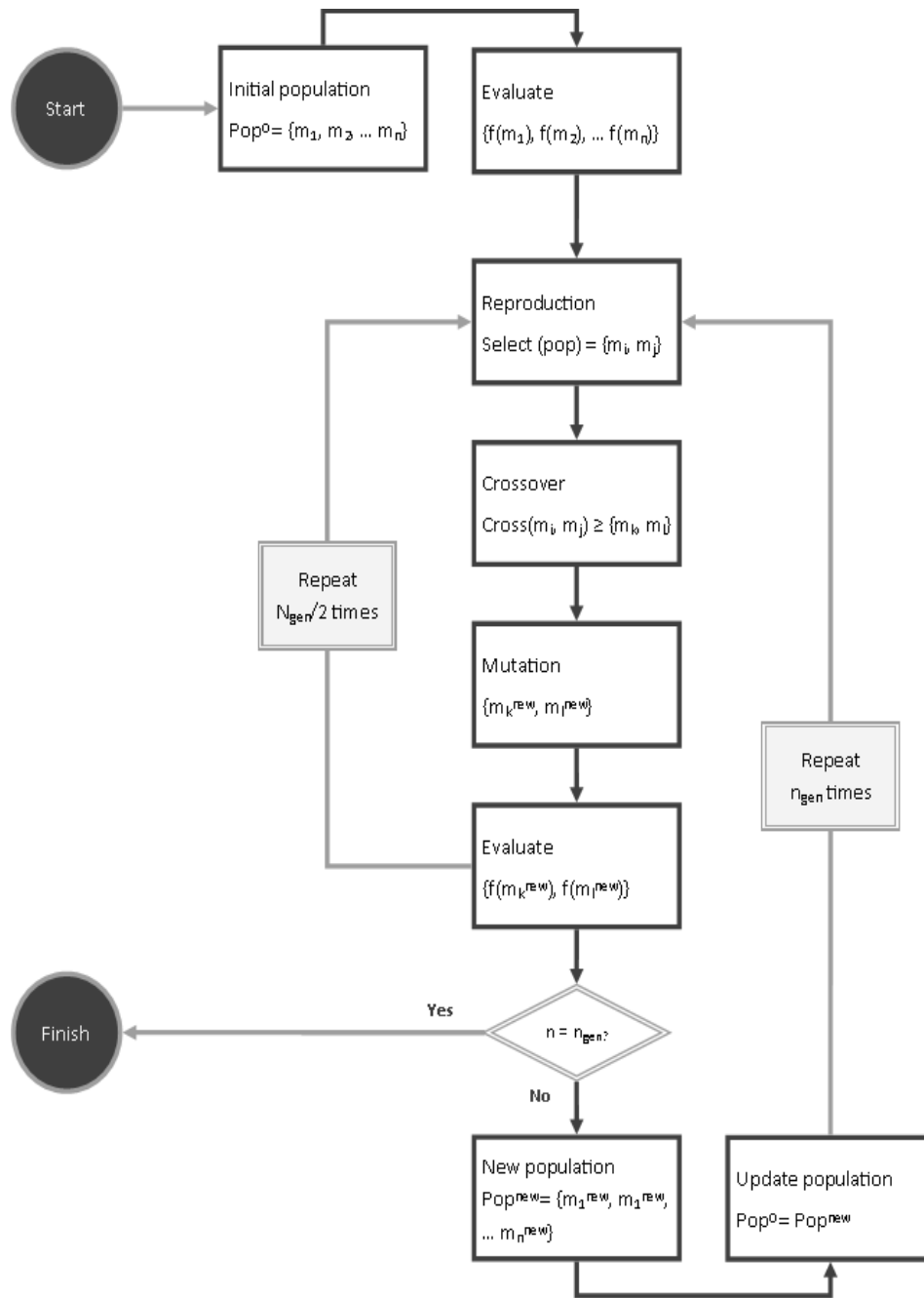


Figure 2. Schematic diagram of Genetic Algorithm

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