Probabilistic Prediction of Well Performance

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ABSTRACT

Predicting well production rate with time plays a very vital role to having an effective reservoir management, guiding investors and making crucial and important decision in any oil and gas industry. Forecasting production rate could be done by either deterministic or probabilistic approach with the latter being more reliable in the face of uncertainty.

The Arp's Decline curve model which is mostly used in predicting reservoir production rate with time has three models: Hyperbolic, Harmonic and Exponential models. This study focuses on the use of exponential model with the aid of a simulator to history match and predicts a filtered well production data.

The result from this study shows that with an assumption of a triangular probability distribution, the Arp's exponential decline model is associated with 45% risk factor as a predicting tool.

Finally, in order to reduce this inherent uncertainty level, the initial production rate (IP) should be double checked before use.

Keywords: production rate, Arp's model, exponential decline, probabilistic prediction

INTRODUCTION

The petroleum industry is driven by profit. This is the topmost factor to consider in the development of petroleum fields. Reserves have to be well estimated before the company's limited available resource is expended on a given project.

One of the most important tasks of a petroleum engineer is estimating, by factual prediction, the amount of oil and gas that could be recovered from a reservoir. Choosing the methodology is critical for accurate forecasts that are, in turn, vital for sound managerial planning. Risks have to be minimized in the process of making decisions based on the recoverable percentage of the original hydrocarbon in place. Production of hydrocarbons declines due to a decline in reservoir energy and/or increases in producing water cut. Graphical plots of performance data provide a time-tested, frequently used technique known as ‘‘decline curve’’ for estimating ultimate recovery from a well, reservoir or field. Decline curve analysis is used for analyzing declining production rates and forecasting future performance of oil and gas wells. Forecasting future production is essential in economic analysis of exploration and production expenditures. Hence, the analysis of production decline curves represents a useful tool for forecasting future production from wells and reservoirs. The basis of this procedure is that factors which have affected production in the past will continue to do so in future.

There are many factors that could affect the accuracy and confidence level placed on production forecast; they may be surface or subsurface with each value having its uncertainties attached to it. These factors include the geological uncertainties; like structure, porosity depositional environment initial fluid saturation. Dynamic uncertainties; like relative

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permeability, fluid properties. Operational uncertainties; flow line capacity, allowable production rate. The challenge is to generate production forecast in spite of these uncertainties.

Most conventional decline curve analyses are based on the classic works of (Arps, 1970), and (Fetkovich, 1980). They illustrate the analysis of well performance data using empirically derived exponential, harmonic and hyperbolic functions. Although the study is completely empirical, its simplicity and the fact that it requires no knowledge of reservoir or well parameters make its use widespread in the upstream petroleum industry, particularly for production prediction and estimating reserves from production decline behavior (Arps, 1970). The likes of Fraim and Watten Barger (1987), Fetkovich et al (1998) Blasingame et al. (1991), McCray (1990) , Palacio and Blasingame (1993), Rodriguez and Cinco-Ley (1993), Camacho et al. (1996) ,Valko et al. (2000) , Li and Home (2005) and (Guo et al. 2007) have all considered different angles of well performance as it affects productivity using different assumptions.

The objectives of this work include;

1. To predict the reservoir performance using Exponential Decline Curve Model with the aid of Risk Software.
2. To estimate the confidence level associated with the models and assumptions
3. To find out using sensitivity analysis which of the input parameters in the exponential model affect production rate the most.

METHODOLOGY

The flow chart below shows at a glance the procedural steps undertaken in actualizing our results.

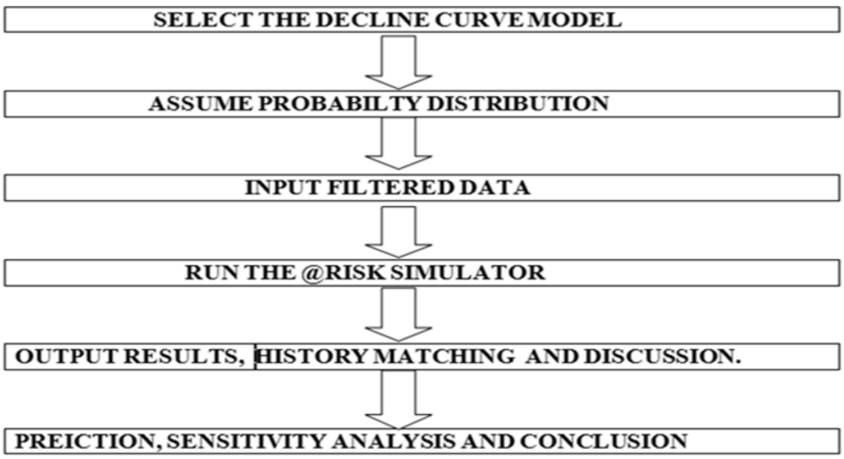

Figure 1. Methodological Steps

MODEL DEFINITON

In this study, the Arp's (1945) decline curve analysis model was used and it is represented mathematically as;

$$q_t = IP\,(1+bD_i t)^{(-1/b)} \quad \text{………………..} \quad (1)$$

The parameter "**b**" is a constant. Its values vary from 0 to 1 pending on the type of decline curve model assumed. Among the three standard decline curve model (i.e Harmonic, Hyperbolic and Exponential), the exponential curve was used for this study. For exponential, b is taken as 0 and equation (1) becomes;

q_t = IP exp(-Dt) ……………….. (2)

Furthermore, equation (2) was used in computing the decline rate (D);

$$D_i = \frac{\ln\left(\frac{q_t}{IP}\right)}{\Delta t} \quad \text{……………….. (3)}$$

DATA GATHERING, FILTERING AND SMOOTHING

For this study, actual production data were collected from a field X in Nigeria in the form of yearly production rates and the number of days the well was produced. The average oil production rates per day were calculated for each year.

In order to obtain a dominant decline trend, the data were filtered and smoothened. The filtering and smoothening of data is necessary becomes of the erratic nature of the production profile when plotted. Since good prediction is predicated on past existing linear condition, erratic data points are filtered out until the profile is smoothened into a linear function. Figure 8 shows the final profile after smoothening. Table 1 shows the input data after filtering. After data filtering is done, the filtered data is plotted against time and the starting point of the dominant decline trend is assumed to be the initial flow rate at time zero, the data that deviate from the dominant decline trend are truncated from the analysis.

Table 1. Well Production Data

Production Rates (STB/DAY)	*Time (Years)*
150.00200	0
133.03810	1
117.99420	2
91.23400	3
92.81751	4
82.32175	5
85.45330	6
64.75658	7
57.43339	8
50.93933	9
45.17973	10
48.00200	11
35.53916	12
31.52041	13
27.95610	14

Defining the Assumed Probabilistic Distribution and Quantitative values Assigned to Each Input Variables before Simulation

Assumption of Probability Distribution

From equation (3) there are four input variables. These are:

1. Decline Rate **(D)**
2. Initial Production Rate(**IP**)
3. Arp's Decline curve Exponent **(b)**
4. Time **(T)**

The @Risk software is a probabilistic tool. It requires fundamental probabilistic assumptions to be made on the input parameters before execution. Based on the frequency of usage in literature, the triangular distribution was assumed for both the initial production rate (IP) and the decline constant (D). No distributions were assigned to decline exponent and time because they are instantaneous variable**.** Use of triangular distribution is indicated when upper and lower limits as well as the most likely value can be specified. It is apparent that the probability of an outcome occurring close to the limits of range generally becomes smaller, unless the distribution happens to be highly skewed to one side.

Values assigned to each of the variable are discussed below;

Decline Rate

A triangular distribution requires a minimum of three values for it to be properly defined. In order to assign appropriate values to the decline rate constant, a little computation has to be done. Using eqn (3) and data from Table (1), IP = 150.002stb/day, q_t = 133.0381stb/day and Δt = 1day.

Thus, D_i= 0.12day^{-1}.

Based on this result, values assigned to D_i were 0.08, 0.12, and 0.16 and the distribution generated by software is given in figure 6.

Arp's Decline curve exponent (b)

Decline exponent, b, was assigned zero. The implication of this is that the exponential decline is being modeled.

Initial Production Rate (q_i)

From table (1), the initial production is given as 150stb/day. However, since the triangular distribution was assumed, two more values have to be logically assumed so that the triangular distribution can be generated by the software. Values assigned are 50,150 and 300 and the generated distribution is given in figure 7

Time

The time was given in days;

Software Simulation Run

The model (Eqn 2) and the actual production data (table 1) are imported into the @RISK software and 10,000 trials were selected. This represents 10,000 possible scenario of simulation.

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History Matching

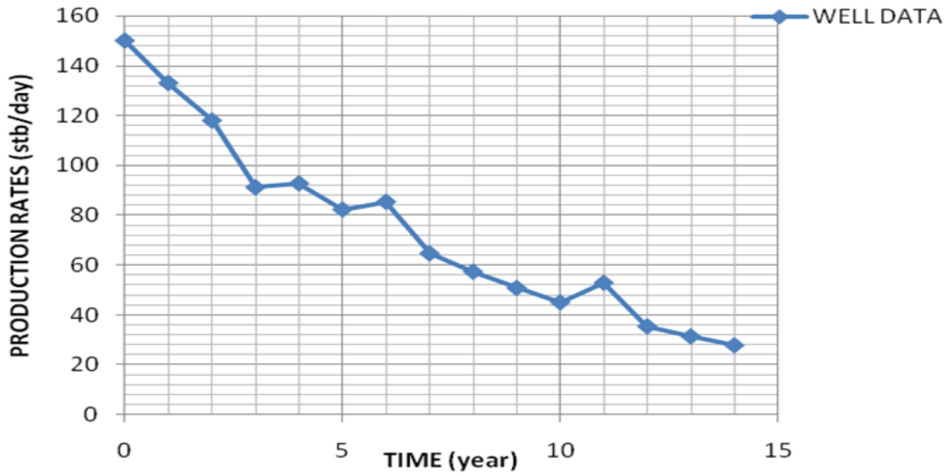

Figure 2. Plot of the filtered Production Rate with Time

Expected Outcome

It is expected that the forecasted result would be “roughly” equal to the actual well production rate and not exact due to the inherent limitation associated with probabilistic simulation.

RESULTS AND DISCUSSION

Validity of the Result

It is expected that the actual filtered production rates for the seven- point data, to be “roughly” equal to the generated software production rates for each time steps. If this is achieved that means that all the assumptions made, mathematical model used and procedures followed are correct. Then the model can confidently be used to predict production rate at any time.

In an attempt to check for the validity of our approach thus far, variation between the outputted P55 production rates and the actual data for each time step was computed as shown in Table 3. It is shown from this table that the initial established deviated points (3rd, 6th and 11th year) have variations greater than ±5 stb/day.

This was expected. Taking a look at Figure 2, it can be seen that these data points were originally off the decline trend.

In summary, one could deduce that the entire work and study, (i.e. software, assumptions, model and procedures) are validated.

Table 2. History Matched result @RISK

	Rates (STB/DAY)						
P (%)	*3rd YR*	*4th YR*	*5th YR*	*6th YR*	*10th YR*	*11th YR*	*12th YR*
5	52.0	45.9	40.5	35.7	21.5	18.81	16.3
55	*73.01*	*92.49*	*82.08*	*93.0*	*44.84*	*39.66*	*35.53*
95	175.0	155.9	139.10	123.9	79.52	71.3	64.64

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History Matching

To ascertain whether the chosen model and assumptions made would give a good forecast, history matching was carried out before data smoothening. Seven (7) points were chosen from the filtered data sets. The points chosen include 3rd, 4th, 5th, 6th, 10th, 11th and 12th year.

Table 2 shows the result of only three of the probable outcomes (P5, P55 and P95) of the forecasted production rates when the @RISK software was run using the seven- point data. It is observed that the outputted flow rate was triangularly distributed as shown in appendix A. With the 10,000 simulated trials, P55 gave the most likely output for seven time steps considered. Table 2 summarizes the results.

Table 3. Result of Comparative Study

Time (YEAR)	*Actual Well Rates (STB/DAY)*	*Forecasted Rates (STB/DAY)*	*Variation (STB/DAY)*
		P55	ΔRATE (±)
3	91.23000	105.090	13.86
4	92.81751	93.300	0.327
5	82.32175	82.210	0.2417
6	85.45330	73.010	12.443
10	45.17973	44.843	0.336
11	48.00200	39.655	8.347
12	35.53916	35.201	0.338

Production Rate Prediction

Table 4. Predicted Production Rate beyond the Given Actual Data

Time (Years)	*Forecasted Production Rate (STB/DAY)*
	P55
15	24.79
16	20.44
17	17.01

After model validation and data smoothening, the next was to carry out prediction. Table 4 and Fig 3 show the predicted production for the 15th, 16th and17th year for P55. From the prediction, it could be deduced that the production rate declines over time. This is valid because it conforms to what is obtainable in practice.

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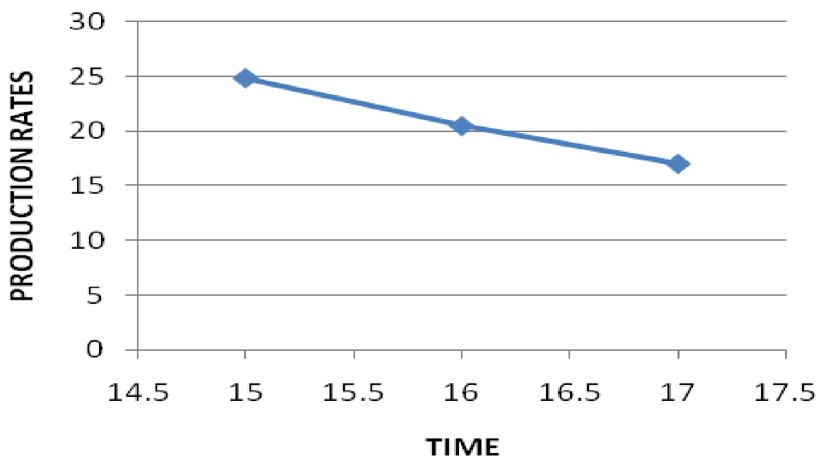

Figure 3. Predicted Profile

Table 4 and Fig 3 show the predicted production for the 15th, 16th and17th year. From the forecast it could be deduced that the production rate declines over time. This is valid because it conforms to what is obtainable in practice.

Sensitivity Analyses

Figure 4 and 5 show the result of the sensitivity analyses carried out on two variables (initial production and decline rates) using two time steps- 4th and 5th year.

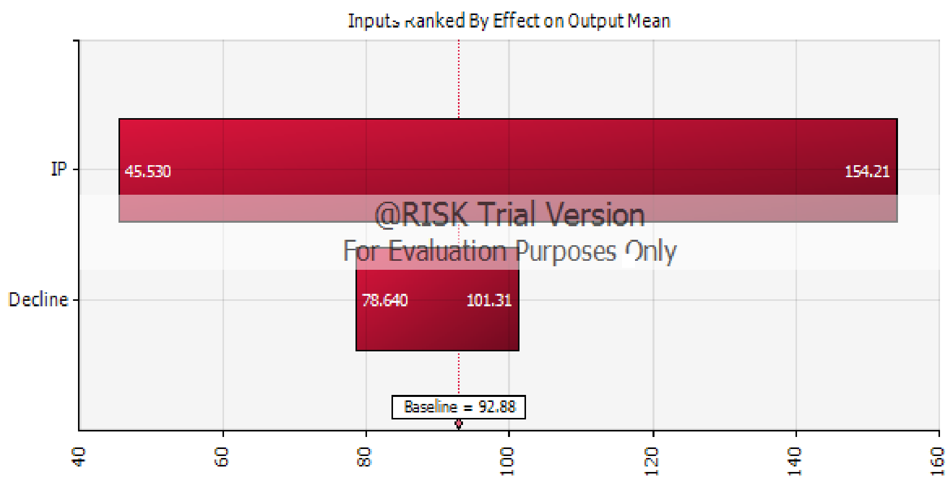

Figure 4. Sensitivity Chart at the 4th Year

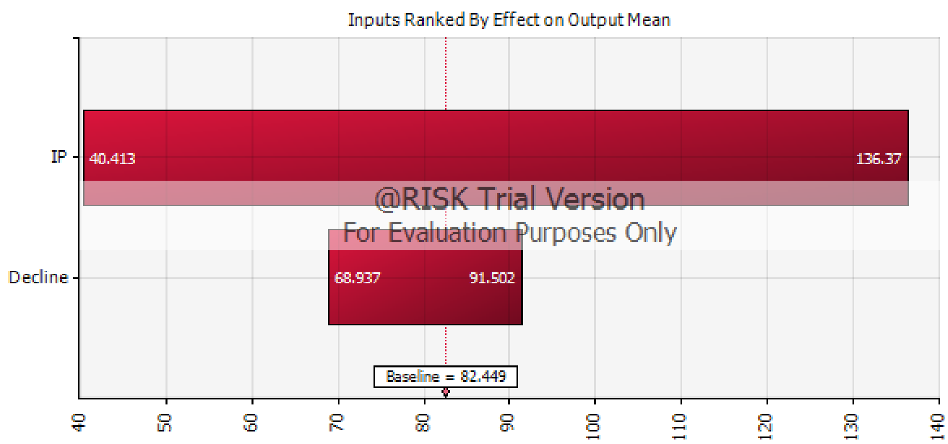

Figure 5. Sensitivity chart at the 5th Year

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From both charts, it can be seen that the initial production rate affects the model the most. Thus, to arrive at an accurate result, values assigned to the initial production rate **(IP)** should be properly checked.

CONCLUSION

From this work, the following conclusions are made;

1. With the assumptions chosen for this research work, the Arps exponential model has a 55% certainty that a predicted production rate will occur
2. @Risk tool is a veritable tool for estimating risks associated with model prediction.
3. Initial production rate **(IP)** is a key parameter in assuring the validity and accuracy of prediction using Arp's exponential curve model.
4. Probabilistic predictions are more reliable and flexible to deal with when taking decisions in that it gives us not only the outcome of a prediction result, but also how likely these outcomes are.

Nomenclature

q_t: Oil production rate (stb/day)

IP: Initial production rate (stb/day)

D: exponential decline constant (1/day)

T: Time (day)

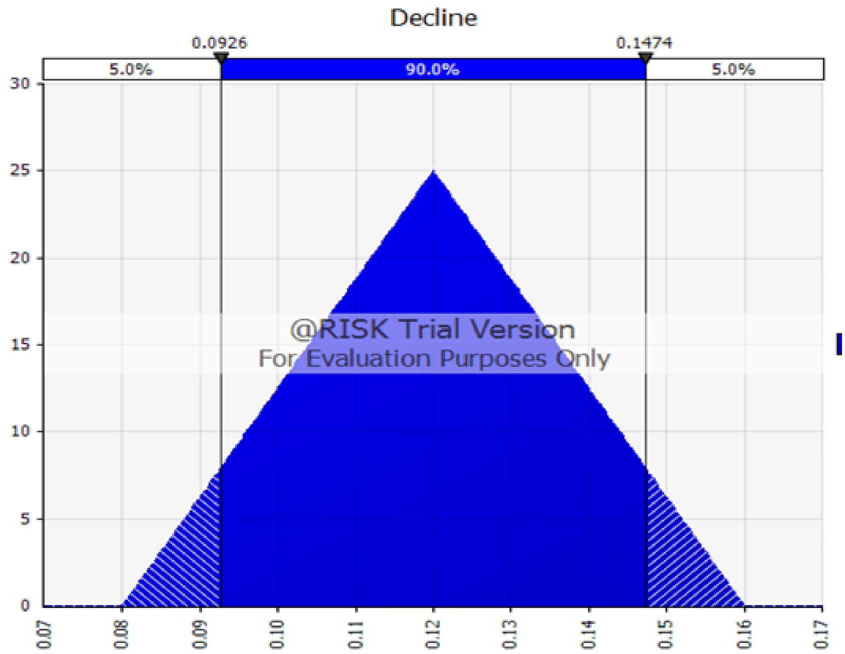

Figure 6. Triangular Probability Distribution Assigned to the Decline rate

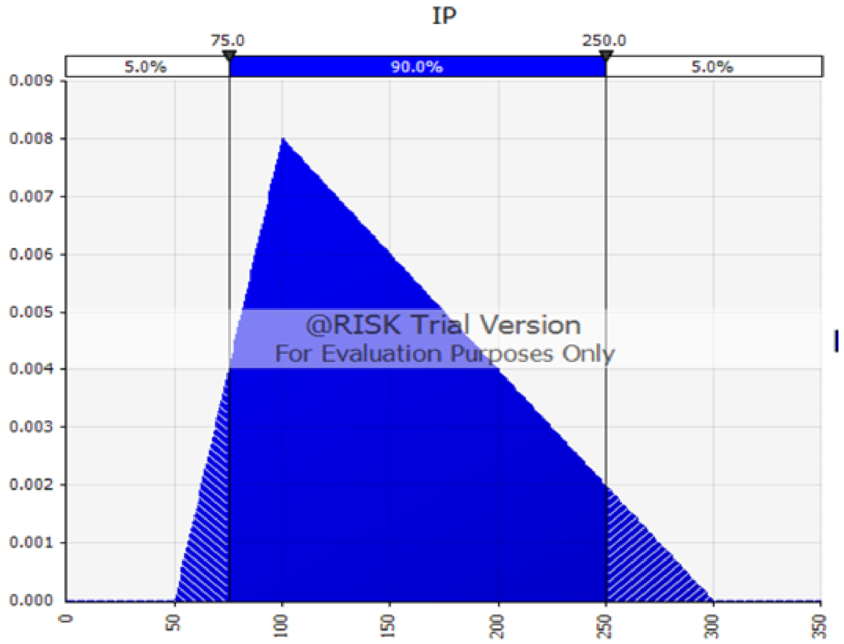

Figure 7. Triangular Probability Distribution Assigned to IP

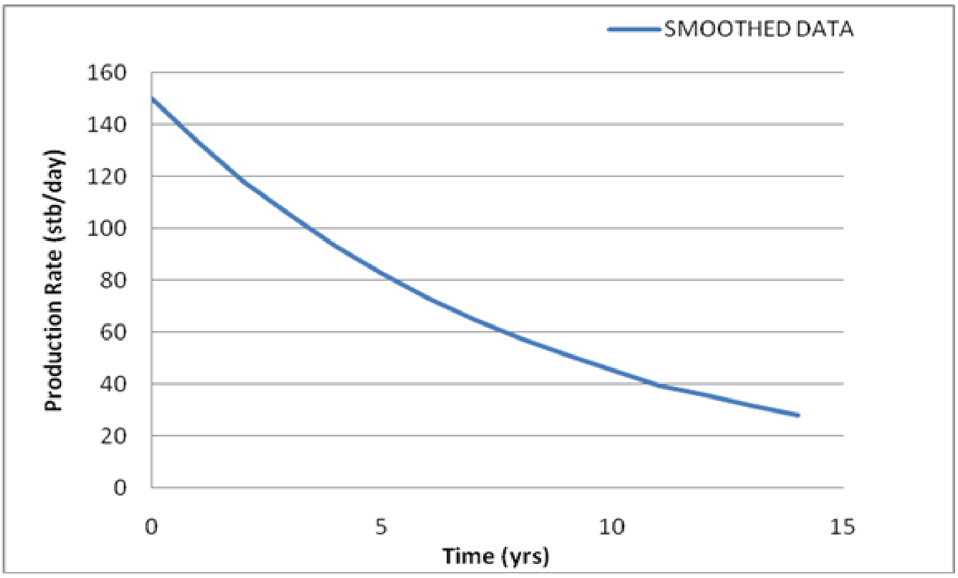

Figure 8. Smoothed data Curve after Data Filtering

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APPENDIX

HISTORY MATCHED RESULTS

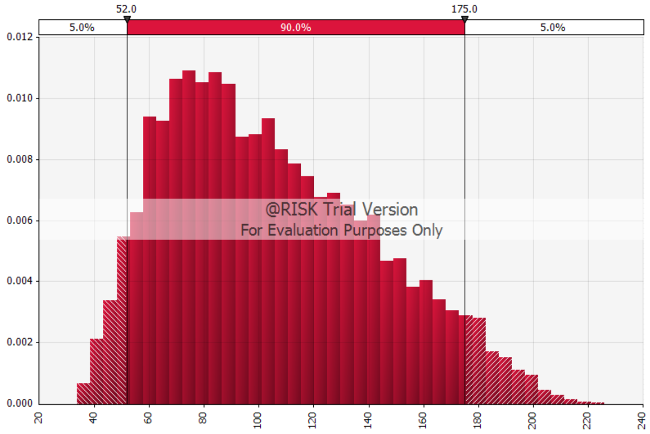


Fig A1: History Matched Result for the 3rd year

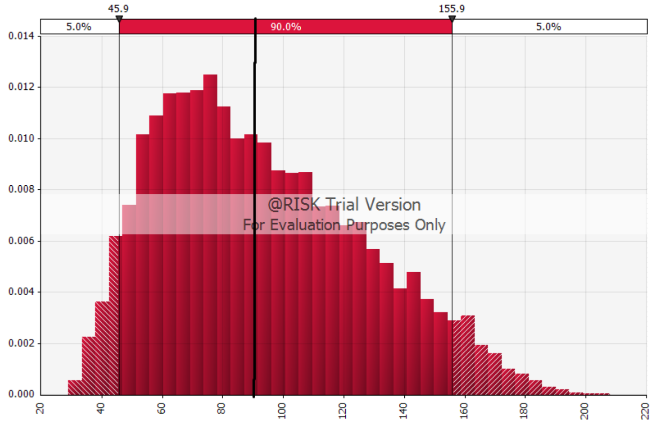
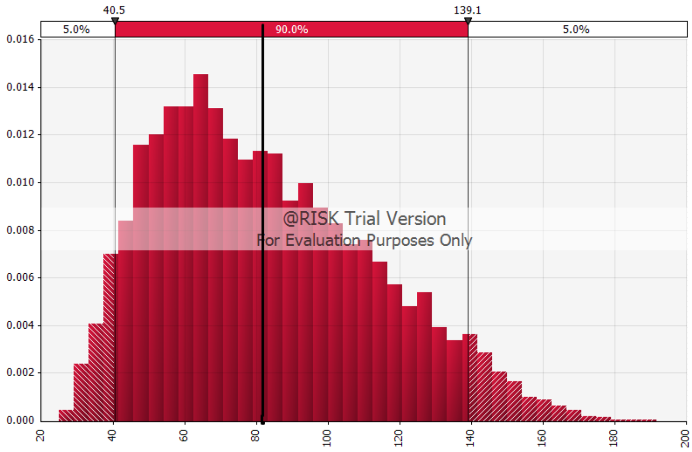


Fig A2: History Matched Result for the 4th year



A3: History Matched Result for the 5th year

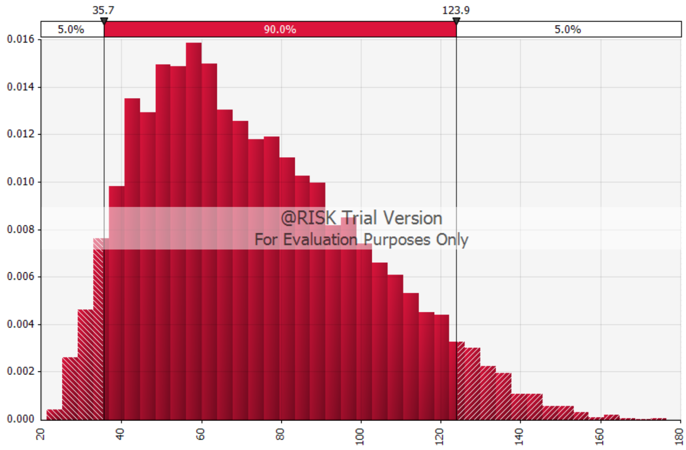


Fig A4: History Matched Result for the 6th year

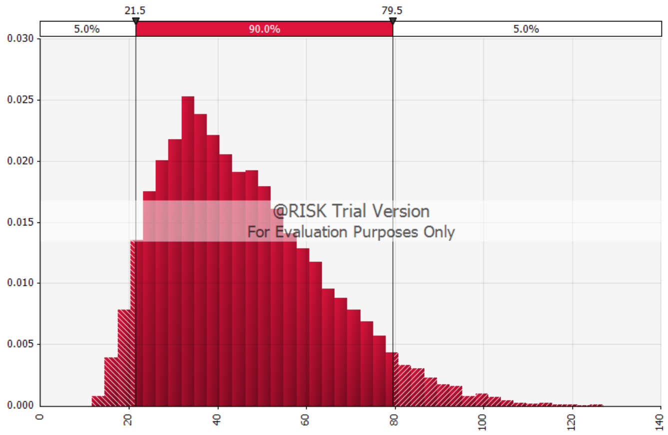


Fig A5: History Matched Result for the 10th year

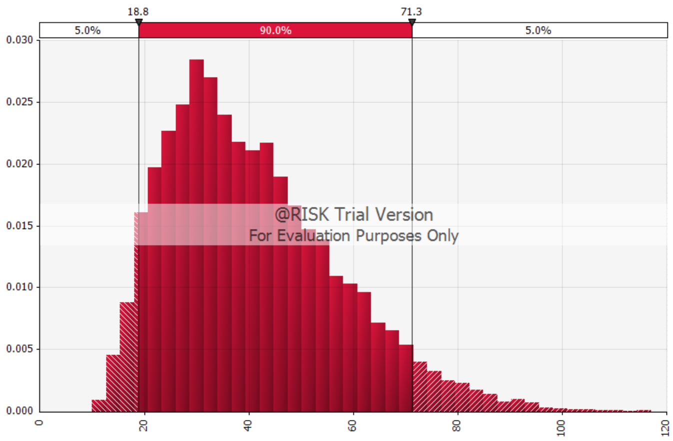


Fig A6: History Matched Result for the 11th year

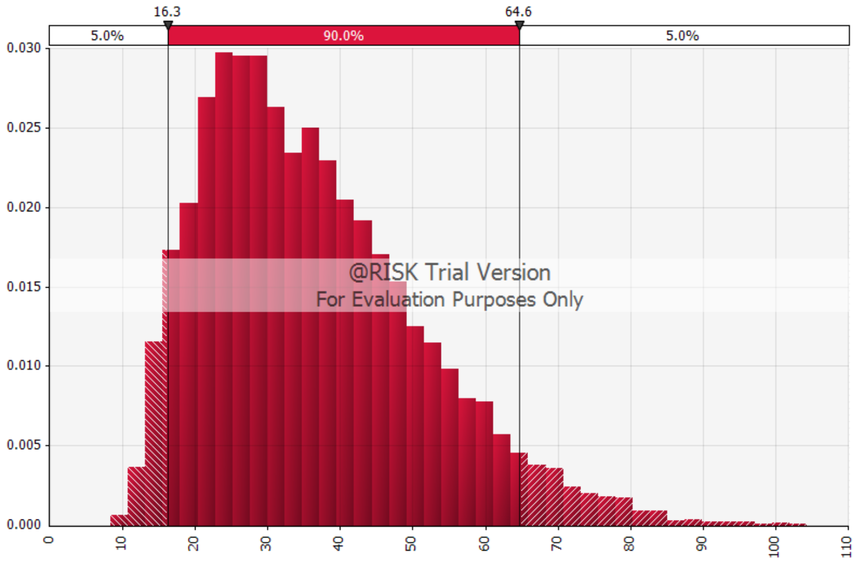


Figure A7: History Matched Result for the 12th year

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