AAPG International Conference
Barcelona, Spain
September 21-24, 2003

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Probabilistic Pay Flags and Reservoir Quality in Greater Burgan Field, Kuwait

In order to account for uncertainty in assignments of Reservoir Quality (RQ) flags (i.e., pay sands plus wet or swept sands) for new reservoir modeling in Greater Burgan Field, Kuwait, a technique was developed to create flags that reflect probabilistic analysis. This allows us to analyze the range of possible RQ within a single well (for better reservoir management), and allows us to see the effect of RQ uncertainty on full-field reservoir models. The technique is based on formation producibility, defined by porosity and permeability measurements from conventional cores. These measurements are compared to key wireline log responses, which were then used to develop an algorithm that could be applied to the entire field. We used a combination of log-curve crossplots such as Sw vs. Vshale, Phie vs. Rt, etc., along with traditional porosity cutoffs to create our algorithm.

Whenever a RQ assignment is made, based on wireline logs, there is uncertainty in the interpretation. There are many causes for this uncertainty: thin bed effects, shaly sands, tool resolution near bed boundaries, inconsistent log measurements, etc. As an example, Fig. 1 shows a zone where gamma ray and neutron logs suggest that the formation may be sandstone, while resistivity and density suggest shale. Our goal was to develop a method to reflect all types of uncertainty in Burgan Field, and output a reasonable range of possible outcomes, using probabilistic analysis to quantify the outcomes. Because of the sheer size of Burgan Field (current reservoir models contain 65 million cells), using vendor software to incorporate uncertainty is not practical, so the following method has been applied to achieve our goal of accurately representing the uncertainty in log interpretation.

The first challenge was to build a series of criteria relating wireline log measurements to standard cumulative

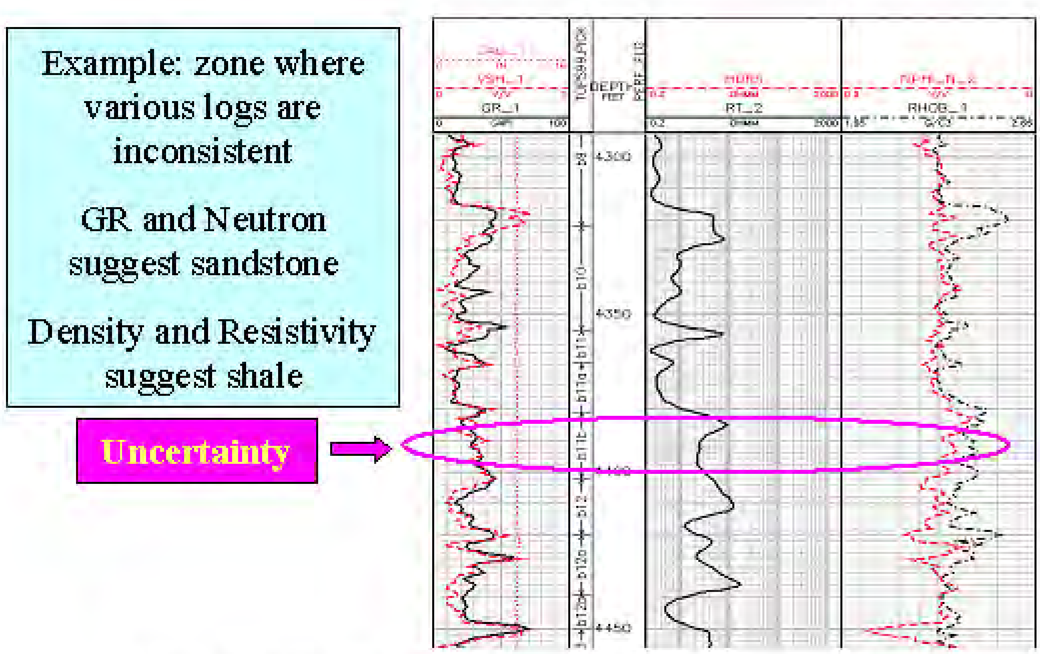

Fig. 1 – Zone of uncertainty due to inconsistent log responses

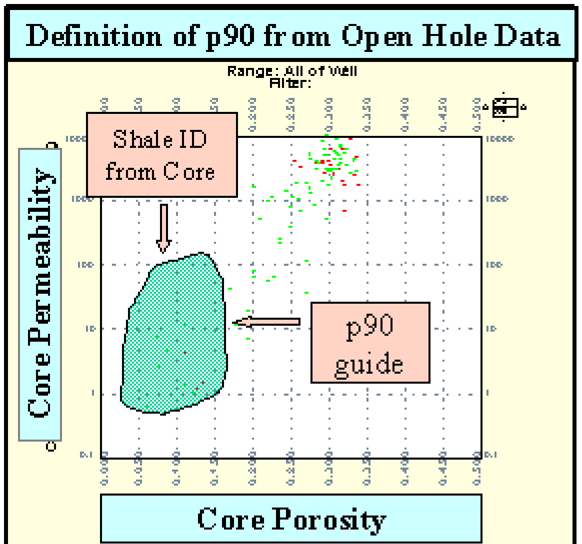

Fig. 2 – PKS data from shale plugs show properties of non-reservoir, a good place to put a p90 guideline

probability functions. For any well, a standard definition of the p10 function states that there is only a 10% chance that the well contains less than the p10 amount (a pessimistic estimation). Likewise, the p90 function states that there is a 90% chance that the well contains less than the p90 amount (an optimistic estimation). However, to create payflags that can be transferred to geologic models, more detail is needed since well log data are sampled several times per foot. Criteria were developed to provide a probability estimation for every sample in the well log, and based on the log responses, assign a probability to that sample.

To develop these criteria, we assumed that non-reservoir could be identified, and anything else could be Reservoir Quality. Non-reservoir can be identified using crossplots such as effective porosity vs. resistivity or Vsh vs. Sw. In Fig. 2, core properties of plugs identified as non-reservoir are shown. In our wells, anything that has not been identified as non-reservoir is assigned a p90 RQ flag. As a cross-check, when core data is compared to the p90 RQ flag, reservoir rock should be observed in up to 1 out of 10 places where non-reservoir was assigned!! This has been observed in several follow-up cores, so we feel the p90 criteria are quite robust.

Fig. 3 shows our p10 RQ guideline. At effective porosities above 24%, there is very little chance that the rock is non-reservoir. Just below 24%, there seems to be a small but significant chance (about 10%) that the rock will be non-reservoir. So by only counting the very best reservoir rock, this is a good place for the p10 cutoff. When comparing the p10 flag to core, we occasionally see zones of silty low perm that have been assigned as p10 reservoir rock. This can usually be traced to subtly-bad logs due to rugose borehole.

Unlike p90 and p10, it is difficult to physically define p50 RQ. Fig. 4 shows how we chose the guideline, about halfway between the p10 and p90 cutoff. Comparing predicted results to core show reasonable matches in total amounts of RQ.

Whatever method is selected to assign probabilistic pay flags, results should be consistent with characteristics of good p10-p50-p90 models. We would expect to have more RQ uncertainty in shaly sand, thinly-bedded, or finely laminated reservoirs than in massive clean sands. Fig. 5 shows a cumulative probability plot for a reservoir unit containing massive, clean, high porosity sandstone. Note that the difference between total p10 RQ, p50 RQ, and p90 RQ is very small, reflecting the high confidence in the good quality of this reservoir. On the other hand, Fig. 6 is a cumulative probability plot from a unit that is a relatively interbedded sand/shale with a mix of clean and shaly sandstones. Note the relatively large difference between p10 RQ and p90 RQ.

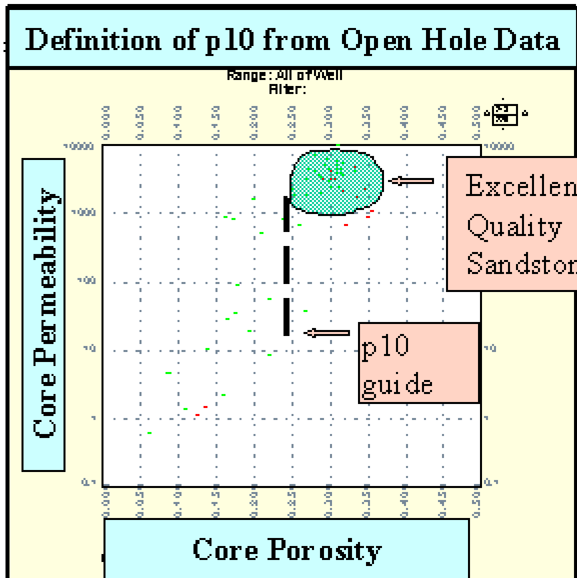

Fig. 3 – PKS data show properties of high-quality reservoir, a good place to put a p10 guideline.

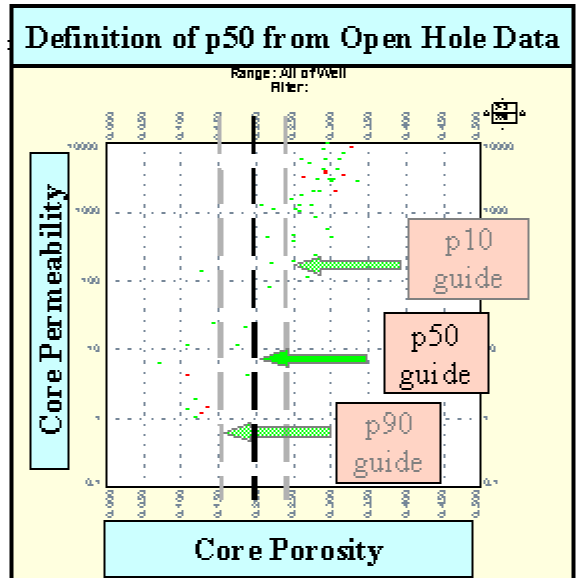

Fig. 4 – Choosing the p50 guideline between the p10 and p90 lines

We now want to distribute RQ into a reservoir model. A common procedure used in the industry is to take all the p10 RQ distributions from each well, put them all into one model and call that the p10 RQ model. As long as there is more than one well in a field, the probability that every well in the field has a p10 RQ distribution is much lower than 10%. If one has a reasonable set of p10-p50-p90 RQ distributions, probability theory can be used to guide how the distributions should be allocated. For any cumulative probability curve, the value at the p10 level can be used as an average value to represent 25% of the total probability, the value at the p50 level can be used as an average to represent 50% of the total probability, and the value at the p90 level can be used to represent 25% of the total probability. Summing (0.25*p10) + (0.5*p50) + (0.25*p90) leads to the statistical Expected Value. To get the Expected Value for RQ in a given number of wells in a field, statistically one would expect that 25% of the wells could be represented by a p10 RQ flags, 50% of the wells by p50 RQ flags, and the last 25% of the wells by p90 RQ flags. Fig. 7 shows an example field with 8 wells, and one possible realization of how the different RQ distributions might be arranged.

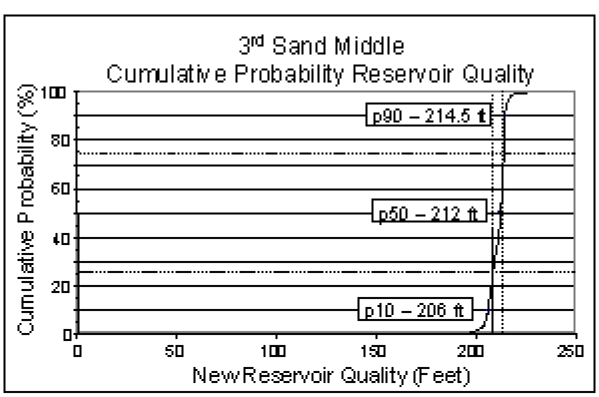

Figure 5. Cumulative probability curve for the 3rd Sand Middle Reservoir Quality.

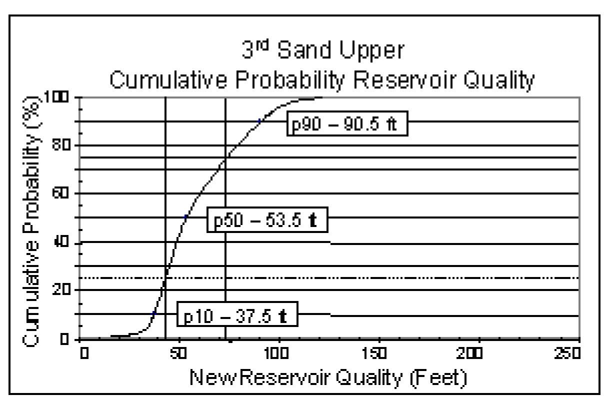

Figure 6. Cumulative probability curve for the 3rd Sand Upper Reservoir Quality.

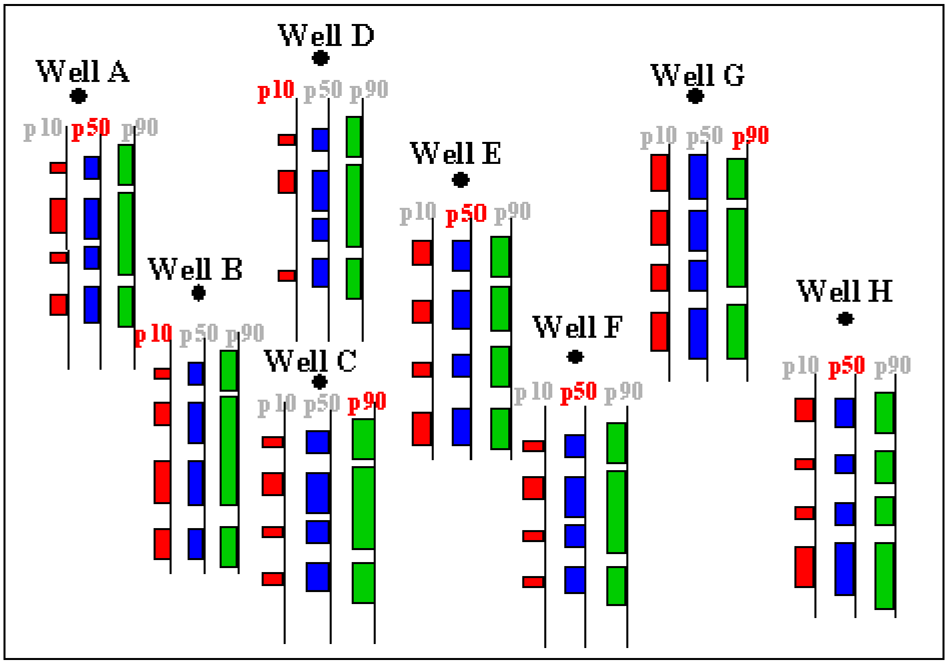

Fig. 7 – Example field of 8 wells. Red font highlights the RQ distribution that was selected. Note that 25% of the wells have a p10 RQ, 50% of the wells have a p50 RQ, and 25% of the wells have a p90 RQ.

Note that we are using the same probability distribution for the whole well (i.e., the entire well A has a p10 RQ distribution, well B has a p90 RQ distribution, etc.). There can be much discussion generated over the scale at which the probability distributions change. Within a well, we could allow Reservoir 1 to have a p10 RQ, and Reservoir 2 to have a p90 distribution, etc. For a large number of wells, this would have the effect of collapsing the statistical uncertainty. To stay conservative and to honor some of the physical causes for uncertainty (such as a logging tool may have been reading poorly for the whole well), we decided to keep our probability distribution constant throughout each well.
Statistically, we want to make a large number of realizations in order to gain confidence that our estimates of RQ net-to-gross are valid. Since our reservoir models have 65 million cells, creating large numbers of reservoir models was not practical.

The distribution of properties in a simulation model is generally designed to match the distribution of properties seen in the well control (Fig. 8). Since the net-to-gross in the simulation model is proportional to the net-to-gross of the wells used to create the model, then for a series of model realizations, the summed total RQ of the wells in any

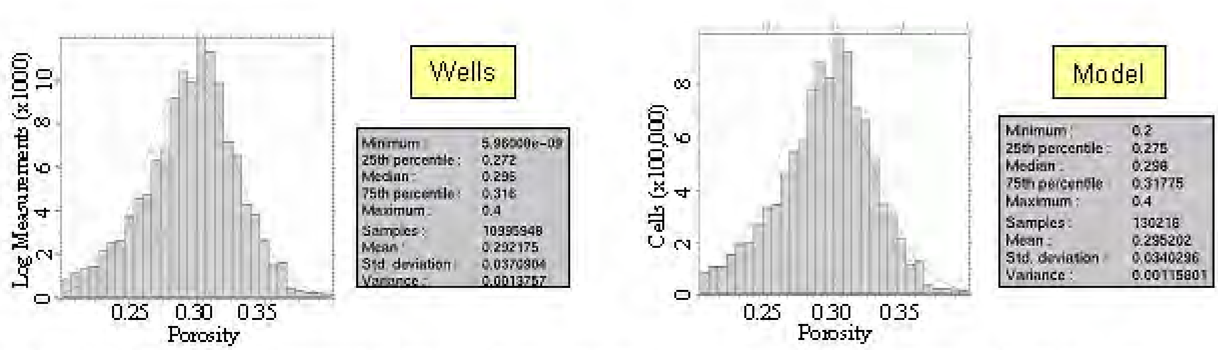

Fig. 8 – Example of how properties from a model are matched to properties from the wells

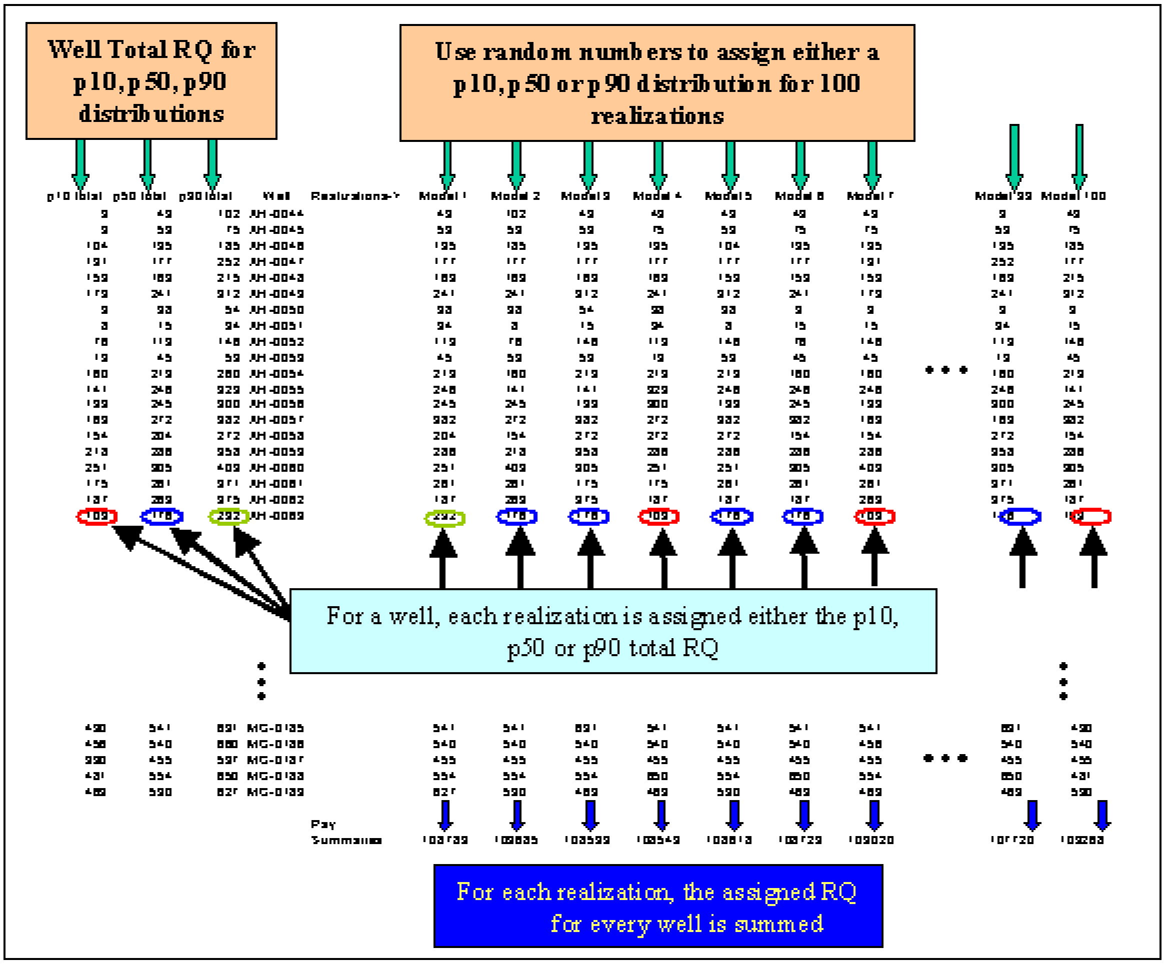

Fig. 9 – Spreadsheet created to assign p10, p50, or p90 values for a given number of realizations. Note that the Total RQ from all wells is summed for each realization.

realization can be used to rank the total RQ of that model. This assumption/constraint negates the need to build a large number of reservoir models to study the effect of net-to-gross uncertainty.

Monte Carlo simulation was applied to approximate a true p10, p50, and p90 RQ model. Fig. 9 shows one way this can be accomplished. For each well, the total p10, p50, and p90 RQ is summed and entered into the spreadsheet. Many realizations are created using a random number generator. For any given realization, approximately 25% of the wells will have a p10 RQ, 50% will have a p50 RQ, and the other 25% will have a p90 RQ. For every realization, the total RQ from every well is summed. The summed RQ from every realization can be converted into a cumulative probability function (Fig. 10). From this function, we select the realization most likely to represent a true p10, p50, and p90 RQ model. In Fig. 10, we see that the total RQ in realization #42 best represents the p10 RQ solution, realization #4 best represents a p50 solution, and realization #83 best represents a p90 solution.

Since the RQ at each well is treated as an independent occurrence, the distributions are totally random, and it is common for a p90 well to be located next to a p10 well. Further, some realizations could have proportionally more p90 in the northern areas and more p10 in the southern areas. The goal of the approach to improve the representation of uncertainty. This method provides an alternative to either ignoring uncertainty in the geologic model, or by incorrectly assigning all wells in a p10 RQ model to have p10 RQ distributions.

Results from applying these techniques showed that the biggest benefit occurs in fields where there is a large

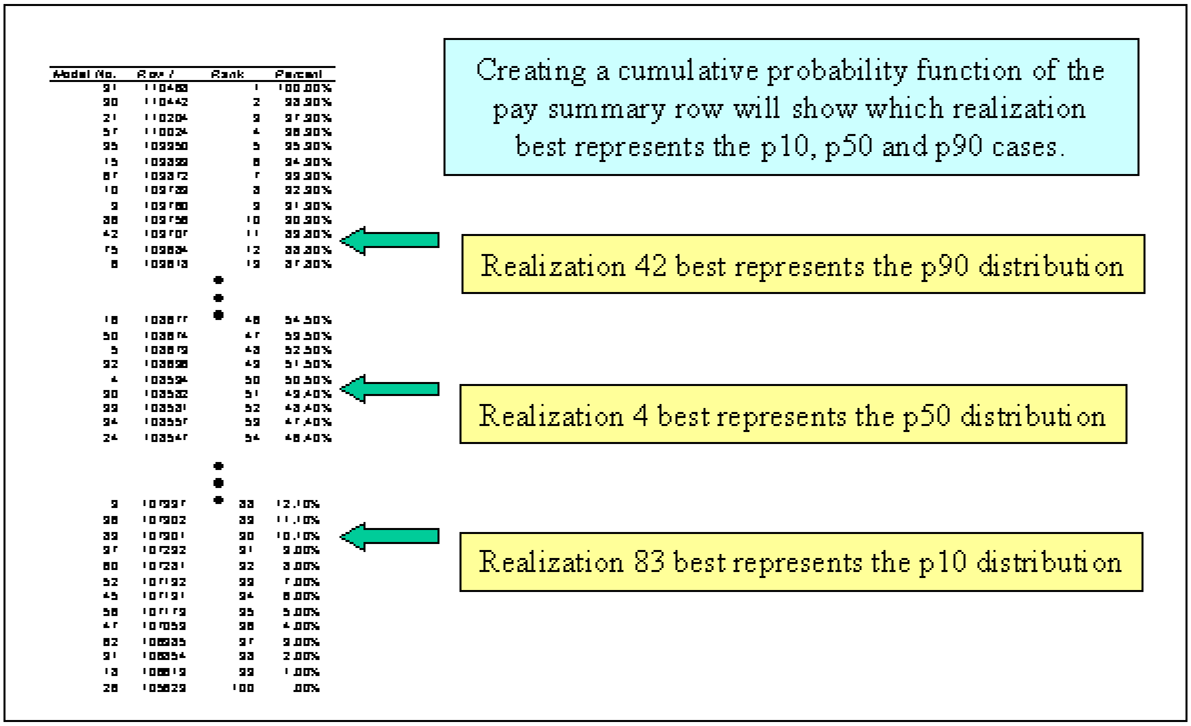

Fig. 10 – The summed realizations from Fig. 9 can be sorted into a cumulative probability function, from which the best p10, p50, and p90 realization can be selected.

uncertainty in RQ due to thin beds or shaliness, or in fields with relatively small well control. Looking at summed RQ from a large number of realizations as in Fig. 9, we expect a field with only 10 wells to have a large difference in summed RQ between the p10 realization and the p50 realization (>15%). For a geologically-similar field with 500 wells, the difference in summed RQ between the p10 and p50 collapses to about 1%.