Jenny Walton
Electricity Commission
Level 7, ASB Tower,
2 Hunter Street
PO Box 10041
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29th October 2004

Dear Jenny

Re: Draft Grid Investment Test

This letter is Norske Skog Tasman's submission on the proposals promoted in the paper titled "Draft Grid Investment Test".

We have found it difficult to simply answer the questions raised in the paper, mainly because we have some concerns about the underlying approach. The Commission appears to be of a view that all transmission investment proposals should be evaluated by exactly the same methodology. We disagree with this view and advocate that each transmission investment proposal should be evaluated according to the parameters that have a material impact on that proposal.

A large part of the complexity surrounding transmission investment decisions relates to uncertainties in exogenous parameters (such as demand growth). We are pleased that the Commission appears to be of the view that any decisions need to account for these uncertainties. However we do not agree with the methodologies proposed by the Commission.

In this submission we will answer those questions where we either disagree with the Commission, or wish to express a view.

Q3: Do you agree that cost-benefit test (incorporating probabilistic planning analysis) can be used even if a deterministic grid reliability standard is adopted, and if not, why not?

Yes Norske Skog agrees on the basis that a deterministic reliability standard can be converted into an equivalent probabilistic standard.

Q4: Do you agree with the Commission's proposal to apply a cost-benefit test to all reliability investment proposals, and if not, why not?

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Norske Skog Tasman does not agree that the ***same*** cost-benefit analysis should be used for all proposals. Only those parameters that have a bearing on the proposal should be included in the cost-benefit analysis.

If projects are small or "no-brainers" a much less rigorous cost-benefit analysis can be applied.

Q9: Does an initial central value for unserved energy of $20,000/MWh reflect a balanced assessment of current New Zealand and international evidence? If not, how would you assess that evidence?

No. A thorough survey of electricity consumers in NZ will provide a reasonable estimate of the value of unserved energy.

Q10: Referring to the discussion in section 6.3 of the Frontier report, are there other empirical studies that should be reviewed to form an initial value for unserved energy?

No. See answer to Q9.

Q11: Should a central value for unserved energy be adopted, or should separate values be assigned for different categories of consumer? If separate values should be assigned, what categories would you adopt and what values would you assign? Would consumers expect to pay different transmission charges if the transmission services they received reflected consideration of different unserved energy values?

Separate values should not only be assigned for different categories of consumers but also different geographical regions. Our view is that different consumers value unserved energy differently and therefore a global value is inappropriate.

Q12: Do you agree that sensitivities of $10,000/MWh and $30,000/MWh be used where the size and cost magnitude of the project warrant the additional analysis, and if not, why not?

No. As much as $20,000/MWh appears to us to have no justification so does $10,000/MWh and $30,000/MWh. In any case we question the purpose of sensitivity analysis, and we will discuss this in our answers to later questions.

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Q14: Should the GIT be applied with less rigour and comprehensiveness for grid investments with capital costs between $1 million and $5 million than for investments costing more than $5 million? If yes, is it necessary to specify what must be included in such analyses?

Yes. No it is not necessary to specify ahead of time what must be included in such analyses. Only those parameters that materially affect an investment decision need be considered.

Q15: Are there other variables the Commission should include in its description of the current status of the electricity industry, and if so, what are those variables?

At the risk of appearing pedantic our view is that the items listed in paragraphs 62 and 64 are parameters involving uncertainty, not variables. There may well be other parameters that have a material impact on individual projects such as availability of fuel.

Q17: Is the choice between least-cost and bidding approaches likely to materially affect the choice of grid investment versus alternatives to transmission, and if so, why?

Possibly. For instance in a constrained area a new generation project sponsored by a participant with existing market power is unlikely to be offered into the market with the same strategy as a new entrant into that area.

Q18: Do you agree that the least cost approach, supplemented with sensitivity analysis of 'realistic bidding' approaches, is the most practicable approach for New Zealand?

No. We do not believe that one single approach is appropriate for New Zealand. Where warranted, consideration of market power should be included in a cost-benefit analysis by applying techniques such as Cournot-Nash equilibria. This would include projects that could potentially reduce existing market power as well as projects that could potentially supplement existing market power, or even create market power.

Q25: Should competition benefits be included in the GIT, and if so, how should they be measured?

See answer to Q18.

Q27: Should Government policies that reflect externalities and that explicitly impose costs or benefits on electricity market parties be included in the GIT?

Yes, and the uncertainties surrounding such government policy should also be included in the GIT.

Q28: Should the Commission assess projects against several base case scenarios? If not, how should the Commission deal with uncertainty regarding future generation location?

Q29: Do you agree with the Commission's approach of replacing proposed grid investments with alternative arrangements if they are already in a base case scenario? If no, what other approach should be adopted?

Q30: Do you agree sensitivity analysis should be conducted on the parameters listed above? What other variables should be considered for sensitivity analysis, and why?

In order to answer these three questions we must express our views that the approach being recommended by the Commission is inappropriate. We see little value in sensitivity analysis as this approach merely simulates the likely outcomes of a decision under a variety of uncertain outcomes. It does not assist planners to make better decisions in the first place that are robust against all possible outcomes. Please refer to a brief explanation of this point that we attach as appendix 2 by Professor Stein Wallace, of Molde University in Oslo, a world expert in the area of decision making under uncertainty[1].

We assume that the Real Options approach is being contemplated to help make better decisions but for reasons we will discuss in our answer to Q31 and Q32 we think this is a misguided approach.

We expect that the five base case scenarios that the Commission expects to publish will represent some plausible outcomes related to entire New Zealand electricity industry, such as fuel discovery. If so then we find it difficult to understand how these scenarios will necessarily have much relevance to many transmission investment decisions.

Some (and in some cases all) of the items mentioned in paragraph 105 are likely to have a material influence on transmission investment systems. Therefore these parameters should be used to represent the uncertainties that each transmission investment will be considered under.

[1] A full paper is available in Operations Research, Vol 48, No 1, Jan-Feb 2000, pp 20-25, Decision Making Under Uncertainty: Is Sensitivity Analysis Of Any Use?, S.W. Wallace.

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Q31: Should the Commission use real options analysis where it is practicable to do so?
How important do you think it is to value flexibility in regard to decisions to be made under the GIT, and in what circumstances is it most important to value flexibility?

No the Commission should not use Real Options analysis. Frontier Economics explained some of the flaws in trying to apply Real options analysis to investments within the electricity industry in Annex 4 of their report. Further to Frontier's comments we observe that Real Options is predicated on the assumption that all risks can be hedged against with market instruments. This is impossible for transmission investments. For instance there are no instruments that replicate all demand growth outcomes. Therefore Real Option analysis is inappropriate.

Yes the Commission should value flexibility under any circumstance where there exists uncertainty in the exogenous parameters, but not, as we have explained, using Real options Analysis.

The state of the art methodology for determining decisions under uncertainty is Stochastic Programming[2]. A stochastic program enables decisions to be determined that are robust against all possible outcomes. The value of more information being revealed in the course of time is implicitly captured by what is known as a wait and see model[3]. We attach a useful description of this approach as Appendix 2.

Q32: If it is complicated to apply real options analysis, should the Commission initially focus on the scenario analysis approach and develop real options analysis at a later stage?

As explained above we believe that the Commission should not use Real Options analysis. However we are very concerned by the implication in the Q32 that the Commission appears to be prepared to compromise the quality of decision making in order to simplify the approach. This appears to risk potentially inferior decisions being made. We have already expressed our view that the approach taken to evaluate each decision should reflect the complexity of the decision, and therefore a standard approach is not appropriate. On this basis we believe that there may be many cases where the cost-benefit analysis will not involve complex modelling.

However in more complex cases we believe that the analysis should be of a high quality and that there should never be a compromise for the sake of

[2] See for instance www.stoprog.org
[3] See Stochastic Programming, J.R. Birge and Louveaux, Springer Verlag, 2000.

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simplicity of modelling. Of course with all models there will be a need for approximations but that is an entirely different matter from choosing a simplistic approach in the first place.

Q33: In regard to the NPV analysis, which decision rule should be adopted, and why? Is the probability-weighted approach likely to be too complicated, and achieve spurious accuracy?

It is our opinion that the probability-weighted approach (to a small extent) reflects the benefits that can be obtained from stochastic programming. Rather than being too complicated we feel it is likely to be too simple, unless a small number of scenarios with associated probabilities accurately reflects the probability distributions of the pertinent parameters.

Q34: Is a decision rule required now to choose between the NPV result and the real options result if they conflict?

We trust that the Commission will realise that this question is not relevant in the light of the flaws surrounding NPV and real options analysis. In our opinion the Commission should develop sufficient expertise so that it can decide the most appropriate method of analysis for each investment proposal.

Q35: Do you agree with the assessment in Table 2? If not, what assessments do you think should be changed and why?

We agree with the intentions underlying the Grid Investment test, but we feel that many of the details will undermine the efficiency of the GIT. Our concerns have been expressed already in this submission.

Kind Regards,

Graeme Everett

Appendix 1 – from http://home.himolde.no/~wallace/scenarios.htm

Scenario based planning

Scenario based planning is a very popular tool today, much used and much misused. It is a very valuable tool when correctly applied. First, to properly understand when it can and when it cannot be used, we must distinguish between two situations.

1. The problem of finding good decision alternatives.
2. The problem of evaluating existing decision alternatives.

It is the first use that is dangerous, but still very popular. The basis is the incorrect assumption that if you wish to find the decision that maximizes expected profit (or expected utility or whatever you wish to do), you can learn about this decision by studying individual scenarios. Almost all textbooks in operations research tell us to use sensitivity analysis (what-if-analysis) to study optimality when some parameters are not fully known. Sensitivity analysis is just another word for scenario analysis, and there is no theoretical basis for using this approach. There is no clear connection between what is best on average, and what is good in individual future situations. In my article on sensitivity analysis, I explain in detail why scenario analysis cannot be used to find good candidate decisions. The result of such an approach can be arbitrarily bad. So the use of scenarios (or sensitivity analysis) to see what happens under uncertainty is just operations research folklore, with no theoretical basis. Good candidates cannot generally be found by studying individual scenarios.

Evaluating existing alternative decisions is a different matter. Using scenarios to see how the different possible decisions behave under different assumptions about the future is indeed the correct way of comparing alternatives. This is in principal the same as simulation, a term less popular than scenario analysis these days. Note that scenario analysis (simulation) can be used to say which of a number of candidate decisions (strategies) is best, but not how good it is. There may be other decisions that are arbitrarily much better, we cannot know from scenario analysis.

For scenario analysis to make any sense, it is important that scenarios are defined such that they are independent of our decisions. The purpose of scenario analyses is to find out what we ought to do under varying environments. If we start to define scenarios that are dependent on our own decisions, we are very likely to get lost in a very advanced way.

A major issue in strategic planning is to identify scenarios, that is, to identify which random events are most important for us (or our company). Picking the right ones and dropping the unimportant ones is what makes the basis for a good strategic plan. And when you observe the major uncertain events, remember that they may all be (statistically) dependent. Forgetting dependencies may lead to disasters. Alternatively, we may simply require random variables used in scenario analyses to be independent. If two random events are dependent, most likely, there are some more basic random variables that are independent. They should then be used.

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Appendix 2 (from www.stoprog.org/spintroduction.html)

Stochastic Programming Introduction *

Introduction

Stochastic programming is a framework for modelling optimization problems that involve uncertainty. Whereas deterministic optimization problems are formulated with known parameters, real world problems almost invariably include some unknown parameters. When the parameters are known only within certain bounds, one approach to tackling such problems is called robust optimization. Here the goal is to find a solution which is feasible for all such data and optimal in some sense. Stochastic programming models are similar in style but take advantage of the fact that probability distributions governing the data are known or can be estimated. The goal here is to find some policy that is feasible for all (or almost all) the possible data instances and maximizes the expectation of some function of the decisions and the random variables. More generally, such models are formulated, solved analytically or numerically, and analyzed in order to provide useful information to a decision-maker.

The most widely applied and studied stochastic programming models are two-stage linear programs. Here the decision maker takes some action in the first stage, after which a random event occurs affecting the outcome of the first-stage decision. A recourse decision can then be made in the second stage that compensates for any bad effects that might have been experienced as a result of the first-stage decision. The optimal policy from such a model is a single first-stage policy and a collection of recourse decisions (a decision rule) defining which second-stage action should be taken in response to each random outcome. A good introductory example of such a model is the gas-company example on the NEOS web site, which we summarize below.

Example

The gas company example has a planning horizon of two years. In the first year the gas company buys gas from the market, delivers some to its customers right away and puts the rest in storage for next year. The following year the company can supply from storage or buy from the market. The decision variables are:
1) how much gas to purchase and deliver,
2) how much gas to purchase and store, and
3) how much gas to take from storage and deliver to customers.

The decision depends on the price of gas in year 1 and year 2, the storage cost (say $1 per unit per year), the size of the storage facility, and the demand in each period. With this information the problem can be modelled as a simple linear program with the objective to minimize overall cost. In practice the price and demand in year 2 will be uncertain. Suppose that year 1 is a normal year and that year 2 can be one of three equally likely scenarios: normal, cold, or very cold. Each of these scenarios has different data as shown in the following table:

Scenario	Probability	Gas Cost ($)	Demand (units)
Normal	1/3	5	100
Cold	1/3	6	150
Very Cold	1/3	7.5	180

Forming and solving the stochastic linear program gives the following solution:

Year	Scenario	Purchase to Use	Purchase to Store	Storage	Cost ($)
1	Normal	100	100	100	1100
2	Normal	0	0	0	0
2	Cold	50	0	0	300
2	Very Cold	80	0	0	600

Expected Cost = $1400

Although stochastic programming encompasses a wide range of methodologies, the two-stage gas-company example illustrates some important general differences between stochastic programming models and deterministic models. In the gas-company example there are three equally likely scenarios. A common approach adopted by planners is to seek an optimal policy by computing an optimal solution for each scenario separately. The candidate solutions here are to store either 0 or 180 units of fuel for the next stage. The optimal policy (as delivered by the stochastic program) is to store 100 units. This does not correspond to the optimal solution in any of the scenarios. (It is also different from the storage policy of 143.33 units obtained by solving an optimization problem with averaged data.) The solution from the stochastic program is well-hedged, building in some flexibility to meet the uncertain demand in the second stage.

A second important observation for the gas-company model is that the sequencing of decisions and observations is important. In constructing a stochastic programming model, it is not enough just to specify the decision variables: the modeller must also construct the model in such a way that prevents decisions that anticipate future uncertain events. In the example, if the company could anticipate demand then it would store 0, 0, or 180 units in the first stage depending on the future weather outcome. However this is not an implementable policy.

A third observation about the example is that the objective function in this case does not account for the variation in outcomes. The model minimizes an expected cost, and its optimal policy gives costs of $1100, $1400, and $1700 under each scenario. If this were a one-shot decision then this spread of outcomes might be seen as unacceptable for the gas company owner if they are unwilling to accept some outcome that costs $1700. Modelling different attitudes to risk is possible in the stochastic programming framework by using piecewise linear, or more general nonlinear, objective functions.

Although two-stage stochastic linear programs are often regarded as the classical stochastic programming modelling paradigm, the discipline of stochastic programming has grown and broadened to cover a wide range of models and solution approaches. Applications are widespread, from finance to fisheries management. An alternative modelling approach uses so-called chance constraints. These do not require that our decisions are feasible for (almost) every outcome of the random parameters, but require feasibility with at least some specified probability. For details of this approach see the Introduction to Chance-Constrained Programming by Rene Henrion.

One natural generalization of the two-stage model extends it to many stages. Here each stage consists of a decision followed by a set of observations of the uncertain parameters which are gradually revealed over time. In this context stochastic programming is closely related to decision analysis, optimization of discrete event simulations, stochastic control theory, Markov decision processes, and dynamic programming.

How does stochastic programming differ from these models? In general terms the discipline combines the power of mathematical programming with advanced probability techniques, to attack optimization problems that involve uncertainty. A mathematical programming approach has important benefits: the tools of convex analysis and duality theory can be applied to yield important insights and develop solution techniques based on decomposing large problems into manageable pieces. The tools of mathematical programming are also indispensible in handling general constraints on states and decision variables. (The addition of constraints is often a serious impediment to dynamic programming techniques as it increases the dimension of the state space, which can lead to an intractable problem.) An important (current) restriction for stochastic programming problems - in contrast to dynamic programming problems - is that the probability distributions of the random parameters are assumed to be given, and cannot depend on the decisions taken.

For an excellent introduction to stochastic programming and a discussion of its relationship to related areas see the lecture notes Optimization under Uncertainty (PS) by R.T. Rockafellar.

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Applications

Stochastic programming has been applied in the following areas:

Agriculture
Capacity planning
Energy
Finance
Fisheries management
Forestry
Military
Production control
Scheduling
Sport
Telecommunications
Transportation
Water management

Solving stochastic programs

Solution approaches to stochastic programming models are driven by the type of probability distributions governing the random parameters. A common approach to handling uncertainty is to define a small number of scenarios to represent the future. For example in the gas company example the random outcomes were modelled by three scenarios. In this case it is possible to compute a solution to the stochastic programming problem by solving a deterministic equivalent linear program. These problems are typically very large scale problems, and so, much research effort in the stochastic programming commmunity has been devoted to developing algorithms that exploit the problem structure, in particular in the hope of decomposing large problems into smaller more tractable components. Here convexity is a key property. Details of these approaches can be found in the recent tutorial talk by John Birge.

When the probability distributions of random parameters are continuous, or there are many random parameters, one is faced with the problem of constructing appropriate scenarios to approximate the uncertainty. One approach to this problem constructs two different deterministic equivalent problems, the optimal solutions of which provide upper and lower bounds on the optimal value z^* of the original problem. For details see the tutorial talk by Chanaka Edirisinghe.

An alternative solution methodology replaces the random variables by a finite random sample and solves the resulting (deterministic) mathematical programming problem as one would do for the finite scenario case (see above). This is often called an external sampling method. Under fairly mild conditions one can obtain a statistical estimate of the optimal solution value that converges to z* as the sample size increases. External sampling methods typically take one sample before applying a mathematical programming method. A number of algorithmic procedures (see the second half of the Birge paper) have been developed to take repeated samples during the course of the algorithm. This is often called an internal sampling method. Details of the convergence properties of external and internal sampling methodologies can be found in the recent papers by David Morton (PS) and Alexander Shapiro (PDF).

Stochastic integer programming models arise when the decision variables are required to take on integer values. In most practical situations this entails a loss of convexity and makes the application of decomposition methods problematic. Techniques for solving stochastic integer programming models is an active research area (see the tutorial paper by Rüdiger Schultz (PDF)).

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