Photonic Network Communications, 10:2, 123–140, 2005


# Capacity Planning of Survivable Mesh-based Transport Networks under Demand Uncertainty

Dion Leung*, Wayne D. Grover

*Department of Electrical and Computer Engineering, University of Alberta, TRLabs, 7th Floor, 9107-116 Street, Edmonton, Alberta, Canada T6G 2V4*

*E-mail: dion.leung@trlabs.ca, grover@trlabs.ca*

Received June 10, 2004; Revised March 8, 2005; Accepted March 11, 2005

**Abstract.** Almost all existing work on the design of survivable networks is based on a specific demand forecast to which one optimizes routing and transport capacity assignment for a single target planning view. In practice these single-forecast models may be used repetitively by a planner to consider a range of different scenarios individually, hoping to develop intuition about how to proceed. But this is not the same as having a planning method that can inherently and quantitatively consider a range of possible futures all at once. Our approach considers both the cost of initial design construction and the expected cost of possible augmentations or "recourse" actions required in the future, adapting the network to accommodate different actual future demands. In practice, these recourse actions might include lighting up a new DWDM channel on an existing fiber or pulling-in additional cables, or leasing additional capacity from third party network operators, and so on. A stochastic linear programming approach is used to achieve designs for which the total cost of current outlays plus the expected future recourse costs is minimized. Realistic aspects of optical networking such as network survivability based on shared spare capacity and the modularity and economy-of-scale effects are considered. These are not only important practical details to reflect in planning, but they give the "future-proof" design problem for such networks some unique aspects. For instance, what is the working capacity under one future scenario that may not waste capacity if that demand scenario does not materialize, because the same channels may be used as shared spare capacity under other future scenarios. Similarly economy-of-scale effects bear uniquely on the future-proof planning problem, as the least-cost strategy on a life-cycle basis may actually be to place more capacity today than current requirements would suggest. This is of obvious relevance to planners given the recent hard times in the telecommunications industry, causing a tendency to minimize costs now regardless of the consequences.

**Keywords:** survivable mesh network design, demand uncertainty, stochastic integer linear programming, capacity planning, optical transport network planning

## 1 Introduction

In the last decade we have experienced rapid advances in telecommunications technology in a deregulated competitive market. Network operators have traditionally depended on demand forecasts to justify the substantial investment needed to ensure that needed capacity is available at the right time. When telephony was dominant, forecasts were generally accurate enough for planning with existing methods. But with the more recent diversification of services, changing usage patterns, and a lack of historical data on the new emerging data applications, accurate forecasting of future demand volumes and patterns for transport network planning has become extremely difficult [1–3].

In such a dynamic and uncertain environment, a difficult but important question in network planning is how best to cope with uncertainty of the forecast demand, since almost certainly the actual demand volume and pattern will turn out to be different from the nominal forecast to which a network design or capacity investment was planned. This is not an altogether new reality in capacity planning for businesses in

*Corresponding author.

general, but in the specific case of optical transport networking, the degree of volatility of possible future demand scenarios and the need to deal with survivability considerations inherently in the basic design problem are both unprecedented, and therefore impose new challenging design issues.

While methods for the capacity design of survivable networks have developed significantly in the last decade, essentially all methods in use today, for both ring- and mesh-based transport designs, are based on a specific target of an assumed future demand matrix which represents the anticipated demand pattern at the end of the current planning and deployment cycle. The most common approach to dealing with uncertainty has been the straightforward use of "safety margins" of added capacity [4]. The trouble with simple application of safety factor multipliers to either the input demand matrix or the otherwise ordinarily solved for capacities is that it helps ensure *feasibility* of the resulting design, but not the *optimality* of the design in the sense of being truly "future-proofed", the most ready and likely to cope with the future demand as can be for the given total investment level. In the competitive carrier market where transport investment represents a significant portion of the overall corporate expenditure, a more systematic and scientific approach to coping with demand uncertainty therefore seems preferable.

## 1.1 Background

### *1.1.1 Capacity Planning as a Two-Part Investment Problem*

In the problems of survivable capacity network design, a typical objective is to determine the minimum amount of total capacity required to both serve and protect a specific forecast demand matrix. The protection that is built into the design is usually to ensure against any possible single-span failure scenario (e.g., fiber cut) with efficient sharing of spare capacity over non-simultaneous failure scenarios. This single-period approach has been predominantly used in finding the optimal working and spare capacity placement and to ensure restorability upon span or node failures.

There is no question that single-period, single-forecast design methods have been, and will continue to be, enormously useful in production planning tools and for technology selection studies and comparative research on different basic network architectures. Over the last decade they have been used extensively to develop understandings about capacity efficiency [5], the ability to deal with multiple failures [6], operational simplicity [7], network evolution strategies [8], effects of capacity-modularity [9], and so on. But these methods only produce "snapshot" designs that are optimal to a single forecast. If the actual demand matrix differs from the one predicted, the initial design, which may now be already deployed, may no longer be the most cost-effective one. An ability to design networks that in some sense are most likely to be able to cope economically with future uncertainty is therefore certainly of interest and potentially useful.

To incorporate demand uncertainty in survivable network design, we adopt the basic idea of stochastic programming (SP) with linear recourse [10] as a mathematical framework. The concept of SP with linear recourse can be explained as a two-part[1] investment decision process. The first part considers the budget $\boldsymbol{X}$ to be invested *at present* and the second part represents the corrective or "recourse" action $\boldsymbol{Y}$ to take place *in future* when uncertainty unfolds. Compared to the traditional approach, the two-part model better reflects the complete life-cycle investment costs associated with capacity planning by facilities-based service providers[2] today. The recourse costs which we will consider include mainly the cost of "lighting up" (i.e., fully equipping and commissioning) new fiber system and/or additional single channels on those systems needed for either protection or working capacity. The recourse costs might also represent the penalty cost of leasing capacity from third-party network operators. In this regard, economy of scale effects can be early-on appreciated to be important in future-proof planning: to minimize present costs, small capacity modules may be preferred, e.g., OC-48s and/or single wavelengths. But if over a certain span demand increases unexpectedly, the cost of adding more capacity in small modules in future may exceed the cost of having simply invested once at the start in large-capacity modules, say OC-192s and/or whole multi-wavelength waveband equipment. One form of future recourse that we do not consider here is changes to the physical network topology itself. This is generally a very major separate decision in network planning with quite high one-time costs associated with new physical rights-of-way acquisition, installation of ducting, power and so on. Thus our approach is presently limited to future-proofed capacity investment planning where under all future scenarios the physical layer graph topology remains constant as given in the initial network.

### *1.1.2 Types of Demand Uncertainty*

An important aspect of planning under uncertainty is to first define the scope of uncertainty considered, since it helps to determine what mathematical technique to be used for solving the complex decision problems. To narrow down the possible ranges of demand uncertainty in the capacity planning problem, we are guided by a general classification model by Courtney, Kirkland and Viguerie [13] which divides the notion of uncertainty into four different levels:

**Level I**: A Clear-Enough Future—In this case, network planners can develop a single forecast of the demand that is precise enough for the capacity design problem. In the past where telephony was dominant in transport networks, and exhibited (as it still does) a virtually uncertain 3 or 4% per annum growth, this assumption might be acceptable and traditional methods can be used to obtain optimal solutions.

**Level II**: Alternative Futures—Here the future can be described as one characterized by relatively few different outcomes or discrete alternate future scenarios. These scenarios represent a range of possibilities and each is associated with a probability measure, even though the probability might be difficult to quantify.

**Level III**: A Range of Futures—A range of plausible futures can be identified and the range of possibilities should define the boundaries of the demand space in which the network is expected to serve. What distinguishes this form of uncertainty from Level II is that there may be a near continuum of finely different discrete future scenarios, many times larger than in Level II.

**Level IV**: True Ambiguity—This is the most uncertain and probably the most undesirable level of uncertainty to try to plan for since multiple dimensions of uncertainty interact to create an environment that is virtually impossible to predict. There is simply no basis to forecast the future.

While general strategies and analytic tools are proposed to deal with different levels of uncertainty in [13], and the real uncertainty of the transport network planning problem might be classified as being in Level III, to concisely explain the general idea of the proposed formulation, we will develop a Level II type of approximation. In effect we recognize that there is a continuum of strictly different future demand scenarios, but think most planners would agree that a smaller number of "characteristically different" scenarios can still meaningfully represent the future. The use of SP to deal with such uncertainty is well-known [10,14] and it has been used to solve capacity planning problems in the electric utility and semiconductor industries [15–17] but not yet to our knowledge in optical network transport planning in general and with only one exception has not yet been applied to network design with built-in survivability assurances.

### *1.1.3 Background on Span-Restorable Mesh-Based Networks*

In this work we consider mesh-oriented survivable networking for the basis of the next generation optical transport networks. Mesh-based transport is considerably more efficient in spare capacity sharing and flexible in routing demands than ring-based survivable networks. Among the approaches available for mesh-based transport

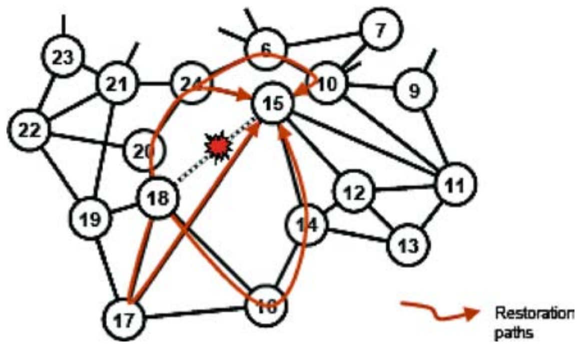


*Fig. 1.* Illustrating the general concept of span restoration [18].

networks, we presently work with span-restorable (SR) networks. In span restoration, multiple replacement paths that re-route affected signal flows are formed between the immediate end nodes of the failure span itself (See Fig. 1). The replacement paths can be pre-computed prior to the span failure either centrally, or via distributed pre-planning (DPP) using the same embedded restoration protocol that can operate adaptively in real-time if needed [18]. The operational principles and the capacity design models of a span restorable network have been well studied in sources such as [5–9, 18–23].

While we acknowledge there are many other different kinds of mesh-based survivability schemes in general (e.g. path-based, segmented-path, shared or dedicated, etc…), the intention of this study is to propose and develop a basic framework using span-restorable network as a vehicle for research, so that such framework and principles can later be adapted to apply for other survivability architectures as well.

### 1.2 Related Work

Methods of designing more traditional types of telecommunication networks under demand uncertainty have been studied by Sen et al. [24] in the context of private line services network and Gaivoronski in ATM networks [25]. But aside from one other investigator that recently considered the problem (Kennington et al. [26]) in DWDM survivable networks, the literature that considers both network survivability and demand uncertainty is extremely limited. In [24] and [25], two-stage stochastic linear programs were proposed to find robust solutions under short-term demand fluctuations, where the private line requests are updated on a monthly basis. Due to the assumptions that each demand pair can take on 5–10 possible demand values and approximately 100 origin-destination (OD) pairs were considered, the number of discrete demand scenarios is enormous (i.e., $5^{100}$). With this uncertainty (clearly Level III category), specific heuristics and sampling techniques, such Stochastic Decomposition [24] and the Stochastic Quasi-gradient method [25], were developed for solving these large-scale stochastic programs. While the computational aspects of solving large-scale stochastic optimization problems are significant and on-going topics in mathematical research area [27, 28], the main goal of this work is to develop new capacity planning concepts and to provide general guidelines of how one can adopt the SP framework for his or her own planning problem under demand uncertainty.

A well known alternative to stochastic linear programming to plan against uncertainty is called Robust Optimization (RO). This has been used to solve problems relating to financial asset allocation and electric power capacity planning. Mulvey et al. present an excellent overview of RO with some motivational examples [29–31]. In [26], Kennington et al. adopts the idea of Mulvey and uses the RO method for solving routing and provisioning problems over DWDM networks. In contrast to the SP approach where there is a notion of "correcting" or "augmenting" the initial design through future decision, in RO, the idea is to find solely a "present decision" that minimizes the expected penalty (or called "regret" in [26]) due to the undesirable outcomes. Hence, if one of the what-if scenarios occurs, in SP, we explicitly know that we need Y units of capacity to augment the initial decision, whereas in RO, corrective actions are not part of the modeling consideration. In certain kinds of problems though, where it is not possible to alter the current outcome once it is decided, RO offers more flexible ways to describe the penalty than SP because no recourse action (nor the associated recourse cost to coping with the future) can be defined. Hence depending on whether the present decisions can be corrected and how we measure the impact of consequences, both SP and RO are both valid mathematical models for decision makers in dealing with uncertainty.

Recent work by Birkan and Kennington et al. [32] is probably the first publication that combines demand uncertainty and network survivability in a single optimization model. Building upon the RO model in [26], Birkan and Kennington extend it to include network survivability schemes, such as 1+1 dedicated protection, shared backup path protection, and *p*-cycles protection. While both SP and RO approaches provide the mathematical framework for incorporating uncertainty into the decision modeling, we believe that the SP approach more realistically reflects the capacity planning problem for a competitive facilities-based network operators standpoint, in a sense that operators could (and would) generally add capacity as needed to serve their growing customers.

There is another area of survivable network planning strategy called Multi-period Planning that considers incremental capacity and/or topology expansions in a multi-period time horizon [33–35]. In these studies, the demand forecast for each period is assumed to be known with certainty. By incorporating the entire time evolution of traffic demand and the cost data into account, the multi-period planning approach is proven to be a more cost-effective than a sequential single-period approach, where the expansion strategy is done separately in a chronological order. Although multi-period planning can deal with demand traffic evolution to some degree, we should note that this technique is as dependent on assumed perfect future forecasts as single period traditional methods. In fact, the effect of demand uncertainty can only increase as the length of the planning horizon increases.

### 1.3 Outline

The rest of the paper is organized as follows. In Section 2, we introduce two stochastic programming models for designing span-restorable networks under demand uncertainty. The first model corresponds to the SP model for minimum total cost including expected recourse costs where capacity is not modular. This serves as the basic framework onto which we add the details of modularity and the economies-of-scale in the second model. Section 3 gives details of the pan European test network and demand patterns. The experimental results are presented and their significance is discussed in Section 4. The overall conclusion is offered in Section 5.

## 2 Optimization Models for Span-Restorable Network Design under Uncertainty

We will now develop the optimization model including definition of the mathematical means through which we can capture the notion of future recourse to repair any shortcoming in the initial design in the face of future demand that is different from the nominal forecast. As mentioned, we work with span-restorable mesh networks. In this regard, our starting point is the model first introduced by Herzberg and Bye [21] to minimizing the total spare capacity cost of a fully span-restorable network, plus the extensions by Doucette and Grover [9] to create a *joint* formulation. In the joint model, the routing of demands is simultaneously optimized with the placement of spare capacity so as to minimize total working plus spare capacity in a survivable network.

### 2.1 Two-Part Span-Restorable Design (TP-SR) without Modularity

The key concept for the two-part span-restorable design can be explained as follows. In the first part, a budget $\boldsymbol{X}$ is invested initially and the second part considers the cost of a corrective action $\boldsymbol{Y(k)}$ to take place if a future scenario $\boldsymbol{k}$ (modeled by a set of scenarios $k \in U$) occurs. In our problem, the present outlay $\boldsymbol{X}$ is the cost of an initial network design that is assured to serve and protect all demands of the defined *nominal forecast*, $k_0$. The expected recourse cost $\boldsymbol{Y}$ is the mathematical expectation of recourse costs over all future scenarios $k$ which are possible and differ from $k_0$. Note that the nominal forecast can itself be arbitrarily certain—in many applications of this model it can represent the *current actual* demand pattern. Because the number of significantly different demand scenarios for long-term planning is typically in the order of tens (i.e., Level II model) [5–9, 13–26], the more general stochastic integer program can in practice be represented as an integer program of the deterministic equivalent form, for which standard solvers can be used. The two-part span-restorable capacity design (TP-SR) is as follows:

**Sets:**

- $S$ Set of all spans in the network, indexed by $j$ or $i$.
- $U$ Set of all possible future demand scenarios to be considered, index $k$
- $D$ Set of all origin-destination (OD) pairs in a demand matrix, index $r$
- $Q^r$ Set of pre-determined eligible working routes for OD pair $r$, index $q$
- $P_i$ Set of pre-determined eligible restoration routes available upon the failure of span i, index $p$

**Parameters:**

- $C_j$ Present cost of a unit capacity placed on span $j$
- $R_j$ Recourse cost of placing an extra unit capacity on span $j$ to cope with the unfolding of demand uncertainty. $R_j$ can simply be a multiplicative value of $C_j$, or any other absolute value specific for each span $j$
- $P_k$ Probability estimate for demand scenario $k$
- $d_k^r$ Magnitude of the bi-directional (integer) demand on node pair $r$ in scenario $k$
- $\zeta_j^{r,q}$ Equal to one if the $q$th eligible route for demands between node pair $r$ uses span $j$, zero otherwise
- $\delta_{i,j}^p$ Equal to one if the $p$th eligible route for span $i$ uses span $j$, zero otherwise

**Variables:**

- $w_j$ Number of working capacity units on span $j$ for the design
- $s_j$ Number of spare capacity units on span $j$ for the design
- $y_{j,k}$ Number of additional working capacity units that would have to be placed on span $j$ in future to cope with scenario $k$
- $z_{j,k}$ Number of additional spare capacity units required on span $j$ under future demand scenario $k$
- $g_k^{r,q}$ Working flow assigned on the $q$th working route to serve OD pair $r$in scenario $k$
- $f_{i,k}^p$ Restoration flow assigned on the $p$th restoration route upon the failure of span $i$ in scenario $k$

**TP-SR:** Minimize

$$\sum_{j\in S} C_j \cdot (w_j + s_j) + \sum_{j\in S}\sum_{k=U} P_k \cdot R_j \cdot (y_{j,k} + z_{j,k}) \tag{Obj. 1}$$

Subject to:

$$\sum_{q\in Q^r} g_k^{r,q} = d_k^r \quad \forall r \in D; \quad \forall k \in U \tag{1}$$

$$\sum_{r\in D}\sum_{q\in Q^r} \zeta_j^{r,q} \cdot g_k^{r,q} = w_j + y_{j,k} \quad \forall j \in S; \quad \forall k \in U \tag{2}$$

$$\sum_{p\in P_i} f_{i,k}^p = w_i + y_{i,k} \quad \forall i \in S; \quad \forall k \in U \tag{3}$$

$$s_j + z_{j,k} \geq \sum_{p\in P_i} \delta_{i,j}^p \cdot f_{i,k}^p \qquad \forall (i,j) \in S^2; \quad i \neq j; \quad \forall k \in U \tag{4}$$

$$y_{j,k}, z_{j,k} = 0 \quad k = 0; \quad \forall j \in S \tag{5}$$

The objective is to minimize the total cost of the network design (i.e. the first term in Obj. 1) plus the expected value of the future costs to augment the design to serve each possible demand scenario $k \in U$. The parameter $C_j$ is the present cost of a unit capacity on span $j$ and $R_j$ is the recourse cost if extra working capacity $y_{j,k}$ and/or spare capacity $z_{j,k}$ has to be added to span $j$ in the future under scenario $k$. In the general cost model where recourse costs are specific to each span to reflect practical realities such as dark fiber existing on some spans, but not on others, or the cost of leasing capacity on particular spans or routes from a third party carrier, and so on. For comparative study, we will use a common recourse cost factor for all spans, i.e., $R_j = \alpha^* C_j$ and hereafter we refer $\alpha$ as the recourse cost factor.

In each scenario $k$, constraint (1) allocates the demand flows $g^{r,q}$ of OD pair $r$ onto working routes $q$ in $Q^r$, representing a set of pre-determined eligible routes for the demands. Constraint (2) determines the working capacity $w_j$ required on each span to simultaneously serve the demand flows. $\zeta_j^{r,q}$ is an input parameter which is 1 if the $q$th working route for OD pair $r$ uses span $j$, zero otherwise. For any scenario $k$ where there is a mismatch between the level of demands and the initially installed working capacities, extra working capacities $y_{j,k}$ are added to serve the unexpected demands in the future design.[3]

Constraints (3) and (4) correspond to the network survivability constraints based on span restoration. Note that other span-based restoration schemes such as $p$-cycles can also be adapted to this formulation by employing a corresponding set of constraints here that are specific to the particular other restoration mechanism used. Constraint (3) ensures that the total of all restoration flow $f_{i,k}^{p}$, assigned to the eligible routes in $P_i$ when span $i$ fails, satisfies the restoration requirement for that failure scenario (i.e. the total working capacity affected). Although this constraint enforces 100% restorability of each individual span, multiple levels of service-survivability (i.e. multiple quality-of-protection service classes) could also be considered in the formulation by adding the detailed constraints of the type developed in [23] at this point in the model. Constraint (4) generates the required spare capacities $s_j$ to support the largest of all simultaneously imposed restoration flows crossing each span under each failure scenario and in every demand scenario. If there is a shortage in spare capacity $s_j$ on span $j$ under possible scenario $k$, extra spare capacities $z_{j,k}$ would be added. A very important detail is how we assert that the nominal forecast *must* be satisfied while for all other scenarios, we only consider their cost of repair should they arise. This is done simply by imposing $y_{j,k} = 0$ and $z_{j,k} = 0$ for $k_0$ in constraint (5), which says that there can be no "extra" capacity of either type associated with ensuring the routability and restorability constraints above. This forces the design to contain adequate "present capacities," $w_j$ *and* $s_j$, for the nominal scenario $k_0$. The corresponding constraints can, for all other scenarios, be satisfied by the admission of non-zero "possible future additional capacities" $y_{j,k}$ and $z_{j,k}$. As a result of this effect, it is easy to note that two other quite relevant types of design can also be obtained:

(i) If constraint (5) is simply deleted, the design that results is the network which represents the least expected (total) cost strategy over all possible futures. In this case what is built "today" in effect is the component of all possible future networks required, that is common enough to the range of future outcomes to be worth investing in at present, given the cost of capacity at present is less than in future (with recourse cost factors >1). Conversely, if the recourse cost factor is less than 1, the optimal present network cost can in fact be zero since it is more economical to wait and build the network when uncertainty unfolds.

(ii) If constraint (5) is asserted for *all* recourse capacity variables, i.e., $y_{j,k} = z_{j,k} = 0$ for all span $j$ and all scenarios $k$, then the design that results is the special case of a network that is guaranteed at initial construction to serve all defined future scenarios. In the language of [10] this brute-force kind of future-proofing is what is called a "fat solution". It serves all possible future scenarios by its basic design but is also the most expensive strategy in general.

In the results, we will make various comparisons between the main TP-SR design model and the two related extremes that are so easily derived from it simply by variants on Constraint (5). Unlike the traditional span-restorable design whose objective is to minimize solely the initial total capacity, this two-part model allows us to minimize present investment as well as the expected consequences and risk (characterized by $R_j$) of the present decision. It is also interesting to note that an associated output from this model is not only full details of the present network to build, but also each of the specific future *recourse actions* (through $y_{j,k}$ and $z_{j,k}$) that are required to cope for whatever demand scenario actually arises. Implicitly in this model, the coping or adaptation information not only says where to add capacities, how to route the unexpected (relative to nominal) working demand and updates to the restoration routing plans, but it may also include changes in the routing of one or more existing paths as part of the overall future adaptation plan. The frequency of such implied re-routing is thought to be quite low in the basic non-modular model, however. Because even under joint optimization it is generally known that shortest routes tend to remain near-optimal for working paths.

### 2.2 Two-Part Span-Restorable Design with Modularity and Economy of Scale Effects (TP-MSR)

In practice the available capacity increments of actual transmission systems are usually modular in nature. The costs of increasing modular sizes follow some stair-step function versus capacity. For instance, typical module sizes in SONET may be OC-12, OC-48, OC-192, etc. and an OC-192 will generally cost significantly less than four times the cost of an OC-48. In other words there is economy of scale in transmission capacity. This is an effect that can be of benefit to network operators when included in network planning.

The significance and advantages of directly incorporating modular-capacity effects into the network design formulation have already been discussed in [9]. But there is even greater motivation and relevance to considering modularity in the context of "future proof" planning. A large capacity module obviously costs more than a smaller one, and in a current design only context, it may not prove in. But if the design problem is also somehow forward-looking, the greater present expenditure on a large module may reduce future recourse costs. Especially when significant economy-of-scale effects are present, it is reasonable to expect that modularity may be a very important effect in reducing total of both present and future recourse costs. Thus, what is appealing about the following formulation is that we combine modularity and economy-of-scale effects, and bring them into the two-part optimization framework. This model (TP-MSR) and some new notations required are as follows. All previously defined sets, parameters and variables continue to apply. To these we add:

**Additional Set:**

$M$: Set of module capacities (e.g., $M=4$).

**Additional Parameters:**

$Z^m$: Number of capacity units for the $m$th module size (e.g. 3, 12, 48, 192).

$C_j^m$: Cost of a module of size $m$ placed on span $j$ and is used to reflect different degrees of economy-of-scale.

$R_j^m$: Recourse cost factor of a module of size $m$ placed on span $j$ relative to $C_j^m$.

**Additional Variables:**

$n_j^m$: Number of modules of type $m$ placed on span $j$ for the initial design.

$e_{j,k}^m$: Number of extra modules of type $m$ required on span $j$ to cope with the uncertain demand scenario $k$

**TP-MSR:** Minimize

$$\sum_{m\in M}\sum_{j\in S} C_j^m \cdot n_j^m + \sum_{m\in M}\sum_{j\in S}\sum_{k=U} P_k \cdot R_j^m \cdot e_{j,k}^m \tag{Obj. 2}$$

Subject to (1), (2), (3), (4) and

$$w_j + s_j \le \sum_{m\in M} Z^m \cdot n_j^m \quad \forall j \in S \tag{6}$$

$$y_{j,k} + z_{j,k} \le \sum_{m\in M} Z^m \cdot e_{j,k}^m \quad \forall j \in S;\ \forall k \in U \tag{7}$$

$$e_{j,k}^m = 0 \quad k=0;\ \forall j \in S;\ \forall k \in U \tag{8}$$

The new objective function (Obj. 2) minimizes the total of the cost of all *modules initially placed* plus the expected cost of extra capacity module placements in future. $C_j^m$ is the cost of placing a single module $m$ on span $j$ at present, and $R_j^m$ is the cost of placing new modules $m$ on span $j$ in the future as needed. Constraint (6) asserts that the capacity of the set of initially placed modules is adequate for the current demands and their protection. Constraint (7) relates the presently placed modular capacities to the unfulfilled requirements that are implied under each future outcome scenario, which collectively determine the expected recourse cost in the second part of the objective function. Constraint (8) plays the same role as (5), ensuring that the design is a fully feasible for the nominal demand forecast (or presently existing demand).

## 3 Experimental Design

### 3.1 Economy of Scale Model for Capacity

Let us now define a general model for module costs (i.e., $C_j^m$ parameter) under various economies-of-scale assumptions. Given the cost of a minimum common-factor module, the cost of a larger module size (size2) is:

$$\text{For cost scheme } m \times n \times : \text{Cost(size2)} = \text{Cost(size1)} \cdot n^{\frac{\log(\text{size2}/\text{size1})}{\log\,(\text{m})}} \tag{9}$$

where $m$ and $n$ characterize the economy of scale effect in that we obtain "$m$ times capacity for $n$ times the cost." This is denoted "$m \times n \times$" economy of scale. For example, the cost of 48-channel module under $4x$ $2x$ economy of scale

*Table 1.* Cost of modules under different economy-of-scale scenarios.

| Economy of Scale | Module Size 3 | Module Size 12 | Module Size 48 | Module Size 192 |
|---|---|---|---|---|
| $2\times 2\times$ | 30 | 120 | 480 | 1920 |
| $3\times 2\times$ | 30 | 72 | 173 | 414 |
| $4\times 2\times$ | 30 | 60 | 120 | 240 |
| $6\times 2\times$ | 30 | 51 | 88 | 150 |

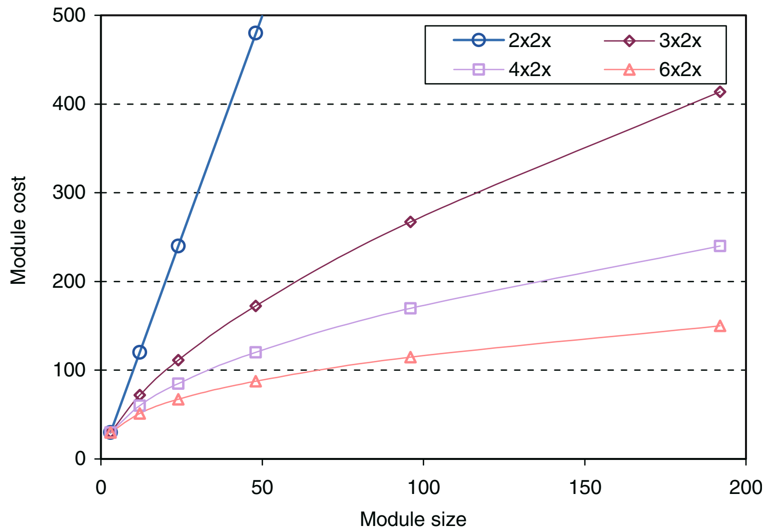


*Fig. 2.* Illustrating the difference in module cost among various economies-of-scale.

is 120, provided that the cost of a 3-channel module is 30 (i.e., $size1 = 3$; $\mathrm{Cost}(size1) = 30$; $size2 = 48$; $m = 4, n = 2$). Of course if we set any $m = n$ we return to linear cost with capacity. Table 1 lists the actual economy of scale cost-capacity progressions generated by this model and used in our following test cases.

### 3.2 Test Networks and Nominal Demand Forecast

A well-documented pan European network, COST239 network [36], is used to implement both non-modular and modular design formulations. This network has 11 nodes and 26 spans with an average nodal degree of 4.7. The topology is shown in Fig. 3. The next step is to generate a nominal demand forecast and a set of plausible demand scenarios. For the nominal forecast, we chose to create it based on a gravity-based demand model [9], rather than the proposed forecast published in [36]. The gravity-based model assumes that the number of bi-directional demands exchanged between two nodes is proportional to the product of the degrees of the two nodes and inversely proportional to the distance between them. Although this model may not reflect the present real-world demand traffic, it does allow us or other researchers to reproduce the exact starting demand forecast or other repeatable demand scenarios for future comparative studies. The distances in Equation (10) refer to Euclidean distances between any two nodes (a,b) and the constant is simply a uniform scaling factor for adjusting the traffic to the desired volume level. Table

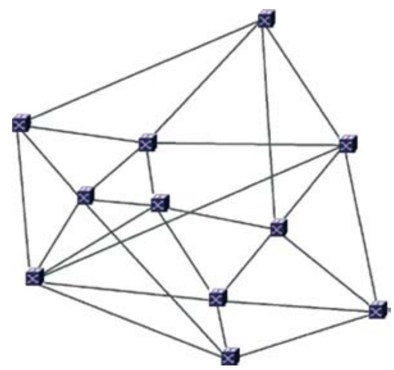

*Fig. 3.* The COST239 network topology.

*Table 2.* Topology and nominal forecast characteristics.

| Nodes | Spans | Span Distance [min, avg, max] | No. of OD Pairs | Demand/Pair | Total Demand | Constant in (10) |
|---|---|---|---|---|---|---|
| 11 | 26 | [210, 579, 1310] | 55 | 9.76 | 547 | 60 |

*Table 3.* Characteristics of the random demand scenarios.

| Demand Scenario, k | Total Demand Volume, $\sum_{r\in D} d_k^r$ | Relative Demand Volume, $\sum_{r\in D} d_k^r / \sum_{r\in D} d_0^r$ | Pattern Forecast Accuracy[4] | Assigned Probability, $P_k$ |
|---|---|---|---|---|
| 0 (nominal) | 547 | 1.00 | 1.00 | 0.079 |
| 1 | 146 | 0.27 | 0.85 | 0.063 |
| 2 | 299 | 0.55 | 0.85 | 0.066 |
| 3 | 457 | 0.84 | 0.85 | 0.072 |
| 4 | 597 | 1.09 | 0.87 | 0.072 |
| 5 | 744 | 1.36 | 0.85 | 0.071 |
| 6 | 955 | 1.75 | 0.91 | 0.067 |
| 7 | 911 | 1.67 | 0.81 | 0.065 |
| 8 | 1107 | 2.02 | 0.86 | 0.061 |
| 9 | 1287 | 2.35 | 0.85 | 0.057 |
| 10 | 1358 | 2.48 | 0.81 | 0.051 |
| 11 | 1546 | 2.83 | 0.85 | 0.045 |
| 12 | 1571 | 2.87 | 0.85 | 0.043 |
| 13 | 1874 | 3.43 | 0.86 | 0.042 |
| 14 | 1878 | 3.43 | 0.84 | 0.039 |
| 15 | 2187 | 4.00 | 0.88 | 0.030 |
| 16 | 2088 | 3.82 | 0.83 | 0.029 |
| 17 | 2217 | 4.05 | 0.86 | 0.021 |
| 18 | 2367 | 4.33 | 0.86 | 0.019 |
| 19 | 2718 | 4.97 | 0.86 | 0.0072 |
| Min | 146 | 0.27 | 0.81 | 0.0072 |
| Mean | 1343 | 2.53 | 0.85 | 0.05 |
| Max | 2718 | 4.97 | 0.91 | 0.079 |

2 summarizes the properties of the network and nominal demand forecast.

$$\text{demand}(a,b) = \text{int}\left[\frac{\text{nodal degree}_a \times \text{nodal degree}_b}{\text{distance}_{a-b}} \cdot \text{constant}\right] \tag{10}$$

### 3.3 Alternate Futures for the Test Case

To reflect the alternative futures, a set of 20 future demand scenarios was also generated, where one represents the "$k_0$" nominal forecast, and the other 19 demands patterns are generated by random variation around the values of the $k_0$ demand matrix and assigned a decreasing probability $P(k)$ based on their total absolute value difference from the $k_0$ demand scenario, as shown in Fig. 4. Note that although 20 scenarios were used for this particular study, one can always increase or reduce the number of scenarios for different level of uncertainty characterization. However, in order to solve a large-scale stochastic formulation (e.g., scenarios are in the order of thousands), stochastic sampling or decomposition techniques as discussed in Section 1.2 might be required to break down the problem into manageable blocks. Table 3 summaries the characteristics of the demand scenarios. For research purposes, we generate these future scenarios in a systemic way. But in practice, network planners can substitute the actual "what-if" scenarios that they are most interested in or concerned about, as the suite of scenarios given to the model. Notably these can be the same set of detailed what-if scenarios the planners may already typically develop for separate study with conventional single-forecast design tools.

### 3.4 Eligible Routes for the Design Formulations

The last experimental aspect is the generation of eligible route sets (i.e., $Q^r$ and $P_i$). While we

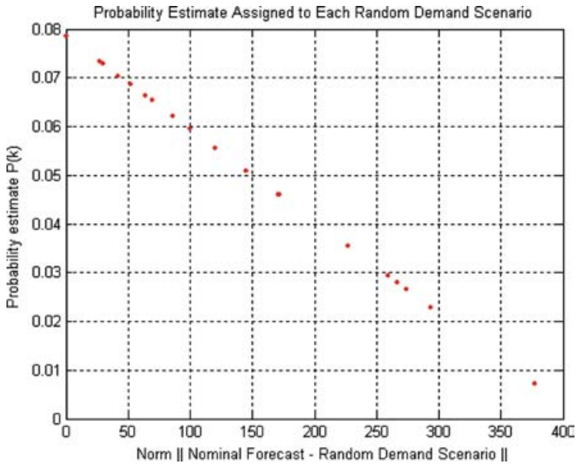


*Fig. 4.* Probability assignment for input demand scenarios.

can numerate all distinct routes to form our eligible route sets, in practice, short-distance routes are often preferred to meet physical specifications such as optical signal path quality and restoration speed. A study by Herzberg also shows that screening out the unnecessarily long routes often helps to speed up the computation process without losing true optimality [21]. Hence for the following experiment, 5 shortest working routes (by distance) for each OD pair and 10 shortest restoration routes (also by distance) for each span are selected as the eligible route sets. These result in a total of 275 eligible working routes and 260 eligible restoration routes.

## 4 Results and Discussion

The two formulations were implemented in AMPL [38] and solved with CPLEX 9.0 MIP Solver [39] on a four-processor Ultrasparc at 450 MHz and 4 GB of RAM running Sun Solaris 8 OS. For the TP-SR formulation, all designs were obtained to a MIPGAP of 1% (guarantee to be within 1% of the optimum) and within twenty minutes of run time. For the TP-MSR designs run times were considerably longer due to the additional dimension of modularity $M$, the MIPGAP was therefore relaxed to 10%.

### 4.1 General Observations of Two-Part Capacity Planning Strategy

Table 4 shows the results of the TP-SR (non-modular) formulation and compares them to the conventional span-restorable design with four different recourse costs.

In the "conventional" approach, we consider a minimum-cost span-restorable mesh design based solely on the nominal forecast. The cost of this conventional design refers to the "initial cost". The initial cost for TP-SR designs is the cost of the first part to build, which might include certain initially built-in added capacities to hedge against possible future costs of recourse. The "expected future cost" for both cases refers to the probability-weighted cost of adding needed capacity to adjusting the initial design to cope with future requirements, i.e. $\sum_{j\in S}\sum_{k=U} P(k)\cdot R_j\cdot(y_{j,k}+z_{j,k})$.

At low recourse cost (i.e., when $R_j = C_j$), the advantage of the two-part design is insignificant because it costs the same in the future to take recourse as it does to build it in now. However, as the recourse cost increases, the long-term benefit of building a more "future proof" network now, and paying less in the future for recourse becomes obvious. At a recourse cost factor of 3, the two-part design has expected whole life cost that is approximately 19% lower than the strategy of building a currently optimal network to an assumed known forecast, and augmenting it as needed in future. The cost benefit of the two-part design increases as the recourse cost assumption increases.

In Fig. 5, we compare the future-aware designs to conventional designs that attempt to have some future-proofing by considering demand matrices other than the nominal forecast. The "expected forecast" is the probability-weighted demand pattern calculated based on the 20 scenarios and the "maximum forecast" is where each OD pair takes the maximum demand of all the scenarios. We see that TP-SR approach always outperforms these pre-tuning forecast attempts with the conventional model. At low recourse cost, the "maximum forecast" design tends to over-build the capacity initially and fail to exploit the advantage of building in future. The "expected forecast" design also suffers from paying expensive penalty in the high recourse region.

Hence with no consideration of the recourse in advance and unconsciously making an investment plan targeted on single demand forecast, the conventional approach can easily lead to a capacity plan that will suffer from either severe capacity surplus or deficiency.

*Table 4.* Comparison between conventional and two-part designs (cost in thousands).

| Design | Conv. | TP-SR | Conv. | TP-SR | Conv. | TP-SR | Conv. | TP-SR |
|---|---|---|---|---|---|---|---|---|
| Recourse Cost Factor, $\alpha$ | 1 | | 2 | | 3 | | 5 | |
| Initial Cost | 532 | 533 | 532 | 942 | 532 | 1,308 | 532 | 1,527 |
| Expected Future Cost | 557 | 557 | 1,115 | 620 | 1,672 | 488 | 2,787 | 503 |
| Total | 1,089 | 1,090 | 1,647 | 1,562 | 2,204 | 1,796 | 3,319 | 2,030 |
| Difference | 0.09% | | 5.16% | | 18.51% | | 38.84% | |

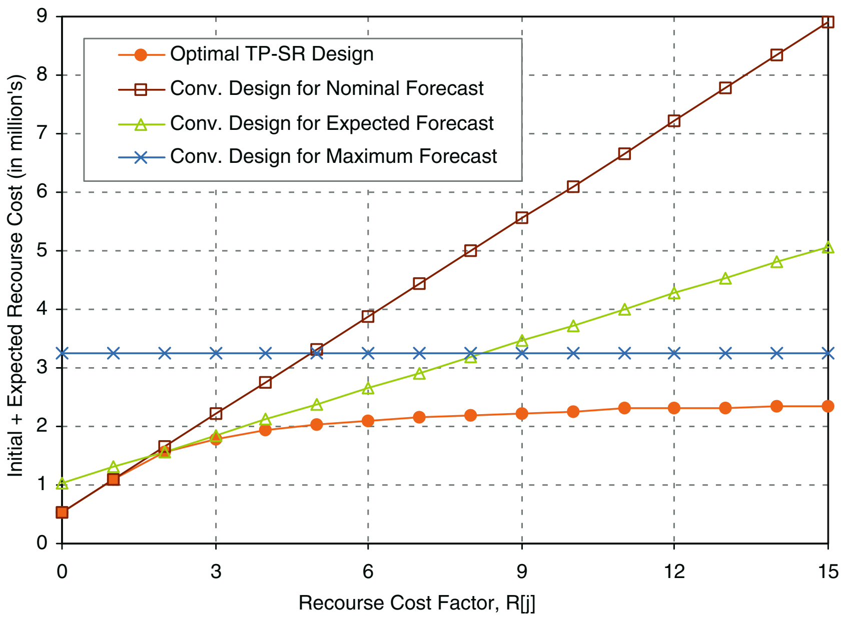


*Fig. 5.* Cost-benefit of the (non-modular) future-aware designs over different conventional designs.

While it is important to portray in general how the recourse factor affects the overall long-term cost, it is also meaningful to show the trade-off between the long-term cost and the initial design cost under different recourse assumptions, as illustrated in Fig. 6. As should be expected, at a recourse factor of one (or less), the optimal initial design is simply the one designed for the $k_0$ nominal forecast alone with conventional methods. And if we increase the cost of the initial designs (i.e., the successive points to the right), we will end up over-building the capacity unnecessarily. This makes sense because under low recourse assumption, we are encouraged to build only what is needed now, and wait for the future as there is so little penalty to add more later. As the recourse cost factor increases, however, we can optimize the present investment and come up with a capacity configuration that has the least expected repair cost to cope with future scenarios. For the highest recourse, the top curve indicates that the optimal initial design cost to invest is about 2.66 million, where the expected future cost is zero. In fact, this corresponds to an initial design that completely satisfies all of the possible scenarios without any future additions (i.e. the “fat solution” we mentioned in Section 2.1).

### 4.2 Effects of Modularity and Economy-of-Scale: Results with TP-MSR

For tests with the modular capacity design formulation, we used the same input demand sets as described in Section 3. Four module sizes, namely Size-3, Size-12, Size-48 and Size-192 as well as

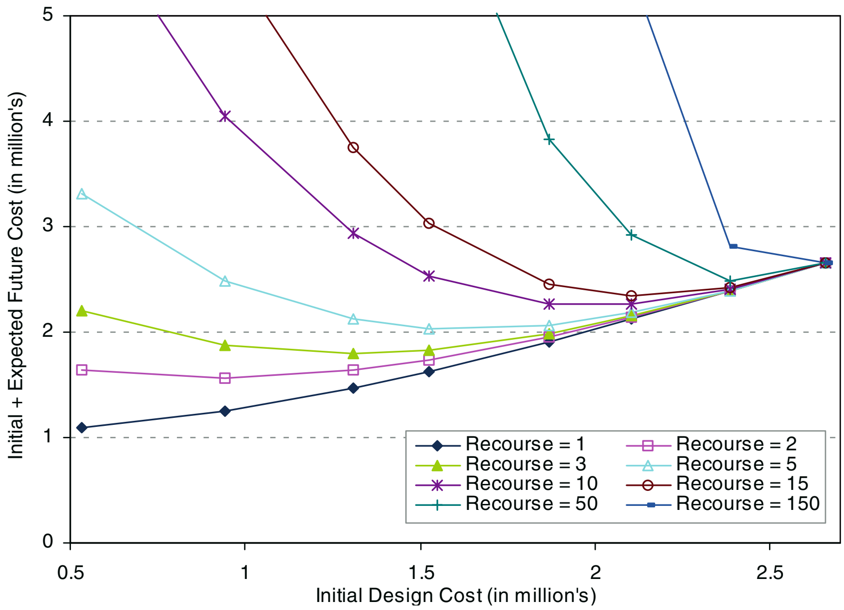


*Fig. 6.* Total versus initial cost of future-aware designs at varying recourse cost factors.

*Table 5.* Comparison between conventional and TP-MSR designs under $2 \times 2\times$ model.

| Design | Conv. | TP-MSR | Conv. | TP-MSR |
|---|---|---|---|---|
| Recourse Cost Factor | 3 | | 10 | |
| Initial Cost | 5407 | 13,740 | 5407 | 18,953 |
| Expected Future Cost | 17,299 | 4746 | 57,290 | 4556 |
| Total | 22,706 | 18,486 | 62,697 | 23,509 |
| Difference | 18.59% | | 62.50% | |

*Table 6.* Comparison between conventional and TP-MSR designs under $3 \times 2\times$ model.

| Design | Conv. | TP-MSR | Conv. | TP-MSR |
|---|---|---|---|---|
| Recourse Cost Factor | 3 | | 10 | |
| Initial Cost | 2397 | 3850 | 2397 | 5183 |
| Expected Future Cost | 4640 | 1008 | 15,526 | 603 |
| Total | 7037 | 4858 | 17,923 | 5786 |
| Difference | 30.96% | | 67.72% | |

*Table 7.* Comparison between conventional and TP-MSR designs under $4 \times 2\times$ model.

| Design | Conv. | TP-MSR | Conv. | TP-MSR |
|---|---|---|---|---|
| Recourse Cost Factor | 3 | | 10 | |
| Initial Cost | 1559 | 2459 | 1559 | 3068 |
| Expected Future Cost | 2023 | 493 | 6741 | 294 |
| Total | 3582 | 2952 | 8300 | 3,362 |
| Difference | 17.59% | | 59.49% | |

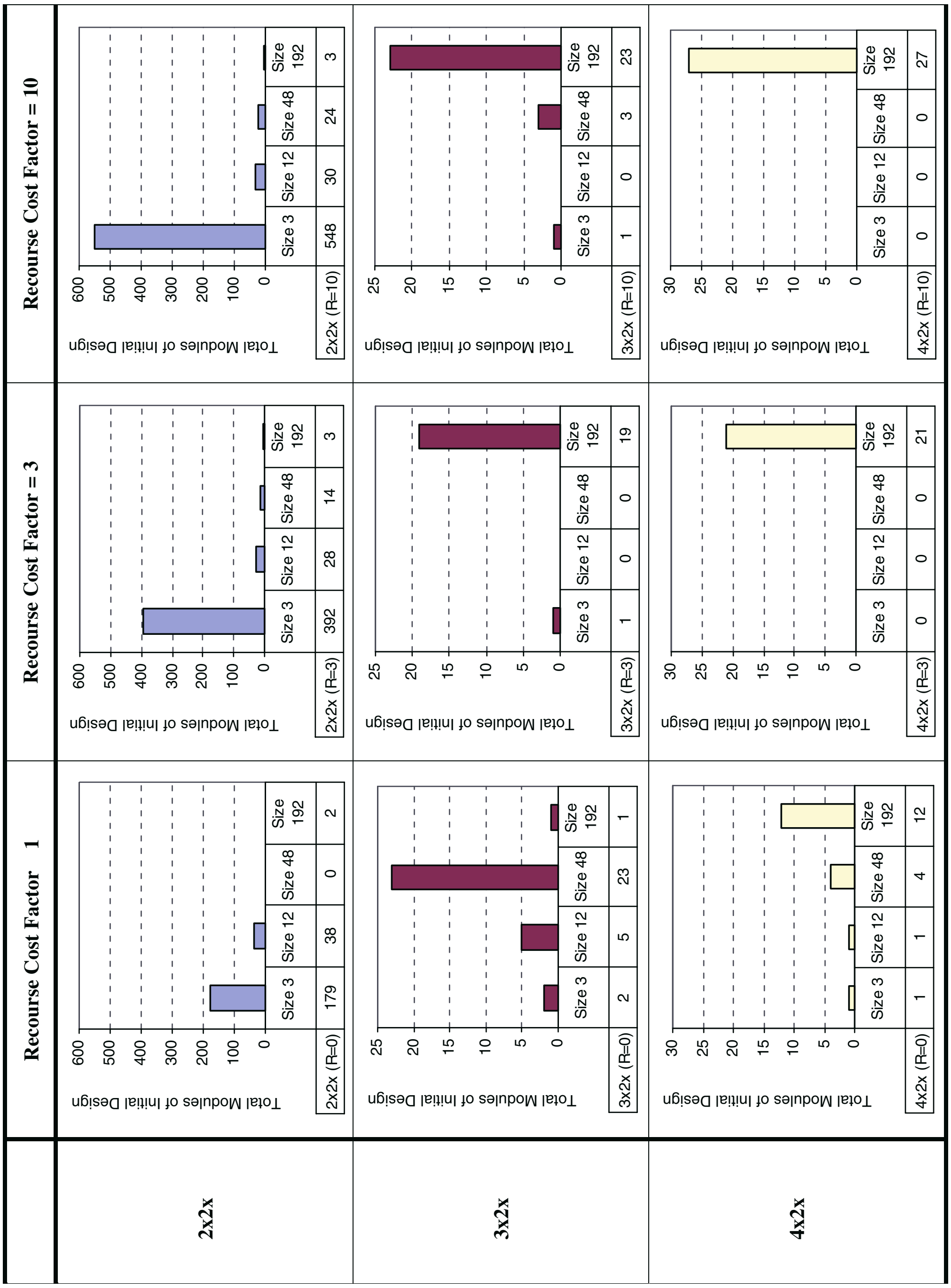


*Fig. 7.* Initial design costs under various influences of recourse costs and economy-of-scales.

three economies-of-scale (i.e. $2 \times 2\times, 3 \times 2\times, 4 \times 2\times$) were assumed. The associated module costs are listed in Table 1. Although in practical systems the absolute capacity values may differ from those used here, the total range of capacities represented and the number of such module types are quite characteristic of actual SONET OC-n line systems commercially available.

Tables 5 to 7 compare the results of the conventional and TP-MSR designs under different economy of scale assumptions. Similar to the previous finding of the non-modular designs in Section 4.1, the two-part modular model shows significantly lower expected total life cost than traditional designs. For recourse cost factor less than one (i.e., $\alpha \leq 1$), the optimal designs are equivalent to the conventional designs that is strictly built for the nominal forecast. In the cases where $\alpha = 3$ or $\alpha = 10$, the TP-MSR designs result in a total expected cost reduction of $\sim 22\%$ and $\sim 63\%$ (on average) compared to the conventional designs that is faced with the same range of possible futures. In particular under the $3 \times 2\times$ model, the cost reductions are the greatest.

Figure 7 identifies a complete set of optimal designs and each figure in the matrix corresponds to the optimal initial design for a unique recourse and economy-of-scale combination. The optimal designs are arranged with increasing recourse cost factors for each column and classified by different economies of scale in each row. As we move from the left to right column, we see that higher recourse costs generally encourage building more expensive initial designs to reduce the expected penalty in the future. Moving the top to bottom row we also see how economy of scale generally favors the installation of large-size capacity modules. In the case where $\alpha \leq 1$, the largest size modules change from 179 *size-3* modules, to 23 *size-48* modules to 12 *size-192* modules. For higher recourse cost factors, the benefit of deploying large size systems is even more obvious (i.e. the optimal size jumps from *size-3* to *size-192*). Probably the most interesting scenarios are when we have the strongest economy-of-scale and high recourse cost assumption, i.e. the $4 \times 2 \times (\alpha = 3)$ and $4 \times 2 \times (\alpha = 10)$ designs. In these cases the optimal initial designs consist of only the largest modules.

## 5 Concluding Discussion

We have developed two integer program formulations for the design of non-modular and modular span-restorable networks under demand uncertainty. Stochastic programming is used as the mathematical framework to model these formulations that minimizes the initial cost of network build and the expected value of future recourse actions to augment the design to serve the possible "what-if" demand scenarios. One significant finding from this study is that if the cost of building future capacity is greater than that of building it now, the notion of taking the recourse cost and future demand scenarios into a two-part capacity design becomes very vital since such design could lead to huge long-term cost saving, comparing to traditional designs that consider only a single nominal forecast. For the non-modular design under a recourse cost factor of 3, an approximately 19% cost reduction is observed. Under the $3 \times 2\times$ economy of scale model, the two-part modular design leads to 31% saving of the expected total life cost. Another interesting observation is when modularity and moderate economy of scale (i.e., $3 \times 2\times$ or stronger) are considered, the most future-proof designs tend to deploy large modular systems rather than many small-size modules.

While in this particular study we work with span-restorable networks and assume uniform recourse cost factor for all spans, the two-part formulations can be adapted to other survivable network architectures, and the recourse costs can also be set specifically for each span to reflect the cost of lighting up new fiber system or leasing capacity from a third-party carrier or any other practical realities. In fact, some issues about recourse costs warrant some specific closing comments. One general view of the future is that "capacity is always on an ever-decreasing cost curve"—so would recourse cost factors always be less than one? If this were so, then optimum strategy is always just to build the minimum that is needed right now, and add anything else that is needed in future. Given the hard times the telecom industry has recently endured, a common attitude is, perhaps understandably, similarly to minimize costs now regardless of the future consequences.

But in practice channels cannot be cost-effectively added one at a time just when needed, at ever decreasing cost. Clearly where actual installation of cables is involved, there is a very high recourse cost associated with pulling in more cable or digging up streets a second time. Similarly, incremental growth to blindly exceed the space, power or cooling capacities in equipment housings or, say, the maximum port counts on a cross-connect, all trigger a large recourse cost to upgrade such basic infrastructure in future from an initially inadequate first installation. A modular cost addition of an OC-48 in future to an initial OC-48 may still cost more than if an OC-192 was placed initially. In addition, each "truck roll", each maintenance action scheduled and each network change all trigger added operational expenses and risks associated with in-service upgrades. There are also opportunity costs associated with having to take recourse in future, as opposed to having the capacity already present in a future-proof design. For instance, even if the actual equipment cost were free, the very act of taking recourse in future means that more staff were involved, staff that were not then working on other opportunities or problems, and there may even have been customer impact and lost revenues associated with not having capacity present in advance when needed. Thus, when assigning recourse costs in this type of future-planning model, it is important to take all factors into account, including even the possible costs of potential new revenues or customers that may not be accessible if time for recourse is first required. Thus, when fully considered, it seems unlikely that any actual planning problems would collapse into the trivial case of all recourse costs being less than unity. Even if the transmission equipment itself was given away by vendors, there are always significant real operational and business costs associated with having to corrective actions. This planning model allows one to find just the right balance between putting off some eventualities into the future, while building to accommodate others right now.

## Acknowledgments

We would like to thank Rainer Iraschko (from Telus) and Peter Giese (from TRLabs) for valuable comments on the manuscript.

## Notes

1. While the term "two-stage" is generally used in Stochastic Programming literature, we say "two-part" to avoid confusion with the predominance of other work in network design where "two-stage" implies that two successive computational "stages" are used. Equivalently, the form of model we develop is also known as a bicriteria optimization problem. But as we pose the problem, it is solved in a single computational stage or step. The application of the two-stage concept is based in part on previous work presented in [11].
2. By facilities-based providers, we refer to the ones that own or lease a substantial portion of the plant, property and equipment necessary to provide a broad range of integrated communications services. Level 3 Communications [12], Global Crossing and Qwest Communications are some examples.
3. Note that the "extra" working capacities $y_{j,k}$ (and later $z_{j,k}$ for spare capacities) take only zero or positive values. This means that no *removal* of initially installed capacity is ever anticipated. This does not imply, however, that the future demand scenarios only represent growth in demands. Under each future scenario here, some demands decrease while others increase. If, under a given future scenario, some initially placed capacity is unused, this is accepted simply as an implication of what was nonetheless an optimum overall strategy. On the other hand, any actually present capacity is as fully and efficiently re-used by the solver under every future scenario before new recourse costs are added, so there is a great built-in propensity not to have very much unused capacity in future scenarios.
4. Pattern forecast accuracy (PFA) was proposed in [37] as a measure to quantify the extent by which an actual future demand pattern differs from that which was forecast. Its value ranges from one (when the actual demand pattern is identical to the forecast) to zero (for a complete mismatch).

## References

[1] R. Fildes, V. Kumar, Telecommunications demand forecasting–a review, International Journal of Forecasting, vol. 18, no. 4, (2002), pp. 489–522.

[2] T. Islam, D. G. Fiebig, N. Meade, Modelling multinational telecommunications demand with limited data, International Journal of Forecasting, vol. 18, no. 4, (2002), pp. 605–624.

[3] L.G. Kazovsky, G. Khoe, M. Deventer, Future telecommunication networks: Major trend projections, IEEE Communications Magazine, vol. 36, no. 11, November 1998, pp.122–127

[4] S. Verbrugge, D. Colle, M. Pickavet, P. Demeester, Common planning practices for network dimensioning under traffic uncertainty, 4th International Workshop on the Design of Reliable Communication Networks (DRCN 2003), Banff, Alberta, Canada, (October 19–22, 2003), pp. 317–324.

[5] W. D. Grover, J. Doucette, M. Clouqueur, D. Leung, D. Stamatelakis, New options and insights for surviv-

able transport networks, IEEE Communications Magazine, vol. 40, no. 1, (January 2002), pp. 34–41.
[6] M. Clouqueur, W. D. Grover, Dual failure availability analysis of span-restorable mesh networks, IEEE Journals on Selected Areas of Communications (JSAC), vol. 20, no. 4, (May 2002), pp. 810–821.
[7] W. D. Grover, The protected working capacity envelope concept: an alternate paradigm for automated service provisioning, IEEE Communications Magazine, vol. 2, no. 1, (January 2004), pp. 62–69.
[8] M. Clouqueur, W. D. Grover, D. Leung, O. Shai, Mining the rings: strategies for ring-to-mesh evolution, 3rd International Workshop on the Design of Reliable Communication Networks (DRCN 2001), Budapest, Hungary, (October 2001), pp. 113–120.
[9] J. Doucette, W. D. Grover, Influence of modularity and economy-of-scale effects on design of mesh-restorable DWDM networks, IEEE JSAC, vol. 18, no. 10, (October 2000), pp. 1912–1923.
[10] P. Kall, S. Wallace, Stochastic Programming, (John Wiley & Sons, Chichester, New York, 1994).
[11] D. Leung, W. D. Grover, Restorable mesh network design under demand uncertainty: Toward "future proof" transport investments, Optical Fiber Communication Conference (OFC 2004), Los Angeles, California, (February 22–27, 2004), pp. ThO2.
[12] Level 3 Communications, Inc. 2002 Annual Report. http://www.level3.com. [date accessed: June 4, 2004]
[13] H. Courtney, J. Kirkland, P. Viguerie, Strategy under uncertainty, Harvard Business Review, vol. 75, no. 6, (November 1997), pp. 67–79.
[14] G. B. Dantzig, Linear programming under uncertainty, Management Science, vol. 1, no. 3/4, (April – July, 1955), pp. 197–206.
[15] S. J. Hood, S. Bermon, F. Barahona, Capacity planning under demand uncertainty for semiconductor manufacturing, IEEE Trans. On Semiconductor Manufacturing, vol. 16, no. 2, May 2003, pp. 273–280.
[16] H. D. Sherali, A. L. Soyster, F. H. Murphy, S. Sen, Intertemporal allocation of capital costs in electric utility capacity expansion planning under uncertainty, Management Science, vol. 30, no. 1, (January 1984), pp. 1–19.
[17] D. T. Gardner, J. S. Rogers, Planning electric power systems under demand uncertainty with different technology lead times, Management Science, vol. 45, no. 10, (Oct 1999), pp. 1289–1306.
[18] W. D. Grover, Self-organizing broadband transport networks, IEEE Proceedings: Special Issue on Communications in the 21st Century, vol. 85, no. 10, (October 1997), pp. 1582–1611.
[19] W. D. Grover, Mesh-based Survivable Networks: Options for Optical, MPLS, SONET and ATM Networking (Prentice Hall PTR, August 2003).
[20] M. Clouqueur, Availability of service in mesh-restorable transport networks, Ph.D. Thesis, University of Alberta, Edmonton, Alberta, Canada, November 2003.
[21] M. Herzberg, S. Bye, An Optimal Spare Capacity Assignment Model for Survivable Network with Hop Limits, (IEEE GLOBECOM 1994, San Francisco, USA), pp. 1601–1606.
[22] R. R. Iraschko, M. MacGregor, W. D. Grover, Optimal capacity placement for path restoration in STM or ATM mesh survivable networks, IEEE/ACM Transactions on Networking, vol. 6, no. 3, (June 1998), pp. 325–336.
[23] W. D. Grover, M. Clouqueur, Span-restorable mesh network design to support multiple quality of protection (QoP) service-classes, 1st Int'l Conference on Optical Communications and Networks (ICOCN'02), Singapore, (Nov. 11–14, 2002), pp. 321–323.
[24] S. Sen, R. Doverspike, S. Cosares, Network planning with random demand, Telecommunication Systems 3, (1994), pp. 11–30.
[25] A. Gaivoronski, Stochastic programming approach to the network planning under uncertainty, Optimization in Industry 3, (John Wiley & Sons, 1995), pp. 145–163.
[26] J. Kennington, E. Olinick, K. Lewis, A. Ortynski, G. Spiride, Robust solutions for the DWDM routing and provisioning problem: Models and algorithms, Optical Networks Magazine, vol. 4, no. 2, (March 2003), pp. 74–84.
[27] J. L. Higle, S. Sen, Stochastic decomposition: An algorithm for stage linear programs with recourse, Mathematical Operations Research, vol. 16, (1991), pp. 650–669.
[28] Yu. Ermoliev, R. J. Wets (eds), Numerical Techniques for Stochastic Optimization, (Berlin: Springer Verlag, 1988).
[29] J. M. Mulvey, Solving robust optimization models in finance, IEEE/IAFE 1996 Conference on Computational Intelligence for Financial Engineering, (March 24–26, 1996), pp. 1–13.
[30] J. M. Mulvey, R. J. Vanderbei, S. A. Zenios, Robust optimization of large-scale systems, Operations Research, vol. 43, no. 2, (March 1995), pp. 264–281.
[31] D. Bai, T. Carpenter, J. Mulvey, Making a case for robust optimization models, Management Science, vol.43, no.7, (July 1997), pp. 895–907.
[32] G. Birkan, J. Kennington et. al, Making a case for using integer programming to design DWDM networks, Optical Networks Magazine, vol. 4, no. 6, (November 2003), pp. 107–120.
[33] M. Pickavet, P. Demeester, Long-term planning of WDM networks: A comparison between single-period and multi-period techniques, Photonic Network Communications, vol. 1, no. 4, (August 1999), pp. 331–346.
[34] T. H. Wu, R. H. Cardwell, M. Boyden, A multi-period design model for survivable network architecture selection for SONET interoffice networks, IEEE Transactions on Reliability, vol. 40, no. 4, (October 1991), pp. 417–427.
[35] N. Geary, A. Antonopoulos, E. Drakopoulos, J. O'Reilly, Analysis of optimisation issues in multi-period DWDM network planning, Proceedings of the IEEE Conference on Computer Communications (INFOCOM), Anchorage, Alaska, (April 2001), pp. 152–158.

[36] D. A. Schupke, C. G. Gruber, A. Autenrieth, Optimal configuration of *p*-cycles in WDM networks, IEEE International Conference on Communications (ICC 2002), New York City, NY, (April 28 – May 2, 2002), pp. 2761–2765.

[37] D. Leung, W. D. Grover, Comparative ability of span restorable and path protected network designs to withstand uncertainty in the demand forecast, Proceedings of the 18th National Fiber Optic Engineers Conference (NFOEC 2002), Dallas, (Sept. 15–19, 2002), pp. 1450–1461.

[38] R. Fourer, D. Gay, B. Kernighan, AMPL: A modeling language for mathematical programming. (Fraser Publishing Company, Danvers, MA, 1993).

[39] ILOG corporate website, ILOG Optimization Product – ILOG CPLEX, http://www.ilog.com/products/cplex/ [date accessed: June 4, 2004].

**Dion Leung** received his B.Sc. degree in electrical engineering from the University of Alberta in 2000. As a recipient of the scholarships from Engineering Research Council of Canada (NSERC), the Alberta Informatics Circle of Research Excellence (iCORE) and TRLabs, he conducts research with the Network Systems Group at TRLabs and is currently finishing his Ph.D. degree at the University of Alberta. In the past, he held an ASIC Design Verification Engineer position with Nortel, Nepean, Ontario, Canada and a Mixed-signal IC Design Engineer position with PMC-Sierra, Burnaby, British Columbia, Canada. Funded by the Japan Society for the Promotion of Science (JSPS), he also participated in a summer program and conducted collaborative research with the Advanced Network Architecture Research Group in Osaka University, Osaka, Japan. Besides his research interest in the area of transport network modeling and planning, he also received a project management certificate and has been a communications director for Hong Kong Canada Business Association, Edmonton Section (HKCBA). He is a member of IEEE, Project Management Institute (PMI), the Association of Professional Engineers, Geologists and Geophysicists of Alberta (APEGGA).

**Wayne D. Grover** obtained his B.Eng from Carleton University, an M.Sc. from the University of Essex, and Ph.D. from the University of Alberta, all in Electrical Engineering. He had 10 years experience as scientific staff and management at BNR (now Nortel Net-works) on fiber optics, switching systems, digital radio and other areas before joining TRLabs as its founding Technical VP in 1986. In this position he was responsible for the development of the TRLabs research program and contributing to development of the TRLabs sponsorship base and he saw TRLabs through its early growth as a start-up to over the 100-person level. He now functions as Chief Scientist - Network Systems, at TRLabs and as Professor, Electrical and Computer Engineering, at the University of Alberta. He has patents issued or pending on 26 topics to date and in has received two TRLabs Technology Commercialization Awards for the licensing of restoration and network-design related technologies to industry. He is a recipient of the IEEE Baker Prize Paper Award for his work on self-organizing networks, as well as an IEEE Canada Outstanding Engineer Award, an Alberta Science and Technology Leadership Award and the University of Alberta's Martha Cook-Piper Research Award. In 2001–2002 he is also holder of a prestigious NSERC E.R.W. Steacie Memorial Fellowship. He is a P.Eng. in the Province of Alberta and a member of SPIE and a Fellow of the IEEE.