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A network option portfolio management framework for adaptive transportation planning

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ABSTRACT

A real option portfolio management framework is proposed to make use of an adaptive network design problem developed using stochastic dynamic programming methodologies. The framework is extended from Smit's and Trigeorgis' option portfolio framework to incorporate network synergies. The adaptive planning framework is defined and tested on a case study with time series origin–destination demand data. Historically, OD time series data is costly to obtain, and there has not been much need for it because most transportation models use a single time-invariant estimate based on deterministic forecasting of demand. Despite the high cost and institutional barriers of obtaining abundant OD time series data, we illustrate how having higher fidelity data along with an adaptive planning framework can result in a number of improved management strategies. An insertion heuristic is adopted to run the lower bound adaptive network design problem for a coarse Iran network with 834 nodes, 1121 links, and 10 years of time series data for 71,795 OD pairs.

1. Background

Conventional practice in transportation planning relies on a passive approach to project investment. Each project is typically evaluated in a single long range future forecast year, and then compared against other projects on a year-to-year basis for funding without any adaptation to changing conditions over time. Although project investment decisions are made on a year-to-year basis with the long term plan in mind (Kim et al., 2008; Salling and Banister, 2009), there is a lack of a systematic framework to continually evaluate projects against each other under changing conditions. There is increasing interest from public sector agencies to adopt a more active management style of project management. In an ongoing National Cooperative Highway Research Program (NCHRP) study, Caplice and Dahlburg (2011) point to the flaws of forecasting with point estimates and suggest a qualitative scenario planning approach to identify long term possible future scenarios which can be monitored using news updates as "sensors in the ground". Nonetheless, recent surveys of public agencies continue to report an ongoing mismatch between the state of practice and the state of the art and the desire to address that gap (Hatzopoulou and Miller, 2009).

Given the gap, one might expect to find a robust academic literature devoted to time dependent transportation planning. Multi-period transportation network design was proposed as early as the 1970s (Steenbrink, 1974). However, a number of important advances in this field were only made in recent years due to modeling and computational complexities. Wei and Schonfeld (1993) and Kim et al. (2008) provide heuristics for solving multi-period discrete network design problems under a deterministic setting. Szeto and Lo published a number of papers in the area of deterministic multi-period continuous network design, the most recent of which include tolling (Szeto and Lo, 2008) and cost recovery (Lo and Szeto, 2009).

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However, practitioners' skepticism of state-of-the-art deterministic network design models (Hatzopoulou and Miller, 2009) call to question whether purely deterministic approaches are sufficient under a world of greater uncertainty. Sensitivity approaches have been developed to address this concern for deterministic single period model solutions (Salling and Banister, 2009) as well as for multi-period network design (Szeto and Lo, 2005). The conclusions of these studies indicate a greater need for more flexible, adaptive planning approaches.

A number of attempts at incorporating uncertainty in network design and investment models have been considered, although stochastic demand and capacity are generally dealt with using stationary, static distributions with scenario planning approaches. Stochastic programming efforts have been applied to bi-level network design problems where congestion effects occur (Waller and Ziliaskopoulos, 2001; Chen and Yang, 2004) as well as in facility location and inventory management problems (Shu et al., 2005; Snyder et al., 2007). These studies do not consider multi-period, time-dependent design decisions with stochastic variables.

Ukkusuri and Patil (2009) propose a multi-period stochastic network design problem formulation that accounts for elastic demand. They formulate the model of allocating design variables to a number of links as a mathematical program with equilibrium constraints (MPEC) with stochastic demand over multiple time periods. However, this formulation does not treat future period investment decisions as explicit options that depend on the realization of all the stochastic elements up to that point, as an adapted process.

A truly flexible planning approach requires consideration of multiple periods and adaptive decision-making which is essentially stochastic dynamic programming. Chow and Regan (2011b) propose a Link Investment Deferral Option Set (LIDOS) and a lower bound solution for this problem. LIDOS is a stochastic dynamic programming approach to network design, which is re-christened as an adaptive network design problem (ANDP) for simplicity. In the problem, each link investment is treated as a separate option whose investment could impact the value of other link investments. Details of the ANDP can be found in Chow and Regan (2011b). The current research serves as a companion piece; its contribution is the definition of a transportation planning framework that embodies the ANDP, using concepts from portfolio management that incorporates real option strategies. Both concepts of portfolio management and real options are defined in Section 2. The framework is empirically tested on a network where time series OD data is available so that illustrative comparisons of planning strategies can be made against more conventional and current state of the art practices.

2. Real option portfolio management

In the competitive private sector, many firms have adopted portfolio management methods to systematically manage sets of projects over time. Cooper et al. (1998) define portfolio management:

"*Portfolio management is a dynamic decision process, whereby a business's list of active new product (and R&D) projects is constantly updated and revised. In this process, new projects are evaluated, selected, and prioritized; existing projects may be accelerated, killed, or de-prioritized; and resources are allocated and reallocated to the active projects. The portfolio decision process is characterized by uncertain and changing information, dynamic opportunities, multiple goals and strategic considerations, interdependence among projects, and multiple decision-makers and locations*."

As portfolio management, transportation planning should involve a systematic balancing between short term profits (in terms of welfare benefits) and long term growth considerations. Risk should factor into the valuation of projects and overall strategic goals of the organization. To some degree, transportation planning already embodies elements of portfolio management. Short term project programming incorporates long range planning forecasts; multiple projects are deterministically compared against one another; and project objectives are related directly to long term social welfare or sustainability goals. However, there are still many gaps to be found: a lack of an adaptive mechanism in the planning process, which is largely due to lack of data collected for that purpose, and a lack of consideration for uncertainty. Anecdotal evidence indicates an emerging realization from practitioners to this effect. For example, Wells (2010) presents a portfolio management process adopted by the Federal Aviation Administration to centralize management of operations. Wiegmans (2010) and Olavson et al. (2010) apply portfolio management methods to freight and logistics for managing risk in supply chain networks. Both studies propose reducing risk by diversifying transport options into a portfolio of options. Neither one explicitly quantifies the value of adaptation within their portfolio.

Portfolio management that explicitly incorporates value from adaptation is demonstrated by Luehrman (1998) using real option theory. Real option theory is an investment evaluation method derived from corporate finance. The underlying concept is simply to enable continuous decision-making within some time horizon. By doing so, the decision can be adapted to the latest data to maximize its value. In option theory, this argument considers an investment as a right that can expire as opposed to a static obligation. Real option methods have been shown to be most effective in high capital cost industries with high profit volatility. Luehrman's real option portfolio management model can be illustrated with an option space shown in Fig. 1. A review of real option theory pertaining to transportation is provided in Chow and Regan (2011a).

Under this framework, the traditional discounted cash flow (DCF) method of evaluating projects is represented in the upper regions of "never" and "now". Portfolio management approaches that do not utilize real option theory would incorrectly quantify the value of all projects in the portfolio as static commitments. In reality, treating investments as options instead of commitments can expand the space into a number of other strategic considerations as shown in Fig. 1. Multiple

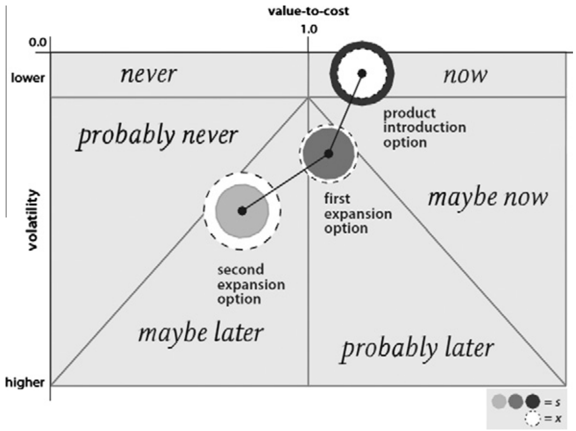

Fig. 1. Luehrman's option space for portfolio management (Luehrman, 1998).

projects in the portfolio can be evaluated as a sequence, where one project's option value is dependent on the value of other projects. Luehrman shows that portfolio management done in such a fashion offers a powerful tool for decision-makers. Not only can they decide whether to make an investment, they can also identify investment options in the portfolio that need further nurturing so that they can blossom into profitable ventures over time. For example, a portfolio manager might consider adding new features to an option to differentiate the product to increase its value to cost ratio. Other strategies include investing more in the option, managing the cost of the option, or consider introducing a product later or earlier in time. As time progresses, passive management would result in options that drift up and to the left as information is revealed and the option eventually expires.

Smit and Trigeorgis (2006) improve upon this real option portfolio management framework by considering an option space that features two axes based on the two components of Trigeorgis' (1996) strategic net present value framework shown in the following equation.

$$Expanded\ NPV\ (Option\ Value) = NPV + Option\ Premium \quad (1)$$

The NPV, or Net Present Value, is a static expected present value of benefits minus the costs. The value of the Option Premium depends on the option strategy as well as the underlying stochastic variable(s) from which the value is derived. Smit and Trigeorgis (2006) also define the Option Premium as a "Present Value of Growth Options" (PVGO). An example option space is shown in Fig. 2, where a white circle represents the magnitude of an investment cost and the black circle represents the value of the project. In the figure, the project located in Region 4 has a negative NPV but investing in it would enable the opportunity to invest in the profitable project in Region 2. The further to the right or down a project is located, the more desirable it is. Fixed sequences of options in a portfolio can be quantified as a string of connected options where the first one will be furthest down and the last project is furthest up. Like Luehrman's option space, the options here gradually drift up and to the left, although the upward motion is now indirectly caused by decreasing growth option values as information is updated and uncertainties are reduced over time. One benefit of this option space representation is that it overcomes the problem of representing multi-dimensional volatilities or options that are functions of the underlying volatility.

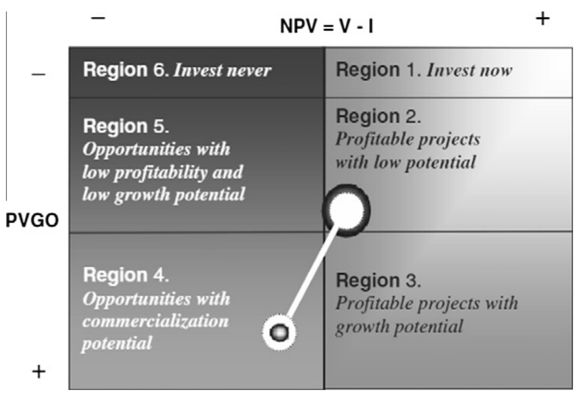

Fig. 2. Smit and Trigeorgis option space for portfolio management (Smit and Trigeorgis, 2006).

Smit and Trigeorgi's framework does not consider interacting options under a network setting. As discussed in Chow and Regan (2011a), the extension of Eq. (1) to include network effects introduces additional option premiums that capture network synergies. A real option portfolio management framework for transportation planning can be attained by using the ANDP solution methodology from Chow and Regan (2011b) to evaluate each transportation project as a real option.

3. Proposed transportation network option portfolio management framework

The framework is presented with occasional references to the numerical results from Chow and Regan (2011b) for benchmark purposes in extending the ideas there to those proposed here.

3.1. Framework overview

The transportation network option portfolio management framework is a dynamic decision-support tool for adapting multiple network investment and design decisions over time. For example, a planning agency that adopts this framework would identify an optimal set of decisions for each design element using the ANDP every year, either to continue an investment strategy or to stop that strategy. The agency would also make use of the information provided in the option space to determine which options may require further attention. Over the next year, the agency would gather new data, update their stochastic variables, and re-run the ANDP and update the portfolio option space. The option space is similar to the one presented in Smit and Trigeorgis (2006). However, due to the intractability of the ANDP and the need to fall back on a lower bound formulation, certain implications are made of the options shown in the space. Fig. 3 shows an example of how the five projects summarized in Table 2 from Chow and Regan (2011b) would be represented in this option space, and what that means.

Like Smit's and Trigeorgis' option space, a black circle denotes the immediate payoff from investing in a project whereas a white circle denotes the investment cost. A newly proposed dashed circle is used to represent the options that are to be invested immediately. The six regions have a somewhat different interpretation under a network option portfolio framework. Region 1 and Region 6 are the same. Region 2, with positive NPV and some small degree of growth options along with ordered staging premium derived from network synergies implies an option that is isolated from other network improvements. Region 3 offers options that have strong network performance and strong network synergies. Region 4 options have negative NPV, but investing in these "connectors" can provide synergistic opportunities with other network improvements. Lastly, Region 5 options offer little network synergies but low network performance.

In the example shown in Fig. 3, five projects are considered for investment for the sample network in Chow and Regan (2011b). Each of the projects is composed of two discrete link improvements. The option values for the sequence

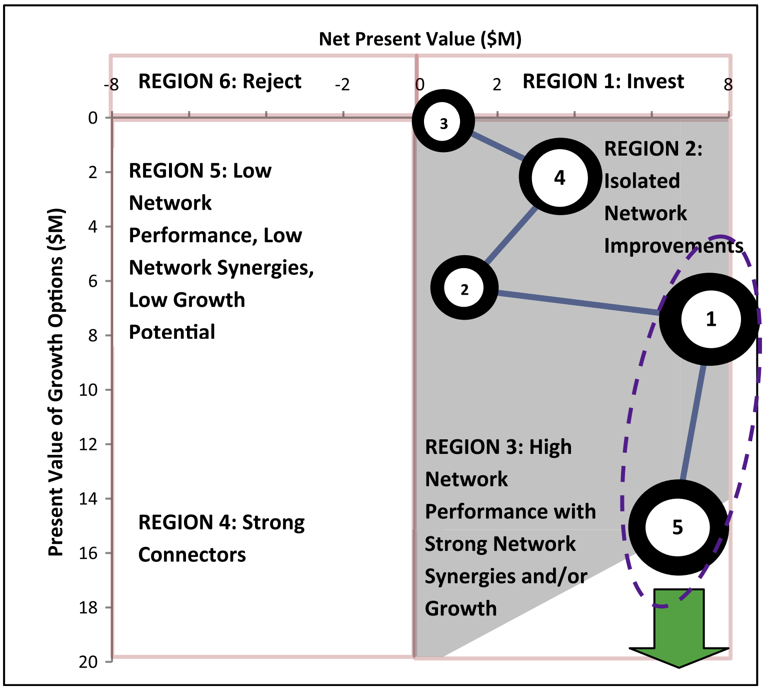

Fig. 3. Example option space representation of a transportation network option portfolio.

{5, 1, 2, 4, 3} represents the sequence with the maximum first option value – other potential sequences would fall into the gray shaded region bordered by project 5 in Fig. 3. As the best fixed sequence, it is actually a lower bound to a true solution of the ANDP (hence the green arrow pointing down). In the true solution, any improvements that are not made immediately can be re-ordered in the future. The sequence shown in Fig. 3 does not include this additional flexibility. Because of this, the sequence itself is treated as an instrument of the model, not as a final model output. Only the investment decisions for each option and their option values are taken from the model output.

3.2. Elements of the framework

Portfolio management of a transportation network involves a number of elements. The first element is specific to any portfolio management framework: aligning a portfolio to the strategic objectives of the organization. The second element is specific to real option valuation: defining the underlying stochastic elements for which the organization is most concerned with measuring and monitoring risk. The third element is specific to a transportation network: the underlying network evaluation and performance measures for determining the value of an option need to be decided.

3.2.1. Portfolio scope

The scope of the portfolio is defined to align with the strategic objectives and constraints of the organization. As noted in Cooper et al. (1998), portfolio management is about balancing between a number of strategic trade-offs: short term gain versus long term growth; risk versus return; breadth versus depth. Some key control parameters are:

- *Available Resources*: this can be capital, labor, or other form of limited resource that can be allocated to any of the network improvements in the portfolio. The key is to have centralized authority on these resources and have them impact the network improvements when allocated to them.
- *Time Horizons*: the planning horizon is the time span allowed to make changes to the portfolio, whereas the service lifecycle of the project is the length of time it would be of service to the network. Infinite service life considerations (with the assumption of repeating investments) can be made.
- *Discount Rates*: discount rates represent trade-offs between short term and long term, and are often dictated by the organization or environment. Finding an appropriate discount rate can be crucial to a portfolio because in some cases, such as in environmental planning, there are long term impacts or an unclear value of time. Different discount rates may be used for invested projects that have a risk of performance versus a risk-free discount rate where there is no uncertainty.
- *Product Distribution*: defining the set of products for which resources can be allocated determines the trade-off between risk and return as well as breadth versus depth. For example, Wiegmans (2010) identifies a number of freight carrier modes for diversifying the risk of unreliable goods delivery. Focusing only on truck carriers may earn a shipper greater contractual benefits to reduce the price resulting in a greater depth of investment, but spreading the goods delivered to rail and waterway can reduce the risk borne by the single truck mode. In transportation network management the primary products are link or node improvements.

3.2.2. Stochastic elements

The inherent nature of adaptive planning includes time-dependent stochastic elements. Part of transportation network portfolio management is identifying those elements that need to be treated as stochastic variables, and being able to obtain time series data to feed the portfolio. Determining an appropriate model of the time series data is also important as certain models may fit better than others.

A number of variables specific to transportation networks can be stochastic, depending on the scope of the portfolio and the strategic goals of the managing agency, including:

- *Origin–Destination Demand*: long term transportation planning typically exhibits a high degree of volatility in demand estimates on road networks or transit ridership. Lack of abundant demand data is one reason for this uncertainty. Operational and tactical level portfolios can also exhibit OD demand uncertainty, such as non-recurrent events like sports games on traffic networks. The tests conducted in Chow and Regan (2011a,b) consider independent OD demand.
- *Network Costs*: a number of variables can be modeled as stochastic variables, such as link capacities (direct) or fuel costs (indirect). Link capacities in long term planning can involve pavement or infrastructure degradation; short term capacities can be due to incidents or weather. Fuel costs effect network portfolios based on fleet networks such as freight and transit, and can also impact planning for road networks if traveler demand is dependent on travel costs.
- *Network Improvement Costs*: project cost overruns are significant issues that can be modeled as stochastic improvement cost variables. Final costs of projects can be orders of magnitude higher than initial estimates, as practitioners have learned from the Big Dig and the English Channel Tunnel. An indirect approach to model improvement costs may treat resource availability as a stochastic variable.
- *Mode Choices*: in multimodal network portfolios, the mode choice of travelers or shippers is often difficult to predict, especially when introducing a new mode into a system. Under those circumstances, being able to model the mode choice or split as a stochastic variable using available data may provide some adaptability to the portfolio.

Different stochastic processes can be used to model the random variables, depending on the appropriateness of the model and the type of effect desired. A select few are shown here:

- *Brownian Motion*: this process is normally distributed with a variance that is proportional to the length of time, subject to a mean drift parameter and constant volatility parameter for the variance proportionality. For non-negative variables that follow exponential growth rates, a more appropriate process is the geometric Brownian motion (GBM). The same parameters as Brownian motion are used, but the process is fitted to a lognormal distribution time-variant. The GBM is used in population variables such as OD demand. Saphores and Boarnet (2006) use a variation of this process that includes an upper population barrier. Chow and Regan (2011a,b) use a standard GBM for each OD pair.
- *Mean-Reverting Process*: this process, also called an Ornstein–Uhlenbeck process or an ARIMA process for discrete time, is appropriate for variables that feature some inertial tendencies. In addition to mean and volatility parameters, there is also a mean reversion parameter to capture the rate of return towards the mean value. This process is likely suitable for operational portfolios and for capturing market share variables such as mode choice. Tsai et al. (in press) use this process for truckload spot pricing.
- *Poisson Jump Process*: discrete random events such as regulation approval, new developments, and incidents that may cause significant shifts in improvement costs can be modeled with jump processes.

Combinations of these various features are also possible. For example, a geometric Brownian motion with mean reversion can be used to model stochastic variables. Other issues related to stochastic elements are dimensionality and estimation. Multidimensionality can be accounted for, although this can lead to computational issues due to the size of the covariance matrix that needs to be estimated. Estimation methods have been developed for these processes, such as maximum likelihood estimation. For example, Tsai et al. (in press) estimate a mean-reverting process using maximum likelihood and variogram analysis. Goodness of fit tests can be performed to evaluate estimated models. For example, Marathe and Ryan (2005) discuss goodness of fit with normality and independence tests using Chi-Squared and Shapiro–Wilk *W* tests. More detailed queries of different estimation methods for these non-stationary stochastic processes are referred to Campbell et al. (1997).

3.2.3. Network evaluation

The third component of the framework is specific to network options. Evaluation of the portfolio options depends on the type of network evaluation that is in place, which depends on the strategic goals of the organization. A firm like Amazon.com may be solely interested in facility location and vehicle routing problems that are evaluated with network evaluations that have fixed link costs and capacities. On the other hand, an MPO interested in providing a sustainable infrastructure for transporting commuters would be interested in network design problems that incorporate congestion effects, using traffic assignment problems to capture the individual route choice behavior of travelers. The underlying requirement is a portfolio composed of projects that exist as link (A) or node (N) improvements in a network G(N, A). Beyond that, there are innumerable network flow problems for quantifying objectives of different designs. Several are described here to present a flavor of the general applicability of the framework:

- *Hitchcock Transportation Problem*: this network flow problem assumes every node is either a source or a sink for demand, and every node is connected to every other node.
- *Transshipment Problem*: a more generalized form of the Hitchcock transportation problem, where a subset of nodes are neither sinks nor sources. Link costs are fixed, although they may be capacitated. Internet, freight and supply chain networks can be evaluated with this problem.
- *Traffic Assignment Problem*: this is essentially a transshipment problem where the links costs are now functions of link flows. This is a common problem to use to evaluate networks where flow variables act independently as agents, such as road networks. The examples used in Chow and Regan (2011a,b) make use of a traffic assignment problem for network evaluation.
- *Set Covering Problem*: this belongs to a class of node-based facility location problems that relies on integer variables. The network itself may be treated much like a Hitchcock transportation problem in determining transport costs between nodes, but overlaid with integer variables for particular service node locations.
- *Traveling Salesman Problem*: this problem defines sub-tours within a network with fixed link costs. Like the set covering and facility location problems, the touring problems tend to be difficult to solve because of the use of integer variables.

3.3. Implementation issues

Successful implementation of this portfolio framework for transportation planning requires availability of time series data for the variable of concern, and the capability to handle realistic numbers of projects within the portfolio. As indicated in Chow and Regan (2011b), the exact simulation-based method for ANDP becomes intractable for realistic numbers of projects. Evaluating a portfolio of nine projects would require O(9!) network evaluations.

An insertion heuristic is considered, much like the ones used in tour construction heuristics for traveling salesman problems and for project sequencing as shown Alidaee et al. (2001). Alidaee et al. discuss two types of greedy algorithms

Table 1
Greedy heuristic applied to Sioux Falls projects.

Volatility	Deferral decisions	Option 1 ($M)	Gap (%)
Exact solution from Chow and Regan (2011b) Table 3			
0.05	Invest all	19.64	–
0.25	Invest 1,5; defer 2,3,4	19.92	–
0.30	Invest 1,5; defer 2,3,4	20.69	–
0.35	Invest 1,5; defer 2,3,4	21.53	–
0.40	Defer all	24.39	–
Greedy insertion solution			
0.05	Invest all	19.64	0
0.25	Invest 1,3,5; defer 2,4	19.76	0.80
0.30	Invest 1,5; defer 2,3,4	20.69	0
0.35	Invest 1,5; defer 2,3,4	21.30	1.07
0.40	Defer all	24.00	1.60

for project sequencing. Both projects iteratively add a $(k+1)$th project to a growing sequence of k projects until the full sequence is assembled. The G1 algorithm is a computationally faster algorithm that simply chooses among the remaining projects to add the $(k+1)$th project to the end of a growing sequence of k projects to maximize value. The G2 algorithm, on the other hand, considers insertion of a $(k+1)$th project in every possible order within the established kth sequence. This heuristic assumes that the addition of a $(k+1)$th project does not disrupt the optimality of the existing order in the k projects in the sequence, which does not hold for options with strong interaction effects. The G2 insertion algorithm is implemented for evaluating the lower bound ANDP.

Algorithm 1: Greedy Insertion.

1. Initiate a sequence with only the first project
2. For each additional project in the project set,
   (a) Consider inserting the $(k+1)$th project in the $k+1$ locations between current projects in the ordered sequence
      (i) If the sequence being evaluated is new, evaluate the NPV and store the values in an archive of sequences and corresponding NPVs; else make use of the stored sequence value to avoid duplicating costly network evaluations
      (ii) Evaluate the option value using Gamba's (2002) algorithm for the given sequence, as described in Chow and Regan (2011b)

   (b) Keep the insertion with the highest first budget-feasible project option value and repeat 2)

The budget-feasibility check in (A1.2b) ensures immediate investments made will not exceed the available budget. The complexity is reduced from O(L!) in the exact method to a polynomial time efficiency of $O(L*(L+1)/2)$. This algorithm can be applied to the variant formulations of the ANDP as well, such as the deterministic staging problem (which is used in the case study). Future research can also investigate its applicability to other heuristics such as the one developed by Kim et al. (2008).

3.3.1. Test on Sioux Falls results

Algorithm 1 is tested on the sample network results from Chow and Regan (2011b) and presented in Table 1. Due to a change in data structure to the code used to run the network flow models to speed up the algorithms, the exact solution methods are rerun with slightly different results from those reported earlier. Table 1 shows that the performance gap for a small, highly connected network does not degrade too much (0–1.60% in these instances), although investment decisions may change (for $\sigma = 0.25$). Future research should consider global search heuristics such as tabu search, genetic algorithm, or GRASP.

4. Case study: Iran intercity network

Historically, OD time series data is costly to obtain, and there has not been much need for it because most transportation models use a single point time horizon based on deterministic forecasting of demand. Although there are some notable exceptions in the United States (Thompson-Graves et al., 2006), there has generally been a lack of effort in establishing policies to aggressively collect such data for passenger travel. And, private companies are typically unwilling to freely share data related to freight movements due to issues related to competition (Chow et al., 2010). Therefore, agencies have not used OD time series data in either passenger or freight planning models. With the high cost and institutional barriers of obtaining abundant OD time series data, we wish to investigate how valuable this data might be when paired with the right model. The following case study investigates the potential value of having time series data for transportation planning by enabling the proposed portfolio management framework. A deterministic staging model and a static single-period investment strategy are also considered for benchmarking the portfolio management framework against conventional methods.

Such a comparison is not meant to be a validation process. In fact, validation as is done for forecasting models is not appropriate in this research because the proposed framework is a normative model based on a network optimization program. None of the three planning models presented in the case study are "wrong" in any sense; rather, the real option portfolio framework is considered a higher fidelity planning model that makes use of more data. A true comparison of forecasting methods can be conducted after multiple implementations and following up with hindsight studies, as per Flvbjerg et al.'s (2005) efforts.

All the Iran intercity network and project data was obtained from the Iran Road Maintenance and Transportation Organization (RMTO, 2010) and from the Construction and Development of Transportation Infrastructure Company (CDTIC, 2010). A GIS representation is constructed and shown in Fig. 4.

The network consists of 834 nodes, of which 300+ are designated as origins or destinations from which trucks enter or leave a city. The total data set includes 71,795 OD pairs. Because these origins and destinations can change from year to year, all 834 nodes are considered to be centroids for network evaluation purposes. There are 1121 links connecting these nodes.

Iran's road transportation fleet consists of 253,000 heavy trucks and 25,000 buses and minibuses. This fleet is in charge of carrying 160 billion ton-kilometers of cargo and 60 billion passenger-kilometers in the country in 2009. The Ministry of Road and Transportation is responsible for building roads, railway tracks, airports and ports in the country and is in charge of the road, air and marine transportation. The ministry is also in charge of making plans for expansion of facilities in various transportation areas based on defensive priorities and economic and social development schemes. The Organization for Transportation and State Terminals is in charge of the land transportation. In addition to its headquarters in Tehran, the organization has a representative office in every province that supervises transportation-related affairs. The maintenance of freeways is also among the responsibilities of this organization (RMTO, 2010).

The government invested in a major construction effort over the past 15 years to increase the capacity and accessibility of the road network. One of its strategic goals is to provide a high level of service along the international transit routes to increase the transit cargo between Iranian ports in the Persian Gulf and the Caspian Sea via a north–south corridor. Due to some major sector inefficiencies and recent economic growth, traffic congestion in the inter-urban road network has become a serious problem.

The data includes a network in the base year 2001 and a forecast completed network in 2015 which accounts for planned infrastructure developments. There are 135 different changes that take place in this network, either as new links, link expansions, or free flow travel time reductions. Since budget information is not available for these projects, the budget for each discrete improvement is assumed using the size of the improvement as a determinant. A total of 20,294 units of cost are established for all 135 improvements based on this budget estimation method. The nine individual link investments are evaluated separately to determine their NPVs at year 0. These NPVs are presented in Table 2.

Projects 1, 7, 4, 8, and 3 are all part of a north–south corridor development plan. The corridor is a significant connector for transport of port freight between the Caspian Sea and the Persian Gulf. Started initially with one lane in each direction, the corridor has gradually expanded to multiple lanes. As of 2011 these sections were all complete. Projects 5 and 6 cover a route in the northwest part of the country. As of early 2011, the development phase for these projects had not yet started. Project 2 is an alternative route for part of the north–south corridor that started development in 1998 and was more than 90% complete as of 2010. Lastly, project 9 is a southeast route that started development in 2007 and was 20% complete as of 2010. For the case study analysis, all nine projects are assumed to be 0% complete at project start to evaluate the planning process from the proposed framework.

4.1. Portfolio scope

The portfolio of this case study is defined by the following characteristics.

- *Available Resources*: nine projects are selected for evaluation as a portfolio. The total cost of the nine projects is an initial budget of 5256 units. The individual costs of each project are shown in Table 2. A factor of $\lambda = 0.001$ is assumed for converting network system savings from network improvements into annual social benefit.

Table 2
Summary of the nine link investments in case study.

Project ID	Link ID	Origin	Destination	Description	Improvement	Cost units	Solo project NPV
1	114	Shiraz	Safa Shahr	Part of North–South corridor	Type 5 → Type 1	580	338.756
2	119	Qazvin	Rasht	Alternative route for North–South corridor	Type 5 → Type 1	608	2029.846
3	125	Isfahan	Qum	Part of North–South corridor	Type 5 → Type 1	1032	1785.182
4	158	Abade	Shahreza	Part of North–South corridor	Type 5 → Type 1	496	288.610
5	241	Ardebil	Bostan Abad	A route in northwest part of country	Type 5 → Type 1	588	−472.752
6	242	Bostan Abad	Tabriz	A route in northwest part of country	Type 5 → Type 1	320	139.420
7	438	Safa Shahr	Abade	Part of North–South corridor	Type 5 → Type 1	340	285.303
8	472	Shahreza	Isfahan	Part of North–South corridor	Type 5 → Type 1	312	220.556
9	846	Narmashir (near Bam)	Zahedan	A route in southeast part of country	Type 5 → Type 1	980	−801.946
All	–			–	–	5256	3812.975
NPV > 0	–			–	–	3688	5087.674

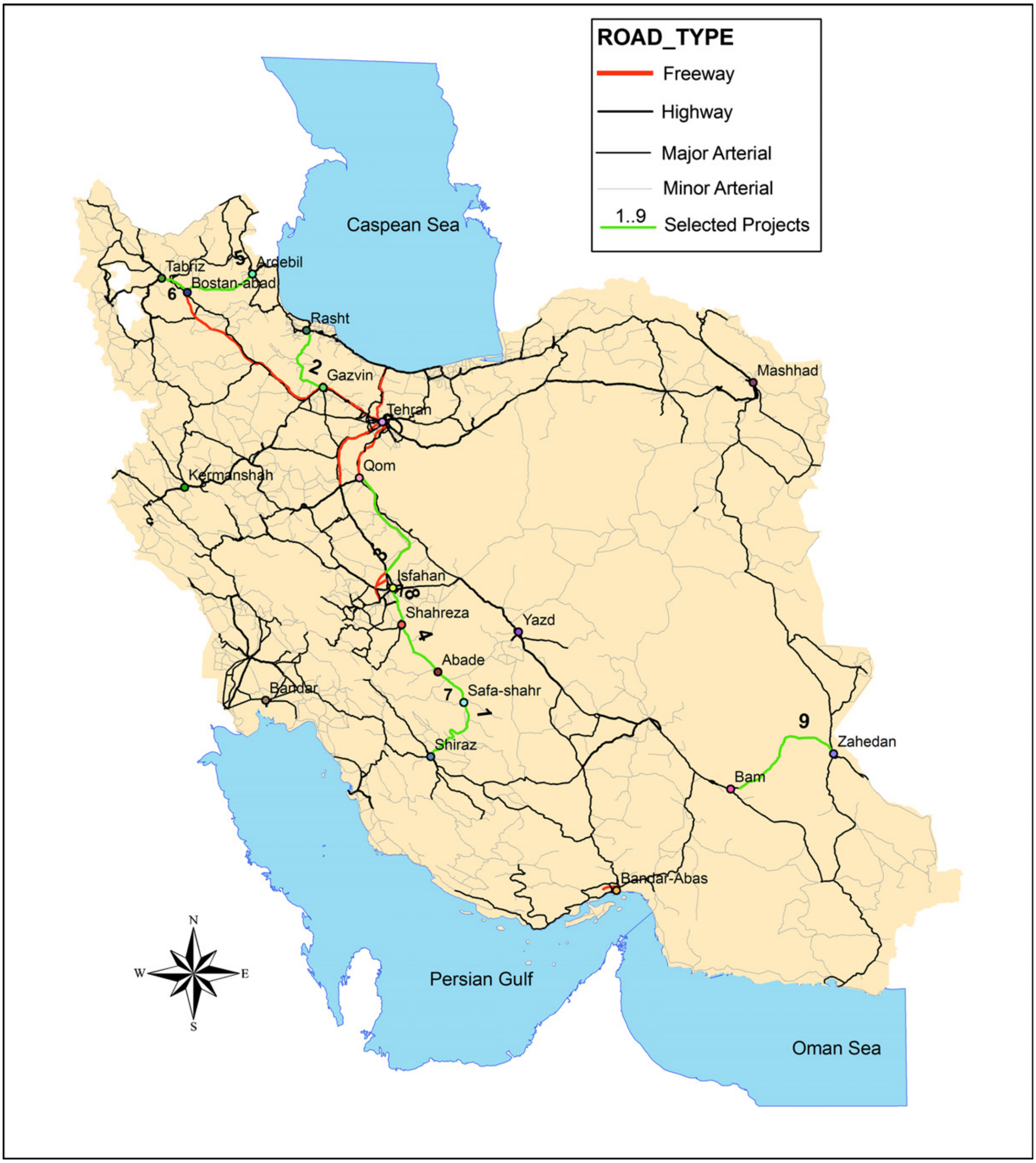

Fig. 4. Iran intercity road network.

- *Time Horizons*: the planning horizon is assumed to be 5 years, with infinite service life for computing the present values. Investments are assumed to complete construction immediately (no lag or offset).
- *Discount Rates*: a single discount rate of 10% is used. End of period convention is used (Chow and Regan (2011a,b) had a beginning of period convention).
- *Product Distribution*: The products are discrete link capacity and free flow speed improvements, as defined with a link performance function from the Bureau of Public Roads (BPR). Links are assumed to belong to one of the following 5 road types representing the number of lanes and speed limit in kph: type 1 – freeway with 4 lanes and 120 kph, type 2 – highway with 3 lanes and 80 kph, type 3 – asphalt with 2 lanes and 60 kph, type 4 – asphalt with 1 lane and 45 kph, and type 5 – a low capacity lane (assumed to have ½ the capacity of a regular lane) with 30 kph. Improvements are upgrades from one road type to another.

4.2. Stochastic elements

Independent geometric Brownian motion is assumed for each OD pair. For the first year of the 5-year horizon, there is a sample of 7 years of OD data available to estimate the processes. Maximum likelihood estimation is used. Given the large (71,795 OD pairs) number of estimated processes, the limited number of samples per OD pair, and the illustrative purpose of the case study, a goodness of fit test is not conducted. Instead, summary statistics of the estimated parameters are provided in Table 3. The parameters appear to be fairly consistent as they are updated year to year.

4.3. Network evaluation

A multi-commodity network flow model without capacity constraints or congestion effects (transshipment problem) is assumed for evaluating the system costs. Due to lack of OD data for passenger vehicles for the networks, a multi-class user equilibrium model that accounts for congestion is not used. Intrazonal movements are ignored.

Not all of the link investments result in route changes because of the coarseness of the nationwide intercity network and the use of a simple transshipment problem for evaluating system cost. Furthermore, the investments do not share any network effects with one another. The sum of the NPVs of the nine individual link investments is equal to the NPV of the sum of the link investments made simultaneously. This works to our advantage; because of the lack of network effects between the options, the solutions should be optimal using the greedy insertion heuristic.

Additional considerations are made for the ANDP. One hundred simulation paths are used for the multi-option LSM algorithm (step 2.a.ii in Algorithm 1) with 5 basis functions for estimating future expected option values.

5. Results and discussion

Three planning approaches are applied to the base year. The static single period investment approach uses only the base year OD demand for selecting the optimal design. The deterministic staging uses the historical data from 1995 to 2001 to estimate the OD demand growth in the next 5 years to determine when to invest to maximize expected NPV. The portfolio management approach uses the same historical data but assumes that the OD demand is a set of independent stochastic variables, resulting in a dynamic decision that is updated each year from 2001 to 2006.

5.1. Single period investment strategy

In this planning model, it is assumed that the nine link improvements are all considered for investment immediately assuming that the OD demand remains static, using an NPV criteria for design. The OD demand obtained in the year 2001 is assumed to be the build year. As shown in Table 2, link 5 and link 9 result in negative NPVs. The design that maximizes the NPV is the set of links {1, 2, 3, 4, 6, 7, 8}, rejecting the remaining two links {5, 9}. If all nine links are invested in immediately in 2001, the NPV assuming static OD demand is 3813 units. On the other hand, the 7-link investment design results in an NPV of 5088 units. A single run of the transshipment problem to determine the NPV takes 4 s on MATLAB using a Dijkstra shortest path routine coded as a mex-file in XP mode on a 64-bit Intel Core i7 Windows 7 operating platform with 2.67 GHz and 4 GB RAM.

Despite the lack of flexibility in this approach, it is the generally accepted practice for many planning agencies. A future build year is often assumed with a preferred alternative chosen to maximize the value of the investment under the conditions in that single year.

5.2. Multi-period deterministic staging strategy

In this approach, the OD demand growth rate is estimated using maximum likelihood from the previous 7 years of OD data (1995–2001). The greedy heuristic is applied to the deterministic staging variant of the ANDP, with the additional information on expected OD demand growth rates. In the base year, the mean geometric OD growth rate among the 71,795 OD

Table 3
Summary of OD parameter statistics by year.

	Year 0	Year 1	Year 2	Year 3	Year 4	Year 5
Mean OD value	19.2810	21.3813	26.5970	28.6868	29.4349	30.7776
Max OD value	137.113	152.282	214.543	239.070	195.349	224.979
Mean OD drift value	0.0329	0.0330	0.0337	0.0337	0.0338	–
Min OD drift value	−0.5348	−0.5327	−0.4031	−0.3896	−0.4208	–
Max OD drift value	19.1458	16.5123	14.1922	12.8694	11.4712	–
Mean OD volatility	0.0494	0.0506	0.0522	0.0543	0.0560	–
Max OD volatility	6.1445	5.6530	5.2654	4.9657	4.6829	–

Table 4
Heuristic solution for deterministic staging with 5-year horizon and 10% discount rate.

Link	NPVs	Year to invest
1	696.482	2006 (year 5)
2	7872.761	2006
3	3006.027	2006
4	19,719.720	2006
5	0	Reject
6	576.571	2006
7	40,825.280	2006
8	12,483.070	2006
9	0	Reject

pairs is 0.0057, with a minimum of −1.3625 and a maximum of 1.5146. The run time for the greedy heuristic for this network is 1073 s (18 min) on the same hardware and software settings as described in Section 5.1.

The solution obtained from the greedy heuristic is to defer link investments {1, 2, 3, 4, 6, 7, 8} until the 5th year before investing in them, and to give up link investments {5, 9}. This is because of the high growth rates in the ODs. These high growth rates lead to an optimal timing of the beneficial projects at the expiration period to maximize the discounted value of the investments. The expected NPVs and associated decisions are shown in Table 4.

Besides for the offset in investment timing, the investment decisions are the same as the static planning approach. This approach in transportation planning is considered the state-of-the-art. However, even this approach treats the investment decision as a single point in time by committing to the plan without any adaptation.

5.3. Network option portfolio management

Unlike the other two methods, the portfolio framework includes the volatilities of the truck OD pairs up to the time the decision is made. Second, this decision is repeated each year (or continuously if the agency prefers – in this study we use discrete time intervals to reflect agency decision-making) until the time horizon is reached. A summary of the parameters used for the OD values and drift and volatility parameters for the geometric Brown motions are presented in Table 3. There is a major hike in demand between years 1 and 2, but from years 3 to 4 there is a decrease in peak demand. The drift and volatility parameters are not estimated for the fifth year since they are not needed for simulating future OD in the expiration year.

The first run of the greedy insertion heuristic for the lower bound ANDP with 9 projects on the 834 node, 1121 link network with 5-year horizon and 100 simulation paths takes 105,168 s (29 h). Subsequent runs in the future years are proportionately shorter because of the reduced time horizons. The optimal set of decisions is to defer until the last year, and to invest in link investments {1, 2, 3, 4, 6, 7, 8, 9} that year while rejecting link investment 5. Although there appears to be no change in the option decisions over the first 4 years, the option space in Fig. 5 tells a different story of the evolution of this portfolio.

The final year where investments are made are outlined with an orange dashed border. White arrows are used to show where the first option in each sequence is located to find the lower bound threshold. The option space shows that the portfolio starts out in Region 4 to Region 5, indicating some poor investment but with some potential growth opportunities. In year 0, it appears that project 9 is the worst project of the portfolio. By year 5, project 9 becomes a good investment and only project 5 is rejected. Compared to the other two planning methods, the adaptive approach ends up with a different set of investment decisions.

The magnitudes of the PVGO values depend on the network performance evaluations, which in turn depend on the quality of the network data. Given the limited coarse intercity network data that is available for evaluating these projects, the significance of the high volatilities in the portfolio is exacerbated. More accurate quantifications of the option value would require more detailed network data. For the time being, relative comparisons of projects within the portfolio can be made.

5.3.1. Portfolio management strategies

A transportation network portfolio manager in charge of this hypothetical portfolio has a number of strategies available to them. In year 0, project 9 appears to be allocated far off from the rest of the options in the portfolio. At that point, the manager may wish to reduce the budget intentionally and re-run the ANDP. The manager may instead choose to examine the OD pairs affected by project 9 and apply marketing strategies to increase demand, which might affect the drift parameter(s) for the respective OD pairs and result in a higher PVGO for project 9. The time horizon of 5 years may be re-evaluated: perhaps increasing or decreasing it might improve the overall prospects of the option space. If early commitment is desired (for example due to strategic benefit of signaling interest in a network improvement to other agencies) – additional data can be sought to reduce the volatility in OD demand for the projects in Region 2 and Region 3. Early commitment trade-offs with deferral are discussed in the future research in Section 6.2.

In year 1, there is a slight shift among some of the portfolio options toward the left, and a major reduction in PVGOs. The PVGO reduction is expected, but the leftward shift is due to realization of ODs such that expected NPVs are reduced for some

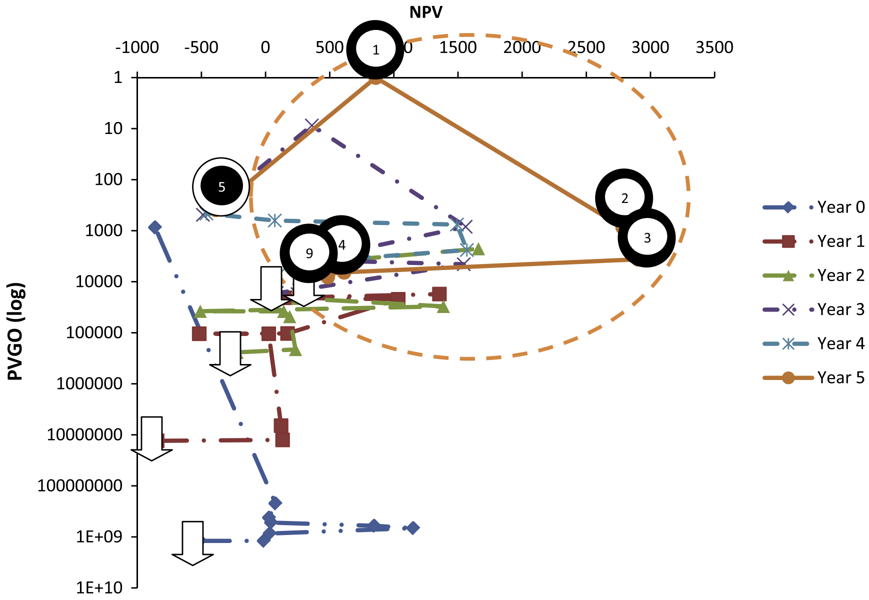

Fig. 5. Option space evolution of the portfolio during throughout the planning horizon.

projects. Under these circumstances, the projects that shifted left should be evaluated. Improvement costs may be examined to determine if they can be reduced by negotiations with contractors or cost-reducing technologies. Alternative designs should be considered.

In year 2 to year 4, the projects appear to gravitate up and to the right. The rightward shifts indicate positive changes in the assessment of OD demand from trucks. Volatilities appear to be settling as well, although not enough to warrant immediate investments. In year 3 and year 4, project 5 begins to stick out as a Region 5 project that does not offer much opportunity value. During those years, if there is interest in improving project 5, other related projects connecting project 5 with other areas in the network may be considered to increase its PVGO value. A combination of marketing strategies and cost reducing considerations can be made to improve its expected NPV. The type of improvement may be re-considered with other alternatives that may become more beneficial than the one decided back in year 0.

By year 5, eight of the projects in the portfolio can be invested upon immediately while project 5 is rejected. At that point, a new time horizon may be drawn up and new projects can be considered.

6. Conclusion

6.1. Policy implications

A number of lessons can be learned from this research study.

First, there is an agreement in the literature that static planning is insufficient in a world of greater uncertainty, but up until now it has been restricted due to lack of data and lack of analytical tools. Given the recent development of an adaptive network design approach, an adaptive portfolio management framework is appealing to transportation network managers. Such a framework can be implemented if data is available using the ANDP as an underlying engine for project evaluation and decision support.

While many of the assumptions simplify the case study and prevent actual policy-making decisions from being recommended, our model does make use of real OD demand and a coarse intercity road network, providing an example of how this data can be exploited. It is clear from the results and observations that even when treating only truck ODs as sources of volatility there is a significant amount of leverage in employing an adaptive planning approach. Even with a limited 5 year planning horizon, the adaptive planning framework is able to weather the volatile demand environment observed during those 5 years.

Applying the framework to transportation planning allows decision-makers to dynamically manage their projects from a central authority and compare immediate benefits to various risks. The framework allows managers to continuously monitor their projects and provides visual flags for attention with the option space. Fig. 5 and Section 5.3.1 clearly show that even a continuous set of deferral decisions over a 5 year period can provide a manager with an abundance of information for planning strategies under an option portfolio framework and option space. This is a call to arms to planning agencies – MPOs and transportation agencies – to consider adopting a portfolio management planning framework and acquiring the data for it.

Due to the general applicability of the framework to different network evaluation methods, it can be adopted by both public sector planning organizations and private firms. Case studies examining supply chains of global technology giants like

HP or Amazon.com can illustrate the benefit of evaluating network improvement projects that incorporate some of the effects of network synergies using the adaptive network design lower bound solution.

6.2. Future research

One area that is heavily discussed in Smit and Trigeorgis (2006), but not touched upon here, is the trade-off between deferral and commitment. Deferring an investment has the benefit of gathering new information. On the other hand, from a game theoretic perspective, committing to an investment sends signals to competitors which can force them to act in ways that may be strategically beneficial to the organization. This is the idea behind first mover advantages, and Smit and Trigeorgis' framework incorporates this game theoretic approach. When other players are ignored there tends to be a bias towards deferring investments. Taking account of the multiple players in a network setting would allow decision-makers to truly evaluate the benefits of network improvement timing against agency–agency or agency–public interactions. Such a framework provides a more balanced and realistic view of network strategic planning that warrants further study. Examples of benefits of a game theoretic network portfolio framework include high speed rail investment in an airline dominated industry; cooperative bidding of projects between state transportation departments and local city agencies; and investment of alternative fuel infrastructure by competing providers when consumer demand is responsive to first movers.

Future research should also consider other heuristics such as tabu search or genetic algorithm to allow a greater number of projects for evaluation; large-dimensional covariance matrix estimation for considering correlated OD stochastic processes; and combining this model with integrated land use models so that infrastructure investment decision-making can be dynamically integrated along with activity interactions and travel demand. Further, this problem lends itself to distributed programming because the sequential lengthy evaluations can each be viewed as independent "copies" of the problem.

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