

A tutorial on geometric programming

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Abstract A geometric program (GP) is a type of mathematical optimization problem characterized by objective and constraint functions that have a special form. Recently developed solution methods can solve even large-scale GPs extremely efficiently and reliably; at the same time a number of practical problems, particularly in circuit design, have been found to be equivalent to (or well approximated by) GPs. Putting these two together, we get effective solutions for the practical problems. The basic approach in GP modeling is to attempt to express a practical problem, such as an engineering analysis or design problem, in GP format. In the best case, this formulation is exact; when this is not possible, we settle for an approximate formulation. This tutorial paper collects together in one place the basic background material needed to do GP modeling. We start with the basic definitions and facts, and some methods used to transform problems into GP format. We show how to recognize functions and problems compatible with GP, and how to approximate functions or data in a form compatible with GP (when this is possible). We give some simple and representative examples, and also describe some common extensions of GP, along with methods for solving (or approximately solving) them.

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1 The GP modeling approach

A *geometric program* (GP) is a type of mathematical optimization problem characterized by objective and constraint functions that have a special form. The importance of GPs comes from two relatively recent developments:

- New solution methods can solve even large-scale GPs extremely efficiently and reliably.
- A number of practical problems, particularly in electrical circuit design, have recently been found to be equivalent to (or well approximated by) GPs.

Putting these two together, we get effective solutions for the practical problems. Neither of these developments is widely known, at least not yet. Nor is the story over: Further improvements in GP solution methods will surely be developed, and, we believe, many more practical applications of GP will be discovered. Indeed, one of our principal aims is to broaden knowledge and awareness of GP among potential users, to help accelerate the hunt for new practical applications of GP.

The basic approach is to attempt to express a practical problem, such as an engineering analysis or design problem, in GP format. In the best case, this formulation is exact; when this isn't possible, we settle for an approximate formulation. Formulating a practical problem as a GP is called *GP modeling*. If we succeed at GP modeling, we have an effective and reliable method for solving the practical problem.

We will see that GP modeling is not just a matter of using some software package or trying out some algorithm; it involves some knowledge, as well as creativity, to be done effectively. Moreover, success isn't guaranteed: Many problems simply cannot be represented, or even approximated, as GPs. But when we do succeed, the results are very useful and impressive, since we can reliably solve even large-scale instances of the practical problem.

It's useful to compare GP modeling and modeling via general purpose nonlinear optimization (also called nonlinear programming, or NLP). NLP modeling is relatively easy, since the objective and constraint functions can be any nonlinear functions. In contrast, GP modeling can be much trickier, since we are rather constrained in the form the objective and constraint functions can take. Solving a GP is very easy; but solving a general NLP is far trickier, and always involves some compromise (such as accepting a local instead of a global solution). When we do GP modeling, we are limiting the form of the objective and constraint functions. In return for accepting this limitation, though, we get the benefit of extremely efficient and reliable solution methods, that scale gracefully to large-scale problems.

A good analogy can be made with linear programming (LP). A linear program is an optimization problem with an even stricter limitation on the form of the objective and constraint functions (i.e., they must be linear). Despite what appears to be a very restrictive form, LP modeling is widely used, in many practical fields, because LPs can be solved with great reliability and efficiency. (This analogy is no accident—LPs and GPs are both part of the larger class of *convex optimization problems*.)

This tutorial paper collects together in one place the basic background material needed to do GP modeling. We start with the basic definitions and facts, and some methods used to transform problems into GP format. We show how to recognize functions and problems compatible with GP, and how to approximate functions or data in a form compatible with GP (when this is possible). We give some simple and representative examples, and also describe some common extensions of GP, along with methods for solving (or approximately solving) them. This paper does not cover the detailed *theory* of GPs (such as optimality conditions or duality) or *algorithms* for solving GPs; our focus is on *GP modeling*.

This tutorial paper is organized as follows. In Sect. 2, we describe the basic form of a GP and some simple extensions, and give a brief discussion of how GPs are solved. We consider feasibility analysis, trade-off analysis, and sensitivity analysis for GPs in Sect. 3, illustrated with simple numerical examples. In Sect. 4, we give two longer examples to illustrate GP modeling, one from wireless communications, and the other from semiconductor device engineering. We move on to *generalized geometric programming* (GGP), a significant extension of GP, in Sect. 5, and give a number of examples from digital circuit design and mechanical engineering in Sect. 6. In Sect. 7, we describe several more advanced techniques and extensions of GP modeling, and in Sect. 8 we describe practical methods for fitting a function or some given data in a form that is compatible with GP. In Sect. 9 we describe some extensions of GP that result in problems that, unlike GP and GGP, are difficult to solve, as well as some heuristic and nonheuristic methods that can be used to solve them. We conclude the tutorial with notes and references in Sect. 10.

2 Basic geometric programming

2.1 Monomial and posynomial functions

Let x_1, \dots, x_n denote n real positive variables, and $x = (x_1, \dots, x_n)$ a vector with components x_i . A real valued function f of x , with the form

$$f(x) = cx_1^{a_1} x_2^{a_2} \cdots x_n^{a_n}, \quad (1)$$

where $c > 0$ and $a_i \in \mathbf{R}$, is called a *monomial function*, or more informally, a *monomial* (of the variables x_1, \dots, x_n). We refer to the constant c as the *coefficient* of the monomial, and we refer to the constants a_1, \dots, a_n as the *exponents* of the monomial. As an example, $2.3x_1^2 x_2^{-0.15}$ is a monomial of the variables x_1 and x_2 , with coefficient 2.3 and x_2 -exponent -0.15 .

Any positive constant is a monomial, as is any variable. Monomials are closed under multiplication and division: if f and g are both monomials then so are fg and f/g . (This includes scaling by any positive constant.) A monomial raised to any power is also a monomial:

$$f(x)^\gamma = (cx_1^{a_1} x_2^{a_2} \cdots x_n^{a_n})^\gamma = c^\gamma x_1^{\gamma a_1} x_2^{\gamma a_2} \cdots x_n^{\gamma a_n}.$$

The term ‘monomial’, as used here (in the context of geometric programming) is similar to, but differs from the standard definition of ‘monomial’ used in algebra.

In algebra, a monomial has the form (1), but the exponents a_i must be nonnegative integers, and the coefficient c is one. Throughout this paper, ‘monomial’ will refer to the definition given above, in which the coefficient can be any positive number, and the exponents can be any real numbers, including negative and fractional.

A sum of one or more monomials, i.e., a function of the form

$$f(x) = \sum_{k=1}^K c_k x_1^{a_{1k}} x_2^{a_{2k}} \cdots x_n^{a_{nk}}, \quad (2)$$

where $c_k > 0$, is called a *posynomial function* or, more simply, a *posynomial* (with K terms, in the variables x_1, \dots, x_n). The term ‘posynomial’ is meant to suggest a combination of ‘positive’ and ‘polynomial’.

Any monomial is also a posynomial. Posynomials are closed under addition, multiplication, and positive scaling. Posynomials can be divided by monomials (with the result also a posynomial): If f is a posynomial and g is a monomial, then f/g is a posynomial. If γ is a nonnegative integer and f is a posynomial, then f^γ always makes sense and is a posynomial (since it is the product of γ posynomials).

Let us give a few examples. Suppose x , y , and z are (positive) variables. The functions (or expressions)

$$2x, \quad 0.23, \quad 2z\sqrt{x/y}, \quad 3x^2y^{-.12}z$$

are monomials (hence, also posynomials). The functions

$$0.23 + x/y, \quad 2(1 + xy)^3, \quad 2x + 3y + 2z$$

are posynomials but *not* monomials. The functions

$$-1.1, \quad 2(1 + xy)^{3.1}, \quad 2x + 3y - 2z, \quad x^2 + \tan x$$

are not posynomials (and therefore, not monomials).

2.2 Standard form geometric program

A *geometric program* (GP) is an optimization problem of the form

$$\begin{aligned} &\text{minimize} && f_0(x) \\ &\text{subject to} && f_i(x) \leq 1, \quad i = 1, \dots, m, \\ & && g_i(x) = 1, \quad i = 1, \dots, p, \end{aligned} \quad (3)$$

where f_i are posynomial functions, g_i are monomials, and x_i are the optimization variables. (There is an implicit constraint that the variables are positive, i.e., $x_i > 0$.) We refer to the problem (3) as a geometric program in *standard form*, to distinguish it from extensions we will describe later. In a standard form GP, the objective must be posynomial (and it must be minimized); the equality constraints can only have the form of a monomial equal to one, and the inequality constraints can only have the form of a posynomial less than or equal to one.

As an example, consider the problem

$$\begin{aligned} \text{minimize} \quad & x^{-1}y^{-1/2}z^{-1} + 2.3xz + 4xyz \\ \text{subject to} \quad & (1/3)x^{-2}y^{-2} + (4/3)y^{1/2}z^{-1} \leq 1, \\ & x + 2y + 3z \leq 1, \\ & (1/2)xy = 1, \end{aligned}$$

with variables x , y and z . This is a GP in standard form, with $n = 3$ variables, $m = 2$ inequality constraints, and $p = 1$ equality constraints.

We can switch the sign of any of the exponents in any monomial term in the objective or constraint functions, and still have a GP. For example, we can change the objective in the example above to $x^{-1}y^{1/2}z^{-1} + 2.3xz^{-1} + 4xyz$, and the resulting problem is still a GP (since the objective is still a posynomial). But if we change the sign of any of the coefficients, or change any of the additions to subtractions, the resulting problem is not a GP. For example, if we replace the second inequality constraint with $x + 2y - 3z \leq 1$, the resulting problem is *not* a GP (since the left-hand side is no longer a posynomial).

The term *geometric program* was introduced by Duffin, Peterson, and Zener in their 1967 book on the topic (Duffin et al. 1967). It's natural to guess that the name comes from the many geometrical problems that can be formulated as GPs. But in fact, the name comes from the geometric-arithmetic mean inequality, which played a central role in the early analysis of GPs.

It is important to distinguish between *geometric programming*, which refers to the family of optimization problems of the form (3), and *geometric optimization*, which usually refers to optimization problems involving geometry. Unfortunately, this nomenclature isn't universal: a few authors use 'geometric programming' to mean optimization problems involving geometry, and vice versa.

2.3 Simple extensions of GP

Several extensions are readily handled. If f is a posynomial and g is a monomial, then the constraint $f(x) \leq g(x)$ can be handled by expressing it as $f(x)/g(x) \leq 1$ (since f/g is posynomial). This includes as a special case a constraint of the form $f(x) \leq a$, where f is posynomial and $a > 0$. In a similar way if g_1 and g_2 are both monomial functions, then we can handle the equality constraint $g_1(x) = g_2(x)$ by expressing it as $g_1(x)/g_2(x) = 1$ (since g_1/g_2 is monomial). We can maximize a nonzero monomial objective function, by minimizing its inverse (which is also a monomial).

As an example, consider the problem

$$\begin{aligned} \text{maximize} \quad & x/y \\ \text{subject to} \quad & 2 \leq x \leq 3, \\ & x^2 + 3y/z \leq \sqrt{y}, \\ & x/y = z^2, \end{aligned} \tag{4}$$

with variables $x, y, z \in \mathbf{R}$ (and the implicit constraint $x, y, z > 0$). Using the simple transformations described above, we obtain the equivalent standard form GP

$$\begin{aligned} & \text{minimize} && x^{-1}y \\ & \text{subject to} && 2x^{-1} \leq 1, \quad (1/3)x \leq 1, \\ & && x^2y^{-1/2} + 3y^{1/2}z^{-1} \leq 1, \\ & && xy^{-1}z^{-2} = 1. \end{aligned}$$

It's common to refer to a problem like (4), that is easily transformed to an equivalent GP in the standard form (3), also as a GP.

2.4 Example

Here we give a simple application of GP, in which we optimize the shape of a box-shaped structure with height h , width w , and depth d . We have a limit on the total wall area $2(hw + hd)$, and the floor area wd , as well as lower and upper bounds on the aspect ratios h/w and w/d . Subject to these constraints, we wish to maximize the volume of the structure, hwd . This leads to the problem

$$\begin{aligned} & \text{maximize} && hwd \\ & \text{subject to} && 2(hw + hd) \leq A_{\text{wall}}, \quad wd \leq A_{\text{flr}}, \\ & && \alpha \leq h/w \leq \beta, \quad \gamma \leq d/w \leq \delta. \end{aligned} \tag{5}$$

Here d, h , and w are the optimization variables, and the problem parameters are A_{wall} (the limit on wall area), A_{flr} (the limit on floor area), and $\alpha, \beta, \gamma, \delta$ (the lower and upper limits on the wall and floor aspect ratios). This problem is a GP (in the extended sense, using the simple transformations described above). It can be transformed to the standard form GP

$$\begin{aligned} & \text{minimize} && h^{-1}w^{-1}d^{-1} \\ & \text{subject to} && (2/A_{\text{wall}})hw + (2/A_{\text{wall}})hd \leq 1, \quad (1/A_{\text{flr}})wd \leq 1, \\ & && \alpha h^{-1}w \leq 1, \quad (1/\beta)hw^{-1} \leq 1, \\ & && \gamma wd^{-1} \leq 1, \quad (1/\delta)w^{-1}d \leq 1. \end{aligned}$$

2.5 How GPs are solved

As mentioned in the introduction, the main motivation for GP modeling is the great efficiency with which optimization problems of this special form can be solved. To give a rough idea of the current state of the art, standard *interior-point* algorithms can solve a GP with 1000 variables and 10000 constraints in under a minute, on a small desktop computer (see Boyd and Vandenberghe 2004). For sparse problems (in which each constraint depends on only a modest number of the variables) far larger problems are readily solved. A typical sparse GP with 10000 variables and 1000000 constraints, for example, can be solved in minutes on a desktop computer.

(For sparse problems, the solution time depends on the particular sparsity pattern.) It's also possible to optimize a GP solver for a particular application, exploiting special structure to gain even more efficiency (or solve even larger problems).

In addition to being fast, interior-point methods for GPs are also very robust. They require essentially no algorithm parameter tuning, and they require no starting point or initial guess of the optimal solution. They *always* find the (true, globally) optimal solution, and when the problem is infeasible (i.e., the constraints are mutually inconsistent), they provide a certificate showing that no feasible point exists. General methods for NLP can be fast, but are not guaranteed to find the true, global solution, or even a feasible solution when the problem is feasible. An initial guess must be provided, and can greatly affect the solution found, as well as the solution time. In addition, algorithm parameters in general purpose NLP solvers have to be carefully chosen.

In the rest of this section, we give a brief description of the method used to solve GPs. This is not because the GP modeler needs to know how GPs are solved, but because some of the ideas will resurface in later discussions.

The main trick to solving a GP efficiently is to convert it to a nonlinear but *convex optimization problem*, i.e., a problem with convex objective and inequality constraint functions, and linear equality constraints. Efficient solution methods for general convex optimization problems are well developed (Boyd and Vandenberghe 2004). The conversion of a GP to a convex problem is based on a logarithmic change of variables, and a logarithmic transformation of the objective and constraint functions. In place of the original variables x_i , we use their logarithms, $y_i = \log x_i$ (so $x_i = e^{y_i}$). Instead of minimizing the objective f_0 , we minimize its logarithm $\log f_0$. We replace the inequality constraints $f_i \leq 1$ with $\log f_i \leq 0$, and the equality constraints $g_i = 1$ with $\log g_i = 0$. This results in the problem

$$\begin{aligned} & \text{minimize} && \log f_0(e^y) \\ & \text{subject to} && \log f_i(e^y) \leq 0, \quad i = 1, \dots, m, \\ & && \log g_i(e^y) = 0, \quad i = 1, \dots, p, \end{aligned} \tag{6}$$

with variables $y = (y_1, \dots, y_n)$. Here we use the notation e^y , where y is a vector, to mean componentwise exponentiation: $(e^y)_i = e^{y_i}$.

This new problem (6) doesn't look very different from the original GP (3); if anything, it looks more complicated. But unlike the original GP, this transformed version is convex, and so *can be solved very efficiently*. (See Boyd and Vandenberghe 2004 for convex optimization problems, including methods for solving them; Sect. 4.5 gives more details of the transformation of a GP to a convex problem.)

It's interesting to understand what it means for the problem (6) to be convex. We start with the equality constraints. Suppose g is a monomial,

$$g(x) = cx_1^{a_1} x_2^{a_2} \cdots x_n^{a_n}.$$

Under the transformation above, it becomes

$$\log g(e^y) = \log c + a_1 \log x_1 + \cdots + a_n \log x_n = \log c + a_1 y_1 + \cdots + a_n y_n,$$

which is an *affine* function of variables y_i . (An affine function is a linear function plus a constant.) Thus, a monomial equality constraint $g = 1$ is transformed to a *linear equation* in the new variables,

$$a_1 y_1 + \cdots + a_n y_n = -\log c.$$

(In a convex optimization problem, all equality constraint functions must be linear.)

The posynomial inequality constraints are more interesting. If f is a posynomial, the function

$$F(y) = \log f(e^y)$$

is convex, which means that for any y , \tilde{y} , and any θ with $0 \leq \theta \leq 1$, we have

$$F(\theta y + (1 - \theta)\tilde{y}) \leq \theta F(y) + (1 - \theta)F(\tilde{y}). \quad (7)$$

The point $\theta y + (1 - \theta)\tilde{y}$ is a (componentwise) weighted arithmetic mean of y and \tilde{y} . Convexity means that the function F , evaluated at a weighted arithmetic mean of two points, is no more than the weighted arithmetic mean of the function F evaluated at the two points. (For much more on convexity, see Boyd and Vandenberghe 2004).

In terms of the original posynomial f and variables x and \tilde{x} , the convexity inequality above can be stated as

$$f(x_1^\theta \tilde{x}_1^{1-\theta}, \dots, x_n^\theta \tilde{x}_n^{1-\theta}) \leq f(x_1, \dots, x_n)^\theta f(\tilde{x}_1, \dots, \tilde{x}_n)^{1-\theta}. \quad (8)$$

The point with coefficients $x_i^\theta \tilde{x}_i^{1-\theta}$ is a weighted *geometric* mean of x and \tilde{x} . The inequality (8) above means that the posynomial f , when evaluated at a weighted geometric mean of two points, is no more than the weighted geometric mean of the posynomial f evaluated at the two points. This is a very basic property of posynomials, which we'll encounter later.

We emphasize that in most cases, the GP modeler does not need to know how GPs are solved. The transformation to a convex problem is handled entirely by the solver, and is completely transparent to the user. To the GP modeler, a GP solver can be thought of as a reliable black box, that solves any problem put in GP form. This is very similar to the way a numerical linear algebra subroutine, such as an eigenvalue subroutine, is used.

3 Feasibility, trade-off, and sensitivity analysis

3.1 Feasibility analysis

A basic part of solving the GP (3) is to determine whether the problem is feasible, i.e., to determine whether the constraints

$$f_i(x) \leq 1, \quad i = 1, \dots, m, \quad g_i(x) = 1, \quad i = 1, \dots, p \quad (9)$$

are mutually consistent. This task is called the *feasibility problem*. It is also sometimes called the *phase I problem*, since some methods for solving GPs involve two

distinct phases: in the first, a feasible point is found (if there is one); in the second, an optimal point is found.

If the problem is infeasible, there is certainly no optimal solution to the GP problem (3), since there is no point that satisfies all the constraints. In a practical setting, this is disappointing, but still very useful, information. Roughly speaking, infeasibility means the constraints, requirements, or specifications are too tight, and cannot be simultaneously met; at least one constraint must be relaxed.

When a GP is infeasible, it is often useful to find a point \hat{x} that is as close as possible to feasible, in some sense. Typically the point \hat{x} is found by minimizing some measure of infeasibility, or constraint violation. (The point \hat{x} is not optimal for the original problem (3) since it is not feasible.) One very common method is to form the GP

$$\begin{aligned} &\text{minimize} && s \\ &\text{subject to} && f_i(x) \leq s, \quad i = 1, \dots, m, \\ &&& g_i(x) = 1, \quad i = 1, \dots, p, \\ &&& s \geq 1, \end{aligned} \tag{10}$$

where the variables are x , and a new scalar variable s . We solve this problem (which itself is always feasible, assuming the monomial equality constraints are feasible), to find an optimal \bar{x} and \bar{s} . If $\bar{s} = 1$, then \bar{x} is feasible for the original GP; if $\bar{s} > 1$, then the original GP is not feasible, and we take $\hat{x} = \bar{x}$. The value \bar{s} tells us how close to feasible the original problem is. For example, if $\bar{s} = 1.1$, then the original problem is infeasible, but, roughly speaking, only by 10%. Indeed, \bar{x} is a point that is within 10% of satisfying all the inequality constraints.

There are many variations on this method. One is based on introducing independent variables s_i for the inequality constraints, and minimizing their product:

$$\begin{aligned} &\text{minimize} && s_1 \cdots s_m \\ &\text{subject to} && f_i(x) \leq s_i, \quad i = 1, \dots, m, \\ &&& g_i(x) = 1, \quad i = 1, \dots, p, \\ &&& s_i \geq 1, \quad i = 1, \dots, m, \end{aligned} \tag{11}$$

with variables x and s_1, \dots, s_m . Like the problem above, the optimal s_i are all one when the original GP is feasible. When the original GP is infeasible, however, the optimal x obtained from this problem typically has the property that it satisfies most (but not all) of the inequality constraints. This is very useful in practice since it suggests which of the constraints should be relaxed to achieve feasibility. (For more on methods for obtaining points that satisfy many constraints, see Boyd and Vandenberghe 2004, Chap. 11.4.)

GP solvers unambiguously determine feasibility. But they differ in what point (if any) they return when a GP is determined to be infeasible. In any case, it is always possible to set up and solve the problems described above (or others) to find a potentially useful ‘nearly feasible’ point.

3.2 Trade-off analysis

In *trade-off analysis* we vary the constraints, and see the effect on the optimal value of the problem. This reflects the idea that in many practical problems, the constraints are not really set in stone, and can be changed, especially if there is a compelling reason to do so (such as a drastic improvement in the objective obtained).

Starting from the basic GP (3), we form a *perturbed GP*, by replacing the number one that appears on the right-hand side of each constraint with a parameter:

$$\begin{aligned} & \text{minimize} && f(x) \\ & \text{subject to} && f_i(x) \leq u_i, \quad i = 1, \dots, m, \\ & && g_i(x) = v_i, \quad i = 1, \dots, p. \end{aligned} \quad (12)$$

Here u_i and v_i are positive constants. When $u_i = 1$ and $v_i = 1$, this reduces to the original GP (3). We let $p(u, v)$ denote the optimal value of the perturbed problem (12) as a function of u and v . Thus, the value $p(\mathbf{1}, \mathbf{1})$ (where $\mathbf{1}$ denotes a vector with all components one) is equal to the optimal value of the original GP (3).

If $u_i > 1$, then the i th inequality constraint for the perturbed problem,

$$f_i(x) \leq u_i,$$

is *loosened*, compared to the inequality in the standard problem,

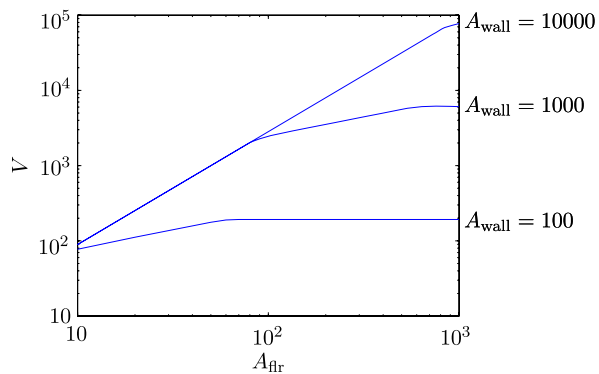
$$f_i(x) \leq 1.$$

Conversely, if $u_i < 1$, then the i th inequality constraint for the perturbed problem is *tightened* compared to the i th inequality in the standard problem. We can interpret the loosening and tightening quantitatively: for $u_i > 1$, we can say that the i th inequality constraint has been loosened by $100(u_i - 1)$ percent; for $u_i < 1$, then we can say that the i th inequality constraint has been tightened by $100(1 - u_i)$ percent. Similarly, the number v_i can be interpreted as a *shift* in the i th equality constraint.

It's important to understand what $p(u, v)$ means. It gives the optimal value of the problem, after we perturb the constraints, and then *optimize again*. When u and v change, so does (in general) the associated optimal point. There are several other perturbation analysis problems one can consider. For example, we can ask how sensitive a particular point x is, with respect to the objective and constraint functions (i.e., we can ask how much f_i and g_i change when we change x). But this perturbation analysis is unrelated to trade-off analysis.

In optimal trade-off analysis, we study or examine the function $p(u, v)$ for certain values of u and v . For example, to see the optimal trade-off of the i th inequality constraint and the objective, we can plot $p(u, v)$ versus u_i , with all other u_j and all v_j equal to one. The resulting curve, called the *optimal trade-off curve*, passes through the point given by the optimal value of the original GP when $u_i = 1$. As u_i increases above one, the curve must decrease (or stay constant), since by relaxing the i th constraint we can only improve the optimal objective. The optimal trade-off curve flattens out when u_i is made large enough that the i th constraint is no longer relevant. When u_i is decreased below one, the optimal value increases (or stays constant). If u_i is decreased enough, the perturbed problem can become infeasible.

Fig. 1 Optimal trade-off curves of maximum volume V versus maximum floor area A_{flr} , for three values of maximum wall area A_{wall}



When multiple constraints are varied, we obtain an *optimal trade-off surface*. One common approach is to plot trade-off surfaces with two parameters as a set of trade-off curves for several values of the second parameter. An example is shown in Fig. 1, which shows optimal trade-off curves of optimal (maximum) volume versus A_{flr} , for three values of A_{wall} , for the simple example problem (5) given on page 72. The other problem parameters are $\alpha = 0.5$, $\beta = 2$, $\gamma = 0.5$, $\delta = 2$.

The optimal trade-off curve (or surface) can be found by solving the perturbed GP (12) for many values of the parameter (or parameters) to be varied. Another common method for finding the trade-off curve (or surface) of the objective and one or more constraints is the *weighted sum method*. In this method we *remove* the constraints to be varied, and add positive weighted multiples of them to the objective. (This results in a GP, since we can always add a positive weighted sum of monomials or posynomials to the objective.) For example, assuming that the first and second inequality constraints are to be varied, we would form the GP

$$\begin{aligned} &\text{minimize} && f(x) + \lambda_1 f_1(x) + \lambda_2 f_2(x) \\ &\text{subject to} && f_i(x) \leq 1, \quad i = 3, \dots, m, \\ &&& g_i(x) = 1, \quad i = 1, \dots, p. \end{aligned} \quad (13)$$

By solving the weighted sum GP (13), we always obtain a point on the optimal trade-off surface. To obtain the surface, we solve the weighted sum GP for a variety of values of the weights. This weighted sum method is closely related to *duality theory*, a topic beyond the scope of this tutorial; we refer the reader to Boyd and Vandenberghe (2004) for more details.

3.3 Sensitivity analysis

Sensitivity analysis is closely related to trade-off analysis. In sensitivity analysis, we consider how *small* changes in the constraints affect the optimal objective value. In other words, we are interested in the function $p(u, v)$ for u_i and v_i near one; this means that the constraints in the perturbed GP (12) aren't very different from the constraints in the original GP (3). Assuming that the optimal objective value $p(u, v)$ is differentiable (which need not be the case, in general) at $u_i = 1$, $v_i = 1$, changes in optimal objective value with respect to small changes in u_i can be predicted from the

partial derivative

$$\left. \frac{\partial p}{\partial u_i} \right|_{u=1, v=1}.$$

This is nothing more than that slope of the trade-off curve as it passes through the point $u = 1, v = 1$.

It is more useful to work with a normalized derivative, that gives the fractional or relative change in the optimal objective, given a fractional or relative change in u_i . We define the *optimal sensitivity*, or just *sensitivity*, of the GP (3), with respect to the i th inequality constraint, as

$$S_i = \frac{\partial \log p}{\partial \log u_i} \bigg|_{u=1, v=1} = \frac{\partial \log p}{\partial u_i} \bigg|_{u=1, v=1}. \quad (14)$$

(This is the slope of the trade-off curve on a log-log plot.) The optimal sensitivities are also called the *optimal dual variables* for the problem; see Boyd and Vandenberghe (2004). The sensitivity S_i gives the (approximate) fractional change in optimal value per fractional change in the right-hand side of the i th inequality. Since the optimal value p decreases when we increase u_i , we always have $S_i \leq 0$. If the i th inequality constraint is not tight at the optimum, then we have $S_i = 0$, which means that a small change in the right-hand side of the i th constraint (loosening or tightening) has no effect on the optimal value of the problem.

As an example, suppose we have $S_1 = -0.2$ and $S_2 = -5.5$. This means that if we relax the first constraint by 1% (say), we would expect the optimal objective value to decrease by about 0.2%; if we tighten the first inequality constraint by 1%, we expect the optimal objective value to increase by about 0.2%. On the other hand if we relax the second inequality constraint by 1%, we expect the optimal objective value to decrease by the much larger amount 5.5%; if we tighten the first constraint by 1%, we expect the optimal objective value to increase by the much larger amount 5.5%. Roughly speaking, we can say that while both constraints are tight, the second constraint is much more tightly binding than the first.

For equality constraints we define the optimal sensitivity the same way:

$$T_i = \frac{\partial \log p}{\partial \log v_i} \bigg|_{u=1, v=1} = \frac{\partial \log p}{\partial v_i} \bigg|_{u=1, v=1}. \quad (15)$$

Here the sign of T_i tells us whether a small increase in the right-hand side of the i th equality constraint increases or decreases the optimal objective value. The magnitude tells us how sensitive the optimal value is to the right-hand side of the i th equality constraint.

Optimal sensitivities can be very useful in practice. If a constraint is tight at the optimum, but has a small sensitivity, then small changes in the constraint won't affect the optimal value of the problem much. On the other hand, a constraint that is tight and has a large sensitivity is one that (for small changes) will greatly change the optimal value: if it is loosened (even just a small amount), the objective is likely to decrease considerably; if it is tightened, even just a little bit, the optimal objective value will increase considerably. Roughly speaking, a constraint with a large sensitivity can be considered more strongly binding than one with a small sensitivity.

Table 1 Changes in maximum volume with changes in floor and wall area constraints. The first two columns give the change in the constraints. The third column gives the actual change in maximum volume, found by solving the GP with the new constraints, and the fourth column gives the change in maximum volume predicted by the optimal sensitivities

ΔA_{flr}	ΔA_{wall}	ΔV	ΔV_{pred}
0%	0%	0%	0%
0%	+5%	+6.1%	+6.3%
0%	−5%	−6.5%	−6.3%
+5%	0%	+1.0%	+1.2%
−5%	0%	−1.5%	−1.2%
+5%	−5%	−6.1%	−5.0%

The optimal sensitivities are also useful when a problem is infeasible. Assuming we find a point that minimizes some measure of infeasibility, the sensitivities associated with the constraints can be very informative. Each one gives the (approximate) relative change in the optimal infeasibility measure, given a relative change in the constraint. The constraints with large sensitivities are likely candidates for the ones to loosen (for inequality constraints), or modify (for equality constraints) to make the problem feasible.

One very important fact is that when we solve a GP, *we get the sensitivities of all constraints at no extra cost*. This is because modern methods for solving GPs solve both the primal (i.e., original) problem, and its dual (which is related to the sensitivities) simultaneously. (See Boyd and Vandenberghe (2004).)

To illustrate these ideas, we consider again the simple example problem (5) given on page 72. We solve the problem with parameters

$$A_{\text{flr}} = 1000, \quad A_{\text{wall}} = 200, \quad \alpha = 0.5, \quad \beta = 2, \quad \gamma = 0.5, \quad \delta = 2.$$

The associated maximum volume is $V = 5632$. The optimal sensitivities associated with the floor area constraint and the wall area constraint are

$$S_{\text{flr}} = 0.249, \quad S_{\text{wall}} = 1.251.$$

(These are both positive since increasing the area limits *increases* the maximum volume obtained.) Thus we expect that a 1% increase in allowed floor space to result in around 0.25% increase in maximum volume, and a 1% increase in allowed wall space to result in around 1.25% increase in maximum volume.

To check these approximations, we change the two wall area constraints by various amounts, and compare the predicted change in maximum volume (from the sensitivities) with the actual change in maximum volume (found by forming and solving the perturbed GP). The results are shown in Table 1. The sensitivities give reasonable predictions of the change in maximum volume when the constraints are tightened or loosened. One interesting pattern can be seen in the data: the maximum volume predicted by the sensitivities is always *more* than the actual maximum volume obtained. In other words, the prediction of the objective based on the sensitivities is always larger than the true optimal objective obtained. This is always the case, due to the convex optimization formulation; see Boyd and Vandenberghe (2004), Chap. 5.6.2.

4 GP examples

In this section we give two simple examples of GP applications.

4.1 Power control

Several problems involving power control in communications systems can be cast as GPs (see, e.g., Kandukuri and Boyd 2002; Julian et al. 2002; Foschini and Miljanic 1993). We consider a simple example here. We have n transmitters, labeled $1, \dots, n$, which transmit at (positive) power levels P_1, \dots, P_n , which are the variables in our power control problem. We also have n receivers, labeled $1, \dots, n$; receiver i is meant to receive the signal from transmitter i . The power received from transmitter j , at receiver i , is given by

$$G_{ij} P_j.$$

Here G_{ij} , which is positive, represents the path gain from transmitter j to receiver i . The *signal power* at receiver i is $G_{ii} P_i$, and the *interference power* at receiver i is $\sum_{k \neq i} G_{ik} P_k$. The *noise power* at receiver i is given by σ_i . The *signal to interference and noise ratio* (SINR) of the i th receiver/transmitter pair is given by

$$S_i = \frac{G_{ii} P_i}{\sigma_i + \sum_{k \neq i} G_{ik} P_k}. \quad (16)$$

We require that the SINR of any receiver/transmitter pair is at least a given threshold S^{\min} :

$$\frac{G_{ii} P_i}{\sigma_i + \sum_{k \neq i} G_{ik} P_k} \geq S^{\min}, \quad i = 1, \dots, n.$$

We also impose limits on the transmitter powers,

$$P_i^{\min} \leq P_i \leq P_i^{\max}, \quad i = 1, \dots, n.$$

The problem of minimizing the total transmitter power, subject to these constraints, can be expressed as

$$\begin{aligned} & \text{minimize} && P_1 + \dots + P_n \\ & \text{subject to} && P_i^{\min} \leq P_i \leq P_i^{\max}, \quad i = 1, \dots, n, \\ & && G_{ii} P_i / (\sigma_i + \sum_{k \neq i} G_{ik} P_k) \geq S^{\min}, \quad i = 1, \dots, n. \end{aligned}$$

This is not a GP, but is easily cast as a GP, by taking the inverse of the SINR constraints:

$$\frac{\sigma_i + \sum_{k \neq i} G_{ik} P_k}{G_{ii} P_i} \leq 1/S^{\min}, \quad i = 1, \dots, n.$$

(The left-hand side is a posynomial.) This allows us to solve the power control problem via GP.

This simple version of the problem can also be solved using linear programming, by expressing the SINR constraints as linear inequalities,

$$\sigma_i + \sum_{k \neq i} G_{ik} P_k \leq G_{ii} P_i / S^{\min}, \quad i = 1, \dots, n.$$

But the GP formulation allows us to handle the more general case in which the receiver interference power is any posynomial function of the powers. For example, interference contributions from intermodulation products created by nonlinearities in the receivers typically scale as polynomials in the powers. Third order intermodulation power from the first and second transmitted signals scales as $P_1 P_2^2$ or $P_1^2 P_2$; if terms like these are added to the interference power, the power allocation problem above is still a GP. Choosing optimal transmit powers in such cases is complex, but can be formulated as a GP.

4.2 Optimal doping profile

We consider a simple version of a problem that arises in semiconductor device engineering, described in more detail in Joshi et al. (2005). The problem is to choose the *doping profile* (also called the *acceptor impurity concentration*) to obtain a transistor with favorable properties. We will focus on one critical measure of the transistor: its *base transit time*, which determines (in part) the speed of the transistor.

The doping profile, denoted $N_A(x)$, is a positive function of a space variable x over the interval $0 \leq x \leq W_B$, where W_B is the *base width*. The base transit time, denoted τ_B , is determined by the doping profile. A simplified model for τ_B is given by

$$\tau_B = \int_0^{W_B} \frac{n_i^2(x)}{N_A(x)} \left(\int_x^{W_B} \frac{N_A(y)}{n_i^2(y) D_n(y)} dy \right) dx, \quad (17)$$

where n_i is the intrinsic carrier concentration, and D_n is the carrier diffusion coefficient. Over the region of interest, these can be well approximated as

$$D_n(x) = D_{n0} \left(\frac{N_A(x)}{N_{\text{ref}}} \right)^{-\gamma_1}, \quad n_i^2(x) = n_{i0}^2 \left(\frac{N_A(x)}{N_{\text{ref}}} \right)^{\gamma_2},$$

where N_{ref} , D_{n0} , n_{i0} , γ_1 , and γ_2 are (positive) constants. Using these approximations we obtain the expression

$$\tau_B = \kappa \int_0^{W_B} N_A(x)^{\gamma_2-1} \left(\int_x^{W_B} N_A(y)^{1+\gamma_1-\gamma_2} dy \right) dx, \quad (18)$$

where κ is a constant.

The basic optimal doping profile design problem is to choose the doping profile to minimize the base transit time, subject to some constraints:

$$\begin{aligned} & \text{minimize} && \tau_B \\ & \text{subject to} && N_{\min} \leq N_A(x) \leq N_{\max} \quad \text{for } 0 \leq x \leq W_B, \\ & && |N'_A(x)| \leq \alpha N_A(x) \quad \text{for } 0 \leq x \leq W_B, \\ & && N_A(0) = N_0, \quad N_A(W_B) = N_c. \end{aligned} \quad (19)$$

Here N_{\min} and N_{\max} are the minimum and maximum values of the doping profile, α is a given maximum (percentage) doping gradient, and N_0 and N_c are given initial and final values for the doping profile. The problem (19) is an infinite dimensional problem, since the optimization variable is the doping profile N_A , a function of x .

To solve the problem we first discretize with $M + 1$ points uniformly spaced in the interval $[0, W_B]$, i.e., $x_i = i W_B / M$, $i = 0, \dots, M$. We then have the approximation

$$\hat{\tau}_B = \kappa \frac{W_B}{M+1} \sum_{i=0}^M v_i^{\gamma_2-1} \left(\frac{W_B}{M+1} \sum_{j=i}^M v_j^{1+\gamma_1-\gamma_2} \right), \quad (20)$$

where $v_i = N_A(x_i)$. This shows that $\hat{\tau}_B$ is a posynomial function of the variables v_0, \dots, v_M . We can approximate the doping gradient constraint $|N'_A(x)| \leq \alpha N_A(x)$ as

$$(1 - \alpha W_B / (M + 1)) v_i \leq v_{i+1} \leq (1 + \alpha W_B / (M + 1)) v_i, \quad i = 0, \dots, M - 1.$$

(We can assume M is large enough that $1 - \alpha / M > 0$.)

Using these approximations, the optimal doping profile problem reduces to the GP

$$\begin{aligned} &\text{minimize} && \hat{\tau}_B \\ &\text{subject to} && N_{\min} \leq v_i \leq N_{\max}, \quad i = 0, \dots, M, \\ & && (1 - \alpha W_B / (M + 1)) v_i \leq v_{i+1} \leq (1 + \alpha W_B / (M + 1)) v_i, \\ & && i = 0, \dots, M - 1, \\ & && v_0 = N_0, \quad v_M = N_c, \end{aligned}$$

with variables v_0, \dots, v_M .

Now that we have formulated the problem as a GP, we can consider many extensions and variations. For example, we can use more accurate (but GP compatible) expressions for the base transit time, a more accurate (but GP compatible) approximation for the intrinsic carrier concentration and the carrier diffusion coefficient, and we can add any other constraints that are compatible with GP.

5 Generalized geometric programming

In this section we first describe some extensions of GP that are less obvious than the simple ones described in Sect. 2.3. This leads to the idea of *generalized posynomials*, and an extension of geometric programming called *generalized geometric programming*.

5.1 Fractional powers of posynomials

We have already observed that posynomials are preserved under positive integer powers. Thus, if f_1 and f_2 are posynomials, a constraint such as $f_1(x)^2 + f_2(x)^3 \leq 1$ is

a standard posynomial inequality, once the square and cube are expanded. But the same argument doesn't hold for a constraint such as

$$f_1(x)^{2.2} + f_2(x)^{3.1} \leq 1, \quad (21)$$

which involves fractional powers, since the left-hand side is not a posynomial. Nevertheless, we can handle the inequality (21) in GP, using a trick.

We introduce new variables t_1 and t_2 , along with the inequality constraints

$$f_1(x) \leq t_1, \quad f_2(x) \leq t_2, \quad (22)$$

which are both compatible with GP. The new variables t_1 and t_2 act as upper bounds on the posynomials $f_1(x)$ and $f_2(x)$, respectively. Now, we replace the (nonposynomial) inequality (21) with the inequality

$$t_1^{2.2} + t_2^{3.1} \leq 1, \quad (23)$$

which is a valid posynomial inequality.

We claim that we can replace the nonposynomial fractional power inequality (21) with the three inequalities given in (22) and (23). To see this, we note that if x satisfies (21), then x , $t_1 = f_1(x)$, and $t_2 = f_2(x)$ satisfy (22) and (23). Conversely, if x , t_1 , and t_2 satisfy (22) and (23), then x , $t_1 = f_1(x)$, and $t_2 = f_2(x)$ satisfy (22) and (23). Here we use the critical fact that if t_1 and t_2 satisfy (23), and we reduce them (for example, setting them equal to $f_1(x)$ and $f_2(x)$, respectively) then they still satisfy (22). This relies on the fact that the posynomial $t_1^{2.2} + t_2^{3.1}$ is an *increasing function* of t_1 and t_2 .

More generally, we can see that this method can be used to handle any number of positive fractional powers occurring in an optimization problem. We can handle any problem which has the form of a GP, but in which the posynomials are replaced with positive fractional powers of posynomials. We will see later that positive fractional powers of posynomials are special cases of *generalized posynomials*, and a problem with the form of a GP, but with f_i fractional powers of posynomials, is a *generalized GP*.

As an example, consider the problem

$$\begin{aligned} &\text{minimize} && \sqrt{1+x^2} + (1+y/z)^{3.1} \\ &\text{subject to} && 1/x + z/y \leq 1, \\ &&& (x/y + y/z)^{2.2} + x + y \leq 1, \end{aligned}$$

with variables x , y , and z . This problem is *not* a GP, since the objective and second inequality constraint functions are not posynomials. Applying the method above, we

obtain the GP

$$\begin{aligned} & \text{minimize} && t_1^{0.5} + t_2^{3.1} \\ & \text{subject to} && 1 + x^2 \leq t_1, \\ & && 1 + y/z \leq t_2, \\ & && 1/x + z/y \leq 1, \\ & && t_3^{2.2} + x + y \leq 1, \\ & && x/y + y/z \leq t_3. \end{aligned}$$

We can solve the problem above by solving this GP, with variables x , y , z , t_1 , t_2 , and t_3 .

This method for handling positive fractional powers can be applied recursively. For example, a (nonposynomial) constraint such as

$$x + y + ((1 + xy)^{1/2} + (1 + y/z)^{1/2})^{3.1} \leq 1$$

can be replaced with

$$x + y + t_1^{3.1} \leq 1, \quad t_2^{1/2} + t_3^{1/2} \leq t_1, \quad 1 + xy \leq t_2, \quad 1 + y/z \leq t_3,$$

where t_1 , t_2 , and t_3 are new variables.

The same idea also applies to other composite functions of posynomials. If f_0 is a posynomial of k variables, with all its exponents positive (or zero), and f_1, \dots, f_k are posynomials, then the composition function inequality

$$f_0(f_1(x), \dots, f_k(x)) \leq 1$$

can be handled by replacing it with

$$f_0(t_1, \dots, t_k) \leq 1, \quad f_1(x) \leq t_1, \dots, f_k(x) \leq t_k,$$

where t_1, \dots, t_k are new variables. This shows that products, as well as sums, of fractional positive powers of posynomials can be handled.

5.2 Maximum of posynomials

In the previous section, we showed how positive fractional powers of posynomials, while not posynomials themselves, can be handled via GP by introducing a new variable and a bounding constraint. In this section we show how the same idea can be applied to the maximum of some posynomials. Suppose f_1 , f_2 , and f_3 are posynomials. The inequality constraint

$$\max\{f_1(x), f_2(x)\} + f_3(x) \leq 1 \tag{24}$$

is certainly not a posynomial inequality (unless we have $f_1(x) \geq f_2(x)$ for all x , or vice versa). Indeed, the maximum of two posynomials is generally not differentiable (where the two posynomials have the same value), whereas a posynomial is everywhere differentiable.

To handle (24) in GP, we introduce a new variable t , and two new inequalities, to obtain

$$t + f_3(x) \leq 1, \quad f_1(x) \leq t, \quad f_2(x) \leq t$$

(which are valid GP inequalities). The same arguments as above show that this set of constraints is equivalent to the original one (24).

The same idea applies to a maximum of more than two posynomials, by simply adding extra bounding inequalities. As with positive fractional powers, the idea can be applied recursively, and indeed, it can be mixed with the method for handling positive fractional powers. As an example, consider the problem

$$\begin{aligned} &\text{minimize} && \max\{x + z, 1 + (y + z)^{1/2}\} \\ &\text{subject to} && \max\{y, z^2\} + \max\{yz, 0.3\} \leq 1, \\ &&& 3xy/z = 1, \end{aligned}$$

which is certainly not a GP. Applying the methods of this and the previous section, we obtain the equivalent GP

$$\begin{aligned} &\text{minimize} && t_1 \\ &\text{subject to} && x + z \leq t_1, \quad 1 + t_2^{1/2} \leq t_1, \\ &&& y + z \leq t_2, \\ &&& t_3 + t_4 \leq 1, \\ &&& y \leq t_3, \quad z^2 \leq t_3, \\ &&& yz \leq t_4, \quad 0.3 \leq t_4, \\ &&& 3xy/z = 1. \end{aligned}$$

5.3 Generalized posynomials

We say that a function f of positive variables x_1, \dots, x_n is a *generalized posynomial* if it can be formed from posynomials using the operations of addition, multiplication, positive (fractional) power, and maximum.

Let us give a few examples. Suppose x_1, x_2, x_3 are positive variables. The function

$$\max\{1 + x_1, 2x_1 + x_2^{0.2}x_3^{-3.9}\}$$

is a generalized posynomial, since it is the maximum of two posynomials. The function

$$(0.1x_1x_3^{-0.5} + x_2^{1.7}x_3^{0.7})^{1.5}$$

is a generalized posynomial, since it is the positive power of a posynomial. All of the functions appearing in the examples of the two previous sections, as the objective or on the left-hand side of the inequality constraints, are generalized posynomials.

As a more complex example, the function

$$\begin{aligned} h(x) = & (1 + \max\{x_1, x_2\})(\max\{1 + x_1, 2x_1 + x_2^{0.2}x_3^{-3.9}\} \\ & + (0.1x_1x_3^{-0.5} + x_2^{1.7}x_3^{0.7})^{1.5})^{1.7} \end{aligned}$$

is a generalized posynomial. This can be seen as follows:

- x_1 and x_2 are variables, and therefore posynomials, so $h_1(x) = \max\{x_1, x_2\}$ is a generalized posynomial.
- $1 + x_1$ and $2x_1 + x_2^{0.2}x_3^{-3.9}$ are posynomials, so $h_2(x) = \max\{1 + x_1, 2x_1 + x_2^{0.2}x_3^{-3.9}\}$ is a generalized posynomial.
- $0.1x_1x_3^{-0.5} + x_2^{1.7}x_3^{0.7}$ is a posynomial, so $h_3(x) = (0.1x_1x_3^{-0.5} + x_2^{1.7}x_3^{0.7})^{1.5}$ is a generalized posynomial.
- h can be expressed as $h(x) = (1 + h_1(x))(h_2(x) + h_3(x))^{1.7}$ (i.e., by addition, multiplication, and positive power, from h_1 , h_2 , and h_3) and therefore is a generalized posynomial.

Generalized posynomials are (by definition) closed under addition, multiplication, positive powers, and maximum, as well as other operations that can be derived from these, such as division by monomials. They are also closed under composition in the following sense. If f_0 is a generalized posynomial of k variables, for which no variable occurs with a negative exponent, and f_1, \dots, f_k are generalized posynomials, then the composition function

$$f_0(f_1(x), \dots, f_k(x))$$

is a generalized posynomial.

A very important property of generalized posynomials is that they satisfy the convexity property (7) that posynomials satisfy. If f is a generalized posynomial, the function

$$F(y) = \log f(e^y)$$

is a convex function: for any y , \tilde{y} , and any θ with $0 \leq \theta \leq 1$, we have

$$F(\theta y + (1 - \theta)\tilde{y}) \leq \theta F(y) + (1 - \theta)F(\tilde{y}).$$

In terms of the original generalized posynomial f and variables x and \tilde{x} , we have the inequality

$$f(x_1^\theta \tilde{x}_1^{1-\theta}, \dots, x_n^\theta \tilde{x}_n^{1-\theta}) \leq f(x_1, \dots, x_n)^\theta f(\tilde{x}_1, \dots, \tilde{x}_n)^{1-\theta},$$

for any θ with $0 \leq \theta \leq 1$.

5.4 Generalized geometric program

A *generalized geometric program* (GGP) is an optimization problem of the form

$$\begin{aligned} &\text{minimize} && f_0(x) \\ &\text{subject to} && f_i(x) \leq 1, \quad i = 1, \dots, m, \\ & && g_i(x) = 1, \quad i = 1, \dots, p, \end{aligned} \tag{25}$$

where g_1, \dots, g_p are monomials and f_0, \dots, f_m are generalized posynomials. Since any posynomial is also a generalized posynomial, any GP is also a GGP.

While GGP's are much more general than GPs, *they can be mechanically converted to equivalent GPs* using the transformations described in Sects. 5.1 and 5.2. As a result, GGP's can be solved very reliably and efficiently, just like GPs. The conversion from GGP to GP can be done automatically by a parser, that automatically carries out the transformations described in Sects. 5.1 and 5.2 as it parses the expressions describing the problem. In particular, the GP modeler (or user of a GGP parser) *does not need to know the transformations* described in Sects. 5.1 and 5.2. The GP modeler only needs to know the rules for forming a valid GGP, which are very simple to state. There is no need for the user to ever see, or even know about, the extra variables introduced in the transformation from GGP to GP.

Unfortunately, the name 'generalized geometric program' has been used to refer to several different types of problems, in addition to the one above. For example, some authors have used the term to refer to what is usually called a *signomial program* (described in Sect. 9.1), a very different generalization of a GP, which in particular cannot be reduced to an equivalent GP, or easily solved.

Once we have the basic idea of a parser that scans a problem description, verifies that it is a valid GGP and transforms it to GP form (for numerical solution), we can add several useful extensions. The parser can also handle inequalities involving negative terms in expressions, negative powers, minima, or terms on the right-hand side of inequalities, in cases when they can be transformed to valid GGP inequalities. For example, the inequality

$$x + y + z - \min\{\sqrt{xy}, (1 + xy)^{-0.3}\} \leq 0 \quad (26)$$

(which is certainly not a valid generalized posynomial inequality) could be handled by a parser by first replacing the minimum with a variable t_1 and two *upper bounds*, to obtain

$$x + y + z - t_1 \leq 0, \quad t_1 \leq \sqrt{xy}, \quad t_1 \leq (1 + xy)^{-0.3}.$$

Moving terms around (by adding or multiplying) we obtain

$$x + y + z \leq t_1, \quad t_1 \leq \sqrt{xy}, \quad t_1^{0.3} \leq 1, \quad 1 + xy \leq t_2,$$

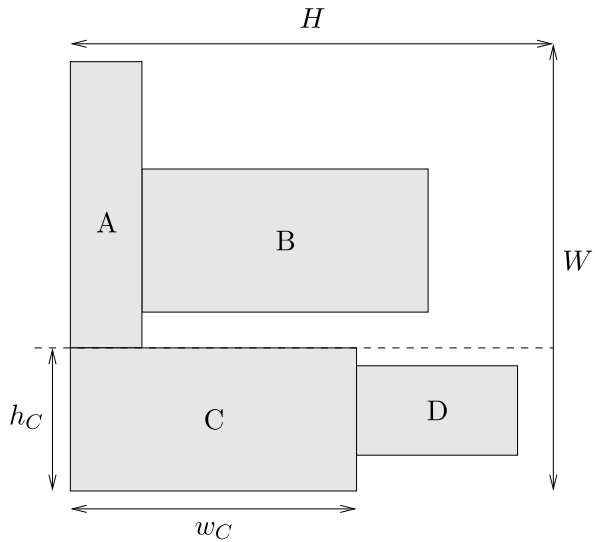
which is a set of posynomial inequalities. (Of course we have to be sure that the transformations are valid, which is the case in this example.)

The fact that a parser can recognize an inequality like (26) and transform it to a set of valid posynomial constraints is a double-edged sword. The ability to handle a wider variety of constraints makes the modeling job less constrained, and therefore easier. On the other hand, few people would immediately recognize that the inequality (26) can be transformed, or understand *why* it is a valid inequality. A user who does not understand why it is valid will have no idea how to modify the constraint (e.g., add terms, change coefficients or exponents) so as to maintain a valid inequality.

6 GGP examples

In this section we give simple examples of GGP applications.

Fig. 2 A floor planning example with four rectangles A, B, C, and D



6.1 Floor planning

In a *floor planning problem*, we have some rectangles that are to be configured and placed in such a way that they do not overlap. The objective is usually to minimize the area of the *bounding box*, which is the smallest rectangle that contains the rectangles to be configured and placed. Each rectangle can be reconfigured, within some limits. For example we might fix the area of each rectangle, but not the width and height separately.

The constraint that the rectangles do not overlap makes the general floor planning problem a complicated combinatorial optimization or packing problem. However, if the *relative positioning* of the boxes is specified, the floor planning problem can be formulated as a GP, and therefore easily solved (see Boyd and Vandenberghe 2004, Chap. 8.8, or the early paper of Rosenberg 1989). For each pair of rectangles, we specify that one is left of, or right of, or above, or below the other. This information can be given in many ways, such as a table, a pair of graphs (one for horizontal and one for vertical relations), or a *slicing tree*; see Boyd and Vandenberghe (2004), Chap. 8.8, or Sherwani (1999).

Instead of describing the general case, we will consider a specific example with 4 rectangles, labeled A, B, C, and D, shown in Fig. 2. The relative positioning constraints are:

- A is to the left of B.
- C is to the left of D.
- A and B are above C and D.

These guarantee that the rectangles do not overlap.

The width of A and B together is $w_A + w_B$, and the width of C and D together is $w_C + w_D$. Therefore the width of the bounding box is

$$W = \max\{w_A + w_B, w_C + w_D\}.$$

The height of A and B together is $\max\{h_A, h_B\}$, and the height of C and D together is $\max\{h_C, h_D\}$, so the height of the bounding box is

$$H = \max\{h_A, h_B\} + \max\{h_C, h_D\}.$$

The bounding box area is

$$WH = \max\{w_A + w_B, w_C + w_D\}(\max\{h_A, h_B\} + \max\{h_C, h_D\}).$$

This expression looks complicated, but we recognize it as a generalized posynomial of the variables w_A, \dots, w_D and h_A, \dots, h_D .

The problem of minimizing bounding box area, with given rectangle areas and limits on aspect ratios, is

$$\begin{aligned} \text{minimize} \quad & \max\{w_A + w_B, w_C + w_D\}(\max\{h_A, h_B\} + \max\{h_C, h_D\}) \\ \text{subject to} \quad & h_A w_A = a, \quad h_B w_B = b, \quad h_C w_C = c, \quad h_D w_D = d, \\ & 1/\alpha_{\max} \leq h_A/w_A \leq \alpha_{\max}, \dots, 1/\alpha_{\max} \leq h_D/w_D \leq \alpha_{\max}. \end{aligned}$$

This is a GGP, with variables w_A, \dots, w_D and h_A, \dots, h_D . The parameters a, b, c , and d are the given rectangle areas, and α_{\max} is the maximum allowed aspect ratio. The more general case (i.e., with many more rectangles, and more complex relative positioning constraints) is also easily posed as a GGP.

Let's look at a specific numerical instance of our simple example, with areas

$$a = 0.2, \quad b = 0.5, \quad c = 1.5, \quad d = 0.5.$$

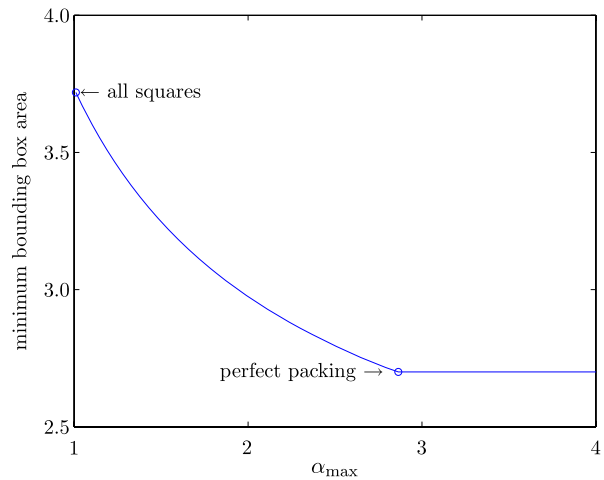
Figure 3 shows optimal trade-off curve of minimum bounding box area versus the maximum aspect ratio α_{\max} . Naturally, the minimum area obtained decreases as we relax (i.e., loosen) the aspect ratio constraint. At the upper left is the design corresponding to $\alpha_{\max} = 1$. In this case each of the rectangles is fixed to be square. The flat portion at the right part of the trade-off curve is also easily understood. With a loose enough constraint on aspect ratio, the rectangles can configure themselves so that they give a perfect packing; there is no unused space inside the bounding box. In this case, the bounding box area is just the sum of the rectangle areas (which are given), which is clearly optimal. The trade-off plot shows that this perfect packing occurs for $\alpha_{\max} \geq 2.86$.

6.2 Digital circuit gate sizing

We consider a digital circuit consisting of a set of *gates* (that perform logic functions), interconnected by wires. For simplicity we'll assume that each gate has a single *output*, and one or more *inputs*. Each output is connected via a wire to the inputs of one or more other gates, or some external circuitry. Each input is connected to the output of another gate, or to some external circuitry. A *path* through the circuit is a sequence of gates, with each gate's output connected to the following gate's input. We assume that the circuit topology has no loops, i.e., no paths start and end at the same gate.

Each gate is to be *sized*. In the simplest case, each gate has a variable $x_i \geq 1$ associated with it, which gives a scale factor for the size of the transistors it is made

Fig. 3 Optimal trade-off curves of minimum bounding box area versus maximum aspect ratio α_{\max}



from. The scale factors of the gates, which are the optimization variables, affect the total circuit area, the power consumed by the circuit, and the speed of the circuit (which determines how fast the circuit can operate).

The area of a scaled gate is proportional to the scale factor x_i , so total circuit area has the form

$$A = \sum_{i=1}^n a_i x_i,$$

where a_i is the area of gate i with unit scaling. Similarly, the energy lost when a gate transitions (i.e., its output changes logic value) is also approximately proportional to the scale factor. The total power consumed by the circuit has the form

$$P = \sum_{i=1}^n f_i e_i x_i,$$

where f_i is the frequency of transition of the gate, and e_i is the energy lost when the gate transitions. Total circuit power and area are both posynomial functions of the scale factors.

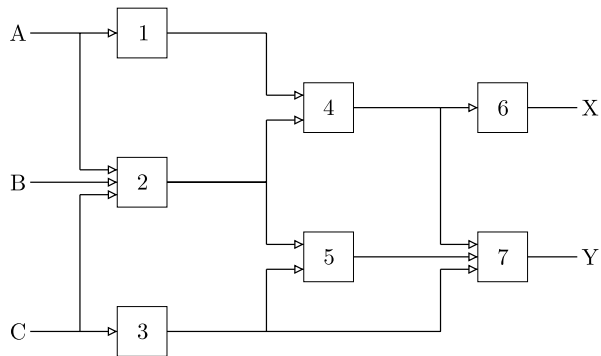
Each gate has an *input capacitance* C_i , which is an affine function of its scale factor:

$$C_i = \alpha_i + \beta_i x_i,$$

and a *driving resistance* R_i , which is approximately inversely proportional to the scale factor:

$$R_i = \gamma_i / x_i.$$

The *delay* D_i of a gate is the product of its driving resistance, and the sum of the input capacitances of the gates its output is connected to (if it is not an output gate)

Fig. 4 Digital circuit with 7 gates

or its load capacitance (if it is an output gate):

$$D_i = \begin{cases} R_i \sum_{j \in F(i)} C_j & \text{for } i \text{ not an output gate,} \\ R_i C_i^{\text{out}} & \text{for } i \text{ an output gate.} \end{cases}$$

(Here $F(i)$ is the set of gates whose input is connected to the output of gate i and C_i^{out} represents the load capacitance of an output gate.) Combining these three formulas, we see that the gate delay D_i is a posynomial function of the scale factors.

We measure the speed of the circuit using its maximum or worst-case delay D , which is the maximum total delay along any path through the circuit. Since the delay of each gate is posynomial, the total delay along any path is also posynomial (since it is a sum of gate delays). The maximum path delay, over all possible paths, is a generalized posynomial, since it is the maximum of a set of posynomials.

We can pose the digital circuit gate scaling problem as the problem of choosing the scale factors to give minimum delay, subject to limits on the total area and power:

$$\begin{aligned} &\text{minimize} && D \\ &\text{subject to} && P \leq P^{\max}, \quad A \leq A^{\max}, \\ &&& x_i \geq 1, \quad i = 1, \dots, n. \end{aligned}$$

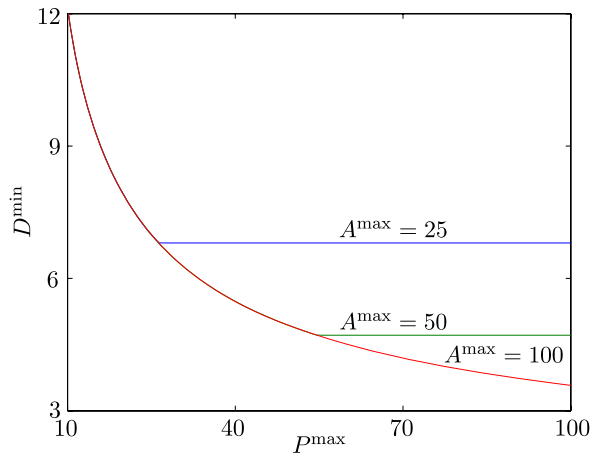
(Here P^{\max} and A^{\max} are given limits on the total power and area.) Since D is a generalized posynomial, this is a GGP.

As a specific example, consider the digital circuit shown in Fig. 4. This small circuit has 7 gates, and only 7 paths. The worst-case delay is given by

$$D = \max\{D_1 + D_4 + D_6, D_1 + D_4 + D_7, D_2 + D_4 + D_6, \\ D_2 + D_4 + D_7, D_2 + D_5 + D_7, D_3 + D_5 + D_6, D_3 + D_7\}. \quad (27)$$

In larger circuits, the number of paths can be very large, and it is not practical to form an expression like (27) for D , by listing the paths. A simple recursion for D can be used to avoid enumerating all paths. We define T_i as the maximum delay over all paths that end with gate i . (We can interpret T_i as the latest time at which the output of gate i can transition, assuming the input signals transition at $t = 0$.) We can compute T_i via a recursion, as follows.

Fig. 5 Optimal trade-off curves of minimum delay D^{\min} versus maximum power P^{\max} , for three values of maximum area A^{\max}



- For gates whose inputs are not connected to other gates, we take $T_i = D_i$.
- For other gates, we take $T_i = \max T_j + D_i$, where the maximum is over all gates that drive gate i .

Finally, we can express the delay D as the maximum over all T_i , over all output gates. Note that this recursion shows that each T_i is a generalized posynomial of the gate scaling factors.

For the particular example described above, the recursion is

$$\begin{aligned}
 T_i &= D_i, \quad i = 1, 2, 3, \\
 T_4 &= \max\{T_1, T_2\} + D_4, \\
 T_5 &= \max\{T_2, T_3\} + D_5, \\
 T_6 &= T_4 + D_6, \\
 T_7 &= \max\{T_3, T_4, T_5\} + D_7, \\
 D &= \max\{T_6, T_7\}.
 \end{aligned}$$

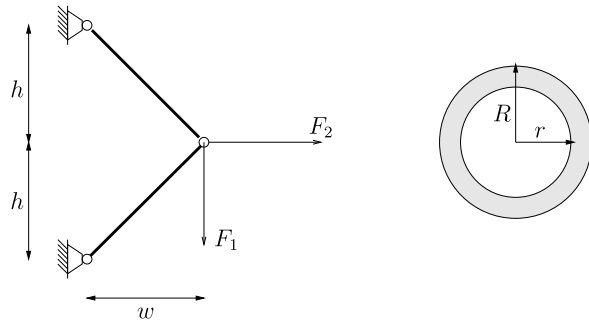
(For this small example, the recursion gives no real savings over the expression (27) above based on enumeration of the paths, but in larger circuits the savings can be dramatic.)

We now consider a specific instance of the problem, with parameters

$$\begin{aligned}
 a_i &= 1, \quad \alpha_i = 1, \quad \beta_i = 1, \quad \gamma_i = 1, \quad i = 1, \dots, 7, \\
 f_1 &= 1, \quad f_2 = 0.8, \quad f_3 = 1, \quad f_4 = 0.7, \quad f_5 = 0.7, \\
 f_6 &= 0.5, \quad f_7 = 0.5, \quad e_1 = 1, \quad e_2 = 2, \quad e_3 = 1, \\
 e_4 &= 1.5, \quad e_5 = 1.5, \quad e_6 = 1, \quad e_7 = 2,
 \end{aligned}$$

and load capacitances $C_6^{\text{out}} = 10$, $C_7^{\text{out}} = 10$. Figure 5 shows optimal trade-off curves of the minimum delay versus maximum allowed power, for three values of maximum area.

Fig. 6 *Left.* Two-bar truss.
Right. Cross section of the bars



6.3 Truss design

We consider a simple mechanical design problem, expanded from an example given in Bazaraa et al. (1993), p. 8. Figure 6 shows a two-bar truss with height $2h$ and width w . The two bars are cylindrical tubes with inner radius r and outer radius R . We are interested in determining the values of h , w , r , and R that minimize the weight of the truss subject to a number of constraints.

The cross-sectional area A of the bars is given by

$$A = 2\pi(R^2 - r^2),$$

and the weight of the truss is proportional to the total volume of the bars, which is given by

$$2A\sqrt{w^2 + h^2}.$$

This is the cost function in the design problem. Since $A = 2\pi(R^2 - r^2)$, it is *not* a generalized posynomial in the original design variables h , w , r , and R . We will address this issue later.

The structure should be strong enough for two loading scenarios. In the first scenario a vertical force F_1 is applied to the node; in the second scenario the force is horizontal with magnitude F_2 . The constraint that the truss should be strong enough to carry the load F_1 means that the stress caused by the external force F_1 must not exceed a given maximum value. To formulate this constraint, we first determine the forces in each bar when the structure is subjected to the vertical load F_1 . From force equilibrium and the geometry of the problem we can determine that the magnitudes of the forces in two bars are equal and given by

$$\frac{\sqrt{w^2 + h^2}}{2h} F_1.$$

The maximum force in each bar is equal to the cross-sectional area times the maximum allowable stress σ (which is a given constant). This gives us the first constraint:

$$\frac{\sqrt{w^2 + h^2}}{2h} F_1 \leq \sigma A.$$

When F_2 is applied, the magnitudes of the forces in two bars are again equal and given by

$$\frac{\sqrt{w^2 + h^2}}{2w} F_2,$$

which gives us the second constraint:

$$\frac{\sqrt{w^2 + h^2}}{2w} F_2 \leq \sigma A.$$

We also impose limits

$$w_{\min} \leq w \leq w_{\max}, \quad h_{\min} \leq h \leq h_{\max}$$

on the width and the height of the structure, and limits

$$1.1r \leq R \leq R_{\max}$$

on the outer bar radius.

The design problem is:

$$\begin{aligned} &\text{minimize} && 2A\sqrt{w^2 + h^2} \\ &\text{subject to} && F_1\sqrt{w^2 + h^2}/h \leq \sigma A, \\ & && F_2\sqrt{w^2 + h^2}/w \leq \sigma A, \\ & && w_{\min} \leq w \leq w_{\max}, \quad h_{\min} \leq h \leq h_{\max}, \\ & && 1.1r \leq R \leq R_{\max}. \end{aligned}$$

This is *not* a GGP in the variables h , w , r , and R , since $A = 2\pi(R^2 - r^2)$ is not a monomial function of the variables. But a simple change of variables converts it to a GGP. We will use A as a *variable*, instead of R . For R , we use

$$R = \sqrt{A/(2\pi) + r^2}, \tag{28}$$

which a generalized posynomial in r and A . Using the variables h , w , r , and A , the problem above is almost a GGP. The only constraint that doesn't fit the required form is

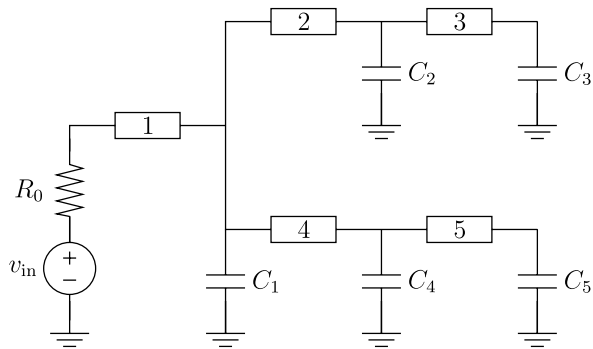
$$1.1r \leq R = \sqrt{A/(2\pi) + r^2}.$$

But we can express this as $1.1^2 r^2 \leq A/(2\pi) + r^2$, i.e.,

$$0.21r^2 \leq A/(2\pi),$$

which is compatible with GGP.

Fig. 7 An interconnect network consisting of an input (the voltage source and resistance) driving a tree of 5 wire segments (shown as boxes labeled $1, \dots, 5$) and capacitive loads C_1, \dots, C_5



In summary, the truss design problem can be expressed as the GGP

$$\begin{aligned}
 &\text{minimize} && 2A\sqrt{w^2 + h^2} \\
 &\text{subject to} && F_1\sqrt{w^2 + h^2}/h \leq \sigma A, \\
 & && F_2\sqrt{w^2 + h^2}/w \leq \sigma A, \\
 & && w_{\min} \leq w \leq w_{\max}, \quad h_{\min} \leq h \leq h_{\max}, \\
 & && \sqrt{A/(2\pi) + r^2} \leq R_{\max}, \\
 & && 0.21r^2 \leq A/(2\pi),
 \end{aligned}$$

with variables h , w , r , and A . (After solving this GGP, we can recover R from A using (28).)

6.4 Wire sizing

We consider the problem of determining the widths w_1, \dots, w_n of n wire segments in an interconnect network in an integrated circuit. The interconnect network forms a tree; its root is driven by the input signal (which is to be distributed), which is modeled as a voltage source and a series resistance. Each wire segment has a given capacitive load C_i connected to it. A simple interconnect network is shown in Fig. 7.

We will use a simple π model for each wire segment, as shown in Fig. 8. The wire resistance and capacitances are given by

$$R_i = \alpha_i \frac{l_i}{w_i}, \quad \bar{C}_i = \beta_i l_i w_i + \gamma_i l_i,$$

where l_i and w_i are the length and width of the wire segment, and α_i , β_i , and γ_i are positive constants that depend on the physical properties of the routing layer of the wire segment. The wire segment resistance and capacitance are both posynomial functions of the wire widths w_i , which will be our design variables.

Substituting this π model for each of the wire segments, the interconnect network becomes a resistor-capacitor (RC) tree. Each branch has the associated wire resistance. Each node has several capacitances to ground: the load capacitance, the capacitance contributed by the upstream wire segment, and the capacitances contributed by

Fig. 8 Wire segment with length l_i and width w_i (left) and its π model (right)

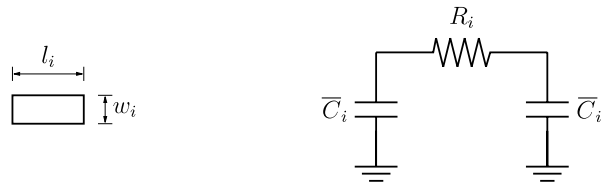
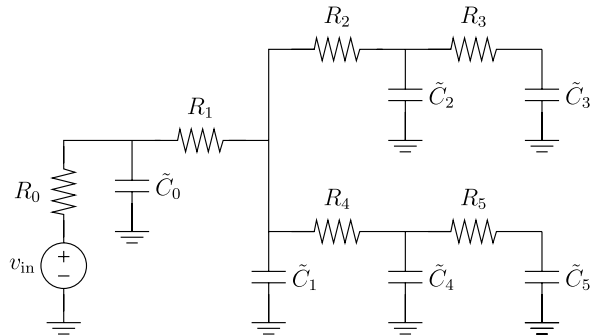


Fig. 9 RC tree model of the interconnect network in Fig. 7 using the π model



each of the downstream wire segments. The capacitances at each node can be added together. The resulting RC tree has resistances and capacitances which are posynomial functions of the wire segment widths w_i . As an example, the network in Fig. 7 yields the RC tree shown in Fig. 9, where

$$\begin{aligned}\tilde{C}_0 &= \bar{C}_1, \\ \tilde{C}_1 &= C_1 + \bar{C}_1 + \bar{C}_2 + \bar{C}_4, \\ \tilde{C}_2 &= C_2 + \bar{C}_2 + \bar{C}_3, \\ \tilde{C}_4 &= C_4 + \bar{C}_4 + \bar{C}_5, \\ \tilde{C}_5 &= C_5 + \bar{C}_5.\end{aligned}$$

When the voltage source switches from one value to another, there is a delay before the voltage at each capacitor converges to the new value. We will use the *Elmore delay* to measure this. (The Elmore delay to capacitor i is the area under its voltage versus time plot, for $t \geq 0$, when the input voltage source switches from 1 to 0 at $t = 0$.) For an RC tree circuit, the Elmore delay D_k to capacitor k is given by the formula

$$D_k = \sum_{i=1}^n \tilde{C}_i \left(\sum R\text{'s upstream from capacitors } k \text{ and } i \right).$$

The Elmore delay is a sum of products of \tilde{C}_i 's and R_j 's, and therefore is a posynomial function of the wire widths (since each of these is a posynomial function of the wire widths). The *critical delay* of the interconnect network is the largest Elmore delay to any capacitor in the network:

$$D = \max\{D_1, \dots, D_n\}.$$

(This maximum always occurs at the leaves of the tree.) The critical delay is a generalized posynomial of the wire widths, since it is a maximum of a set of posynomials.

As an example, the Elmore delays to (leaf) capacitors 3 and 5 in the RC tree in Fig. 9 are given by

$$\begin{aligned} D_3 &= \tilde{C}_3(R_0 + R_1 + R_2 + R_3) + \tilde{C}_2(R_0 + R_1 + R_2) + \tilde{C}_0 R_0 + \tilde{C}_1(R_0 + R_1) \\ &\quad + \tilde{C}_4(R_0 + R_1) + \tilde{C}_5(R_0 + R_1) + \tilde{C}_6(R_0 + R_1), \\ D_5 &= \tilde{C}_5(R_0 + R_1 + R_4 + R_5) + \tilde{C}_4(R_0 + R_1 + R_4) + \tilde{C}_0 R_0 + \tilde{C}_1(R_0 + R_1) \\ &\quad + \tilde{C}_2(R_0 + R_1) + \tilde{C}_3(R_0 + R_1). \end{aligned}$$

For this interconnect network, the critical delay is $D = \max\{D_3, D_5\}$.

Now we can formulate the wire sizing problem, i.e., the problem of choosing the wire segment widths w_1, \dots, w_n . We impose lower and upper bounds on the wire widths,

$$w_i^{\min} \leq w_i \leq w_i^{\max},$$

as well as a limit on the total wire area,

$$l_1 w_1 + \dots + l_n w_n \leq A^{\max}.$$

Taking critical delay as objective, we obtain the problem

$$\begin{aligned} &\text{minimize} && D \\ &\text{subject to} && w_i^{\min} \leq w_i \leq w_i^{\max}, \quad i = 1, \dots, n, \\ &&& l_1 w_1 + \dots + l_n w_n \leq A^{\max}, \end{aligned} \tag{29}$$

with variables w_1, \dots, w_n . This is a GGP.

This formulation can be extended to use more accurate models of wire segment resistance and capacitance, as long as they are generalized posynomials of the wire widths. Wire sizing using Elmore delay goes back to Fishburn and Dunlop (1985); for some more recent work on wire (and device) sizing via Elmore delay, see, e.g., Shyu et al. (1988), Sapatnekar et al. (1993), Sapatnekar (1996).

7 More transformations

In this section we describe a few more advanced techniques used to express problems in GP (or GGP) form.

7.1 Function composition

In Sect. 5.4 we described methods for handling problems whose objective or constraint functions involve composition with the positive power function or the maximum function. It's possible to handle composition with many other functions. As

a common example, we consider the function $1/(1 - z)$. Suppose we have the constraint

$$\frac{1}{1 - q(x)} + f(x) \leq 1, \quad (30)$$

where q and f are generalized posynomials, and we have the implicit constraint $q(x) < 1$. We replace the first term by a new variable t , along with the constraint $1/(1 - q(x)) \leq t$, which can be expressed as the generalized posynomial inequality $q(x) + 1/t \leq 1$, to obtain

$$t + f(x) \leq 1, \quad q(x) + 1/t \leq 1.$$

This pair of inequalities is equivalent to the original one (30) above, using the same argument as in Sect. 5.4.

A more general variation on this transformation can be used to handle a constraint such as

$$\frac{p(x)}{r(x) - q(x)} + f(x) \leq 1,$$

where r is monomial, p , q , and f are generalized posynomials, and we have the implicit constraint $q(x) < r(x)$. We replace this inequality constraint with

$$t + f(x) \leq 1, \quad q(x) + p(x)/t \leq r(x),$$

where t is a new variable.

The idea that composition of a generalized posynomial with $1/(1 - z)$ can be handled in GP can be guessed from its Taylor series,

$$\frac{1}{1 - z} = 1 + z + z^2 + \cdots,$$

which is a limit of polynomials with positive coefficients. This analysis suggests that we can handle composition of a generalized posynomial with any function whose series expansion has no negative coefficients, at least approximately, by truncating the series. In some cases (such as $1/(1 - z)$), the composition can be handled exactly.

Another example is the exponential function. Since the Taylor series for the exponential has all coefficients positive, we can guess that the exponential of a generalized posynomial can be handled as it were a generalized posynomial. One good approximation is

$$e^{f(x)} \approx (1 + f(x)/a)^a,$$

where a is large. If f is a generalized posynomial, the right-hand side is a generalized posynomial. This approximation is good for small enough $f(x)$; if $f(x)$ is known to be near, say, the number b , we can use the approximation

$$e^{f(x)} = e^b e^{f(x)-b} \approx e^b (1 + (f(x) - b)/a)^a,$$

which is a generalized posynomial provided $a > b$.

It's also possible to handle exponentials of posynomials exactly, i.e., without approximation. We replace a term of the form $e^{f(x)}$ with a new variable t , which can

be used anywhere a posynomial can be, and we add the constraint $e^{f(x)} \leq t$ to our problem. This results in a problem that would be a GP, except for the exponential constraint $e^{f(x)} \leq t$. To solve the problem, we carry out the same logarithmic transformation used to solve GPs. First we take the logarithm of the original variables x as well as the new variable t , so our variables become $y = \log x$ and $s = \log t$, and then we take the logarithm of both sides of each constraint. The posynomial objective, posynomial inequality, and monomial equality constraints transform as usual to a convex objective and inequality constraints, and linear equality constraints. The exponential constraint becomes

$$\log e^{f(e^y)} \leq \log e^s,$$

i.e., $f(e^y) \leq s$, which is a convex constraint on y and s , since $f(e^y)$ is a convex function of y . Thus, the logarithmic transformation yields a convex problem, which is not quite the same as the one obtained from a standard GP, but is still easily solved.

In summary, exponential terms can be handled exactly, but with the disadvantage of requiring software that can handle a wider class of problems than GP. For this reason, the most common approach is to use an approximation such as the one described above.

7.2 Additive log terms

In the preceding section, we saw that the exponential of a generalized posynomial can be well approximated as a generalized posynomial, and therefore used in the objective or inequality constraints, anywhere a generalized posynomial can. It turns out that the logarithm of a generalized posynomial can also be (approximately) incorporated in the inequality constraints, but in more restricted ways. Suppose we have a constraint of the form

$$f(x) + \log q(x) \leq 1,$$

where f and q are generalized posynomials. This constraint is a bit different from the ones we have seen so far, since the left-hand side can be *negative*. To (approximately) handle this constraint, we use the approximation

$$\log u \approx a(u^{1/a} - 1),$$

valid for large a , to obtain

$$f(x) + a(q(x)^{1/a} - 1) \leq 1.$$

This inequality is *not* a generalized posynomial inequality, but it can be expressed as the generalized posynomial inequality

$$f(x) + aq(x)^{1/a} \leq 1 + a.$$

Like exponentials, additive log terms can also be handled exactly, again with the disadvantage of requiring specialized software. Using the variables $y = \log x$, we can write $f(x) + \log q(x) \leq 1$ as

$$f(e^y) + \log q(e^y) \leq 1.$$

This is a convex constraint, and so can be handled directly.

7.3 Mixed linear geometric programming

In generalized geometric programming, the right-hand side of any inequality constraint must be a monomial. The right-hand side of an inequality constraint can never be a sum of two or more terms (except in trivial cases, such as when one of the terms is a multiple of the other). There is one special case, however, when it is possible to handle constraints in which the right-hand side is a sum of terms. Consider a problem of the form

$$\begin{aligned} & \text{minimize} && f_0(x) + h_0(z) \\ & \text{subject to} && f_i(x) \leq h_i(z), \quad i = 1, \dots, m, \\ & && g_i(x) = 1, \quad i = 1, \dots, p, \end{aligned} \quad (31)$$

where the variables are $x \in \mathbf{R}^n$ and $z \in \mathbf{R}^k$, f_0, \dots, f_m are generalized posynomials, g_1, \dots, g_p are monomials, and h_0, \dots, h_m are affine, i.e., linear functions plus a constant. This problem form can be thought of as a combination or hybrid of a GGP and a linear program (LP): without the variable x , it reduces to an LP; without the z variable (so the affine functions reduce to constants), it reduces to a GGP. For this reason the problem (31) is called a *mixed linear geometric program*. In a mixed linear geometric program, we partition the optimization variables into two groups: the variables x_1, \dots, x_n , which appear in the posynomials and monomials, and the variables z_1, \dots, z_k , which appear in the affine function part of the objective, and on the right-hand side of the inequality constraints.

Mixed linear geometric programs can be solved very efficiently, just like GGPs. The method uses the usual logarithmic transform for the variables x_1, \dots, x_n , but keeps the variables z_1, \dots, z_k as they are; moreover, we do not take the logarithm of both sides of the mixed constraints, as we do for the standard posynomial inequality or monomial equality constraints. This transformation yields

$$f_i(e^y) \leq h_i(z), \quad i = 1, \dots, m,$$

which are convex constraints in y and z , so the mixed linear geometric program becomes a convex optimization problem. This problem is not the same as would be obtained from a GP or GGP, but nevertheless is easily solved.

7.4 Generalized posynomial equality constraints

In a GGP (or GP), the only equality constraints allowed involve monomials. In some special cases, however, it is possible to handle generalized posynomial equality constraints in GGP. This idea can be traced back at least to 1978 (Wilde 1978).

We first describe the method for the case with only one generalized posynomial equality constraint (since it is readily generalizes to the case of multiple generalized posynomial equality constraints). We consider the problem

$$\begin{aligned} & \text{minimize} && f_0(x) \\ & \text{subject to} && f_i(x) \leq 1, \quad i = 1, \dots, m, \\ & && g_i(x) = 1, \quad i = 1, \dots, p, \\ & && h(x) = 1, \end{aligned} \quad (32)$$

with optimization variables x_1, \dots, x_n , where g_i are monomials, and f_i and h are generalized posynomials. Without the last generalized posynomial equality constraint, this is a GGP. With the last constraint, however, the problem is very difficult to solve, at least globally. (It is a special case of a *signomial program*, discussed in Sect. 9.)

We first form the *GGP relaxation* of the problem (32),

$$\begin{aligned} &\text{minimize} && f_0(x) \\ &\text{subject to} && f_i(x) \leq 1, \quad i = 1, \dots, m, \\ & && g_i(x) = 1, \quad i = 1, \dots, p, \\ & && h(x) \leq 1, \end{aligned} \tag{33}$$

by replacing the generalized posynomial equality with an inequality. This problem is a GGP and therefore easily solved. It is called a relaxation since we have relaxed (or loosened) the last equality constraint, by allowing $h(x) < 1$ as well as $h(x) = 1$.

Let \bar{x} be an optimal solution of the relaxed problem (33). If we have $h(\bar{x}) = 1$, then \bar{x} is also an optimal solution of the original problem (32), and we are done. Of course this need not happen; we can have $h(\bar{x}) < 1$, in which case \bar{x} is not feasible for the original problem. In some cases, though, we can modify the point \bar{x} so that it remains optimal for the relaxation (33), but also satisfies the generalized posynomial equality constraint (and therefore is optimal for the original problem (32)).

Suppose we can find a variable x_k with the following properties:

- The variable x_k does not appear in any of the monomial equality constraint functions.
- The objective and inequality constraint functions f_0, \dots, f_m are all *monotone decreasing* in x_k , i.e., if we increase x_k (holding all other variables constant), the functions f_0, \dots, f_m decrease, or remain constant.
- The generalized posynomial function h is *monotone strictly increasing* in x_k , i.e., if we increase x_k (holding all other variables constant), the function h increases.

Now suppose we start with the point \bar{x} , and increase x_k , i.e., we consider the point

$$\tilde{x} = (\bar{x}_1, \dots, \bar{x}_{k-1}, \bar{x}_k + u, \bar{x}_{k+1}, \dots, \bar{x}_n),$$

where u is a scalar that we increase from $u = 0$. By the first property, the monomial equality constraints are unaffected, so the point \tilde{x} satisfies them, for any value of u . By the second property, the point \tilde{x} continues to satisfy the inequality constraints, since increasing u decreases (or keeps constant) the functions f_1, \dots, f_m . The same argument tells us that the point \tilde{x} has an objective value that is the same, or better than, the point \bar{x} . As we increase u , $h(\tilde{x})$ increases. Now we simply increase u until we have $h(\tilde{x}) = 1$ (h can be increased as much as we like, as a consequence of the convexity of $\log h(e^y)$, where $x = e^y$). The resulting \tilde{x} is an optimal solution of the problem (32). Increasing x_k until the generalized posynomial equality constraint is satisfied is called *tightening*.

The same method can be applied when the monotonicity properties are reversed, i.e., if f_0, \dots, f_m are monotone increasing functions of x_k , and h is strictly monotone decreasing in x_k . In this case we tighten by decreasing x_k until the generalized posynomial constraint is satisfied.

As with the other tricks and transformations described, this one can be automated. Starting with a problem, with the objective and constraint functions given as expressions involving variables, powers, sum, and maximum, it is easy to check the monotonicity properties of the functions, and to determine if a variable x_k with the required monotonicity properties exists.

The same idea can be used to solve a problem with multiple generalized posynomial equality constraints,

$$\begin{aligned} &\text{minimize} && f_0(x) \\ &\text{subject to} && f_i(x) \leq 1, \quad i = 1, \dots, m, \\ & && g_i(x) = 1, \quad i = 1, \dots, p, \\ & && h_i(x) = 1, \quad i = 1, \dots, k, \end{aligned} \tag{34}$$

where f_i and h_i are generalized posynomials, and g_i are monomials. We form and solve the GGP relaxation

$$\begin{aligned} &\text{minimize} && f_0(x) \\ &\text{subject to} && f_i(x) \leq 1, \quad i = 1, \dots, m, \\ & && g_i(x) = 1, \quad i = 1, \dots, p, \\ & && h_i(x) \leq 1, \quad i = 1, \dots, k, \end{aligned} \tag{35}$$

and let \bar{x} denote an optimal solution. In this case, we need a different variable for each generalized posynomial equality constraint, with the monotonicity properties given above. We re-order the variables so that x_1 is the variable we increase to cause $h_1(x)$ to increase to one, x_2 is the variable we increase to cause $h_2(x)$ to increase to one, and so on. The simple method of increasing or decreasing one of the variables until the equality constraint is satisfied cannot be used in this case, since increasing x_1 to make $h_1(x)$ increase to one can *decrease* $h_2(x)$ (and vice versa). But we can find a common adjustment of the variables x_1, \dots, x_k that results in all the equality constraints being tightened simultaneously, by forming and solving an auxiliary GGP:

$$\begin{aligned} &\text{maximize} && x_1 \cdots x_k \\ &\text{subject to} && f_i(x) \leq 1, \quad i = 1, \dots, m, \\ & && g_i(x) = 1, \quad i = 1, \dots, p, \\ & && h_i(x) \leq 1, \quad i = 1, \dots, k, \\ & && f_0(x) \leq f^*, \end{aligned} \tag{36}$$

where f^* is the optimal value of the relaxed problem (35). The feasible set of this problem is the optimal set of the relaxed problem (35); the objective in the auxiliary problem is to maximize the product of the variables used to tighten the equality constraints. Any optimal solution of this auxiliary problem (36) is an optimal solution of the original problem (34). (We can use any objective that puts pressure on the variables x_1, \dots, x_k to increase; for example, we can minimize $1/x_1 + \dots + 1/x_k$.)

As in the case of a single generalized posynomial constraint, it is easy to automate the task of finding a set variables used to tighten the equality constraints, and form the auxiliary problem (36).

8 Approximation and fitting

In this section we first address some fundamental theoretical questions:

- What functions can be approximated by monomials or generalized posynomials?
- When can an optimization problem be approximated as a GGP?

We then discuss practical methods for approximating a given function, or some given data, by a monomial or generalized posynomial function. These fitting and approximation methods can be used to derive GP compatible approximate expressions and problem formulations.

8.1 Theory

Suppose f is a positive function of positive variables x_1, \dots, x_n . We consider the question: When can f be approximated by a monomial or generalized posynomial function?

At least in principle, the answer is simple. We first form the logarithmically transformed function

$$F(y) = \log f(e^y)$$

(which is used to transform a GP to a convex problem). Then we have the following:

- f can be approximated by a monomial if and only if F can be approximated by an affine function, i.e., a constant plus a linear function.
- f can be approximated by a generalized posynomial if and only if F can be approximated by a convex function.

Here we are being informal about what exactly we mean by ‘can be approximated’, but the statements can easily be made precise.

We have already seen that when f is a monomial, the logarithmically transformed function F is affine, and that when f is a generalized posynomial, F is convex. It’s easy to show the converse for monomials: if F is affine, then f is a monomial. The interesting part here is the converse for generalized posynomials, i.e., the observation that if F can be approximated by a convex function, then f can be approximated by a generalized posynomial.

To show this, suppose $F \approx \phi$, where ϕ is a convex function. A basic result of convex analysis is that any convex function can be arbitrarily well approximated by a piecewise linear convex function, expressed as a maximum of a set of affine functions; see, e.g., Boyd and Vandenberghe (2004). Thus, we have b_{ki} for which

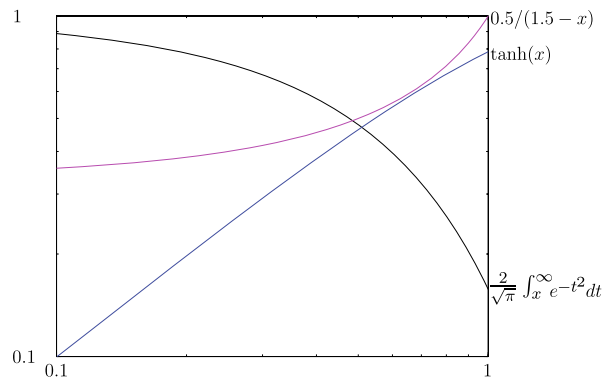
$$F(y) \approx \phi(y) \approx \max_{i=1, \dots, p} (b_{0i} + b_{1i} y_1 + \dots + b_{ni} y_n).$$

Taking the exponential of both sides, and changing variables back to x , we have

$$f(x) \approx \max_{i=1, \dots, p} e^{b_{0i}} x^{b_{1i}} \dots x^{b_{ni}}.$$

The right-hand side is the maximum of p monomials, and is therefore a generalized posynomial. (Such a function is sometimes called a *max-monomial*.)

Fig. 10 The three functions given in (37), on a log-log plot



It can be difficult to determine whether a function of many variables is convex (or nearly convex), but there are a number of techniques that can be used to verify or disprove convexity (see Boyd and Vandenberghe 2004 for much more on this topic). For the special case $n = 1$, convexity is readily determined by simply plotting the function $F(y)$, and checking that it has positive (upward) curvature. This is the same as plotting $f(x)$ on a log-log plot, and checking that the resulting graph has positive curvature. For functions of many variables, we can use the fact that a function is convex only if it is convex when restricted to any line. Thus, we can plot $F(y_0 + tv)$ versus t , for various values of y_0 and v . If any of these plots reveal negative (downward) curvature, then F is not convex.

As an example, we consider the three functions of one variable,

$$\tanh(x), \quad \frac{0.5}{1.5-x}, \quad \frac{2}{\sqrt{\pi}} \int_x^\infty e^{-t^2} dt, \quad (37)$$

and ask whether each can be approximated by a monomial or generalized posynomial, over the range $0.01 \leq x \leq 1$. These functions are plotted on a log-log plot in Fig. 10. From the figure we can see that the first function can be reasonably well fit by a monomial, since its graph is relatively straight. The second function can be fit by a generalized posynomial, since its graph is convex, i.e., curves upward, on this log-log plot. The third function cannot be fit very well by a generalized posynomial, since its graph exhibits substantial downward curvature. (Note, however, that the reciprocal of the third function has upward curvature, and therefore can be fit by a generalized posynomial.)

Convexity of F can be stated in terms of f , our original function. It means that f must satisfy the inequality (8),

$$f(x_1^\theta \tilde{x}_1^{1-\theta}, \dots, x_n^\theta \tilde{x}_n^{1-\theta}) \leq f(x_1, \dots, x_n)^\theta f(\tilde{x}_1, \dots, \tilde{x}_n)^{1-\theta},$$

for any θ with $0 \leq \theta \leq 1$. In other words, when f is evaluated at a weighted geometric mean of two points, it cannot be more than the weighted geometric mean of the function f evaluated at the two points. In Sect. 2.5, we noted that this inequality is satisfied by posynomials; what we know now is that its approximate satisfaction is the necessary and sufficient condition for a function to have a generalized posynomial approximation.

We conclude this section by asking: When can an optimization problem of the form

$$\begin{aligned} & \text{minimize} && f_0(x) \\ & \text{subject to} && f_i(x) \leq 1, \quad i = 1, \dots, m, \\ & && g_i(x) = 1, \quad i = 1, \dots, p, \end{aligned} \quad (38)$$

with positive variables x_1, \dots, x_n , be approximated by a GGP? From the discussion above, we see that the answer is:

- The transformed objective and inequality constraint functions $F_i(y) = \log f_i(e^y)$ must be nearly convex.
- The transformed equality constraint functions $G_i(y) = \log G_i(e^y)$ must be nearly affine.

8.2 Local monomial approximation

We consider the problem of finding a monomial approximation of a differentiable positive function f near a point x (with $x_i > 0$). Asking for a monomial approximation of $f(x)$ near x corresponds to asking for an affine approximation of $F(y) = \log f(e^y)$ near $y = \log x$. But such an approximation is provided by the first order Taylor approximation of F :

$$F(z) \approx F(y) + \sum_{i=1}^n \frac{\partial F}{\partial y_i} (z_i - y_i), \quad (39)$$

which is valid for $z \approx y$. (The derivatives here are evaluated at y .)

We have

$$\frac{\partial F}{\partial y_i} = \frac{1}{f(e^y)} \frac{\partial f}{\partial x_i} e^{y_i} = \frac{x_i}{f(x)} \frac{\partial f}{\partial x_i},$$

where the partial derivatives of f are evaluated at x . Using this formula, and taking the exponential of (39), we get

$$f(e^z) \approx f(x) \prod_{i=1}^n \exp\left(\frac{x_i}{f(x)} \frac{\partial f}{\partial x_i} (z_i - y_i)\right).$$

Defining $w_i = e^{z_i}$, we can express this as

$$f(w) \approx f(x) \prod_{i=1}^n \left(\frac{w_i}{x_i}\right)^{a_i}, \quad (40)$$

where

$$a_i = \frac{x_i}{f(x)} \frac{\partial f}{\partial x_i}$$

(evaluated at x). The approximation (40) is valid for $w \approx x$; the right-hand side is the best local monomial approximation of f near x .

8.3 Monomial fitting

Suppose we are given data points

$$(x^{(i)}, f^{(i)}), \quad i = 1, \dots, N,$$

where $x^{(i)} \in \mathbf{R}^n$ are positive vectors and $f^{(i)}$ are positive constants. The goal is to fit the data with a monomial $f(x) = cx_1^{a_1} \cdots x_n^{a_n}$. In other words, we want to find $c > 0$ and a_1, \dots, a_n so that

$$f(x^{(i)}) \approx f^{(i)}, \quad i = 1, \dots, N.$$

This monomial fitting task can be done several ways.

The simplest approach follows the method used for monomial function approximation. We let $y^{(i)} = \log x^{(i)}$, and replace $f(x^{(i)}) \approx f^{(i)}$ with $\log f(e^{y^{(i)}}) \approx \log f^{(i)}$, to get

$$\log c + a_1 y_1^{(i)} + \cdots + a_n y_n^{(i)} \approx \log f^{(i)}, \quad i = 1, \dots, N.$$

This is a set of linear (approximate) equalities, in the unknowns $\log c, a_1, \dots, a_n$. We can find an approximate solution via least-squares, by choosing $\log c$ and a_1, \dots, a_n to minimize the sum of the squared errors,

$$\sum_{i=1}^N (\log c + a_1 y_1^{(i)} + \cdots + a_n y_n^{(i)} - \log f^{(i)})^2.$$

(In other words, we use simple linear regression to find $\log c$ and a_1, \dots, a_n , given the data $y^{(1)}, \dots, y^{(N)}$ and $f^{(1)}, \dots, f^{(N)}$.)

This simple least-squares method can be modified and extended in several ways. We can introduce weights in the least-squares objective, in order to give more or less weight to the individual errors. We can also *regularize*, by adding a term

$$\lambda \sum_{i=1}^n a_i^2$$

to the least-squares objective, where λ is a positive constant. By adding this term to the least-squares objective (which penalizes the approximation error) we add a penalty for large values of the exponents a_i . The parameter λ is chosen to give a trade-off between good fit and small values of the exponents. We can also regularize with a term of the form

$$\lambda \sum_{i=1}^n |a_i|,$$

which results in a problem that can be posed and solved as a quadratic program (QP). This regularization tends to find good monomial fits with many, or at least several, of the coefficients a_i equal to zero. (See Boyd and Vandenberghe 2004, Chap. 6.5.) In other words, we tend to fit the data using monomials that (where possible) depend on only a few of the variables.

Another useful modification of the basic least-squares method is to add constraints (such as lower and upper bounds) on the unknowns $\log c$ and a_1, \dots, a_n . (The resulting problem can be solved using quadratic programming.) For more on fitting methods, see Boyd and Vandenberghe (2004), Chap. 6.

One drawback of using a simple fitting method applied to the logarithm of the data is that the error or residual is implicitly taken to be

$$|\log f(x^{(i)}) - \log f^{(i)}|.$$

While this residual clearly is small when $f(x^{(i)}) \approx f^{(i)}$, it may not be exactly the residual we care about. For example, we might care about the absolute error, $|f(x^{(i)}) - f^{(i)}|$, or the relative error,

$$r_i = \frac{|f(x^{(i)}) - f^{(i)}|}{f^{(i)}}.$$

The relative error is closely related to the logarithmic residual, but not exactly the same. For $f(x^{(i)}) > f^{(i)}$, we have

$$|\log f(x^{(i)}) - \log f^{(i)}| = \log(1 + r_i),$$

but for $f(x^{(i)}) < f^{(i)}$, we have

$$|\log f(x^{(i)}) - \log f^{(i)}| = \log\left(1 + \frac{|f(x^{(i)}) - f^{(i)}|}{f(x^{(i)})}\right) > \log(1 + r_i).$$

Thus, the logarithmic residual $|\log f(x^{(i)}) - \log f^{(i)}|$ puts more cost on an approximation that underestimates the data, compared to the relative error r_i .

If we do care about the relative error (as opposed to the logarithmic residual implicitly used in the regression method described above) we can choose the unknowns to minimize

$$\sum_{i=1}^N r_i^2 = \sum_{i=1}^N \left(\frac{f(x^{(i)}) - f^{(i)}}{f^{(i)}} \right)^2.$$

This is a *nonlinear least-squares problem*, which can be solved (usually) using methods such as the Gauss-Newton method (Bertsekas 1999; Luenberger 1984; Nocedal and Wright 1999). Unlike linear least-squares methods, nonlinear least-squares methods are not guaranteed to converge to the global minimizer. But these methods work well in practice, if the initial guess is found using logarithmic regression (as described above).

One problem involving the relative error is readily solvable, without resorting to nonlinear least-squares methods. Consider the problem of choosing c and a_1, \dots, a_n to minimize

$$\max_{i=1, \dots, N} \frac{|f(x^{(i)}) - f^{(i)}|}{f^{(i)}},$$

the *maximum relative fitting error*. We can solve this problem exactly, as follows. We select a target value t of maximum relative error, and will try to determine if it

can be achieved by some choice of c and a_1, \dots, a_n . This is the same as determining whether the inequalities

$$\frac{|f(x^{(i)}) - f^{(i)}|}{f^{(i)}} \leq t, \quad i = 1, \dots, N$$

are feasible (by choice of c and a_1, \dots, a_n). (We can take $0 < t < 1$.) We can write these inequalities as

$$f^{(i)}(1 - t) \leq f(x^{(i)}) \leq f^{(i)}(1 + t), \quad i = 1, \dots, N.$$

Now we use the (by now, standard) method of taking logarithms, and using $y^{(i)} = \log x^{(i)}$, to express these as

$$\log(f^{(i)}(1 - t)) \leq \log c + a_1 y_1 + \dots + a_n y_n \leq \log(f^{(i)}(1 + t)).$$

This is a set of linear inequalities in the unknowns $\log c$ and a_1, \dots, a_n , and is easily solved using linear programming. We can use a bisection method to find the smallest value of t for which the set of inequalities is feasible. (See Boyd and Vandenberghe 2004.)

To illustrate these ideas, we consider the function

$$f(x) = \sqrt{1 - (x - 1)^2}, \quad (41)$$

over the interval $[0.1, 1]$. The best local monomial approximation to f , at the point $x = 0.5$, is

$$\widehat{f}_{\text{loc}}(x) = 1.0911x^{0.3333}.$$

This monomial agrees with f at $x = 0.5$, and gives a very good approximation near $x = 0.5$.

To give a fit over the whole interval $[0.1, 1]$, we first generate 100 data points $(x^{(i)}, f(x^{(i)}))$, with $x^{(i)}$ uniformly spaced over the interval $[0.1, 1]$. The monomial obtained by a least-squares fit of an affine function to the logarithmically transformed data $(\log x^{(i)}, \log f(x^{(i)}))$ is

$$\widehat{f}_{\text{ls}}(x) = 1.0695x^{0.3549}.$$

The monomial that minimizes the maximum relative error (for the given data points) is

$$\widehat{f}_{\text{maxrel}}(x) = 1.0539x^{0.3606}.$$

The three monomial approximations \widehat{f}_{loc} , \widehat{f}_{ls} , and $\widehat{f}_{\text{maxrel}}$ are plotted in Fig. 11, along with the original function f . The associated fractional error distributions (for the 100 data points used) are shown in Fig. 12. As expected, the local approximation gives a very good fit near $x = 0.5$, with the end-points $x = 0.1$ and $x = 1$ giving relative errors around 16%. The least-squares logarithmic approximation gives better fit

Fig. 11 The *solid curve* is $f(x) = \sqrt{1 - (x - 1)^2}$. $\hat{f}_{\text{loc}}(x)$: best monomial approximation near $x = 0.5$. $\hat{f}_{\text{ls}}(x)$: monomial approximation obtained via least-squares fitting to logarithmically transformed data. $\hat{f}_{\text{maxrel}}(x)$: monomial approximation that minimizes maximum relative error

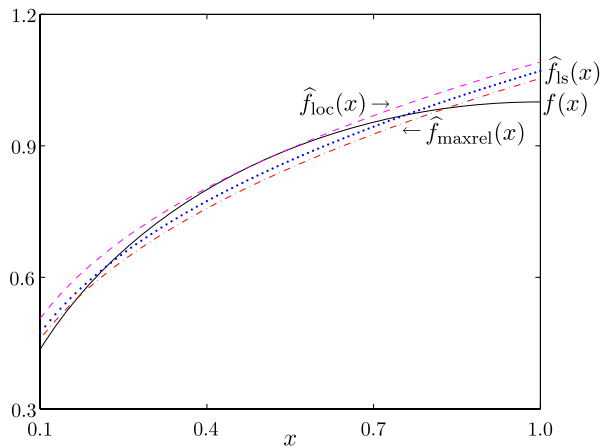
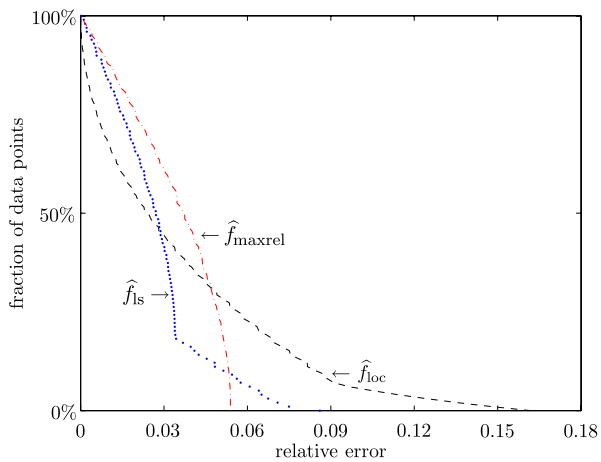


Fig. 12 Relative error distributions for the three monomial approximations \hat{f}_{loc} , \hat{f}_{ls} , and \hat{f}_{maxrel}



across the interval, with most errors under 3%, but maximum relative error exceeding 8%. The minimax relative error approximation has a very tight error distribution, with maximum relative error only 5.3%.

One useful extension of monomial fitting is to include a constant offset, i.e., to fit the data $(x^{(i)}, f^{(i)})$ to a model of the form

$$f(x) = b + cx_1^{a_1} \cdots x_n^{a_n},$$

where $b \geq 0$ is another model parameter. Here f is a posynomial, but with a very special form: a monomial plus a constant. To find such a fit, we simply use monomial modeling to fit the modified data points $(x^{(i)}, f^{(i)} - b)$, for various values of b , and choose the one with the best fit.

The idea of using linear regression and fitting techniques on logarithmically transformed data can be applied to several problems beyond monomial fitting. As an ex-

ample, suppose we have some positive vectors

$$x^{(1)}, \dots, x^{(N)} \in \mathbf{R}^n,$$

and wish to find (approximate) monomial relations that the vectors satisfy, i.e., we wish to find monomials g_1, \dots, g_k for which

$$g_j(x^{(i)}) \approx 1, \quad j = 1, \dots, k, \quad i = 1, \dots, N. \quad (42)$$

This can be done using the singular value decomposition (SVD), or canonical correlations, applied to logarithmically transformed data. We let $y^{(i)} = \log x^{(i)}$, and form the matrix

$$Y = [y^{(1)} y^{(2)} \dots y^{(N)}] \in \mathbf{R}^{n \times N}.$$

The monomial relations (42) correspond to vectors $a_1, \dots, a_k \in \mathbf{R}^{n+1}$ for which

$$[Y^T \mathbf{1}] a_j \approx 0, \quad j = 1, \dots, k, \quad (43)$$

where $\mathbf{1}$ denotes a vector with all components one. To find such vectors (and also the number k), we compute the SVD of the matrix $[Y^T \mathbf{1}]$. The number of small singular values gives us the number of monomial approximate relations in the data, and the vectors a_j are the left singular vectors associated with small singular values.

8.4 Max-monomial fitting

We consider the problem of fitting given data points $(x^{(i)}, f^{(i)})$, $i = 1, \dots, N$, with a max-monomial function, i.e., one of the form

$$f(x) = \max_{k=1, \dots, K} f_k(x),$$

where f_1, \dots, f_K are monomials. When the number of terms K is not specified, this problem can be solved exactly by the usual logarithmic transform, which reduces it to the problem of finding the best convex piecewise linear fit to some data. This problem can be posed as a large quadratic program and therefore solved; see Boyd and Vandenberghe (2004), Chap. 6.5.5. Unfortunately, this approach often leads to a number of terms that is very large, and therefore not practical. On the other hand, it can be very useful to know what the best max-monomial fit to the data is, when there is no limit on the number of terms.

We now concentrate on the case when the number of terms K (or an upper bound on it) is fixed, and presumably not too large. Unlike the monomial fitting problem (which corresponds to the case $K = 1$), finding the best K -term max-monomial fit to the data is not a simple one. But there is a relatively simple method, based on monomial fitting and data point clustering, that works well in practice (Magnani and Boyd 2006).

The algorithm is closely related to the K -means clustering algorithm (Hastie et al. 2001), a well known method for clustering or partitioning a set of points into K subsets, so as to minimize a sum-of-squares criterion. The general algorithm is outlined below:

Simple max-monomial data fitting algorithm.

given initial monomials $f_1(x), \dots, f_K(x)$

repeat

for $k = 1, \dots, K$

 find all data points $x^{(j)}$ for which $f_k(x^{(j)}) = f(x^{(j)})$

 (i.e., data points at which f_k is the largest of the monomials)

 update f_k by carrying out a monomial fit to these data points

until no further improvement occurs

This algorithm first clusters the data points into groups, for which the different monomials give the maximum value. Then, for each cluster of data points, the associated monomial is updated with a monomial fit to the data points. This is repeated until convergence. The algorithm is not guaranteed to converge, but with real data almost always does. The final max-monomial approximation can depend on the initial max-monomial, so the algorithm can be run from several initial max-monomials, and the best final fit taken. During the algorithm, it can happen that no points are assigned to one of the monomials. In this case we can just eliminate this monomial, and proceed with $K - 1$ terms. For this reason, the final max-monomial approximation can have fewer than K terms.

One simple method for generating an initial max-monomial from which to start the algorithm is as follows. We first fit a single monomial to the data (using the methods described above), and then form K versions of it by randomly perturbing the exponents. We express the monomial fit as

$$f_{\text{mon}}(x) = c(x_1/\bar{x}_1)^{a_1} \cdots (x_n/\bar{x}_n)^{a_n},$$

where

$$\bar{x}_i = \left(\prod_{j=1}^N x_i^{(j)} \right)^{1/N}$$

is the geometric mean of the i th component of the data points (i.e., the average value of the i th component on a logarithmic scale). We then form our monomials as

$$f_i(x) = c(x_1/\bar{x}_1)^{a_1 + \delta_{i,1}} \cdots (x_n/\bar{x}_n)^{a_n + \delta_{i,n}},$$

where $\delta_{i,j}$ are independent random variables. This generates K monomials, all near the original one, that are slightly different.

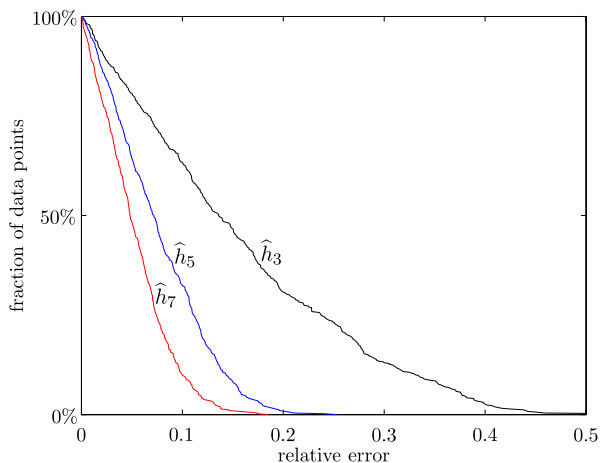
To illustrate this method for max-monomial fitting, we consider a numerical example. The data are generated as samples of the function

$$f(x) = e^{(\log x_1)^2 + (\log x_2)^2},$$

with $N = 500$ data points drawn from a uniform distribution over the region $0.1 \leq x_i \leq 1$. The corresponding logarithmically transformed function is

$$F(y) = \log f(e^y) = y_1^2 + y_2^2,$$

Fig. 13 Relative error distributions for max-monomial approximations, with three terms (\hat{h}_3), five terms (\hat{h}_5), and seven terms (\hat{h}_7)



which is a convex quadratic function of y . According to the theory, then, f can be approximated arbitrarily well by a max-monomial with sufficiently many terms. (But we note that max-monomial fitting works when the data *do not* come from a function that can be arbitrarily well approximated by a max-monomial; in this case, the fitting error does not decrease to zero as the number of monomial terms increases.)

We use the algorithm above, with the simple least-squares logarithmic approximation method for monomial fitting, to find K -term max-monomial approximations, $\hat{h}_K(x)$, for $K = 3, 5$, and 7 . For this example, the final max-monomial found is (nearly) independent of the initial max-monomial, chosen randomly as described above. The associated residual error distributions for the three max-monomial approximations are shown in Fig. 13.

8.5 Posynomial fitting

General nonlinear least-squares methods can be used to find the coefficients and exponents in a posynomial with K terms,

$$\hat{f}(x) = \sum_{k=1}^K c_k x_1^{a_{1k}} x_2^{a_{2k}} \cdots x_3^{a_{3k}},$$

that minimize, e.g., the sum of squares of the relative errors,

$$\sum_{i=1}^N r_i^2 = \sum_{i=1}^N \left(\frac{f^{(i)} - f(x^{(i)})}{f^{(i)}} \right)^2$$

(along with the constraint $c_k \geq 0$). Methods for this type of problem, such as the Gauss-Newton method, or sequential quadratic programming, are local, like the max-monomial fitting method described above. This means that they cannot guarantee convergence to the true minimum; indeed, the final posynomial approximation obtained can depend on the initial one. But these methods often work well in practice,

when initialized with reasonable starting posynomials. Because the final posynomial found depends on the starting posynomial, it is common to run the algorithm from several different starting points, and to take the best final posynomial found.

We can find a starting posynomial using a variation on the method used to initialize the max-monomial fitting algorithm. We first find a monomial fit of the data,

$$f_{\text{mon}}(x) = c(x_1/\bar{x}_1)^{a_1} \cdots (x_n/\bar{x}_n)^{a_n}.$$

We express this as a sum of K identical monomials,

$$f_{\text{mon}}(x) = \sum_{k=1}^K (c/K)(x_1/\bar{x}_1)^{a_1} \cdots (x_n/\bar{x}_n)^{a_n}.$$

Now we perturb the exponents in the monomial terms to give a posynomial with K different terms:

$$\hat{f}(x) = \sum_{k=1}^K (c/K)(x_1/\bar{x}_1)^{a_1+\delta_{i,1}} \cdots (x_n/\bar{x}_n)^{a_n+\delta_{i,n}},$$

where $\delta_{i,j}$ are independent random variables. We use this posynomial as the starting point for a nonlinear least-squares method for fitting.

We illustrate posynomial fitting using the same data points as those used in the max-monomial fitting example given in Sect. 8.4. We used a Gauss-Newton method to find K -term posynomial approximations, $\hat{h}_K(x)$, for $K = 3, 5, 7$, which (locally, at least) minimize the sum of the squares of the relative errors. In this case, the final posynomial obtained does depend substantially on the starting posynomial, so for each K , we solved 20 nonlinear fitting problems with different initial exponents $\delta_{i,n}$ drawn from normal distributions with zero mean and standard deviation $0.2|a_i|$, and take as the final posynomial approximation the best among the 20. The associated residual error distributions (for the 500 data points used) for the three posynomial approximations $\hat{h}_K(x)$, $K = 3, 5, 7$ are shown in Fig. 14.

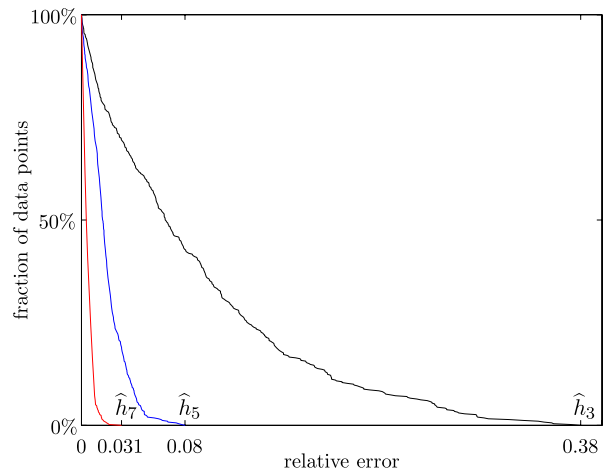
Comparing these error distributions to the ones obtained from max-monomial fitting, we see that posynomial fitting gives a much better fit for the same number of monomial terms. This is often the case when the original data or function is smooth. But the opposite can also occur: for some data, a max-monomial fit can be much better than a posynomial fit with the same number of terms.

We mention one more method for posynomial (and generalized posynomial) fitting. Suppose that we choose a set of r basis functions ϕ_1, \dots, ϕ_r , which are themselves generalized posynomials. These could be monomials, for example, whose exponents are chosen on the basis of some prior knowledge of how the variables affect the function value. Once we have fixed the basis functions, we can find the coefficients c_k for the approximation

$$\hat{f}(x) = c_1\phi_1(x) + \cdots + c_r\phi_r(x),$$

that minimizes the sum of squares of relative errors, subject to the constraint $c_k \geq 0$, as a quadratic programming problem. (This we can solve exactly; we do not have to

Fig. 14 Relative error distributions for the posynomial approximations obtained via nonlinear least-squares fitting.
 \hat{h}_3 : 3-term posynomial fitting.
 \hat{h}_5 : 5-term posynomial fitting.
 \hat{h}_7 : 7-term posynomial fitting



worry about convergence to a local minimum as in max-monomial or general posynomial fitting.)

One interesting variant on this approach is to take a very large number of basis functions, more than we would consider using in the final approximation. We then add to the objective a regularization term of the form $\lambda(c_1 + \cdots + c_r)$, with $\lambda > 0$. This tends to find solutions with many of the c_k equal to zero. Thus, the quadratic program effectively chooses a small subset of the basis functions. (See Boyd and Vandenberghe 2004, Chap. 6.5.)

9 Extensions

In this section we describe some extensions of GP.

9.1 Signomial programming

A *signomial* is a function with the same form as a posynomial (i.e., (2)), where the coefficients c_j are allowed to be negative. A *signomial program* (SGP) is a generalization of a geometric program, which has the form of a GP, but the objective and constraint functions can be signomials:

$$\begin{aligned} &\text{minimize} && f_0(x) \\ &\text{subject to} && f_i(x) \leq 1, \quad i = 1, \dots, m, \\ & && g_i(x) = 1, \quad i = 1, \dots, p, \end{aligned} \tag{44}$$

where f_i and g_i are signomial functions. (As in GP, there is an implicit constraint that the variables are positive, i.e., $x_i > 0$.) Unfortunately some authors use the term ‘generalized geometric program’ to refer to a signomial program.

From a computational point of view, there is a huge difference between a GP (or a GGP) and an SGP. While the globally optimal solution of a GP can always be found efficiently, only a *locally optimal* solution of an SGP can be computed efficiently.

(It's possible to compute the globally optimal solution of an SGP, but this can require prohibitive computation, even for relatively small problems.)

We describe one general method for finding a local solution of an optimization problem that has the same form as a GP, but the objective and inequality constraint functions are not posynomials, and the equality constraint functions are not monomials. (SGP is a special case of this.) At each step we have a current guess $x^{(k)}$. For the objective and each constraint function, we find the best local monomial approximation near the current guess $x^{(k)}$, using the formula (40). We replace the original functions in the optimization problem with these monomial approximations, which results in a GP (in fact, a linear program after the logarithmic transformation). Of course, we cannot trust these approximations for points that are not close to the current guess $x^{(k)}$, so we add some *trust region constraints* to the problem, which limit how much the variables are allowed to differ from the current guess. We might, for example, form the problem

$$\begin{aligned} & \text{minimize} && \hat{f}_0(x) \\ & \text{subject to} && \hat{f}_i(x) \leq 1, \quad i = 1, \dots, m, \\ & && \hat{g}_i(x) = 1, \quad i = 1, \dots, p, \\ & && (1/1.1)x_i^{(k)} \leq x_i \leq 1.1x_i^{(k)}, \quad i = 1, \dots, n, \end{aligned} \tag{45}$$

where \hat{f}_i is the local monomial approximation of f_i at $x^{(k)}$, and \hat{g}_i is the local monomial approximation of g_i at $x^{(k)}$. The problem (45) is a GP, and therefore can be solved efficiently. Its solution is taken as the next iterate $x^{(k+1)}$. The algorithm consists of repeating this step until convergence.

This method is local: It need not converge (but very often does), and can converge to a point that is not the global solution. But if the problem is not too far from a GP, and the starting guess $x^{(0)}$ is good, it can work well in practice.

There are many variations on this method. For example, we do not need to form a monomial approximation of any constraint that is already in GP form in the original problem; if f_i is a posynomial in the original problem (44), then we can leave f_i in the problem (45) used to generate the next iterate. This idea can be taken a step further, when the original problem is an SGP, by forming a monomial approximation only of the offending terms in each constraint, i.e., those that have negative coefficients. A general signomial inequality constraint can be expressed as

$$f(x) = p(x) - q(x) \leq 1,$$

where p and q are both posynomials. (Here p consists of the terms in the signomial f with positive coefficients, and $-q$ consists of the terms in f with negative coefficients.) We write the signomial inequality as

$$p(x) \leq 1 + q(x),$$

and then form a monomial approximation of $1 + q(x)$, say, $r(x)$, at the current point $x^{(k)}$, and substitute the constraint

$$p(x) \leq r(x)$$

(which is GP compatible) in the GP (45) used to form the next iterate.

9.2 Mixed-integer geometric programming

In a *mixed-integer GP*, we have a GP with the additional constraint that some of the variables lie in some discrete set, such as the integers:

$$\begin{aligned} &\text{minimize} && f_0(x) \\ &\text{subject to} && f_i(x) \leq 1, \quad i = 1, \dots, m, \\ & && g_i(x) = 1, \quad i = 1, \dots, p, \\ & && x_i \in \mathbf{N}, \quad i = 1, \dots, k, \end{aligned} \tag{46}$$

where \mathbf{N} denotes the set of natural numbers, i.e., positive integers.

Mixed-integer GPs are in general very hard to solve, and all methods for solving them make some compromise, compared to methods for GP.

- *Heuristic methods* attempt to find good approximate solutions quickly (say, taking about the same time a similar size GP would), but cannot guarantee that the solution found is optimal.
- *Global methods* always find the global solution, but can take an extremely long time to run.

The simplest heuristic method is to ignore the integer constraints in (46), and solve the resulting GP (which can always be done fast). This problem is called the *GP relaxation* of the MIGNP (46), since we have relaxed the integer constraints. The optimal value of the relaxed GP is a lower bound on the optimal value of the MIGNP, since when we relax we expand the feasible set (and therefore reduce the optimal value). To obtain an approximate solution of the MIGNP, we simply round each of the variables x_1, \dots, x_k towards the nearest integer. Then, we fix the integer variables (i.e., treat them as constants) and solve the resulting GP. This second step allows the continuous variables to move around a bit to make up for the rounding. Although this method can work well for some problems, it often works poorly. For example, it often yields a point that is infeasible. One way to deal with this is to first tighten all constraints by some amount, such as 5%, prior to relaxing. This gives the relaxed solution some margin, so the rounded approximate solution has a greater chance of being feasible.

A more sophisticated method is to carry out the rounding in a sequence of steps. First we solve the relaxed GP. Then for each discrete variable that is within, say, 0.1 of an integer, we round it, and fix its value. We then form a new MIGNP, which consists of the original MIGNP, but with the integer variables that were fixed substituted with their fixed values. We then repeat the process, until all integer variables have been fixed. The idea here is that we only round the integer variables in cases where the rounding does little harm (it is hoped).

The most common global methods are *branch and bound* algorithms (Lawler and Wood 1966; Moore 1991). They are nonheuristic, in the sense that they maintain a provable upper and lower bound on the (globally) optimal objective value, and ultimately find the true global solution. Branch and bound algorithms can be (and often are) slow, however. In the worst case they require effort that grows exponentially with problem size, but in some cases we are lucky, and the methods converge with much less effort.

A typical branch and bound methods works as follows. We solve the relaxed GP, which gives us a lower bound on the optimal value of the MIGP, and we also use some heuristic (such as rounding) to find a locally optimal approximate solution. If it is feasible, and its objective value is close enough to the lower bound, we can take it as a guaranteed nearly optimal solution, and quit. If this is not the case, we choose an integer variable x_i and *branch*. To do this we choose some integer e , and observe that if x_i^* is the optimal value of x_i (for the MIGP) then either $x_i^* \leq e$ or $x_i^* \geq e + 1$. We form two *children MIGPs*, from the original one, by adding these two constraints to the original problem. We then repeat on each of these children. Eventually, the constraints on the integer variables become equality constraints, at which point we have GPs, and the relaxation yields the exact global solution. The hope is that this happens within a reasonable number of steps. Branch and bound algorithms differ in the heuristics used to choose a variable to branch on, and on which children MIGPs to process at each step.

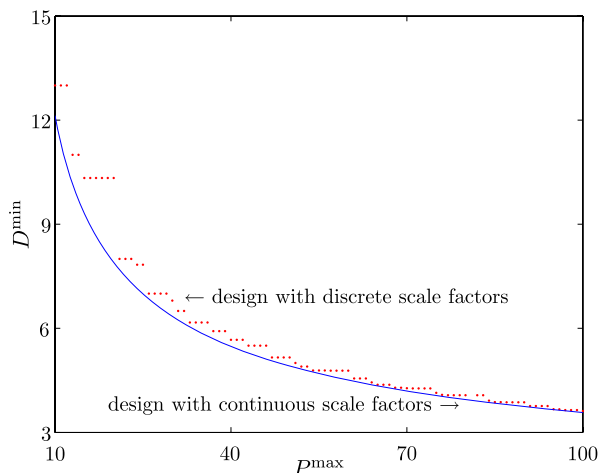
As an example of mixed integer geometric programming, we revisit the digital circuit gate scaling problem considered in Sect. 6.2, with an additional twist: we require that the scale factors must take integer values. The gate scaling problem is then the MIGP

$$\begin{aligned} & \text{minimize} && D \\ & \text{subject to} && P \leq P^{\max}, \quad A \leq A^{\max}, \\ & && x_i \in \mathbf{N}, \quad i = 1, \dots, n. \end{aligned} \quad (47)$$

(The requirement that the gate scaling factors are integers is natural, since the individual devices in the gates can be obtained by replicating an integer number of the devices appearing in the minimum sized gate.)

Now we consider a numerical example, the small digital circuit shown in Fig. 4, with the same parameters as those used in the numerical instance in Sect. 6.2, and maximum area $A^{\max} = 100$. This problem is small enough that we can easily find the global optimum of the MIGP (47) using the branch and bound method. Figure 15 compares the optimal trade-off curve of the minimum delay versus maximum allowed power for the design with discrete scale factors with that for the design with contin-

Fig. 15 Optimal trade-off curves of minimum delay D^{\min} versus maximum power P^{\max} , for the maximum area $A^{\max} = 100$, with and without the constraint that the gate scale factors are integers



uous scale factors. Adding the integer constraints reduces the feasible set, and so can only increase the minimum delay obtained. The plot shows that some values of P^{\max} (such as 40) the penalty paid for integer scale factors isn't large; for other values of P^{\max} (such as 20) the penalty paid for integer scale factors is much larger. (In the general case, of course, the penalty can be much larger, or even make the problem infeasible.)

10 Notes and references

10.1 Origins of geometric programming

Geometric programming was introduced by Duffin, Peterson, and Zener in their (1967) book. Two other early books on geometric programming are by Wilde and Beightler (1967), and Zener (1971). These early books contain much material, such as sensitivity analysis, monomial fitting, and many of the extensions described in this tutorial (fractional powers and exponentials of posynomials, and posynomial equality constraints).

Some of the ideas behind geometric programming can be traced back to earlier work. Although not discussed in this paper, GPs are very closely related via duality to problems involving entropy and cross entropy (see, e.g., Boyd and Vandenberghe 2004, Chap. 5.7), which appeared earlier. For example, in the (1958) paper, Dantzig, Johnson, and White consider a chemical equilibrium problem in what is now recognized as geometric programming dual form. Dual form GPs were called linear-logarithmic programs in the 1960s (see, e.g., Clasen 1963). A history of the development of geometric programming can be found in Peterson's survey (2001).

Sensitivity analysis for geometric programming is discussed in (Dembo 1982; Dinkel et al. 1978; Kyparsis 1988, 1990; Rijckaert and Walraven 1985). Recent work on *robust geometric programming* (a variation on GP in which the coefficients in the posynomials are uncertain) can be found in (Federowicz and Rajgopal 1999; Hsiung et al. 2006; Singh et al. 2005). Some recent work on mixed-integer geometric programming and signomial programming can be found in the papers (Alejandre et al. 2004; Choi and Bricker 1995, 1996b; Maranas and Floudas 1997; Serali 1998; Tsai et al. 2002; Yun and Xi 1997; Yang and Bricker 1997).

10.2 Algorithms and software

In the early work by Duffin, Peterson, Zener, and Wilde, GPs were solved analytically via the dual problem (which is possible only for very small problems). Numerical methods for (computer) solution of GPs were developed in the 1970s; see, e.g., Duffin (1970), Avriel et al. (1975), and Rajgopal and Bricker (1990). These methods were based on solving a sequence of linear programs.

The first interior-point method for GP was described by Nesterov and Nemirovsky in 1994, who also established polynomial time complexity of the method (Nesterov and Nemirovsky 1994). More recent work on interior-point methods for GP include Kortanek et al. (1996) and Andersen and Ye (1998). For a general introduction to interior-point methods for convex optimization (and GP in particular) see part III

of Boyd and Vandenberghe (2004). A high quality implementation of a primal-dual interior-point method for GP is available in the MOSEK (2002) software package and the TOMLAB software package (Edvall and Hellman 2005). Both packages include a simple interface to the MathWorks' MATLAB. A primal-dual interior-point solver is also included in the GGPLAB distribution (Mutapcic et al. 2006).

The power of GGP can be utilized conveniently only with a parser that automatically converts a GGP to a GP. A few simple computer programs that automate the transformation from a text description of a GP or GGP into a form suitable for a solver are already available. Examples are CVX (Grant et al. 2005), GGPLAB (Mutapcic et al. 2006), and YALMIP (Löfberg 2003), which have a simple interface that recognizes some GGPs, and automatically forms and solves the resulting GPs. Most examples in this paper are included in the library of examples for GGPLAB and CVX. While the current generation of GP and GGP software is for experts only, we can expect in the next few years rapid progress in GP and GGP solution speed, as well as user-friendly interfaces for specifying (and debugging) GPs and GGPs.

10.3 Applications

Since its inception, GP has been closely associated with applications in engineering. Early applications of geometric programming include nonlinear network flow problems, optimal control, optimal location problems, and chemical equilibrium problems. These are described in the books (Avriel 1980; Beightler and Phillips 1976; Duffin et al. 1967; Nijhamp 1972; Wilde 1978; Wilde and Beightler 1967; Zener 1971) and survey papers (Ecker 1980; Peterson 1976).

Geometric programming has been used in a variety of problems in digital circuit design; see Boyd et al. (2005), Sapatnekar (2004) for more on GP-based digital circuit sizing and optimization. In 1985 Fishburn and Dunlop used geometric programming for transistor and wire sizing in digital integrated circuit design. Since then many digital circuit design problems have been formulated as GPs or related problems:

- Gate sizing (Chu and Wong 2001b; Cong and He 1998; Coudert et al. 1996; Kasamsetty et al. 2000; Marković et al. 2004; Matson and Glasser 1986; Pattanaik et al. 2003; Sancheti and Sapatnekar 1996; Sapatnekar et al. 1993; Shyu et al. 1988; Swahn and Hassoun 2006)
- Wire sizing (Chen and Wong 1999; Chen et al. 2004; Cong and He 1996; Cong and Koh 1994; Cong and Leung 1995; Cong and Pan 2002; Gao and Wong 1999; Kay and Pileggi 1998; Lee et al. 2002; Lin and Pileggi 2001; Sapatnekar 1996)
- Buffering and wire sizing (Chu and Wong 1999, 2001a)
- Simultaneous gate and wire sizing (Chen et al. 1999; Jiang et al. 2000)
- Sizing and placement (Chen et al. 2000; Lou et al. 1999)
- Routing (Borah et al. 1997)
- Design with multiple supply voltages (Krishnamurthy and Carley 1997)
- Yield maximization (Boyd et al. 2006; Kim et al. 2007; Patil et al. 2005)
- Power optimization (Bhardwaj et al. 2006; Bhardwaj and Vrudhula 2005; Horowitz et al. 2005; Satish et al. 2005)
- Parasitic reduction (Qin and Cheng 2003)
- Clock skew optimization (Sathiyamurthy et al. 1998)

These are all based on gate delay models that are compatible with geometric programming; see Kasamsetty et al. (2000), Sakurai (1988), Sutherland et al. (1999), Rubenstein et al. (1983), Abou-Seido et al. (2004) for more on such models. Some of the papers listed above develop custom methods for solving the resulting GPs, instead of using general purpose interior-point methods (see, e.g., Chu and Wong 2001a, 2001b; Ismail et al. 2000; Young et al. 2001). See (Boyd et al. 2005; Sapatnekar 2004) for more on GP-based digital circuit sizing.

In 1997, Hershenson, Boyd, and Lee applied GP to analog integrated circuit design (Hershenson et al. 2001). GP is applied to RF circuit design in (Hershenson et al. 1999; Mohan et al. 1999, 2000), operational amplifier design in (Dawson et al. 2001; Hershenson 2003; Hershenson et al. 1998; Mandal and Visvanathan 2001; Vanderhaegen and Brodersen 2004), mixed signal IC design in (Colleran et al. 2003; Hassibi and Hershenson 2002; Hershenson 2002), switching regulator design in (Lee et al. 2003), configurable analog/RF circuit design in (Li et al. 2004; Xu et al. 2004), and transformer design in (Jabr 2005). GP compatible models for analog circuit design are discussed in (Aggarwal and O'Reilly 2006; Daems et al. 2003; Kim et al. 2004; Kiely and Gielen 2004). Geometric programming has also been used for floorplanning in the context of circuit design (Moh et al. 1996; Rosenberg 1989; Young et al. 2001).

Applications of geometric programming in other fields include:

- Chemical engineering (Clasen 1984; Salomone and Iribarren 1993; Salomone et al. 1994; Wall et al. 1986)
- Environment quality control (Greenberg 1995; Smeers and Tyteca 1984)
- Resource allocation in communication and network systems (Boche and Stańczak 2004; Chiang 2005a; Chiang and Boyd 2004; Chiang et al. 2002a, 2002b; Dutta and Rama 1992; Greenberg 1995; Julian et al. 2002; Kandukuri and Boyd 2002; Palomar et al. 2003)
- Information theory (Ben-Tal and Teboulle 1986; Ben-Tal et al. 1988; Chiang and Boyd 2004; Karlof and Chang 1997; Klafszky et al. 1992; Muqattash et al. 2006)
- Probability and statistics (Bricker et al. 1997; El Barmi and Dykstra 1994; Feigin and Passy 1981; Fuh and Hu 2000; Hu and Wei 1989; Mazumdar and Jefferson 1983; Stark and Machida 1993; Vardi 1985)
- Structural design (Adeli and Kamal 1986; Chan and Turllea 1978; Chen 1992; Dhillon and Kuo 1991; Hajela 1986; Vanderplaats 1984)
- Computer system architecture design (Trivedi and Sigmon 1981)
- Inventory control (Abou-El-Ata and Kotb 1997; Abuo-El-Ata et al. 2003; Cheng 1991; Hariri and Abou-El-Ata 1997; Jung and Klein 2001; Lee and Kim 1993; Scott et al. 2004)
- Production system optimization (Choi and Bricker 1996a)
- Mechanical engineering (Jha 1990; Sonmez et al. 1999)
- Transportation engineering (Wong 1981)
- Management science (Corstjens and Doyle 1979)
- Computational finance (Rajasekera and Yamada 2001)
- Geometric modeling (Cheng et al. 2002; Cheng et al. 2005a, 2005b)
- Systems and control theory (Chandra et al. 2004; Yazarel and Pappas 2004)

Some recent books (Boyd and Vandenberghe 2004; Floudas 1999; Hitomi 1996; Papalambros and Wilde 1988; Rao 1996) include engineering applications of geometric programming. We refer the reader to the tutorial paper (Chiang 2005b) for an extensive discussion on applications of geometric programming in communications and information theory.

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References

- Abou-El-Ata M, Kotb K (1997) Multi-item EOQ inventory model with varying holding cost under two restrictions: a geometric programming approach. *Prod Plan Control* 8(6):608–611
- Abou-Seido A, Nowak B, Chu C (2004) Fitted Elmore delay: a simple and accurate interconnect delay model. *IEEE Trans VLSI Syst* 12(7):691–696
- Abuo-El-Ata M, Fergany H, El-Wakeel M (2003) Probabilistic multi-item inventory model with varying order cost under two restrictions: a geometric programming approach. *Int J Prod Econ* 83(3):223–231
- Adeli H, Kamal O (1986) Efficient optimization of space trusses. *Comput Struct* 24:501–511
- Aggarwal V, O'Reilly U-M (2006) Design of posynomial models for MOSFETs: symbolic regression using genetic algorithms. In: Riolo R, Soule T, Worzel B (eds) *Genetic programming theory and practice. Genetic and evolutionary computation*, vol 5. Springer, Ann Arbor, Chap 7
- Alejandro J, Allueva A, Gonzalez J (2004) A general alternative procedure for solving negative degree of difficulty problems in geometric programming. *Comput Optim Appl* 27(1):83–93
- Andersen E, Ye Y (1998) A computational study of the homogeneous algorithm for large-scale convex optimization. *Comput Optim Appl* 10(3):243–269
- Avriel M (1980) *Advances in geometric programming. Mathematical concept and methods in science and engineering*, vol 21. Plenum, New York
- Avriel M, Dembo R, Passy U (1975) Solution of generalized geometric programs. *Int J Numer Methods Eng* 9(1):149–168
- Bazaraa M, Shetty C, Sherali H (1993) *Non-linear programming: theory and algorithms*. Wiley, New York
- Bightler C, Phillips D (1976) *Applied geometric programming*. Wiley, New York
- Ben-Tal A, Teboulle M (1986) Rate distortion theory with generalized information measures via convex programming duality. *IEEE Trans Inf Theory* 32(5):630–641
- Ben-Tal A, Teboulle M, Charnes A (1988) The role of duality in optimization problems involving entropy functionals. *J Optim Theory Appl* 58(2):209–223
- Bertsekas DP (1999) *Nonlinear programming*, 2nd edn. Athena Scientific
- Bhardwaj S, Vrudhula S (2005) Leakage minimization of nano-scale circuits in the presence of systematic and random variations. In: *Proceedings of the 42nd IEEE/ACM design automation conference (DAC)*, pp 535–540, 2005
- Bhardwaj S, Cao Y, Vrudhula S (2006) Statistical leakage minimization through joint selection of gate sizes, gate lengths and threshold. In: *Proceedings of the 12th conference on Asia and South Pacific design automation conference (ASP-DAC)*, pp 953–958, 2006
- Boche H, Stańczak S (2004) Optimal QoS tradeoff and power control in CDMA systems. In: *Proceedings of the 23rd IEEE INFOCOM*, pp 477–486, 2004
- Borah M, Owens R, Irwin M (1997) A fast algorithm for minimizing the Elmore delay to identified critical sinks. *IEEE Trans Comput Aided Des Integr Circuits Syst* 16(7):753–759
- Boyd S, Vandenberghe L (2004) *Convex optimization*. Cambridge University Press, Cambridge
- Boyd S, Kim S-J, Patil D, Horowitz M (2005) Digital circuit optimization via geometric programming. *Oper Res* 53(6):899–932
- Boyd S, Kim S-J, Patil D, Horowitz M (2006) A heuristic method for statistical digital circuit sizing. In: *Proceedings of the 31st SPIE international symposium on microlithography*, San Jose, 2006

- Bricker D, Kortanek K, Xui L (1997) Maximum likelihood estimates with order restrictions on probabilities and odds ratios: a geometric programming approach. *J Appl Math Decis Sci* 1(1):53–65
- Chan A, Turla E (1978) An approximate method for structural optimisation. *Comput Struct* 8(3–4):357–363
- Chandra D, Singh V, Kar H (2004) Improved Routh-Padé approximants: a computer-aided approach. *IEEE Trans Autom Control* 49(2):292–296
- Chen C-P, Wong D (1999) Greedy wire-sizing is linear time. *IEEE Trans Comput Aided Des Integr Circuits Syst* 18(4):398–405
- Chen C-P, Chu C, Wong D (1999) Fast and exact simultaneous gate and wire sizing by Lagrangian relaxation. *IEEE Trans Comput Aided Des Integr Circuits Syst* 18(7):1014–1025
- Chen T-Y (1992) Structural optimization using single-term posynomial geometric programming. *Comput Struct* 45(5–6):911–918
- Chen T-C, Pan S-R, Chang Y-W (2004) Timing modeling and optimization under the transmission line model. *IEEE Trans Very Large Scale Integr Syst* 12(1):28–41
- Chen W, Hsieh C-T, Pedram M (2000) Simultaneous gate sizing and placement. *IEEE Trans Comput Aided Des Integr Circuits Syst* 19(2):206–214
- Cheng T (1991) An economic order quantity model with demand-dependent unit production cost and imperfect production processes. *IIE Trans* 23(1):23
- Cheng H, Fang S-C, Lavery J (2002) Univariate cubic L_1 splines—A geometric programming approach. *Math Methods Oper Res* 56(2):197–229
- Cheng H, Fang S-C, Lavery J (2005a) A geometric programming framework for univariate cubic L_1 smoothing splines. *Ann Oper Res* 133(1–4):229–248
- Cheng H, Fang S-C, Lavery J (2005b) A geometric programming framework for univariate cubic L_1 smoothing splines. *J Comput Appl Math* 174(2):361–382
- Chiang M (2005a) Balancing transport and physical layers in wireless multihop networks: jointly optimal congestion control and power control. *IEEE J Sel Areas Commun* 23(1):104–116
- Chiang M (2005b) Geometric programming for communication systems. *Found Trends Commun Inf Theory* 2(1–2):1–154
- Chiang M, Boyd S (2004) Geometric programming duals of channel capacity and rate distortion. *IEEE Trans Inf Theory* 50(2):245–258
- Chiang M, Chan B, Boyd S (2002a) Convex optimization of output link scheduling and active queue management in QoS constrained packet switches. In: *Proceedings of the 2002 IEEE international conference on communications (ICC)*, pp 2126–2130, 2002
- Chiang M, Sutivong A, Boyd S (2002b) Efficient nonlinear optimization of queuing systems. In: *Proceedings of the 2002 IEEE global telecommunications conference (GLOBECOM)*, pp 2425–2429, 2002
- Choi J-C, Bricker D (1995) Geometric programming with several discrete variables: algorithms employing generalized benders. *Eng Optim* 3:201–212
- Choi J, Bricker D (1996a) Effectiveness of a geometric programming algorithm for optimization of machining economics models. *Comp Oper Res* 23(10):957–961
- Choi J-C, Bricker D (1996b) A heuristic procedure for rounding posynomial geometric programming solutions to discrete value. *Comput Ind Eng* 30(4):623–629
- Chu C, Wong D (1999) An efficient and optimal algorithm for simultaneous buffer and wire sizing. *IEEE Trans Comput Aided Des Integr Circuits Syst* 18(9):1297–1304
- Chu C, Wong D (2001a) Closed form solutions to simultaneous buffer insertion/sizing and wire sizing. *ACM Trans Des Autom Electron Syst* 6(3):343–371
- Chu C, Wong D (2001b) VLSI circuit performance optimization by geometric programming. *Ann Oper Res* 105(1–4):37–60
- Clasen R (1963) The linear logarithmic programming problem. *Rand Corp. Memo. RM-37-7-PR*, June 1963
- Clasen R (1984) The solution of the chemical equilibrium programming problem with generalized benders decomposition. *Oper Res* 32(1):70–79
- Colleran D, Portmann C, Hassibi A, Crusius C, Mohan S, Boyd S, Lee T, Hershenson M (2003) Optimization of phase-locked loop circuits via geometric programming. In: *Proceedings of the 2003 IEEE custom integrated circuits conference (CICC)*, pp 326–328, 2003
- Cong J, He L (1996) Optimal wire sizing for interconnects with multiple sources. *ACM Trans Des Autom Electron Syst* 1(4):478–511
- Cong J, He L (1998) Theory and algorithm of local-refinement-based optimization with application to device and interconnect sizing. *IEEE Trans Comput Aided Des Integr Circuits Syst* 18(4):406–420
- Cong J, Koh C-K (1994) Simultaneous driver and wire sizing for performance and power optimization. *IEEE Trans Very Large Scale Integr Syst* 2(4):408–423

- Cong J, Leung K-S (1995) Optimal wiresizing under Elmore delay model. *IEEE Trans Comput Aided Des Integr Circuits Syst* 14(3):321–336
- Cong J, Pan Z (2002) Wire width planning for interconnect performance optimization. *IEEE Trans Comput Aided Des Integr Circuits Syst* 21(3):319–329
- Corstjens M, Doyle P (1979) Channel optimization in complex marketing systems. *Manag Sci* 25(10):1014–1025
- Coudert O, Haddad R, Manne S (1996) New algorithms for gate sizing: a comparative study. In: *Proceedings of 33rd IEEE/ACM design automation conference (DAC)*, pp 734–739, 1996
- Daems W, Gielen G, Sansen W (2003) Simulation-based generation of posynomial performance models for the sizing of analog integrated circuits. *IEEE Trans Comput Aided Des Integr Circuits Syst* 22(5):517–534
- Dantzig G, Johnson S, White W (1958) Shape-preserving properties of univariate cubic L_1 splines. *Manag Sci* 5(1):38–43
- Dawson J, Boyd S, Hershenson M, Lee T (2001) Optimal allocation of local feedback in multistage amplifiers via geometric programming. *IEEE Trans Circuits Syst I Fundam Theory Appl* 48(1):1–11
- Dembo R (1982) Sensitivity analysis in geometric programming. *J Optim Theory Appl* 37(1):1–21
- Dhillon B, Kuo C (1991) Optimum design of composite hybrid plate girders. *J Struct Eng* 117(7):2088–2098
- Dinkel J, Kochenberger M, Wong S (1978) Sensitivity analysis procedures for geometric programs: Computational aspects. *ACM Trans Math Softw* 4(1):1–14
- Duffin R (1970) Linearizing geometric programs. *SIAM Rev* 12(2):668–675
- Duffin R, Peterson E, Zener C (1967) *Geometric programming—theory and application*. Wiley, New York
- Dutta A, Rama D (1992) An optimization model of communications satellite planning. *IEEE Trans Commun* 40(9):1463–1473
- Ecker J (1980) Geometric programming: Methods, computations and applications. *SIAM Rev* 22(3):338–362
- Edvall M, Hellman F (2005) User's Guide for TOMLAB/GP. Available from http://tomlab.biz/docs/TOMLAB_GP.pdf
- El Barmi H, Dykstra R (1994) Restricted multinomial maximum likelihood estimation based upon Fenchel duality. *Stat Probab Lett* 21(2):121–130
- Federowicz A, Rajgopal J (1999) Robustness of posynomial geometric programming optima. *Math Program* 85(2):421–431
- Feigin P, Passy U (1981) The geometric programming dual to the extinction probability problem in simple branching processes. *Ann Probab* 9(3):498–503
- Fishburn J, Dunlop A (1985) TILOS: a posynomial programming approach to transistor sizing. In: *IEEE international conference on computer-aided design: ICCAD-85. Digest of technical papers*, pp 326–328. IEEE Computer Society Press
- Floudas C (1999) *Deterministic global optimization: theory, algorithms and applications*. Kluwer Academic, Dordrecht
- Foschini G, Miljanic Z (1993) A simple distributed autonomous power control algorithm and its convergence. *IEEE Trans Veh Technol* 42(4):641–646
- Fuh C-D, Hu I (2000) Asymptotically efficient strategies for a stochastic scheduling problem with order constraints. *Ann Stat* 28(6):1670–1695
- Gao Y, Wong D (1999) Optimal shape function for a bidirectional wire under Elmore delay model. *IEEE Trans Comput Aided Des Integr Circuits Syst* 18(7):994–999
- Grant M, Boyd S, Ye Y (2005) *CVX: matlab software for disciplined convex programming*. Available from www.stanford.edu/~boyd/cvx/
- Greenberg H (1995) Mathematical programming models for environmental quality control. *Oper Res* 43(4):578–622
- Hajela P (1986) Geometric programming strategies for large-scale structural synthesis. *AIAA J* 24(7):1173–1178
- Hariri A, Abou-El-Ata M (1997) Multi-item production lot-size inventory model with varying order cost under a restriction: a geometric programming approach. *Prod Plan Control* 8(2):179–182
- Hassibi A, Hershenson M (2002) Automated optimal design of switched-capacitor filters. In: *Proceedings of the 2002 design, automation and test in Europe conference and exhibition (DATE)*, p 1111, 2002
- Hastie T, Tibshirani R, Friedman J (2001) *The elements of statistical learning*. Springer, Berlin
- Hershenson M (2002) Design of pipeline analog-to-digital converters via geometric programming. In: *Proceedings of the 2002 IEEE/ACM international conference on computer aided design (ICCAD)*, pp 317–324, San Jose, 2002

- Hershenson M (2003) Analog design space exploration: efficient description of the design space of analog circuits. In: Proceedings of the 40th design automation conference (DAC), pp 970–973, 2003
- Hershenson M, Boyd S, Lee T (1998) GPCAD: A tool for CMOS op-amp synthesis. In: Proceedings of the 1998 IEEE/ACM international conference on computer aided design (ICCAD), pp 296–303, 1998
- Hershenson M, Hajimiri A, Mohan S, Boyd S, Lee T (1999) Design and optimization of LC oscillators. In: Proceedings of the 2000 IEEE/ACM international conference on computer-aided design (ICCAD), pp 65–69, 1999
- Hershenson M, Boyd S, Lee T (2001) Optimal design of a CMOS op-amp via geometric programming. *IEEE Trans Comput Aided Des Integr Circuits Syst* 20(1):1–21
- Hitomi K (1996) Manufacturing systems engineering: a unified approach to manufacturing technology, production management, and industrial economics, 2nd edn. CRC Press, Boca Raton
- Horowitz M, Alon E, Patil D, Naffziger S, Kumar R, Bernstein K (2005) Scaling, power, and the future of CMOS. In: Proceedings of the 2005 IEEE international electron devices meeting (IEDM), pp 9–15, 2005
- Hsiung K-L, Kim S-J, Boyd S (2006) Tractable approximate robust geometric programming. Manuscript. Available from www.stanford.edu/~boyd/rgp.html
- Hu I, Wei C (1989) Irreversible adaptive allocation rules. *Ann Stat* 17(2):801–823
- Ismail Y, Friedman E, Neves J (2000) Equivalent Elmore delay for RLC trees. *IEEE Trans Comput Aided Des Integr Circuits Syst* 19(7):83–97
- Jabr R (2005) Applications of geometric programming to transformer design. *IEEE Trans Magn* 41(11):4261–4269
- Jha N (1990) A discrete data base multiple objective optimization of milling operation through geometric programming. *ASME J Eng Ind* 112(4):368–374
- Jiang I, Chang Y, Jou J (2000) Crosstalk-driven interconnect optimization by simultaneous gate and wire sizing. *IEEE Trans Comput Aided Des Integr Circuits Syst* 19(9):999–1010
- Joshi S, Boyd S, Dutton R (2005) Optimal doping profiles via geometric programming. *IEEE Trans Electron Devices* 52(12):2660–2675
- Julian D, Chiang M, O'Neill D, Boyd S (2002) QoS and fairness constrained convex optimization of resource allocation for wireless cellular and ad hoc networks. In: Proceedings of the 21st IEEE INFOCOM, pp 477–486, 2002
- Jung H, Klein C (2001) Optimal inventory policies under decreasing cost functions via geometric programming. *Eur J Oper Res* 132(3):628–642
- Kandukuri S, Boyd S (2002) Optimal power control in interference-limited fading wireless channels with outage-probability specifications. *IEEE Trans Wirel Commun* 1(1):46–55
- Karlof J, Chang Y (1997) Optimal permutation codes for the Gaussian channel. *IEEE Trans Inform Theory* 43(1):356–358
- Kasamsetty K, Ketkar M, Sapatnekar S (2000) A new class of convex functions for delay modeling and its application to the transistor sizing problem. *IEEE Trans Comput Aided Des Integr Circuits Syst* 19(7):779–788
- Kay R, Pileggi L (1998) EWA: Efficient wiring-sizing algorithm for signal nets and clock nets. *IEEE Trans Comput Aided Des Integr Circuits Syst* 17(1):40–49
- Kiely T, Gielen G (2004) Performance modeling of analog integrated circuits using least-squares support vector machines. In: Proceedings of the 2004 design, automation and test in Europe conference and exhibition (DATE), pp 16–20, 2004
- Kim J, Lee J, Vandenberghe L, Yang K (2004) Techniques for improving the accuracy of geometric-programming based analog circuit design optimization. In: Proceedings of the 2004 IEEE/ACM international conference on computer-aided design (ICCAD), pp 863–870, 2004
- Kim S-J, Boyd S, Yun S, Patil D, Horowitz M (2007) A heuristic for optimizing stochastic activity networks with applications to statistical digital circuit sizing (to appear in *Optim Eng*). Available from www.stanford.edu/~boyd/heur_san_opt.html
- Klafszky E, Mayer J, Terlaky T (1992) A geometric programming approach to the channel capacity problem. *Eng Optim* 19:115–130
- Kortanek K, Xu X, Ye Y (1996) An infeasible interior-point algorithm for solving primal and dual geometric programs. *Math Program* 76(1):155–181
- Krishnamurthy R, Carley L (1997) Exploring the design space of mixed swing quadrail for low-power digital circuits. *IEEE Trans Very Large Scale Integr Syst* 5(4):389–400
- Kyparsis J (1988) Sensitivity analysis in posynomial geometric programming. *J Optim Theory Appl* 57(1):85–121
- Kyparsis J (1990) Sensitivity analysis in geometric programming: theory and computations. *Ann Oper Res* 27(1):39–64

- Lawler E, Wood D (1966) Branch-and-bound methods: a survey. *Oper Res* 14(4):699–719
- Lee J, Hatcher G, Vandenbergh L, Yang K (2003) Evaluation of fully-integrated switching regulators for CMOS process technologies. In: *Proceedings of the 2003 international symposium on system-on-chip*, pp 155–158, 2003
- Lee W, Kim D (1993) Optimal and heuristic decision strategies for integrated production and marketing planning. *Decis Sci* 24(6):1203–1213
- Lee Y-M, Chen C, Wong D (2002) Optimal wire-sizing function under the Elmore delay model with bounded wire sizes. *IEEE Trans Circuits Syst I Fundam Theory Appl* 49(11):1671–1677
- Li X, Gopalakrishnan P, Xu Y, Pileggi T (2004) Robust analog/RF circuit design with projection-based posynomial modeling. In: *Proceedings of the IEEE/ACM international conference on computer aided design (ICCAD)*, pp 855–862, 2004
- Lin T, Pileggi L (2001) RC(L) interconnect sizing with second order considerations via posynomial programming. In: *Proceedings of the 2001 ACM/SIGDA international symposium on physical design (ISPD)*, pp 16–21, 2001
- Löfberg J (2003) YALMIP. Yet another LMI parser. Version 2.4. Available from <http://control.ee.ethz.ch/~joloef/yalmip.php>
- Lou J, Chen W, Pedram M (1999) Concurrent logic restructuring and placement for timing closure. In: *Proceedings of the 1999 IEEE/ACM international conference on computer-aided design (ICCAD)*, pp 31–35, 1999
- Luenberger D (1984) *Linear and nonlinear programming*, 2nd edn. Addison–Wesley, Reading
- Magnani A, Boyd S (2006) Convex piecewise-linear fitting (submitted to *Optim Eng*). Available from www.stanford.edu/~boyd/cvx_pwl_fit.html
- Mandal P, Visvanathan V (2001) CMOS op-amp sizing using a geometric programming formulation. *IEEE Trans Comput Aided Des Integr Circuits Syst* 20(1):22–38
- Maranas C, Floudas C (1997) Global optimization in generalized geometric programming. *Comput Chem Eng* 21(4):351–369
- Marković D, Stojanović V, Nikolić B, Horowitz M, Brodersen R (2004) Methods for true energy-performance optimization. *IEEE J Solid State Circuits* 39(8):1282–1293
- Matson M, Glasser L (1986) Macromodeling and optimization of digital MOS VLSI circuits. *IEEE Trans Comput Aided Des Integr Circuits Syst* 5(4):659–678
- Mazumdar M, Jefferson T (1983) Maximum likelihood estimates for multinomial probabilities via geometric programming. *Biometrika* 70(1):257–261
- Moh T-S, Chang T-S, Hakimi S (1996) Globally optimal floorplanning for a layout problem. *IEEE Trans Circuits Syst I Fundam Theory Appl* 43(29):713–720
- Mohan S, Hershenson M, Boyd S, Lee T (1999) Simple accurate expressions for planar spiral inductances. *IEEE J Solid State Circuit* 34(10):1419–1424
- Mohan S, Hershenson M, Boyd S, Lee T (2000) Bandwidth extension in CMOS with optimized on-chip inductors. *IEEE J Solid State Circuits* 35(3):346–355
- Moore R (1991) Global optimization to prescribed accuracy. *Comput Math Appl* 21(6-7):25–39
- MOSEK ApS (2002) The MOSEK optimization tools version 2.5. User's manual and reference. Available from www.mosek.com
- Muqattash A, Krunz M, Shu T (2006) Performance enhancement of adaptive orthogonal modulation in wireless CDMA systems. *IEEE J Sel Areas Commun* 23(3):565–578
- Mutapcic A, Koh K, Kim S-J, Boyd S (2006) GGPLAB: a matlab toolbox for geometric programming. Available from www.stanford.edu/~boyd/ggplab/
- Nesterov Y, Nemirovsky A (1994) Interior-point polynomial methods in convex programming. *Studies in applied mathematics*, vol 13. SIAM, Philadelphia
- Nijhamp P (1972) *Planning of industrial complexes by means of geometric programming*. Rotterdam Univ. Press, Rotterdam
- Nocedal J, Wright S (1999) *Numerical optimization*, Springer series in operations research. Springer, New York
- Palomar D, Cioffi J, Lagunas M (2003) Joint Tx-Rx beamforming design for multicarrier MIMO channels: a unified framework for convex optimization. *IEEE Trans Signal Process* 51(9):2381–2401
- Papalambros P, Wilde D (1988) *Principles of optimal design*. Cambridge University Press, Cambridge
- Patil D, Yun Y, Kim S-J, Boyd S, Horowitz M (2005) A new method for robust design of digital circuits. In: *Proceedings of the 6th international symposium on quality electronic design (ISQED)*, pp 676–681, 2005
- Pattanaik M, Banerjee S, Bahinipati B (2003) GP based transistor sizing for optimal design of nanoscale CMOS inverter. In: *Proceedings of the 3rd IEEE conference on nanotechnology*, pp 524–527, 2003

- Peterson E (1976) Geometric programming. *SIAM Rev* 18(1):1–51
- Peterson E (2001) The origins of geometric programming. *Ann Oper Res* 105(1–4):15–19
- Qin Z, Cheng C-K (2003) Realizable parasitic reduction using generalized Y- Δ transformation. In: *Proceedings of the 40th IEEE/ACM design automation conference (DAC)*, pp. 220–225, 2003
- Rajasekera J, Yamada M (2001) Estimating the firm value distribution function by entropy optimization and geometric programming. *Ann Oper Res* 105(1–4):61–75
- Rajpogal J, Bricker D (1990) Posynomial geometric programming as a special case of semi-infinite linear programming. *J Optim Theory Appl* 66(3):444–475
- Rao S (1996) *Engineering optimization: theory and practice*, 3rd edn. Wiley-Interscience, New York
- Rijckaert M, Walraven E (1985) Geometric programming: estimation of Lagrange multipliers. *Oper Res* 33(1):85–93
- Rosenberg E (1989) Optimization module sizing in VLSI floorplanning by nonlinear programming. *ZOR-Methods Model Oper Res* 33(2):131–143
- Rubenstein J, Penfield P, Horowitz M (1983) Signal delay in RC tree networks. *IEEE Trans Comput Aided Des Integr Circuits Syst* 2(3):202–211
- Sakurai T (1988) Approximation of wiring delay in MOSFET LSI. *IEEE J Solid State Circuits* 18(4):418–426
- Salomone H, Iribarren O (1993) Posynomial modeling of batch plants: a procedure to include process decision variables. *Comput Chem Eng* 16(3):173–184
- Salomone H, Montagna J, Iribarren O (1994) Dynamic simulations in the design of batch processes. *Comput Chem Eng* 18(3):191–204
- Sancheti P, Sapatnekar S (1996) Optimal design of macrocells for low power and high speed. *IEEE Trans Comput Aided Des Integr Circuits Syst* 15(9):1160–1166
- Sapatnekar S (1996) Wire sizing as a convex optimization problem: exploring the area-delay tradeoff. *IEEE Trans Comput Aided Des Integr Circuits Syst* 15(8):1001–1011
- Sapatnekar S (2004) *Timing*. Kluwer Academic, Dordrecht
- Sapatnekar S, Rao V, Vaidya P, Kang S (1993) An exact solution to the transistor sizing problem for CMOS circuits using convex optimization. *IEEE Trans Comput Aided Des Integr Circuits Syst* 12(11):1621–1634
- Sathiyamurthy H, Sapatnekar S, Fishburn J (1998) Speeding up pipelined circuits through a combination of gate sizing and clock skew optimization. *IEEE Trans Comput Aided Des Integr Circuits Syst* 17(2):173–182
- Satish N, Ravindran K, Moskewicz M, Chinnery D, Keutzer K (2005) Evaluating the effectiveness of statistical gate sizing for power optimization. Technical report ERL memorandum M05/28, University of California at Berkeley, August 2005
- Scott C, Jefferson T, Jorjani S (2004) Duals for classical inventory models via generalized geometric programming. *J Appl Math Decis Sci* 8(3):191–200
- Sherali H (1998) Global optimization of nonconvex polynomial programming problems having rational exponents. *J Global Optim* 12(3):267–283
- Sherwani N (1999) *Algorithms for VLSI design automation*, 3rd edn. Kluwer Academic, Dordrecht
- Shyu J, Sangiovanni-Vincetelli A, Fishburn J, Dunlop A (1988) Optimization-based transistor sizing. *IEEE J Solid State Circuits* 23(2):400–409
- Singh J, Nookala V, Luo Z-Q, Sapatnekar S (2005) Robust gate sizing by geometric programming. In: *Proceedings of the 42nd IEEE/ACM design automation conference (DAC)*, pp 315–320, 2005
- Smeers Y, Tyteca D (1984) A geometric programming model for the optimal design of wastewater treatment plants. *Oper Res* 32(2):314–342
- Sonmez A, Baykasoglu A, Dereli T, Fliz I (1999) Dynamic optimization of multipass milling operations via geometric programming. *Int J Mach Tools Manuf* 39(2):297–320
- Stark R, Machida M (1993) Chance design costs-A distributional limit. In: *Proceedings of the 2nd international symposium on uncertainty modeling and analysis*, pp 269–270, 1993
- Sutherland I, Sproull B, Harris D (1999) *Logical effort: designing fast CMOS circuits*. Morgan Kaufmann, San Francisco
- Swahn B, Hassoun S (2006) Gate sizing: FinFETs vs 32nm bulk MOSFETs. In: *Proceedings of the 43rd IEEE/ACM design automation conference (DAC)*, pp 528–531, 2006
- Trivedi K, Sigmon T (1981) Optimal design of linear storage hierarchies. *J ACM* 28(2):270–288
- Tsai J-F, Li H-L, Hu N-Z (2002) Global optimization for signomial discrete programming problems in engineering design. *Eng Optim* 34(6):613–622
- Vanderhaegen J, Brodersen R (2004) Automated design of operational transconductance amplifiers using reversed geometric programming. In: *Proceedings of the 41st IEEE/ACM design automation conference (DAC)*, pp 133–138, 2004

- Vanderplaats G (1984) Numerical optimization techniques for engineering design. McGraw-Hill, New York
- Vardi Y (1985) Empirical distributions in selection bias models. *Ann Stat* 13(1):178–203
- Wall T, Greening D, Woolsey R (1986) Solving complex chemical equilibria using a geometric-programming based technique. *Oper Res* 34(3):345–355
- Wilde D (1978) Globally optimal design. Wiley, New York
- Wilde D, Beightler C (1967) Foundations of optimization. Prentice Hall, Englewood Cliffs
- Wong D (1981) Maximum likelihood, entropy maximization, and the geometric programming approaches to the calibration of trip distribution models. *Transp Res Part B Methodol* 15(5):329–343
- Xu Y, Pileggi L, Boyd S (2004) ORACLE: optimization with recourse of analog circuits including layout extraction. In: Proceedings of the 41st IEEE/ACM design automation conference (DAC), pp 151–154, 2004
- Yang H-H, Bricker D (1997) Investigation of path-following algorithms for signomial geometric programming problems. *Eur J Oper Res* 103(1):230–241
- Yazarel H, Pappas G (2004) Geometric programming relaxations for linear system reachability. In: Proceedings of the 2004 American control conference (ACC), pp 553–559, 2004
- Young F, Chu C, Luk W, Wong Y (2001) Handling soft modules in general nonslicing floorplan using Lagrangian relaxation. *IEEE Trans Comput Aided Des Integr Circuits Syst* 20(5):687–629
- Yun K, Xi C (1997) Second-order method of generalized geometric programming for spatial frame optimization. *Comput Methods Appl Mech Eng* 141(1-2):117–123
- Zener C (1971) Eng design by geometric programming. Wiley, New York