The Energy for Growing and Maintaining Cities

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Received: 6 December 2011 / Revised: 12 July 2012 / Accepted: 4 September 2012 / Published online: 22 September 2012

Abstract Herein we develop a means to differentiate between the energy required to expand and the energy required to maintain the economies of cities. A nonlinear model is tested against historical data for two cities, Hong Kong and Singapore. A robust fit is obtained for Hong Kong, with energy for maintenance close to that for growth, while Singapore, with a weaker fit, is growth dominated. The findings suggest that decreases in either of the per unit maintenance or growth demands can simultaneously cause gross domestic product (GDP) and total energy use to increase. Furthermore, increasing maintenance demands can significantly limit growth in energy demand and GDP. Thus, the low maintenance demands for Hong Kong, and especially Singapore, imply that, all other things being equal, GDP and energy use of these cities will continue to grow, though Singapore's higher energy use for growth means it will require more energy than Hong Kong.

Keywords Urban energy · Urban economics · Maintenance and growth · Scaling · Urban metabolism · Sustainable cities

INTRODUCTION

Over the course of history energy has served a pivotal role in the organization, construction, and unfortunately the occasional destruction, of complex systems like human civilizations (Goudsblom 1992; Sieferle 2001; Smil 2008; Spier 2011). From a physical sciences perspective energy gradients are a necessary, though not sufficient condition, for the formation and maintenance of local order in any open system, such as non-equilibrium chemical systems (Nicolis and Prigogine 1977), life and ecosystems (Schneider and Kay 1994). The concentration and availability of high quality

energy has allowed for increasingly larger and denser agglomerations of energy use over time (Chaisson 2008).

Cities are one of the more modern outcomes of this energetic development; in them can be found the bulk of society's inhabitants, their buildings, transportation vehicles, and industrial production, as well as numerous other innovations. Contemporary industrial processes, buildings, and transportation vehicles require large quantities of high quality energy in the form of electricity and fossil fuels, whose supply is decreasing (Westley et al. 2011); while the inhabitants of cities rely on food energy so that they may live, innovate, and prosper. The sourcing of energy to meet these demands are, however, a large contributor to adverse environmental impacts, from local air pollutants (Mage et al. 1996; Parrish and Zhu 2009) to global greenhouse gas emissions (Kennedy et al. 2009; Hillman and Ramaswami 2010).

Energy use in cities is pivotal to their growth and maintenance, as is the case with any open system. The demand for energy in cities, as per Bettencourt et al.'s (2007) examination of urban resource use, broadly includes that which is required for growth and that which is required for maintenance. Indeed, the historical development of cities can be interpreted as evolutions in technology and urban planning that allowed new growth to occur, while always requiring maintaining of existing structures (Kennedy 2011). Further, in other open systems the stage of development can be characterized by the relative amount of activity for growth versus maintenance. In ecosystems, for example, aging systems use more of their energy for maintenance (Odum 1969) and achieve a slower pace of increase in their rate of energy use (Fath et al. 2004). Since cities are open systems, it can be hypothesized that a similar link between energy for growth and for maintenance and the pace of resource use exists in cities, which

would be helpful in managing the long-term sustainability of urban energy demand.

The objective of this paper is to identify the nature of the link between maintenance and growth; how this link relates energy use to economic production; and explore what policy strategies these findings evince. What follows is a discussion of the division of growth and maintenance and its importance in the development of cities and their patterns of resource use; the explanation of previous work on which the efforts herein are based; formulation of a model explaining the relationship between primary energy use and economic output; a test of its applicability to the two cities for which the necessary data could be located, Hong Kong and Singapore; and discussion of the implications of the model to the broader themes of urban energy and economic policy.

Economic Output and the Energy for Growth and Maintenance

The preceding touched on the concept of cities as open systems. Important to this conceptualization is the idea of how such a system changes in terms of its overall energy use and its energy use for growth and maintenance. To assess these changes requires (1) a measurement of how the system changes and (2) differentiation between energy for growth and for maintenance. The measurement used here is the gross (or regional) domestic product (GDP) of cities. The energy for growth and for maintenance then are the energy used to grow and maintain the GDP, respectively. These energy demands can be made apparent with some further detail on what the GDP represents.

The GDP of an economy is the difference between the total output and the intermediate consumption or inputs (see Fig. 1 for reference throughout this explanation). This difference is called the value added, and it is one way of measuring the GDP. The value added is typically computed at each stage of the economic process. For example, consider a simplified power plant whose only input, or intermediate consumption, is coal. The value added by the power plant is the monetary value of the gross amount of electricity it produces minus the amount of energy needed to run the auxiliary systems of the facility, such as pumps and control systems. Likewise, the miner of the coal required certain inputs to extract and process the coal. The miner's sales of coal minus these inputs are the value added by the miner. Summing across all activities of the economy gives a measure of the GDP.

To grow the GDP the economy must increase the difference in total output and intermediate consumption. This can be accomplished by reducing the relative amount of intermediate consumption compared to the total output

Fig. 1 The relationship between the components of GDP and energy for growth and for maintenance

(Fig. 1). The two avenues available to achieving this are by efficiency improvements, both in technologies and processes, and via economies of scale. Thus the energy for growth is the energy investment required to implement efficiency improvements and to achieve economies of scale.

Conversely, an economy with a fixed GDP has a fixed difference between output and intermediate consumption. In such a state all of the energy the economy uses is to maintain this fixed difference. This is not to say that the economy remains unchanged, however. As this is an aggregate measure, internal changes to facilities and industries are possible in such a state, but if the overall system outcome leaves the value added (and GDP) unchanged, the energy consumed in such a case is for maintenance only. This steady-state conceptualization is not entirely dissimilar in spirit to the ecological economics work by Daly, except that in Daly's work on steady-state economies the energy throughput maintains a fixed quantity of artifacts and people (Daly 2010) as opposed to a fixed economic output.

Scaling and Sigmoid Growth Models

The growth dynamics of large, intricate systems is often studied via the use of sigmoid curves. These curves are characterized by initial periods of slow growth; followed by periods of fast growth, ultimately leading to a leveling off at a maximum or ending in a crash following a short-lived peak, a process that mirrors characteristics of succession. Curves of this type have been integral to the study of natural systems (von Bertalanffy 1957; Richards 1959; May 1974), product life cycles (Berry 1991; Kurzweil 2005), and infrastructure (Nakicenovic 1988). At the core of many formulations of sigmoid curves are types of logistic curves which rest on assumptions of scaling

relationships with size. Recently it has been suggested that cities possess a special class of scaling that would lead to excessively fast growth and then decline were it not for ever quickening cycles of innovation (Bettencourt et al. 2007).

The work by Bettencourt et al. (2007) has also identified the apparent universality of scaling in cities—such that cities consistently follow power law scaling when measured along numerous dimensions relative to population. The relationship takes the form $Y(t) = Y_0 N(t)^\beta$, where the use of some resource Y at time t can be predicted based on some initial value Y_0 times the population of the city N to the power β . This relationship is shown to hold for cities in several countries for measures as varied as the number of patents, the amount of housing and the number of post offices and gas stations (Kühnert et al. 2006).

Bettencourt et al. (2007) furthermore link resource requirements for maintenance and growth of a city on a per capita basis. Specifically their formulation states that if R is the average maintenance requirements per unit time per individual and I is the resource requirements for the addition of a new individual, then the resource requirements are $Y = RN + I(dN/dt)$. Substituting the scaling relationship, $Y(t) = Y_0 N(t)^\beta$, into this definition of resource requirements and solving for population change results in the following growth equation:

$$\frac{dN(t)}{dt} = \left(\frac{Y_0}{I}\right)N(t)^\beta - \left(\frac{R}{I}\right)N(t) \quad (1)$$

of which, the analytical solution is (Bettencourt et al. 2007):

$$N(t) = \left[\frac{Y_0}{R} + \left(N(0)^{1-\beta} - \frac{Y_0}{R} \right) e^{-\frac{R}{I}(1-\beta)t} \right]^{\frac{1}{1-\beta}} \quad (2)$$

There are four classes of this solution: (1) economics of scale ($\beta < 1$) leading to sigmoid-type growth characterized by initial growth settling at a carrying capacity; (2) sigmoid-type decay leading to collapse due to resource scarcity; (3) exponential growth ($\beta = 1$); and (4) increasing returns ($\beta > 1$) leading to faster than exponential growth, ending in a singularity in finite time.

MATERIALS AND METHODS

A Growth and Maintenance Model of Energy and Production

Following, we extend the above growth model to estimate the energy used for maintenance and growth with respect to GDP. If GDP per year ($\dot{G}$ in \$/yr, where yr = year) is related to population (N) by:

$$\dot{G}(t) = \dot{G}_{0N} N(t)^{\beta_G} \quad (3)$$

and the rate of primary energy use ($\dot{E}$ [PJ/yr, where PJ = Petajoules]) is related to population by:

$$\dot{E}(t) = \dot{E}_{0N} N(t)^{\beta_E} \quad (4)$$

then the rate of primary energy use is related to GDP by:

$$\dot{E}(t) = \dot{E}_{0N} \left(\frac{\dot{G}(t)}{\dot{G}_{0N}} \right)^{\frac{\beta_E}{\beta_G}} = \dot{E}_0 \dot{G}(t)^\beta \quad (5)$$

with $\beta = \beta_E / \beta_G$, and $\dot{E}_0 = \dot{E}_{0N} / \dot{G}_{0N}^\beta$ [PJ/yr].

If the assumption of per unit scaling relationships for maintenance and growth of the form used by Bettencourt et al. are made on a GDP basis as opposed to a population basis then energy use for maintenance and growth are related to GDP by the following relationship:

$$\dot{E}(t) = E_r \dot{G}(t) + E_e \frac{d\dot{G}(t)}{dt} \quad (6)$$

where E_r [MJ/\$, where MJ = Megajoules] is the average (over space and time) per unit energy use to maintain annual production, and E_e [MJ/(\$/yr)] is the average energy required to expand production by one dollar from one year to the next. Solving Eqs. (5) and (6) for $\dot{G}(t)$ leads to the expression:

$$\frac{d\dot{G}(t)}{dt} = \frac{\dot{E}_0}{E_e} \dot{G}(t)^\beta - \frac{E_r}{E_e} \dot{G}(t) \quad (7)$$

Substituting the solution of this differential equation into Eq. (5) gives, as expected, a sigmoid-type solution of the Bettencourt et al. (2007) variety (for $\beta < 1$) to $\dot{E}(t)$ similar to Eq. (2):

$$\dot{E}(t) = \dot{E}_0 \left[\frac{\dot{E}_0}{E_r} + \left(\dot{G}(0)^{1-\beta} - \frac{\dot{E}_0}{E_r} \right) e^{-\frac{E_r}{E_e}(1-\beta)t} \right]^{\frac{\beta}{1-\beta}} \quad (8)$$

which at time zero is equal to $\dot{E}(0) = \dot{E}_0 \dot{G}(0)^\beta$. Next, we develop solution techniques for testing the model.

Parameter Estimation Technique

The procedure for fitting the model to actual data involves four steps. First, time series data on the primary energy use and GDP of a city is required. Second, performing a linear regression on a linearized version of Eq. (5), by taking the natural logarithm of each side, against the data to determine $\dot{E}_0$ and β is necessary. The third step is a nonlinear regression on Eq. (8) to determine estimates of E_r , E_e , and $\dot{G}(0)$. The final step is a determination of the robustness of the parameter estimates. For the linear regression the confidence intervals are computable from the standard error outputs of most statistical computing packages. A Monte Carlo analysis, a tool usually suited to addressing

uncertainty, is, with the proper modifications, useful for determining the confidence interval for the nonlinear regression. Step two is straightforward enough, but some further explanations on the other steps are necessary.

The importance of step one, time series data, are two-fold. First, the parameter estimation requires several years of data. If the fit and confidence intervals are poor then more data may be required or the model may be insufficient to explain the system dynamics. Second, the approach taken by Bettencourt et al. (2007), whereby the scaling relationships are determined for groups of cities within a region at a point in time, is likely to be insufficient for testing for a scaling relationship in energy use. This is likely, because factors driving energy demand such as climate, land use, and the make-up of industrial sectors vary within regions. This is particularly evident from a population density perspective when it comes to the energy use for transport in cities (Newman and Kenworthy 1999).

To perform step three, the nonlinear regression against Eq. (8), three things are important. First, determining a fit between data on primary energy use and the equation is basically an optimization that searches for a solution that minimizes the error between the fitted curve and the data. Secondly, the parameter values E_r , E_c , and $\dot{G}(0)$ need to be constrained to values greater than or equal to zero throughout the optimization. Finally, starting values, or guesses of the parameters' values are required at the outset of the optimization. As the curve fitting is nonlinear, it is possible to find locally optimal solutions as opposed to globally optimal solutions—thus good guesses are of paramount importance to finding meaningful solutions.

We simplified the management of these issues by reformulating the equation in terms of two new temporary parameters, for the case of $0 < \beta < 1$, which as will be shown in the next section is the case for this study. Doing so allows us to make educated guesses on the initial conditions, set the range of possible values for the parameters and requires regression against two parameters instead of three. The steps we follow proceed thusly: first, for the set of time series data on primary energy $\{f_1 \dots f_n\}$ for the years $\{t_1 \dots t_n\}$ we define the parameter α ($0 < \alpha \leq 1$) such that:

$$\alpha f_1 = \dot{E}(0) = \dot{E}_0 \dot{G}(0)^\beta \quad (9)$$

This states that the first data point will be some fraction larger than the actual energy demand at time zero of the study, $\dot{E}(0)$. This expression, solved for $\dot{G}(0)$ throughout the regression, can also take the form $f_1 = \alpha \dot{E}(0)$, with the same bounds on α . Both forms must be tried in turn to locate the best fit.

Next, we define the parameter λ ($0 < \lambda < 1$) in terms of the upper limit on the rate of energy use that is reached as time approaches infinity, such that:

$$f_n = \lim_{t \rightarrow \infty} \lambda \dot{E}(t) = \lambda \dot{E}_0 \left(\frac{\dot{E}_0}{E_r} \right)^{\frac{\beta}{1-\beta}} \quad (10)$$

which states that the last data point is some fraction less than the amount of energy use per year that is reached as time becomes very large, should things continue on a business as usual basis. This expression is solved for E_r throughout the regression. Finally, to produce guesses of E_c , Eq. (8) can be solved simultaneously at f_1 and f_n to produce:

$$E_c = \frac{E_r(1-\beta)(t_n - t_0)}{\ln \left[\frac{E_r}{\dot{E}_0} \left(\frac{\dot{G}(0)}{\alpha} \right)^{\frac{1-\beta}{\beta}} - 1 \right] - \ln \left[\lambda^{\frac{1-\beta}{\beta}} - 1 \right]} \quad (11)$$

In the case that the alternate form of Eq. (9) is being tested the α term must be adjusted accordingly in Eq. (11).

Thus, for any guess of the constrained parameters α and λ we can calculate the values of the parameters E_r , E_c , and $\dot{G}(0)$. Formulating the regression this way means only a few initial values of α and λ need to be tried since their range of possible values is known and the problem is well conditioned.

The fourth and final stage consists of a Monte Carlo approach similar to that used elsewhere (Alper and Gelb 1990; Lambert et al. 2011) for determining the confidence intervals in the nonlinear regression. The particular method used here differs from previous approaches due to the two-staged regression of this study. The Monte Carlo analysis performed in this study is designed to address the sensitivity to the parameters β and $\dot{E}_0$ resulting from the linear regression of the expression:

$$\ln(\dot{E}(t)) = \ln(\dot{E}_0) + \beta \ln(\dot{G}(t)) + \varepsilon_t \quad (12)$$

where the goal of the regression is to minimize the errors, ε_t . We make the standard assumption that the errors are independent, with constant variance. Thus, for normally distributed errors with mean equal to zero, the parameter estimates will be normally distributed (Weisberg 2005). The errors we find in our analysis are normally distributed with near zero means. Thus, in the Monte Carlo analysis, using the covariance matrix of the linearly fitted parameter values returned by the statistical package, 1000 correlated random values of the linearly fitted parameters are generated and applied to the nonlinear regression to generate the confidence interval of the nonlinear parameters.

Next, this and the other three techniques are applied to the study of Hong Kong and Singapore for the period 1965–2010. The Population and GDP data is from the World Bank World Development Indicators (data.worldbank.org) and Energy Data is from the BP Statistical Review of World Energy 2011 (www.bp.com). Linear regressions are completed using the *lm* function of the R MASS library while the constrained nonlinear regressions

are performed using the *fmin_slsqp* function of the Scipy Python package.

RESULTS

This section presents the results from following the four steps of the previous section. It is important to highlight that these are average values across each city over the whole time period. This model does not produce temporally or spatially disaggregated results of a city. Using time series data for Hong Kong and for Singapore for the study period of 1965 through 2010 we find that scaling relationships do indeed hold for energy, GDP and population as required to satisfy Eqs. (3), (4), and (5). Figure 2 shows the scaling relationship between primary energy use per year and GDP versus population for the study period. Figure 2 verifies that Eqs. (3) and (4) hold over the study period, while Fig. 3, which plots the regression of primary energy use versus GDP, validates Eq. (5). Figures 2 and 3 also illustrate that Singapore has required more energy than Hong Kong during each year of the study period, while Hong Kong has had a larger GDP; these observations will be of importance in later discussions.

With the findings of the regressions in Figs. 2 and 3 it is expected that the growth model linking energy use and GDP—Eqs. (7) and (8)—hold, thus we proceed to the nonlinear regression to verify this expectation. The results of the nonlinear regression for Hong Kong and Singapore are listed in Table 1 for the period 1965 through 2010. The table lists the values determined from performing the regressions once (and the associated R^2 value) and then the averages from the 1000 iterations of the Monte Carlo analysis, including the 95 % confidence interval. Several observations are apparent

Fig. 3 Primary energy versus GDP for Hong Kong and Singapore, 1965–2010. GDP Data is from the World Bank World Development Indicators, and Energy Data from the BP Statistical Review of World Energy 2011

in these results including: (1) how the parameter values compare qualitatively with expectations from the linear regression; (2) the quality of the fit of the nonlinear regression; and (3) comparisons in the amounts of energy required for growth versus maintenance in each city.

First, the value of the parameters largely show good alignment with expectations from the first regressions: the constant of proportionality for GDP, $\dot{G}(0)$, is larger for Hong Kong than Singapore, reflecting Hong Kong's larger economic output; and most of the energy related parameters, namely $\dot{E}_0$ and E_e , for Singapore are larger than those of Hong Kong reflecting Singapore's larger energy demand, with the exception being E_r .

Fig. 2 Primary energy and GDP versus population for Hong Kong and Singapore, 1965–2010. Population and GDP data is from the World Bank World Development Indicators and Energy Data from the BP Statistical Review of World Energy 2011

Table 1 Parameter values and 95 % confidence intervals for regression results for Hong Kong, 1965–2010

Parameter	Hong Kong		Singapore	
	Initial fit	Averages from Monte Carlo analysis $\pm$ 95 % CI	Initial fit	Averages from Monte Carlo analysis $\pm$ 95 % CI
β	0.846	0.846 ± 0.00582	0.798	0.797 ± 0.00130
$\dot{E}_0$ (MJ/yr)	9.71	9.74 ± 0.0261	42.6	42.9 ± 0.207
E_r (MJ/\$)	1.58	1.66 ± 0.0297	0.028	0.119 ± 0.0343
E_e (MJ/(\$/yr))	54.1	52.7 ± 0.421	254	253 ± 0.737
$\dot{G}(0)$ (billion \$/yr)	17.4	17.3 ± 0.0404	3.90	3.97 ± 0.0304
R^2	0.984		0.976	

MJ Megajoules, \$ 2000 USD (American Dollars), CI confidence interval

While the confidence intervals of the other parameters are quite robust, the value of E_r for Singapore shows the least robust confidence interval. A possible source of this slightly larger interval is the pace of Singapore's growth, a vast majority of this growth having basically occurred entirely within the study period (Abou-Abdo et al. 2011). For comparison, Singapore's population increased by 172 % and its GDP per capita by 11 % over the study period, compared to Hong Kong at 96 and 6 %. As the parameters of the model are averages over time and space, this possibly suggests a limitation in this model's ability to adequately describe the most rapidly developing cities.

This limitation may only be in terms of the degree of accuracy in the numeric values, and not in the overall qualitative findings. Figure 4, for instance, also depicts the relative energy use for growth and for maintenance for each of the cities. While caution is needed in interpreting the growth and maintenance curves in this graph due to the fact that this model computes average parameter values, the overall picture is meaningful. Due to Singapore's rapid pace of development, its degree of heavy industry (Fig. 5), its substantial land reclamation efforts, and perhaps its tendency to over invest in new activities (Young 1992),

it is fair to assume that the energy Singapore requires for growth is relatively large, a pattern that is reflected in Fig. 4b. Hong Kong on the other hand has developed over a longer period into an extremely dense settlement with a more service based industry. This agrees with the more even distribution of energy for growth and maintenance in Hong Kong, where maintenance needs have been drawing closer with growth needs over the study period (Fig. 4a).

Save for the potential limitation to the approach for relatively quickly developing cities, the model and technique seem to provide a meaningful approximation to the patterns of urban energy use for Hong Kong since 1965 and to a certain degree for Singapore. Measuring the time and space varying nature of the parameters would, however, be of interest and is an area of future work.

DISCUSSION

With the model showing a robust fit with historical Hong Kong data, it is important to now consider what this may imply for Hong Kong and other cities that may follow this pattern with respect to goals related to energy use and

Fig. 4 Primary energy fit for Hong Kong and Singapore, 1965–2010. The maintenance curve is $E_r \times \dot{G}$ and the growth curve is $E_e \times d\dot{G}/dt$

Fig. 5 Gross value added less intermediate consumption for Hong Kong and Singapore, 1980–2008 by sector (agriculture, not shown, is negligible). Data is from the World Bank World Development Indicators

GDP. There are three details of importance discussed below in these regards. The first is the relationship between per unit energy demands for growth and maintenance on GDP and total energy demand and how this relates to the case of a sustainable world comprised largely of cities. Second, and closely related, is how the per unit energy demands for growth and maintenance relate to the total energy demand potential of cities and the implications on the requirements for increasingly clean sources of energy. Then, thirdly the manipulation of per unit energy demands for growth and maintenance as tools for achieving policy goals are summarized.

With regards to the first detail, rearranging the GDP growth equation, Eq. (7), to the form:

$$\frac{d\dot{G}(t)}{dt} = \frac{\dot{E}_0 \dot{G}(t)^\beta}{E_e} \left(1 - \frac{E_r}{\dot{E}_0} \dot{G}(t)^{1-\beta} \right) \quad (13)$$

suggests how energy use for maintenance and growth is related to the growth in GDP of cities. Specifically, this expression suggests that decreasing per unit energy requirements for maintenance and growth, E_r and E_e , respectively, contribute to an increase in the growth of GDP. Reductions in these parameters correspond to a number of possible changes including: (1) the removal of wastes from existing business processes; (2) increases in thermodynamic efficiencies; and (3) outsourcing of energy intensive activities. Notably, this last change is observed as an important contributor to the increasing degree of pollution associated with newly industrialized nations (Suri and Chapman 1998). This outsourcing is also a key to the progression of a city through its phases of development (Kennedy 2011). Thus, if cities follow the pattern of this model, the key to a world of prosperous, sustainable, environmentally sound cities may require an emphasis on

the first two strategies and diffusion of the resulting innovations.

This can be further highlighted, in that lower values of E_r and E_e result in an overall increase in energy usage due to the increased pace of economic production and as illustrated by Eq. (14), i.e., there is a rebound effect to reducing per unit energy demands.

$$\frac{d\dot{E}(t)}{dt} = \frac{\beta \dot{E}_0^{1/\beta} \dot{E}(t)^{(2\beta-1)/\beta}}{E_e} \left(1 - \frac{E_r}{\dot{E}_0^{1/\beta}} \dot{E}(t)^{(1-\beta)/\beta} \right) \quad (14)$$

The long-term sensitivities to maintenance and growth requirements on energy use and GDP are illustrated graphically in Fig. 6 and address the second topic of discussion relating to the issue of total energy demand potential. In this figure the energy use curves for Hong Kong are generated using the values from the Monte Carlo analysis, then single parameter values are varied in the ranges between the values for Hong Kong and Singapore for E_e in (a) and E_r in (b).

Though reductions in E_r and E_e increase the pace of growth, the lower they are, the sooner the limit to growth, given by Eq. (10), is achieved. Additionally, while changes to E_e do not change this limit, higher values of E_r lower the overall limit to growth—in the case of the values used for Fig. 4, however, these limits are only first approached in the millennium following that depicted. As it stands currently with the values shown in the last section, Hong Kong is far from its limit as energy demands for maintenance have not yet started to overtake energy demands for growth. Should its patterns of resource consumption and pollution continue to grow (Warren-Rhodes and Koenig 2001) with energy demand, pollution, resource scarcity, or thermal impacts of global energy demand (Chaisson 2008) may become the limiting factors to its further growth as

Fig. 6 Sensitivity of energy use to increases in growth and maintenance requirements in Hong Kong. Each of the plots represents a sensitivity analysis against the varying of a single parameter (E_e for **a**,

E_r for **b**, each between the values of these parameters found for Hong Kong (*) and Singapore (**)

opposed to internal maintenance factors. Alternatively, if Hong Kong's growth needs took on the value of Singapore, its growth in energy demand would be significantly limited in the next few decades by this endogenous constraint.

In further reference to Fig. 6, should all things remain equal, it can be expected that production and energy use of cities are thus likely to increase because many sustainability plans, economic strategies (EPA 2008; Rossokha 2009) and technological innovations (Heavenrich 2005; Bertoldi and Atanasiu 2007; Koomey et al. 2011) involve improvements in energy efficiency and reductions in per unit energy use. This could be a boon to economies, so long as the resultant increase in resource use is increasingly non-polluting and from resources renewable on time-scales in agreement with the pace of consumption. It may be possible to do just this through the correct application of policy (Harvey 2010), in concert with entrepreneurship and the markets (Stockholm Memorandum 2011).

That reduced per unit energy requirements are related to economic productivity (Steinberger and Krausmann 2011) and that this drives further resource use (Ayres and Warr 2005; Haberl et al. 2006) are not new concepts. This model, however, points to some possible directions for balancing the competing policy objectives of reducing resource consumption and increasing economic growth, a common subject of discussion (Simon 1998; Victor 2008; Steinberger and Roberts 2010), and the subject of the third and final discussion point of this section.

Specifically, as E_r and E_e change they can modulate energy demand and GDP. If they are increased, GDP growth and energy demand are both slowed. If increased too far, especially in the case of E_r , then a crash can occur as discussed in reference to the Bettencourt et al. (2007) model. To maintain GDP growth, which also implies energy use growth, E_r must satisfy:

$$E_r < \frac{\dot{E}(t)}{\dot{G}(t)} \quad (15)$$

while E_e must simply be greater than zero. As a point of reference, Eq. (15) is satisfied for Hong Kong on average, hence the upward trend in energy use and GDP over the study period. The important takeaway, however, is that, E_r is the inhibitor of growth. If it does not satisfy Eq. (15), contraction will occur, regardless of the value of E_e . Trying to lower E_e in such a state can slow the pace of decline but will not create growth until E_r drops sufficiently low. Whether short periods of decline, such as recessions, are a result of temporary changes to E_r remains an area of future study, though conceivably the skyrocketing energy prices of the 1970s oil crisis could be such a case.

Should inhibiting the pace of growth be desirable, increasing either E_e or E_r perhaps through taxation or removing energy subsidies will work, though if a decline in energy use is desirable it will result in a decrease in GDP, and can only be achieved by a sufficiently large value of E_r . Moreover, should the chosen mechanism be E_e , growth is merely delayed, whereas increasing E_r will constrain both the pace and limits of growth. Thus, it may turn out to be more palatable to apply these measures selectively to activities related to growth in order to delay perhaps until safe, equitable and renewable solutions to energy supply are available.

Pursuing policies goals via these mechanisms, however, requires some caution. In any sufficiently nonlinear dynamic system there is the possibility of bifurcations—seemingly small changes that lead to drastic transitions in the system dynamics (May 1974; Gleick 1988; Strogatz 2000). An example in the current context comes from the model inspiring this work, whereby changes to the value of the scaling parameter β around the critical value of one

leads to completely different system dynamics. Things are further complicated by the issue of unknown dimensions (Westley et al. 2011) and externalities—hidden interrelations as yet unclear that may tie changes in one parameter of this model to changes in the others.

CONCLUSION

This work has presented a model and technique that relates the energy consumption for growth and maintenance to economic output of cities. So long as the model holds there are a number of implications. First, it is suggested that decreasing both types of energy demands on a per unit basis actually leads to an increase in overall energy use; and that decreasing energy for maintenance can also increase the total limit of energy demand. This latter point means that, all other things being equal, the growth of energy demand and economic output of cities with low per unit maintenance energy requirements are not limited by internal factors and that, all else remaining constant, it can be expected that the energy demand and GDP of such cities will tend to increase unabated. The historic apparent link between per unit energy requirements and growth in both GDP and energy implies that should this pattern and economic growth continue, innovation and policy together may play an integral role in achieving a balance with the biosphere. While alternatively, growth in GDP and energy demand can perhaps be slowed or delayed through proper modification to per unit energy requirements as required. In either case, caution must be followed and further research undertaken to account for complications highlighted in the case study.

The model was tested against historical data for Hong Kong and Singapore over the period of 1965–2010. The model produces a good fit with largely robust confidence intervals for both cities. The low maintenance demands for these cities suggest that, all other factors being equal, these cities can expect continued growth in both GDP and energy use; however, the larger energy demand for growth in Singapore means more energy will be required here to sustain the growth than in Hong Kong. This foresight may be useful in planning for sustained supply of the energy required to sustain this growth or to chart new trajectories altogether if supply cannot be ensured.

While it can be said, however, that the findings suggest neither city are maintenance dominated, the results for Singapore are less conclusive due to its fast pace of development and the time-average nature of the parameter values of the model. A longer time series and data for different cities are required to determine the degree to which this issue can be accounted for without requiring significant changes to the model.

Looking beyond the scope of this paper, the benefits to achieving policy objectives through focusing on the per unit growth and maintenance parameters can potentially be thwarted by the difficulty in their effective control. The values of these parameters represent the sum-total of activities of the urban economy. This includes the significantly entrenched and complexly interacting economic activities and energy demands in the existing makeup of industry and infrastructure. These complications necessitate both detailed models that can suitably map urban dynamics (Anderson et al. 1996) and the thorough experimentation of many new approaches to economic and resource sustainability with proper support of successful approaches through to large-scale implementation (Rotmans and Loorbach 2009). Such continued and future efforts are important to the energetics and economics of cities.

Acknowledgments This work has been graciously supported in part by the Natural Sciences and Engineering Research Council of Canada and the Ontario Ministry of Training, Colleges and Universities.

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