Environmental impact assessment under scientific and informational uncertainty

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Expert assessment

Environmental impact assessment by experts in cases of factual uncertainty

Kostas Bithas, Peter Nijkamp and Anastasios Tassopoulos

This study deals with the difficulty that there is usually incomplete knowledge and data about an ecosystem and its environmental–economic interactions, thus hindering the development of a quantitative model for impact assessment. The method brings together a panel of experts and draws on their interdisciplinary expert knowledge of that and similar environmental systems. The panel 'creates' what its members view as likely data which describe instances of the causal relationship(s) under investigation. These artificial data are processed by standard statistical methods to identify the best formal model(s) describing the relevant relationship(s). The model can then be used to estimate environmental impacts caused by various expected external developments (investments projects, environmental policy, and so on). An application to a project in Greece is discussed.

Keywords: environmental impact assessment; interdisciplinary experts; Greece

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ENVIRONMENTAL IMPACT assessment (EIA) nowadays forms an indispensable aspect of an effective environmental management and policy vehicle for a wide variety of environmental issues. Specifically, EIA focuses on the *ex ante* estimation of environmental effects of socio-economic projects and policies, the aim being that adverse effects can be identified and avoided by properly modifying the relevant projects or policies and by adopting specific measures. In addition, EIA may be used as an empirical basis for increasing the scientific knowledge on natural processes and on environmental–economic interactions.

Despite the usefulness of EIA which has fostered considerable scientific effort in recent years, there remains in practice considerable methodological difficulty about the estimation of environmental impacts. In many cases there is incomplete scientific knowledge of the economic–environmental system or processes at hand, while also reliable statistical data are often lacking. Sometimes only qualitative or 'fuzzy' information is available, while the quantitative assessment of environmental impacts is almost impossible (Braat and van Lierop, 1982; 1987).

The present study addresses this mentioned difficulty. It focuses on quantitative environmental impact assessments and tries to overcome the problem of limited scientific knowledge and of informational–statistical uncertainty by using scientific experts' knowledge and combinatorial specification methods.

In general, there are two alternative methodological approaches to EIA (Braat and van Lierop, 1987). First, when there is more-or-less fully available scientific knowledge on the environmental–

A methodology is proposed which uses existing expert knowledge on environmental–economic issues to 'create' observations concerning the causal relationship studied; these can then be processed by standard statistical methods

economic system or phenomenon being studied, proper mathematical cause–effect relationships (functions) can be formulated that describe its operation — and hence also the causal relationship underlying the environmental impact studied — in a reduced form. These functions can be used for quantitative assessment of relevant environmental impacts.

Second, when a sufficient and proper number of (statistical) observations are available on the phenomenon (or causal relationship) which underlies the relevant environmental impacts, the mathematical relationships (functions) can be specified by processing these observations using alternative statistical methods (Malinvaud, 1980). Then, these functions can be used for estimating the relevant environmental impacts.

Note that in the first alternative also, statistical observations are frequently used for estimating the coefficients of an often abstract, mathematical function derived by using the available scientific knowledge; in these cases the model is mainly based on state-of-the-art insight, while statistics are then often of complementary use.

There are, however, various cases in which it is very difficult to acquire or access either the necessary complete scientific knowledge or sufficient statistical data. In these cases, it is problematic to specify the mathematical relationships or functions that formally represent the phenomenon or the causal relationship that leads to the environmental impact studied.

The present study deals with this particular problem. It aims to combine the two alternatives for those situations in which neither option can be used separately to solve the problem. In particular, our study proposes a methodology which uses existing interdisciplinary expert knowledge on environmental–economic issues to 'create' observations concerning the causal relationship studied; these 'observations' can then be processed by standard statistical methods to identify the best specific function that describes formally the relationship or phenomenon which underlies the environmental impacts at hand.

The paper has the following structure. First, the proposed methodology is presented. Then its main elements are discussed in relation to standard methods used in environmental impact assessment, so that its intrinsic merits can be better judged. Finally, the scope and the limitations of this new approach are highlighted, while its potential is assessed on the basis of a simple illustrative application for the Greek region of Olympia.

Proposed methodology

We aim to present formally a real-world picture of a phenomenon that generates environmental impacts, in order to obtain a quantitative estimate or assessment of these impacts. Such an attempt will need to specify a causal relationship whose formal representation consists of one or more mathematical functions (equations).

For instance, consider the relationship between the socio-economic activities in a region and its soil quality (Braat and van Lierop, 1982; 1987). Many obstacles may be encountered in the process of obtaining and specifying relevant mathematical functions. Usually, the phenomenon described by the causal relationship is not exactly known, so that the relevant equations cannot be specified unambiguously; simultaneously, there probably exists only a limited number of statistical observations concerning the causal relationship.

Now we may wish to estimate the impacts on the soil quality, as it is influenced by specific socio-economic activities in a given area; in fact, we should define the function or equation that describes formally the relevant causal relationship. If, however, we have neither complete scientific knowledge nor a sufficient number of (statistical) observations for this relationship, the problem is how to obtain a satisfactory and operational model (mathematical function) which can properly replicate the real-world causal relationship in a reduced form (Bithas and Tassopoulos, 1994). The methodology developed here attempts at least to reduce these obstacles.

We will present systematically the steps of the proposed methodology using as an example the impacts on the soil quality exerted by particular activities in a given area.

Step 1: Composing an experts group

A properly selected, interdisciplinary group of experts on environmental–economic issues is the first step in our approach. The group should have the maximum possible scientific knowledge of the phenomenon under investigation.

This group gathers and considers all existing information on the relevant causal relationship describing the process or phenomenon studied. So, besides all other (often informal) information, the existing statistical information will be accessed by the group. We assume here that this information is not sufficient for specifying and assessing the relevant function by means of standard econometric–statistical methods.

Next, within the limits of time and money, the group may take initiatives or actions to augment the scientific knowledge on the phenomenon at hand. Even experiments, if possible, can be used to obtain more statistical information. If a statistically sufficient number of observations is obtained from these experiments, the modelling activity may proceed immediately with the application of standard statistical methods; in our case, however, we assume that such experiments cannot generate sufficient information.

All additional information is accessed by all members of the group, including even an extensive discussion on the relationships examined, so that all members share a common knowledge base.

Step 2: Creating observations

This step is crucial for the success of the methodology. It aims at 'creating' observations or artificial data for the causal relationship examined; we will call these newly created observations 'hypothetical observations'. They are created on the basis of the 'common knowledge' base established in the previous step. How can this be achieved?

The expert group creates a hypothetical combination for the various independent variables (x_1, x_2, x_3) by attaching a random value to each one. Each random value is restricted to a plausible range given by the real world definition of the variable. Then, the value of the dependent variable y is estimated by the group for this combination of independent variables. The group uses its common knowledge concerning the relationship/phenomenon at hand.

What if the group fails to agree on one value for y for a given combination of x_ns? In this case, group members are exposed to a negotiation via further discussion and exchange of experiences, so that ultimately they may reach an agreed value. If at the end disagreement still prevails, this combination of independent variables is rejected.

The procedure is repeated, until a statistically sufficient number of observations has been agreed. Attention should also be paid to the fact that the hypothetical observations correspond to all reasonably likely aspects or phases of the phenomenon examined and of the possible trends in the relevant environmental impacts. Thus, a properly selected set of combinations for the independent variables is created. Clearly, in this respect, the purposes of each particular case study should be taken into account.

Step 3: Specifying the mathematical function

The next step aims to determine the quantitative form of the abstract relationship. The hypotheses underlying this step are:

a. The functional relationship is assumed to exist in a structural sense; it relates y to the relevant independent variables, to form a statistical model of the problem (Nijkamp, 1979). Specifically, the equation is the abstract mapping relationship for the real-world phenomenon examined. However, an important feature is that the phenomenon under consideration should concern a physical/technical process of a deterministic nature and preferably not social–economic behaviour that involves a significant share of unobservable social stochastic factors (Malinvaud, 1980; Johnston, 1963).

   This does not imply that we should confine our research to the domain of natural phenomena alone. Physical–technical interactions underlying economic and social processes can also be examined, if they do not involve unknown stochastic elements of socio-economic behaviour (Malinvaud, 1980). In our example, the soil quality in the area studied is influenced by the relevant arable cultivation; this influence can be studied by the proposed methodology. In contrast, the relationship between the arable cultivation and the relevant demand for agricultural products induced by the local population is less easy to study in this way, since it may involve several unknown socio-economic stochastic factors.

b. It is assumed that the interdisciplinary group has sufficient knowledge of the phenomenon, so that all relevant factors are included. Moreover, it is assumed that there is no factor contained produced by step 1 that is not really involved in the phenomenon at hand.

c. It is assumed that any one set of hypothetical observations will produce the same equation as would any other possible set of hypothetical or real observations.

d. The hypothetical observations are randomly distributed. This indispensable prerequisite can be fulfilled, since we are able to create the observations by a random selection of values for the independent variables.

Subsequently, the statistical problem is a rather simple and conventional one. We fit a curve (surface) to the given points determined by the set of observations in the n-dimensional space. There are several statistical methods for fitting such a curve; the standard regression method usually prevails (Malinvaud, 1980; Johnston, 1963; Theil, 1971).

In curve-fitting, we may face two alternatives. Either we use only the hypothetical observations, and keep any real-world ones for testing the function; or we can combine the hypothetical observations with any real-world observations to help generate the function.

Step 4: Testing

The estimation of the mathematical expression for the function contains some arbitrary elements which stem from the use of the hypothetical observations. They do not necessarily depict real instances of the relevant phenomenon. Rather, they originate from the informed guesswork of the panel.

To test the function created using hypothetical observations, a given number of real observations are kept back and used as a reference: if the function fits sufficiently these real observations it should be accepted

Thus some kind of testing should be undertaken. Specifically, when we compose the set of observations that will be used to define the function, a given number of real observations should not be included in this set. They will be used as a reference or background sample for testing the function once it has been estimated. If the function fits sufficiently these real observations, then it should be accepted; otherwise, it should be rejected. If it is rejected, the whole process should be repeated from the creation of new observations, until a better function is estimated.

Finally, a function is established which can be accepted as a reliable formal representation of the relationship/phenomenon examined, and is estimated on the basis of the hypothetical observations created by the interdisciplinary group. The scientific knowledge of the group substitutes the lack of real-world statistical observations. As a result, the formal representation of the examined causal relationship describing the phenomenon at hand is obtained.

Referring to our example, we obtain the function that estimates the soil quality (environmental impact) as the effect of some particular socio-economic activities in the region studied. Once the function has been defined, it can be used to estimate the relevant environmental impact under some expected or hypothetical growth of the respective socio-economic activities. Then, if the environmental impact appears to be undesirable, mitigating measures can be taken in advance. The methodology discussed can also be used to identify the environmental impact after these measures have been taken. For this purpose the interdisciplinary group creates another data set describing the new conditions or structure of the phenomenon concerned.

Comparison with conventional approaches

In this section we aim to clarify the properties of the proposed methodology by comparing it with some conventional methodologies used for environmental impact assessment. Usually, when we have statistical observations on a phenomenon causing an environmental impact, we apply standard statistical methods and define the mathematical function that describes formally this phenomenon. In this case, the conventional methods and our proposed methodology are similar. Nevertheless, they are fundamentally different in the way they perform this task. Let us describe the differences by delineating briefly the steps and characteristics of each one.

Conventional statistical methodology

Establishing a quantitative function The target is to establish a quantitative function that represents a real-world phenomenon. The scientific knowledge and the factual experience establish a set of abstract functions which, by assumption, describe the phenomenon at hand. They form the theoretical model of the study (Malinvaud, 1980). This theoretical model will be numerically defined in the following steps. Either it is proven valid or it is rejected; in the latter case another theoretical model is proposed.

Sometimes a theoretical model is not established; then the quantitative function that is estimated in the next step via the statistical observations does not form the 'quantitative law' of the phenomenon. In this case, the function is a quantitative relationship that reflects the statistical observations used, since a 'quantitative' law should describe every observation set and not only the existing one (Theil, 1971). In this respect, the theoretical model encloses the scientific knowledge which takes a formal representation via the use of a random data set. Therefore, the existence of a theoretical model gives the necessary generality to the function f, so that it may be interpreted as a 'law' (Malinvaud, 1980).

This constraint does not hold in the case of physical phenomena where a statistically suitable number of observations suffices to establish the 'quantitative law' of the phenomenon, because physical phenomena lack social stochastic elements that are handled by the theoretical model. In the case of a physical phenomenon, each random set of observations is expected to lead to the same function with any other set of data. Therefore, the function forms the relevant 'quantitative law', even if there is not a theoretical model.

This distinction is important for environmental impact assessment, since in some cases the impact can be described as the outcome of natural causes which do not contain a stochastic behavioural element. However, this is not always the case; indeed, there are cases where the causes are strongly related to social processes and then the relevant social stochastic factors are present.

Processing The existing statistical observations are processed by statistical–mathematical methods, for example, regression methods, and next the function is estimated.

Testing Once the function is defined, it should be tested. More precisely, it should be examined whether the function is actually the 'quantitative law' of the process examined and whether it describes reliably the emergence of the environmental impact. Thus, usual tests of mis-specification (homoscedasticity, autocorrelation and multicolinearity) should be

Table 1. Focal points of the proposed methodology in relation to those of the statistical methodology

Statistical methodology	Proposed methodology
Aims to establish the quantitative law of a natural and/or socio-economic process which results in a certain environmental impact	Aims to establish a quantitative law that describes a technical/natural process which underlies the creation of an environmental impact
A theoretical model is assumed that describes the process examined. The aim is the numerical estimation of the model. (This step is often skipped.)	A suitably selected interdisciplinary scientific group is established. It is assumed that this group is able to grasp the 'logical law' underlining the examined process.
Statistical observations, that describe specific instances of the process, are gathered	The scientific group creates observations that describe certain instances of the process. The hypothetical observations obey the 'logical law' established in the previous step.
The statistical observations are used to estimate the function(s) of the theoretical model	By using the created observations we estimate the function that fits them
The quantitative model is exposed to proper statistical tests. These aim to test the ability of the estimated model to describe the real-world process. Suitable corrections are made, which aim to establish the best possible law for the examined process.	The function is tested against 'real' statistical observations. Suitable corrections are made.

carried out. Indeed, if the defined law is not sufficient, the above tests may suggest a way to establish a better one (Theil, 1971; Breeman, 1973).

Assessing impact The function can be used to assess the relevant environmental impact represented by the respective dependent variable. Then this impact can be estimated under alternative assumptions concerning the trends of relevant causes (independent variables). Therefore, it appears that the establishment of the function gives considerable flexibility for estimating the impact.

Proposed methodology

The proposed methodology aims to quantify a physical phenomenon which underlies the creation of the environmental impact. The specific problem here is the lack of sufficient statistical observations. On the other hand, there may exist, to a considerable extent reliable, scientific knowledge concerning the phenomenon. However, this knowledge does not suffice to establish directly the relevant mathematical representation.

We propose utilising the available scientific knowledge to create a set of observations. The essence of this process is that the members of the interdisciplinary group express the 'logical law' that underlies the process by describing some specific instances of it, although they do not know the quantitative expression of this law. So, they create 'hypothetical observations' according to the rationale behind the logical law. Briefly, the steps of the proposed methodology are:

- the assembly of the interdisciplinary group whose members establish a 'common knowledge pool' that may be regarded as a mapping of a 'logical law' governing the phenomenon;
- in the light of this logical law, the members of the group create observations.
- by processing the created observations, a function f; pertaining to these 'data', is defined. It is assumed that the function represents formally the logical law, so that it may be considered as the quantitative law of the process.
- once the function is defined, any test, such as homoscedasticity, autocorrelation or multicolinearity only plays a marginal role. All these tests aim to establish a proper quantitative law, once we have a set of statistical observations. However, the proposed methodology presumes the existence of this law; indeed it is the logical law that leads to the creation of observations.

The main steps of both our proposed methodology and of the standard statistical approach are systematically presented in Table 1.

Scope of proposed methodology

The above analysis reveals the application field of the proposed methodology. It is particularly appropriate when either physical–technical processes or the physical–material basis of social processes are investigated. In these cases it can be assumed that a group of qualified scientists knows the determinant factors of these processes, and moreover that, to some extent, they know the logical law underlying them. On the other hand, if socio-economic phenomena involving stochastic factors are examined, we cannot expect a group of scientists to know all factors involved and

The proposed methodology is not in conflict with the conventional procedure: rather, the two are complementary, the former applying when observations, which would permit the use of a more rigorous statistical methodology, are not available

Table 2. Existing observations

D*Sq*	D*Ard*	D*Old*	D*Ind*
–2	1	0.1	1
–2.5	2	0.1	3
–3.8	0.2	0.2	0.2

their functioning, as this would assume a complete knowledge of human behaviour which is the main question in the social sciences.

It should be added that the proposed methodology is not in conflict with the statistical/econometric procedure, even in the domain of physical–technical processes. Rather, the two are complementary. Specifically, the proposed methodology applies when statistical observations, which would permit the use of a more rigorous statistical methodology, are not available.

An indispensable prerequisite for applying the proposed methodology is the existence of a considerable level of expert knowledge of the process being studied. Then, although this knowledge may not suffice to quantify directly this process, it can create hypothetical observations describing particular random instances. The created observations lead then to the mathematical representation of the process.

Clearly, the methodology proposed here might lead to some imprecise formal representation of the process examined because of the imprecision hidden in the data created. In some cases, this can be avoided by collecting or creating data by experiments and then the rigorous statistical–econometric methodology can be applied. However, it is often costly or time consuming to obtain real data; then there is some kind of trade-off between the application of these two methodologies.

An example

We now describe the application of the proposed methodology to new activities on the soil quality in the Greek region of Olympia in the western Peloponnese. The soil quality is determined by various land-use and industrial activities in this area as well as by the relevant natural absorption processes. For this case study we apply the proposed methodology, because the necessary data do not exist nor can experiments be performed to generate them. It should be noted that our sole aim is to elaborate and illustrate the properties of the proposed methodology and not to go deeply into the nature of the case study itself.

The interdisciplinary experts group consisted of nine independent scientists working in, and familiar with, the region. For the causal relationship concerned, the interdisciplinary group has stated (based on its expert insight) that the soil quality (*Sq*) is

Table 3. Hypothetical observations

D*Sq*	D*Ard*	D*Old*	D*Ind*
–0.50	0.15	0.02	0
–3	3	0.1	0.5
–0.2	0.2	0.01	1.5
–0.5	0.2	0.01	3
–3	4.5	0.02	3.2
–4	1	0.2	1.2
–5	0.2	0.35	0
–0.1	1.2	0	0.2
–0.09	0.4	0.001	0.5
–0.4	–1	0.001	0.2
–1.0	–2	–0.1	0.3

determined by the density of arable cultivation (*Ard*), by the density of cultivation of olives (*Old*), and by the industrial activities (*Ind*) that process the relevant agricultural production. The relevant general impact function is:

$$(Sq_t - Sq_{t-1}) = \mathrm{f}\,[(Ard_t - Ard_{t-1}), (Old_t - Old_{t-1}), (Ind_t - Ind_{t-1})\,] \qquad (1)$$

Function (1) can be written as follows:

$$\mathrm{D}Sq_t = \mathrm{f}\,(\,\mathrm{D}Ard_t, \mathrm{D}Old_t, \mathrm{D}Ind_t) \qquad (2)$$

where D stands for first-order time differences.

We will now present briefly the effects of each independent variable (cause) on the soil quality. The arable cultivation influences the soil quality because of the chemical pesticides and fertilisers used to increase the density of the crops. In a similar way, the density of cultivation of olives influences the soil quality. Finally, the industrial activities in the area examined co-determine the soil quality because of the disposal of certain kinds of sediments and other industrial wastes. Note that the industrial activities are mainly processing the agricultural production of the region.

For the causal relationship described by functions (1) and (2), there exist only three reliable real-world statistical observations. These are presented in Table 2. They are estimated on the basis of past measurements actually taken in the region.

This number of existing observations does not suffice for the application of standard statistical methods to specify function (1). To overcome this problem, the expert group created a set of hypothetical observations as discussed above; these are presented in Table 3.

The next step is the specification of the function f of (2) by using the hypothetical observations. In this process we deliberately do not make use of any of the existing real observations; these will be used afterwards for testing the function. In this context, the statistical problem of the study is very simple; we have to fit a curve to a number of given points in the

Table 4. Statistical estimations for function (4)

Variable	Coefficient	Standard error	t-statistic
exp(D*Ard*)	–0.027	0.12	–2.18
D*Old*	–16.4	2.23	–5.68
D*Ind*	–0.18	0.29	0.37

R-squared = 0.84
Adjusted R-squared = 0.77
F-statistic = 12.77

n-dimensional space defined by the hypothetical observations.

For this mathematical fitting, 64 candidate functional specifications are examined; they are composed by using the linear combination of the logarithmic, linear, exponential and rational mathematical expressions, in the case of three independent variables. All functional specifications examined are presented in Annex 1. For selecting the most appropriate candidate function, the least squares method is used. Note that the values of Table 3 have been properly scaled before being processed in a least squares method. Candidate 5 gives the lowest least square sum and hence this function is chosen. The most plausible numerical specification, thus, of function (2) is:

$$\mathrm{D}Sq_t = -0.027\exp\mathrm{D}Ard_t - 16.4\mathrm{D}Old_t - 0.18\mathrm{D}Ind_t \qquad (4)$$

Once the function f is specified, it should be tested for its ability to describe the real-world process. An obvious test is to see whether it describes sufficiently the three existing real-world observations in Table 2. By applying function (4) to these observations, we respectively estimate the following values for DSq:

- for the first observation, function f estimates that DSq=–1.7 while the real value is –2;
- for the second observation, function f estimates that DSq=–1.8 while the real value is –2.5; and
- finally, for the third observation f gives DSq=–3.3 while the real value is –3.8.

We apply now the Chow's forecast and breakpoint test which confirms (given the limited sample size) that function (2) fits statistically sufficiently the three real-world observations (Chow, 1960; Korosi and Szekely, 1992). It permits us to accept it as a provisionally reliable formal representation of the process under investigation.

Having specified the function f it can be used to assess the relevant environmental impact (the impact on the soil quality) under expected or hypothetical conditions. A suitable environmental policy may then be designed on the basis of these forecasts. If some policy actions that modify the structure of the physical process that cause this impact are envisaged, the impacts may be gauged by repeating this approach and hence another data set should be created taking into account the new situation. For instance, if a policy aimed at reducing the use of chemical fertilisers and pesticides is introduced, a new set of observations should be created describing the impact on the soil quality under the new conditions.

Having specified the function it can be used to assess the relevant environmental impact under expected or hypothetical conditions: a suitable environmental policy may then be designed on the basis of these forecasts

Epilogue

We have outlined the theoretical basis of a methodology which leads to quantitative estimations of environmental impacts when there is considerable lack of statistical data and of scientific insight concerning the natural process underlying the cause of this impact. The methodology is based on the existing, although limited, knowledge of scientists/experts in the relevant field. In particular, this knowledge is used to create artificial observations which substitute for the lack of actual observations.

The proposed methodology may be applied for modelling original physical processes or physical interactions underlying social phenomena. In this context, it is not in conflict with standard statistical methods, but complementary to them since it applies, under certain conditions, when the statistical technique cannot be applied because of lack of statistical data. This methodology has been illustrated in the present paper by a simple empirical example concerning the estimation of an environmental impact where no other consistent method may be used.

It appears that the methodology traced by the study may constitute a useful scientific instrument for those cases in which neither the scientific knowledge nor the statistical data suffice for assessing environmental impacts by a rigorous method. Therefore, it may be a useful tool for environmental policy design and monitoring.

On the other hand, it seems that some aspects of this methodology require further research and elaboration, so that some rather restrictive conditions may be eliminated or at least relaxed, especially those which concern the creation of the hypothetical observations. It may be useful to use also a range of values instead of a unique value for creating observations, since it makes the process easier for the experts involved.

Annex 1. Candidate functional specifications

1: $y = K + A\exp x_1 + B\exp x_2 + C\exp x_3$
2: $y = K + A\exp x_1 + B\exp x_2 + C\exp x_3$
3: $y = K + A\exp x_1 + Bx_2 + C(1/X_3)$
4: $y = K + A\exp x_1 + B1/X_2 + C(1/X_3)$
5: $y = K + A\exp x_1 + Bx_2 + Cx_3$
6: $y = K + A(1/X_1) + B(1/X_2) + C(1/X_3)$
7: $y = K + A(1/X_1) + B\exp x_2 + Cx_3$
8: $y = K + A(1/X_1) + Bx_2 + Cx_3$
9: $y = K + A(1/X_1) + Bx_2 + C\exp x_3$
10: $y = K + Ax_1 + Bx_2 + Cx_3$
11: $y = K + Ax_1 + B\exp x_2 + C\exp x_3$
12: $y = K + Ax_1 + B(1/X_2) + C(1/X_3)$
13: $y = K + Ax_1 + B\exp x_2 + C(1/X_3)$
14: $y = K + Ax_1 + B(1/X_2) + C\exp x_3$
15: $y = K + A(1/X_1) + B\exp x_2 + Cx_3$
16: $y = K + A(1/X_1) + B\exp x_2 + C\exp x_3$
17: $y = K + Ax_1 + Bx_2 + C\exp x_3$
18: $y = K + Ax_1 + Bx_2 + C1/X_3)$
19: $y = K + Ax_1 + B\exp x_2 + Cx_3$
20: $y = K + Ax_1 + B(1/X_2) + Cx_3$
21: $y = K + A(1/X_1) + B(1/X_2) + C\exp x_3$
22: $y = K + A(1/X_1) + B\exp x_2 + C(1/X_3)$
23: $y = K + A(1/X_1) + Bx_2 + C(1/X_3)$
24: $y = K + A\exp x_1 + B\exp x_2 + Cx_3$
25: $y = K + A\exp x_1 + Bx_2 + C\exp x_3$
26: $y = K + A\exp x_1 + B(1/X_2) + C\exp x_3$
27: $y = K + A\exp x_1 + B(1/X_2) + C\log x_3$
28: $y = K + A\exp x_1 + B\log x_2 + C(1/X_3)$
29: $y = K + A\exp x_1 + B\log x_2 + C\log x_3$
30: $y = K + A(1/X_1) + B\exp x_2 + C\log x_3$
31: $y = K + A(1/X_1) + B\log x_2 + C\log x_3$
32: $y = K + A(1/X_1) + B\log x_2 + C\exp x_3$
33: $y = K + A\log x_1 + B\log x_2 + C\log x_3$
34: $y = K + A\log x_1 + B\exp x_2 + C\exp x_3$
35: $y = K + A\log x_1 + B(1/X_2) + C(1/X_3)$
36: $y = K + A\log x_1 + B\exp x_2 + C(1/X_3)$
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38: $y = K + A(1/X_1) + B\exp x_2 + C\log x_3$
39: $y = K + A\log x_1 + B\log x_2 + C\exp x_3$
40: $y = K + A\log x_1 + B\log x_2 + C(1/X_3)$
41: $y = K + A\log x_1 + B\exp x_2 + C\log x_3$
42: $y = K + A\log x_1 + B1/X_2 + C\log x_3$
43: $y = K + A(1/X_1) + B(1/X_2) + C\log x_3$
44: $y = K + A(1/X_1) + B\log x_2 + C(1/X_3)$
45: $y = K + A\exp x_1 + B\exp x_2 + C\log x_3$
46: $y = K + A\exp x_1 + B\log x_2 + C\exp x_3$
47: $y = K + A\exp x_1 + B\log x_2 + Cx_3$
48: $y = K + A\exp x_1 + Bx_2 + C\log x_3$
49: $y = K + A\log x_1 + B\exp x_2 + Cx_3$
50: $y = K + A\log x_1 + Bx_2 + Cx_3$
51: $y = K + A\log x_1 + Bx_2 + C\exp x_3$
52: $y = K + Ax_1 + B\log x_2 + C\exp x_3$
53: $y = K + A\log x_1 + B\exp x_2 + Cx_3$
54: $y = K + Ax_1 + Bx_2 + C\log x_3$
55: $y = K + Ax_1 + B\log x_2 + Cx_3$
56: $y = K + A\log x_1 + B\log x_2 + Cx_3$
57: $y = K + A\log x_1 + Bx_2 + C\log x_3$
58: $y = K + A\log x_1 + B(1/X_2) + Cx_3$
59: $y = K + A\log x_1 + Bx_2 + C(1/X_3)$
60: $y = K + A(1/X_1) + B\log x_2 + Cx_3$
61: $y = K + A(1/X_2) + Bx_2 + C\log x_3$
62: $y = K + Ax_1 + B\log x_2 + C(1/X_3)$
63: $y = K + Ax_1 + B(1/X_2) + C\log x_3$
64: $y = K + A(1/X_1) + B(1/X_2) + Cx_3$
65: $y = K + Ax_1 + B\log x_2 + C\log x_3$
66: $y = K + Ax_1 + B\exp x_2 + C\log x_3$

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