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CENTRALISED STOCHASTIC SIMULATION PROCESS

Technical Field

The invention relates to the technical field of "Industrial Risk Management" and more specifically to:

- Statistic/probabilistic prediction processes of the probability law on statistic distribution of variations that indicate future behaviour and optimisation of productivity parameters for a number of remote local industrial systems subjected to a common global environment, both random and evolutionary in nature.

- Simulation processes, i.e. which use a predetermined sampling of probable future scenarios of environment state variables.

The invention relates specifically to the following cases:

- Where a vast number of decentralised industrial sites have an unpredictable behaviour given that they are subjected to a common global environment, both random and evolutionary in nature (which we may, in the majority of cases, characterise as a risk environment).

- Where this random and evolutionary environment is currently quantifiable, i.e. that it may be, overall, described numerically through state variables common to all industrial sites (as defined below).

These state variables are actually:

- Either, common to all industrial sites.

- Or, when they appear specific to an industrial site, "quasi common" given that their behaviour is governed by complex relations with other state variables of the model (not specific to said site), in such a way that their probability law may not be analysed independently from that of other state variables common or specific to other sites.

Subsequently, and notably in the description and the claims that follow, the term "common state variables" shall be referred to (by extension) as all state variables of either one of the two types described above. Subsequently, the terms random environment and risk environment shall also be used interchangeably.

According to the invention, an industrial site is understood to be any location with human activity where the object is the production of added value (production flow), that is expressed directly or indirectly in terms of added value, whether it be within the manufacturing, energy, food processing, finance, transport, public health, use of raw materials industries amongst others.

Subsequently, as an application example for the invention and an analysis of the previous work, we shall frequently refer to the financial industry. It is

within this field that the application of probabilistic prediction processes for random behaviour is more commonly used given that it is governed by regulation constraints ("CAD" directives of the Council of European Communities, "Basle Committee" recommendations, "Group of 30" recommendations). However, lessons taken from this invention may be applied within nearly every industrial field. By using the financial field as an example, we understand quantifiable risk (random environment) to be market, credit, counterparty, liquidity risks amongst others. In contracts, non-quantifiable risks may be legal, fraud or media related risks.

The invention relates specifically to the following cases:

- Where the behaviour of environment state variables is unpredictable or uncontrollable, in such a way that these constitute random "risk factors" that may cause a variation and in particular, decreased effectiveness (or a risk on the behaviour of each) of decentralised industrial sites possibly reflected in losses (money, human life, production and so forth).

- Where the effectiveness of each local system may also be described through a numerical productivity indicator according to a local numerical systems analysis model (generally of the type with parameters) that has been previously determined, dependent upon each system and at each instant of all or some state variables and local action parameters which allow the functioning level of the local industrial system to be adjusted.

The invention relates to the industrial fields, that are manufacturing and financial, either public or private, where it is suitable:

- To statistically estimate, and thus mark out at each industrial site a random numerical productivity indicator of a manufacturing industrial type (production, pollution) or financial (profit/loss) or other, and involved in an added value production exercise (manufacturing, agricultural or financial production and so forth).

- To optimise the numerical productivity (or risk) indicator of each industrial site by adjusting local action parameters of that industrial site.

- For the above by, in particular, taking regulation criteria into account that would set limits to this productivity (or risk) indicator.

Description of Previous Work

The second half of the twentieth century became aware of the pernicious risk effects and, as a result, of its cost and the birth of a new science, namely "Risk Management". "Risk Management" is a science that:

- Studies quantifiable or non-quantifiable factors that threaten the productivity or behaviour of an industrial or private system.

- Provides strategic (organisational and process) solutions and tactics (quantitative management methods, for example) in order to combat these factors.

The previous work is concerned with "Risk Management" methods for industrial systems. Thus, patent US6021402 outlines a risk management method for

a network of industrial systems concerned with electric production. Patent US5930762 outlines a risk management system for a device whose behaviour is bound by multiple environment parameters.

The previous work is concerned with five different analysis and/or decision-making methods that relate to risk of random systems:

- Decision tree processes.
- Statistic/probabilistic processes (for e.g., variance-covariance, historic, Monte-Carlo).
- Variational methods (for e.g., "base point value" (PV01)).
- Extreme scenario methods (for e.g., "Stress Testing", "Catastrophe Scenario").
- Artificial intelligence methods.

a) Decision tree processes are used in sequential decision-making processes. A diagram that resembles the branches of a tree depicts all possible events and the sequence of decision choices that are the result of previous decisions. This decision tree method may be only used in very simple cases where anticipated events and the probability of each event are already known. Numerical calculations available with this method are simple and may be implemented without a calculator. However, the method is not sufficient enough to outline the risk structure of complex random systems.

b) In many cases, anticipated events are governed by different state variables whose exact value can not be known. This type of problem is normally analysed through a statistic/probabilistic process. Subsequently, we shall outline the

"statistic/probabilistic process" to estimate the future behaviour of a system subjected to a random environment that may be described through state variables. It is a method that provides a statistic estimate of the probability law in the distribution of variations for a numerical productivity indicator of that system. The latter is achieved with the help of a probability distribution model together with environment state variables (risk factors), all of which is previously determined. This is in contrast with the decision tree process (or any other type of risk analysis) where results are unique values.

c) Variational methods quantify the behaviour outcome of a system where there is variation of one or several environment parameters (state variables). Thus in the financial field, the method known as "base point value" (PV01) quantifies the sensitivity of a securities portfolio with a 0.01% gap (one "base point") through a parallel and uniform move of the interest rate curve be it upwards or downwards. In this case, it will be noted that the probability of occurrence and the range of variation are not known. This is insufficient to describe the reality of risk behaviour for a complex random system.

d) The aim of extreme scenario methods is to estimate the result of particular scenarios occurring on a system. Thus, in the financial field, the "stress testing" method enables interest rates to be adjusted at various points along the curve so, for example, to simultaneously increase an expiration date and decrease another. This method is used in order to simulate what

could happen following a catastrophe scenario (to predict what would only happen very rarely). In this case, it will be noted that time and probability factors are not implicated. This is also insufficient to describe the reality of risk behaviour for a complex random system.

e) In different cases where we would want to predict random changes such as variations in petrol or share prices rather than predict a risk, too many factors come into play that are themselves too unpredictable and difficult to model with mathematical tools. In order to broach these prediction issues, methods known as "artificial intelligence" with "neuron networks" and "expert systems" are used. These artificial intelligence techniques are capable of reasoning with a vague or incomplete information base. This technology was recently used for geological production prediction and market predictions. However, these methods are unsuitable for general risk analysis of industrial systems in view of common, especially regulation, criteria. Thus, patent US5521813 outlines a prediction system of climatic variation consequences on a productive system by using a multiple regression method with neuron network.

The present invention relates specifically to the technological field of statistic/probabilistic processes that aim to provide a statistic estimate of the probability law in the distribution of variations for a numerical productivity indicator of that system. The latter is achieved with the help of a probability distribution model together with environment state

variables. The more common field of the previous work in which statistic/probabilistic risk analysis processes are used is that of finance, and more notably market risks. Within the global financial world, market risk is one that the investor faces due to his lack of knowledge concerning future evolution of common state variables that are market basics, such as share prices, interest rates, currency rates and so on. These market variables, also known as risk factors, determine prices of shares, quota assets and portfolios amongst others.

Risks associated with different financial products may be assessed through certain characteristic numbers, such as time and convexity of investment bonds, beta and expected performance of shares, time value, volatility, delta, gamma, theta, vega (derived in relation to volatility) and so on for bonds. However, these different risk approaches known as "sensitive":

- Are specific to a financial product type.
- Rely on specific distribution hypotheses.
- Are not easy to interpret.
- Often underestimate the global loss risk on a portfolio which is actually of interest to the investor.
- Do not assess the probability level of risk occurrence.
- Do not consider temporal forecast.

It is preferable to have a unified probabilistic and temporal approach to risk. Thus, the previous work used the method known as "Value at Risk" (VaR) as risk indicator for a financial system subjected to a random market environment. For a financial asset (or

portfolio), the VaR is an amount such that the loss incurred on that asset (or portfolio) during a certain time interval does not but exceed the VaR with a given (weak) probability level. Calculation of VaR requires knowledge of the probability law for the loss incurred (numerical productivity indicator). The basic problem with risk analysis statistic/probabilistic processes (and especially VaR calculation processes) is therefore to predict distribution of the probability law and distribution of variations for a numerical productivity indicator (loss in the case of VaR).

The statistic/probabilistic processes that aim to provide a statistic estimate of the probability law in the distribution of variations for a numerical productivity indicator of a system are mainly of two types:

- Those, which we shall subsequently call "simulation":

• That use a generation process of a vast number of statistical sampling with a multi-varied description (of *n*-uplets) probable values linked to state variables (risk parameters).

• That lead to a "point by point histogram" of the probability law structure in the statistic distribution of variations for a numerical productivity indicator of the system (i.e. in its entirety).

• That enable the VaR to be calculated generally, with no previous hypothesis on the probability law in this statistic distribution of variations for a numerical productivity indicator.

- As opposed to those, which we shall subsequently call "analytical" (and which we could also characterise as parametric, normative or synthetic):

• That provide only a few descriptive parameters (in a set number) of the probability law in the statistic distribution of variations for a numerical productivity indicator of the system.

• That impose a particular form to the assessment model of the system's numerical productivity indicator according to state variables (risk parameters), (especially a hypothesis of linearity, a quadratic condition and so on).

• That lead to restrictive hypotheses for specific parameter descriptions of the probability law in the statistic distribution of variations for a numerical productivity indicator.

Thus, the previous work is concerned with four classical VaR estimate methods (and more generally of statistic estimate of the probability law in the statistic distribution of variations for a numerical productivity indicator of a system subjected to a random environment):

- Two analytical statistic/probabilistic methods:

• "Delta normal" technique or "estimated variance-covariance matrix" technique that supposes linear productivity.

• "Delta gamma" technique that takes a quadratic term into account to calculate system productivity.

- And two simulation statistic/probabilistic methods:

• Monte-Carlo simulation method.

• Historical analysis technique.

The invention relates solely to the technical fields of "simulation statistic/probabilistic" processes.

In order to calculate the VaR of a financial portfolio, the following entries are classically used:

- Mathematical models to assess prices of different assets, for e.g.:

• The linear combination price model of price variation on an asset according to risk factor variations (such as the "Sharpe Simple Index Model" for shares, which proposes that share price variation is a first degree function of general market index variation).

• The non-linear price models, such as the "Taylor Development Model" that is independent of the time factor.

• The price models that are a function of time, especially the random stationary model, such as the "Black & Sholes Model" to evaluate options.

- Historical models, i.e. observing prices of different assets over a certain amount of time periods in the past.

The "delta normal" (or linear) method, said of the estimated variance-covariance matrix, was suggested and developed by JP Morgan through its RiskMetrix™ system. It consists of three stages as follows:

- The report of elementary risk factors within which portfolio financial assets may be broken down.

- The distribution of financial flows linked to these aggregated and changing elementary risk factors that correspond to standard expiration dates.

- Effective calculation of VaR.

This method provides the following specific theoretical hypotheses by way of example:

- Risk factors of each asset obey a normal law.

- Asset performance has a linear dependence upon risk factors.

- As a result, overall portfolio performance has a linear dependence upon risk factors.

VaR is calculated using the M matrix known as "variance-covariance", of $n \times n$ dimension in the case of n risk factors and consisting of $n \times (n+1)/2$ variances-covariance of risk factor variations calculated on the basis of a past historical period. In that $(\lambda = \lambda_i^{(i=1...n)})$ represents portfolio sensitivities over different risk factors $(X = X_i^{(i=1...n)})$, VaR is calculated using the following formula:

$$VaR = z\sqrt{{}'\lambda M \lambda} + {}'\lambda \overline{X}$$

where z is the quantile of the reduced normal distribution for the confidence interval value of the retained VaR. In such a way that, according to the variance-covariance matrix method, the risk structure is calculated in an environment of n risk factors by generating n' set parameters of the variance-covariance matrix that describe variances and covariances of risk factor variations. In this sense, the variance-

covariance matrix method is an analytical statistic/probabilistic method. The hypothesis of retained linearity needs strict hypotheses on portfolio sensitivities to be implemented in that it would not be applicable to portfolios with "gamma" or "convexity" risks.

The "delta gamma" method is a more elaborate form of the variance-covariance matrix method. The linearity hypothesis is replaced with a quadratic hypothesis. The method incorporates a second set of sensitivity factors for analysts and requires the application of sophisticated mathematical calculations. Despite its superior position over the "delta normal" methods, the "delta gamma" method is generally unsuitable, especially to assess portfolio risk that includes options reaching maturity or exotic derivative products such as "knock-out" options.

On the contrary, according to the Monte-Carlo simulation method advocated especially by Bankers Trust with its RaRoc 2020™ system:

- A choice is made from a family of assessment models for different risk factors or portfolio assets taken from historical observations.

- From said assets and risk factors, the following estimates are made:

• Distribution of different risk factors and associated parameters namely averages and variance-covariance matrix amongst others.

• Relation between asset prices and risk factors.

- For all different risk factors and on the basis of retained probabilistic models and determined

distribution parameters, a large number (a few hundred to a few thousand) of pseudo-random sampling are extracted with a pseudo-random generator from an estimated distribution of probable future variations of risk factors.

- Sampling values for each simulation in the asset behaviour relation are introduced according to common risk factors.

- A corresponding portfolio value is recreated for each simulation sample.

- A global histogram of the probability law in the statistic distribution of variations for the portfolio value is created without a related previous hypothesis.

In this sense, the Monte-Carlo simulation method is a simulation statistic/probabilistic method.

The historical analysis method advocated especially by Chase Manhattan with the Charisma™ and Risk$™ systems is a simplification of the Monte-Carlo method. According to this historical analysis method, a vast sampling number of probable future variations of risk factors are directly transmitted from the market history. By way of example, the historical VaR of one portfolio day may be estimated from one hundred scenario samples in the following manner:

- Recreated values of risk factors are collected from the market history over the last hundred quotation days.

- A variation percentage for every day is determined for each risk factor. This allows one

hundred multi-valued samplings of probable values for each risk factor to be simulated.

- Sampling values corresponding to each historical observation are introduced into the asset behaviour relation according to common risk factors.

- A corresponding portfolio value is recreated for each historical sample.

- A global histogram of the probability law in the statistic distribution of variations for the portfolio value is created without a related predetermined hypothesis.

In this sense, the historical analysis method is also a simulation statistic/probabilistic method.

The principle behind risk analysis and the use of a "simulation statistic/probabilistic" method is familiar to the previous work and applied to other fields, both financial and industrial. The present invention, which (in combination) entails the use of this method, does not in any way claim responsibility for this method when considered independently. Patent FR2769703 may be referred to, and outlines a process to determine unpredictable analysis of a device using coordinates according to the Monte-Carlo Method. Patent EP0837408 outlines a pulverisation simulation process using the Monte-Carlo Method. Patent WO9905685 outlines an automatic system for industrial surveillance using the Monte-Carlo Method. Patent WO9859322 outlines a system that generates pixel values of an image using the Monte-Carlo Method. Patent WO9852132 outlines a system for allocating organisational resources and assessing resource costs and prices using the Monte-

Carlo Method. Patent WO9850835 outlines a monitoring system that can be programmed to supervise industrial equipment activity using the Monte-Carlo Method. Patent WO9836364 outlines an integral assessment process using the Monte-Carlo Method. Patent US5940810 outlines a technique to estimate complex financial asset value using the Monte-Carlo Method.

The statistic/probabilistic methods that provide an estimate of the probability law in the statistic distribution of variations for a numerical productivity indicator of a system subjected to a random environment (and especially VaR estimate methods) can be divided into two distinct groups:

- Analytical methods, according to which a small set number of descriptive parameters on the statistic behaviour of risk parameters, are generated. These lead to a parameter description of the probability law in the statistic distribution of variations for a numerical productivity indicator of a system. (This is notably the case of the variance-covariance matrix method in "delta normal" and "delta gamma" RiskMetrics™ techniques).

- Simulation methods that use a process of "selective sampling of probable scenarios of environment variables" and according to which a vast number (number may be chosen) of repeated samplings of probable future values and plausible environment variables are generated. These lead to an absolute global histogram description of the probability law in the statistic distribution of variations for a numerical productivity indicator of a system. (This is

notably the case of the Monte-Carlo and historical analysis methods).

The invention relates solely to behaviour analysis processes, notably of a "simulation statistic/probabilistic" type that carries out a "selective sampling (selection) of probable scenarios with a multi-value of environment variables".

The previous work knows how to implement a "simulation statistic/probabilistic" method on a unique site and to notably perform all data acquisitions, statistical calculations and so on in order to determine the probability law in the statistic distribution of variations for a numerical productivity indicator of a system when subjected to a random environment. The previous work also knows how to calculate the VaR of a single financial institution's portfolio by using the "simulation statistic/probabilistic" method.

It is further acknowledged that the previous work is able to repetitively transmit numerical values from a centralised site to a vast number of remote sites. This is especially the case of financial data screens used by Reuters and Bloomberg. A central site is connected to sources of variable and random environment data (share prices, financial assets and so on). This concentrated data is transmitted repetitively in a decentralised way towards a vast number of remote sites (screens of financial operators). However, it will be noted that according to the previous work, the transmitted data is real observable or quasi-observable data (share values), i.e. recreated through calculation

(index values, internal productivity rates, and so on), and is to be used as such. The previous work is unaware of the principle of systematic and repetitive remote transmission of probable samplings with a multi-value of possible future values of environment variables with the aim of recreating a histogram.

The methods of the previous work as outlined above do not allow a satisfactory probabilistic prediction of future behaviour and/or the optimisation of productivity parameters for a number of remote local industrial systems subjected to a common global environment to be performed. In particular, they do not allow good VaR conditions of a number of financial sites managing share portfolios to be simultaneously calculated. Thus:

On the one hand, as has been described above, only statistic/probabilistic processes that aim to provide a statistic estimate of the probability law in the statistic distribution of variations for a numerical behaviour indicator deliver accurate and reliable risk assessment.

On the other hand, amongst the statistic/probabilistic processes:

- A) The analytical method, and in particular, the estimated variance-covariance matrix method, is simple and requires few calculations. It may further be used jointly with various remote sites. Thus, according to a variant used in the previous work, the RiskMetrics™ system provides, from a centralised site via Internet towards a number of remote sites that use its method, a repetitive transmission of a set number

of parameters of the variance-covariance matrix. In such a way that the overall VaR calculation is prioritised between the central and remote sites. However, transmitted values are not probable multi-value samplings of environment variables but simple parameters (see above). The drawback to this method is that it requires very strict base hypotheses (conditional normality, linearity, stationariness) that are not acceptable, in the most part, for financial instruments. Thus, VaR calculation according to the variance-covariance matrix method produces errors in the case of portfolios with "gamma" or "convexity" (namely inversions of convexity or discontinuities) instruments, such as options, structured accounts, "mortgage-backed securities" and so on. Overall, analytical VaR including those that have been perfected, summarise the behaviour of a risk structure with the transmission of a limited number of "Greek" parameters (delta, gamma, vega, theta and so on). In general, this is insufficient to describe environments with complex risk factors.

- B) The classical simulation method, and in particular, the Monte-Carlo simulation method, is considered by the majority of specialists to be the "purest", the most global and forward-looking in its conception. It is undoubtedly the most theoretically correct and precise and may be used for all financial instruments. Nevertheless, it requires complex choices of assessment models and stochastic processes that generate correctly chosen random samplings. This is very complex given the difficulty in assessing certain

instruments and their constant development. It calls upon a large number of specialist teams in order to be correctly implemented on site. Further, it needs a significant number of pseudo-random sample selections to be generated in order to be precise. The availability of large information systems is therefore necessary and expensive. In brief, according to the Monte-Carlo Method in the previous work, each site must have an expensive information system and a broad and experienced team for it to be implemented. In such a way that it is not widely acceptable to the majority of financial institutions or industrial sites that would wish for and be interested in its implementation in order to reduce their risk.

- C) The major inconvenient of the historical analysis by simulation method is its extreme sensitivity to data quality. Actually, one or several unusual observations (be they truly exceptional or containing a mistake at the outset) strongly influence the VaR value over an extended period (equal to the length of historical periods). It is said that the theory of extreme values could overcome this inconvenience. Unfortunately, the amount of calculations involved in its use is prohibitive. Further, the historical VaR are inaccurate and must be completed using appropriate "stress tests". Consequently, and according to the historical method of the previous work, each site must be equipped with a costly information system and a large team to implement it. In such a way that it may also not be accessible to the majority of financial institutions or industrial

sites that would wish for or have an interest in its implementation in order to reduce their risk.

It is acknowledged that the previous work is capable of transmitting the most probable scenario of environment variables towards remote sites (for e.g, televisions). This is especially the case for predictions of meteorological variables (such as winds, temperatures and so on) at various points. However, this does not allow for a global probabilistic view (probability law in the statistic distribution of variations for a numerical behaviour indicator) and is limited to a small number of parameters for each site.

Further, risk management procedures require uniform risk analysis and therefore a unified method in their assessment.

In such a way that the analysis of the previous work emphasises the need for a probabilistic prediction technique of future behaviour (and/or optimisation of productivity parameters) of a vast number of remote local industrial systems (in particular a number of financial sites) subjected to a common global environment. The systems should provide an accurate and reliable risk assessment of a "simulation statistic/probabilistic" type, i.e. working with a selective sampling of probable scenarios of environment variables by using a minimum of:

- Human resources.
- Means of information calculation.

Summary of the Invention

According to the invention, the aim of the "statistic/probabilistic" process by stochastic simulation is to perform in a prioritised way, yet jointly (i.e. simultaneously), the probabilistic prediction of future behaviour and/or the optimisation of productivity parameters of a vast number of remote local industrial systems $(S_u^{(u=1...n)})$. It is applied to the following cases:

- Where these local industrial systems (S_u) are a great distance from one another but are subjected to common and evolutionary global environment (E) that may be numerically described with p state variables $(X_i(t)^{(i=1...p)})$, which are effectively the components of a state vector $(X(t)=X_i(t)^{(i=1...p)})$.

- Where p state variables $(X_i(t)^{(i=1...p)})$ are common to the vast number of n (where n is much greater than » 1) remote local decentralised industrial systems $(S_u^{(u=1...n)})$.

- Where the effectiveness of each local system $(S_u^{(u=1...n)})$ may be further described with a numerical productivity indicator $(I_u^{(u=1...n)})$ according to a local numerical systems analysis model with parameters (D_u) that has been previously set $(I_u = D_u^{(u=1...n)}(\lambda u, X(t)))$ for each system (S_u) and for each instant (t) and is dependent upon:

  • All or some $(X_i(t)^{(i=1...p)})$ state variables of the state vector $(X(t))$.

• A vector of local q action parameters (that may be adjusted) $(\lambda_u = (\lambda_{u1},...,\lambda_{uq}))$.

According to the invention, the stochastic simulation process follows a classical method of a "simulation statistic/probabilistic" type which initially performs a "selective sampling of probable scenarios of environment variables". It then performs a statistical estimate of the probability law in the distribution of variations of a numerical productivity indicator for each local industrial system (S_u) by using this description sampling of joint probability distribution with state variables in a predetermined environment.

However, according to the invention, the additional aim of the process is to:

- Mutually centralise and gather the principal means (information technology and personnel) of producing this selective sampling of probable scenarios for environment variables into one central site.

- Only perform simple or less problematic calculations concerning information technology and specialist personnel at the vast number of local industrial systems.

According to the invention, and in its more general form, the stochastic simulation process is remarkable in that it combines the following two means:

- On the one hand, at a centralised transmitting site (U), a great distance (of several kilometres, if not a several hundred kilometres) from a majority of n remote local industrial systems $(S_u^{(u=1...n)})$:

• In that an "*smp* series of probabilistic simulations" $(W_{ij}^{k(i=1...p,j=1...s,k=1...m)})$ with a multi-value description of environment (E) state variables $(X_i(t)^{(i=1...p)})$ is repetitively generated in a centralised way at successive instants (t_o). According to the invention, this "*smp* series of probabilistic simulations" consists of:

♦ Either a series of "probable future pseudo-states" of environment (E) variables $(X_i(t)^{(i=1...p)})$.

♦ Or a series of "probable future pseudo-variations" of these variables $(\Delta X_i(t)^{(i=1...p)})$.

(these series being simulated at one (or several m where $m \geq 1$) time forecasts $\left(t_k^{(k=1...m)} > t_o\right)$).

• In that this "*smp* series of probabilistic simulations" (W_{ij}^k) with a multi-value description of probable future pseudo-states or pseudo-variations of environment variables is distributed in a decentralised way:

♦ From the transmitting site (U).

♦ Towards a vast number of remote local systems (S_u).

– On the other hand, and independently, at each local system (S_u), the majority of which are a great distance from the centralised transmitting site *(U)*, and repetitively:

• In that said "*smp* series of probabilistic simulations" (W_{ij}^k) with a multi-value description of

probable future pseudo-states or pseudo-variations are collected.

• In that a local statistical and numerical processing is performed on said series of probabilistic simulations (W_{ij}^{k}) that are received to predict the future probabilistic behaviour of local industrial systems (S_u).

If necessary, the vector level of the local action parameters $(\lambda_u)=(\lambda_{u1},...,\lambda_{uq})$ for each local system (S_u) is adjusted to an optimal value that is calculated according to predetermined criteria in order to anticipate, in particular, the probable future behaviour and effectiveness of each system (S_u) subjected to the environment (E) during any one retained time forecast(s) (t_k).

Figures

Of the following drawings:

- Figure 1 describes a classical method recommended by the invention to capture observable measures of the environment status and their transmission by a provider of said observable data to a transmitting site of probabilistic data according to the invention.

- Figure 2 describes the main stages of the process that generates a sampling of probable scenarios of environment state variables by a site transmitting probabilistic data using the Monte-Carlo Method and according to the invention.

- Figure 3 describes the main stages for processing a sampling series of probable scenarios of environment state variables received by a group of three remote local industrial systems functioning according to the invention. One of the three systems is described in detail.

- Figure 4 describes the overall main stages of the process of repetitive stochastic simulation that prioritises by sampling probable scenarios for the probabilistic prediction of future behaviour and/or the optimisation of productivity parameters for a vast number of remote local industrial systems according to the invention.

- Figure 5 describes the overall main stages of a process variant of repetitive stochastic simulation that prioritises by sampling probable variational scenarios with remote adaptation of numerical parameters to calculate productivity of each remote industrial system according to the invention.

- Figures 6, 7 and 8 describe three methods to transmit an "*smp* probabilistic series" from the centralised transmitting site towards a vast number of remote local industrial sites, and three methods to selectively filter the transmitted content of the "*smp* probabilistic series" according to the invention.

- Figure 9 describes a particular use of the process in the finance industry according to the invention.

- Figure 10 describes an alternative use of the invention to perform grouped probabilistic optimisation of certain groups of local industrial systems.

Description of the Invention

Figures 1, 2 and 3 illustrate how the main stages of the stochastic simulation process are generally organised to generate repetive statistical sampling in a centralised way and remote transmission of probable scenarios for the probabilistic prediction of future behaviour and/or the optimisation of productivity parameters for a vast number of remote local industrial systems (S_u). In the retained example, the remote local industrial systems (S_u) are power stations ($S_1,...,S_u...,S_n$) placed in the same environment (E) and making up, in this particular case, an electrical distribution network in a state or region.

Figures 1 and 4 show the environment (E) of power stations connected to a same network and influenced by random phenomena, such as climate (1) that directly affects factory performance (power station productivity, barrier levels), demand characteristics (2) (quality, price) that affect power station revenue, network availability (3) that influences the factory functioning pattern and primary energy characteristics (4) that influence supply costs. These random phenomena regarding network environment (E) are given by way of example. However, it is understood that the random phenomena to be identified are far more extensive and variegated in practice.

Even local random phenomena, as are climatic phenomena, may not be considered independently from phenomena common to all factories, such as petrol price or the demand level on the network. Thus, temperature

close to a factory not only acts upon factory productivity (and therefore its marginal cost) but also interacts with demand level and electricity price. There are strong chances of seeing the local temperature change in correlation with the temperature close to other factories, and therefore to see the latter's marginal cost vary in the same direction and further interact with demand level. Seeking to optimise a factory margin with a statistical analysis of local weather parameters separate from that of global parameters would lead to obvious optimisation mistakes since local and global parameters interact within the same framework of a common global environment.

Figures 1, 4 and 5 show the data providing centre (F_o) which is responsible for collecting observable data that describes the global environment (E) status of an electrical network. In the particular case of the electricity industry, the data providing centre (F_o) may form part of the company that manages the electrical network organisation. However, within other fields, particularly the finance industry, the data providing centre (F_o) is an independent entity (such as Reuters and Bloomberg) that commercially provides observable data to a variety of clients.

A series of r captors $(\gamma_h^{(h=1...r)})$ installed at different points in the environment (E) are designed to observe the state of the environment (E). The data provider (F_o) remotely collects at each instant (t) the r measures of the environment status $(\mu_h(t)^{(h=1...r)})$ from

the captors. At each selected sample instant (t_k), these r measures constitute temporal vector components to measure the environment $(M(t_k)) = (\mu_h(t_k)^{(h=1...r)})$. The data provider (F_o) is equipped with a transmitting device (A_o) of observable data. The latter transmits the emission of observable data on to a network (R_o):

- Either the directly collected measures from the captors (observable variables).

- Or results of deterministic algebraic calculations, such as averages, carried out by the data provider (F_o) on these measures (quasi-observable variables).

Subsequently, observable and quasi-observable variables which we shall globally call "observable variables" are assimilated. The case depicted in figure 1 shows the emission network (R_o) of observable data represented in a diagram by a satellite emission dish (5) that transmits observable data (measures) $(M(t_k)) = (\mu_h(t_k)^{(h=1...r)})$ of the environment (E) to a satellite (6).

According to the invention, a centralised transmitting site (U) is generally described in figure 2. It usually consists of a computer system (7) that is equipped with the following main features:

- A modelling interface (Ω) that allows a mathematician operator to choose between different models and variables.

- A simulation calculator (C) to carry out numerical and statistical calculations.

- A memory bank (H) for probabilistic data.

- A receiving device (B_o) for observable measures.

- A transmitting device (A_p) for series of probabilistic simulations.

This centralised transmitting site (U) is a great distance (several kilometres, if not several hundred kilometres) from a majority of the n remote local industrial systems $(S_u^{(u=1...n)})$, the power stations $(S_1,...,S_u...,S_n)$, that are distributed over the entire state territory and will appear in figures 3 to 8. The receiving device (B_o) for observable measures is represented in a diagram by a satellite reception dish that receives observable data (8) from the satellite (6) in a periodic and continuous flow. The data concerns the r environment measures $(M(t_k)) = (\mu_h(t_k)^{(h=1...r)})$ transmitted by the data provider (F_o) via the emission network (R_o) of observable data. The modelling interface (Ω) is preferably located at the centralised transmitting site (U). In the more general of cases, it is located within the expert site (U') that may be separate from the transmitting site (U) but in all cases at a distance (of several kilometres, if not several hundred kilometres) from a majority of n remote local industrial systems $(S_u^{(u=1...n)})$. At the modelling interface (Ω) or the expert site (U'), the following choices can be made:

- p variables $(X_l^{(l=1...p)})$ of the environment (E) also known as risk factors.

- Time forecasts $\left(t_k^{(k=1...m)}\right)$ of different simulations.

- The descriptive numerical model of the environment (Φ), which defines all p state variables $(X_i(t)^{(i=1...p)}) = (\Phi(\mu_1(t),...,\mu_r(t)))$ in relation to observable measures $(\mu_h(t)^{(h=1...r)})$ (where generally $p \leq r$ but sufficiently great) in such a way that all environment variables $(X_i(t)^{(i=1...p)})$ physically describe at each sampling instant (t_k) the entire global environment (E).

- A statistical law with parameters (model) $(f_\alpha(X_1,...,X_p;t;\Delta t_k))$ for the joint behaviour of risk factors, at time (t) and by time periods $(\Delta t_k^{k=1...m})$, and of state variables $(X_i(t)^{(i=1...p)})$ depicted in its dense joint distribution.

The statistical law (f_α) with parameters (numerically described) is generally chosen by a mathematician specialising in statistical models. It is determined by historical observations. In particular, it may entail normal laws, normal logs and so on, or more generally, a joint statistic distribution of p environment variables $(X_i(t_k)^{(i=1...p)})$ or their temporal variations $(\Delta X_i(t_k)^{i=1...p)})$ and is assessed through appropriate and classical statistic tests (averages, variances, correlations, breaks, extreme behaviours and so forth).

As the observable environment data is received, be it by request or continuously, the memory bank (H) is updated in which the periodic history of value measures $(\mu_h(t)^{(h=1...r)})$ is registered. The calculator (C) calculates

the p variables $(X_i(t)^{(i=1...p)}) = (\Phi(\mu_1(t),...,\mu_r(t)))$ at each successive sampling period with the aid of a descriptive numerical model of the environment (Φ) and the measures vector $(M(t))$,. Preferably, the calculator (C) calculates and repetitively updates the variations history of p state variables $(\Delta X_i(t)^{(i=1...p)})$, which it registers in its memory bank (H). Variations of state variables are understood to be either the difference or ratio of two values of a variable at successive instants, or more generally, any numerical value describing variations (absolute or relative) of the variable between two successive instants.

The calculator (C) is equipped with a simulation system (9) of scenarios, a calibrating system (10) for the statistical law (f_α) with parameters so that it conforms with stored historical observations in the memory bank (H), and a random generator (11) enabling "*smp* probabilistic simulations" (W_{ij}^k) with multi-value descriptions of probable future pseudo-states or pseudo-variations of state variables $(X_i(t)^{(i=1...p)})$ to be repetitively created.

Various functioning methods of the scenario simulation system (9) are described further on. Some generate series of simulations of state variables $(X_i(t)^{(i=1...p)})$ and others, series of simulations of variations of p state variables $(\Delta X_i(t)^{(i=1...p)})$. In such a way that, at the centralised transmitting site (U), an "*smp* series of probabilistic simulation" $(W_{ij}^{k\,i=1...p,j=1...s,k=1...m})$

with multi-value descriptions of probable future pseudo-states or pseudo-variations of the environment (E) is numerically and repetitively generated at successive instants (t_o) by using the dense joint distribution of the statistical law with parameters $(f_\alpha(X_1,...,X_p;t;\Delta t_k))$ retained from the joint behaviour within the time (t) of state variables (X_i).

According to an initial application mode, this "*smp* series of probabilistic simulation" is an "*smp* probabilistic series" (X_{ij}^k) of pseudo-states formed by $s \times m$ p-uplets with a multi-value sampling of future pseudo-states $(X_{ij}(t_k)^{(i=1...p,j=1...s,k=1...m)})$ including possible $s \times m \times p$ numerical values of probable future pseudo-values for p state variables $(X_i(t)^{(i=1...p)})$ and constitutes:

- For each m $(m \geq 1)$ time forecast $\left(t_k^{(k=1...m)}\right)$ of the simulation.

- Of s (where s is much greater than » 1) possible future pseudo-states $(X_j^{k(j=1...s)}) = (X_{ij}(t_k)^{(i=1...p,j=1...s)})$ of the vector for p state variables $(X_i(t_k)^{(i=1...p)})$.

According to a second application mode described in figure 5, this "*smp* variational probabilistic series" (ΔX_{ij}^k) is formed by $s \times m$ p-uplets of a multi-value sampling of future pseudo-variations $(\Delta X_{ij}(t_k)^{(i=1...p,j=1...s,k=1...m)})$ by using the standard value of state variables $(X_i(t_o)^{(i=1...p)})$ and including $s \times m \times p$ numerical

values of probable future pseudo-variations for p state variables $(X_i(t_k)^{(i=1...p)})$ and constitutes:

- For each m $(m \geq 1)$ time forecast $\left(t_k^{(k=1...m)}\right)$ of the simulation.

- Of s (where s is much greater than » 1) possible future numerical pseudo-variations $(\Delta X_{jk}^{(j=1...s)}) = (\Delta X_{ij}(t_k)^{(i=1...p,j=1...s)})$ of the vector for p state variables $(X_i(t_k)^{(i=1...p)})$.

As it appears in figures 2, 3, 4 and 5 with the aid of the transmitting device (A_p) for probabilistic simulation series with which the centralised transmitting site (U) is equipped, said "*smp* probabilistic series" (W_{ij}^k) with a multi-value description of probable future pseudo-states or pseudo-variations is repetitively transmitted at successive instants (t_o), including the $s \times m \times p$ numerical pseudo-values that consist of: (case 1) said "*smp* probabilistic series" (X_{ij}^k) of pseudo-values of state variables $(X_{ij}(t_k)^{(i=1...p,j=1...s,k=1...m)})$, and/or (case 2) said "*smp* variational probabilistic series" (ΔX_{ij}^k) of pseudo-variations $(\Delta X_{ij}(t_k)^{(i=1...p,j=1...s,k=1...m)})$.

As observed in figures 2, 3, 4 and 5, this transmission of probabilistic simulations is done in a decentralised way from the transmitting site (U) at successive instants (t_o) towards the vast number of remote local systems (S_u) via the emission network (R_p) of probabilistic data. In this particular case, the

transmitting device (A_p) for the probabilistic simulation series is represented in a diagram by a satellite emission dish (12) for probabilistic data, namely the "*smp* probabilistic series" (W_{ij}^{k}), which it successively transmits to the satellite (6). In other words, (R_o) and (R_p) networks are one and the same. It is understood that another satellite (other than that used for receiving observable data) or any other type of data transmission method, such as the Internet, could be used for the transmission of probabilistic data.

According to the invention, figure 3 shows how all local industrial systems (S_u) are generally organised. In the example pertaining to the electricity industry, it involves all power stations ($S_1,...,S_u...,S_n$) whose industrial behaviour (production of energy kWs) is affected by the environment (E) described in figure 1.

Each local industrial system ($S_u^{(u=1...n)}$) consists of a fairly similar local computer system (13, 14, 15). The make-up of the local computer system (15) for the industrial system (S_u) is described in figure 3. It is equipped with the following main features:

- A local modelling interface (Ω_u) to configure the site ($S_u^{(u=1...n)}$) according to different variables and models.

- A local calculator (C) to carry out numerical and statistical calculations.

- A local memory bank (H_u).

- A local receiving device (Bp_u) for probabilistic data that is designed and adjusted in order to receive the flow of probabilistic data from the satellite (6).

Note that each local industrial system is equipped with a local satellite dish (16, 17, 18) to receive probabilistic data and a local reception device for probabilistic data. Independently, and within each local industrial system, a succession of "*smp* probabilistic series" (W_{ij}^k) with a multi-value description of probable future pseudo-states or pseudo-variations including $s \times m \times p$ numerical values ($W_{ij}^k = X_{ij}^k$ or ΔX_{ij}^k) are transmitted by the satellite (6) and repetitively collected with the aid of a satellite dish (18) and the local reception device.

Through the local interface (Ω_u), m' ($m' \leq m$) time forecasts are retained from the m said time forecasts $\left(t_k^{(k=1...m)}\right)$. If necessary (in case 2 described above and represented in figure 5), where the local industrial site (S_u) only receives an "*smp* variational probabilistic series" (W_{ij}^k) from the satellite (6), said corresponding (at least for the retained m' time forecasts (t_k)) "*smp* probabilistic series of pseudo-states" (W_{ij}^k) consisting of pseudo-samplings for future states ($X_{ij}(t_k)^{(i=1...p,j=1...s,k=1...m)}$) is locally calculated.

For each retained m' time forecast (t_k), a local systems analysis model (D_u) that has been previously set in order to determine the productivity indicator

$(I_{uj}^{k} = D_u(\lambda_u, (X_{ij}(t_k))$ within each s scenario of received simulations $(j = 1,...,s)$ is numerically applied:

- For at least a particular value $(\lambda_u) = (\lambda_{u1},...,\lambda_{uq})$ of the vector (λ_u) of local action parameters (which may be varied).

- To each simulated s p-uplets of state variables $(X_{ij}(t_k)^{(i=1...p)})$ that corresponds to said time forecast (t_k) retained from the probabilistic pseudo-state series $(X_{ij}(t_k)^{(j=1...s)})$.

Thus, the corresponding simulated s pseudo-values of the productivity indicator $(I_{uj}(t_k, \lambda_u)) = D_u(\lambda_u, (X_{ij}(t_k)^{(i=1...p, j=1...s)})$ are determined. The corresponding s values of the productivity indicator $(I_{uj}(t_k, \lambda_u)^{(j=1...s)})$ are grouped together and arranged according to the productivity level (I_{uj}). The histogram $(\Gamma(I_u))$ is calculated and stored in the local memory bank (H_u) as is the probability distribution (as a number or percentage) $(\Psi_u(I_u))$ of the level reached by the local productivity indicator (I_u) in the configuration (λ_u) according to the local model (D_u). A statistical calculation deduces the value of at least one chosen statistical parameter of adjustment $(V(\lambda_u))$ (such as average, spread type, Value at Risk, utility and so forth) that is characteristic of the probability distribution $(\Psi(\lambda_u, I))$ for productivity levels $(I_u(t_k, \lambda_u)$ according to the vector of local action parameters $(\lambda_u) = (\lambda_{u1},...,\lambda_{uq})$.

If necessary, a numerical optimisation (according to predetermined criteria) of one or many chosen statistical parameters of adjustment $(V(\lambda_u))$ is performed within each local system (S_u). The vector level of local action parameters $(\lambda_u)=(\lambda_{u1},...,\lambda_{uq})$ for each local system (S_u) is then adjusted to a calculated optimal value according to predetermined criteria, notably in order to anticipate the future probable behaviour and effectiveness of each system (S_u) subjected to the environment (E) during any one retained time forecast (t_k).

The aim of one particular application mode of the invention described in figures 3 and 5 is to render modelling of the productivity indicator corresponding to each local action parameter (λ_{uh}) suitable for each local industrial system $(S_u^{(u=1...n)})$. To this end, a generic code (L_h) (that is not dependent upon the local system (S_u)) is assigned to each local action parameter $(\lambda_{uh}^{(h=1...q)})$ at the expert site (U'). A "productivity assessment system" (Π_h) that is regularly updated is set up for each code (L_h), i.e. a programme (produced as a digital file) that is able to calculate, according to the p-uplet of state variables $(X)=(X_i^{(i=1...p)})$ and the local action parameter (λ_{uh}), the corresponding productivity component $(I_{uh})=(\Pi_h(\lambda_{uh},X))$ in such a way that, for each local system (S_u), said local systems analysis model (D_u) consists simply in adding up the

components (I_{uh}) of the productivity indicator corresponding to each local action parameter (λ_{uh}):

$$D_u(\lambda_u, X) = \sum_{h=1}^{q} \Pi_h(\lambda_{uh}, X) \quad (*)$$

The expert site (U') is linked up to the centralised transmitting site by a network (R') through which it transmits the adaptive numerical definitions of the productivity components $(I_{uh_j}^k) = (\Pi_h(\lambda_{uh}, X_j^k))$.

On the one hand, the "*smp* probabilistic series" (W_{ij}^k) with its multi-value description of probable future pseudo-states or pseudo-variations is repetitively transmitted at successive instants (t_o) from the centralised transmitting site by using the retained joint behaviour statistical model $(f_\alpha(X_1,...,X_p;t;\Delta t))$ in time (t) of state variables $(X_i^{(i=1...p)})$. On the other hand, as each new code (L_h) appears or adjustment to the productivity assessment system (Π_h) is made, the pair (L_h, Π_h) is transmitted as a digital file in a centralised way.

At each remote local industrial system (S_u), the productivity component $(I_{uh_j}^k) = (\Pi_h(\lambda_{uh}, X_j^k))$ is calculated:

- For each m' $(m' \leq m)$ retained time forecast (t_k) of the simulation at a local scale (S_u).

- For each $j = 1,...,s$ (where s is much greater than » 1) of possible numerical pseudo-states $(X_j^{k(j=1...s)})$

received or recreated by using the pseudo-variation series (ΔX_{ij}^{k}).

- For each $h=1,...q$ of local action parameters (λ_{uh}).

Subsequently, in summary and according to the above formula (*) of the productivity indicator (I_{uj}^{k}), its histogram is calculated followed by the retained statistical parameter $(V(\lambda_u))$. Finally, the vector of local action parameters (λ_u) is applied in order to optimise the value of the statistical parameter (V).

A particular case of the above application mode consists in productivity assessment systems (Π_h) being proportional to the local action parameter (λ_{uh}), ie that:

$$\Pi_h(\lambda_{uh},X)=\lambda_{uh}\pi_h(X)$$

where (π_h) is called the "marginal productivity assessor". In this case, the local systems analysis model (D_u) amounts to creating a scalar product between the vector of local action parameters (λ_{uh}) and the vector of marginal productivity $(\pi(X))=(\pi_h(X)^{(h=1...q)})$:

$$D_u(\lambda_u,X)=(\lambda_u|\pi(X)) \quad (**)$$

Calculation of the statistical parameter $(V(\lambda_u))$ at the local site (S_u) is thereby simplified and its

optimisation accelerated by previous registration of the marginal productivity series $(\pi_h(X_j^k)_{(h=1...q,j=1...s,k=1...m)})$ in the memory bank (H_u) of the local calculator (C_u).

A first particular variant of the invention's application is also described in figure 4. It concerns the case where, at a centralised transmitting site (U), a variational probabilistic series (ΔX_{ij}^k) formed by $s \times m$ p-uplets of a multi-value sampling of pseudo-variations $(\Delta X_{ij}(t_k)^{(i=1...p,j=1...s,k=1...m)})$ of future states taken from the standard state of state variables $(X_i(t_o)^{(i=1...p)})$ is numerically and repetitively generated at successive instants (t_o) by using the retained joint behaviour statistical model $(f_\alpha(X_1,...,X_p;t;\Delta t))$ in time (t) of state variables (X_i). This series of pseudo-variations includes $s \times m \times p$ numerical values of probable future pseudo-variations for p state variables $(X_i(t_k)^{(i=1...p)})$. It is constituted for each m $(m \geq 1)$ time forecast $\left(t_k^{(k=1...m)}\right)$ of the simulation and each s (where s is much greater than » 1) of possible numerical pseudo-variations $(\Delta X_{ij}(t_k)^{(j=1...s)})$ for p state variables $(X_i(t_k)^{(i=1...p)})$. This "*smp* variational probabilistic series" (ΔX_{ij}^k) of pseudo-variation states $(\Delta X_{ij}(t_k)^{(i=1...p,j=1...s,k=1...m)})$ is transmitted repetitively from the transmitting site (U) in a decentralised way towards the various remote local systems (S_u). This is performed by the transmitting device (A_p) of probabilistic simulation series with the aid of a satellite emission dish (12) for probabilistic

data and via a satellite (6). Independently, and at each local system (S_u), the local receiving device (Bp_u) for probabilistic data repetitively gathers via the local satellite reception dish (16, 17, 18) of probabilistic data at each instant (t_o) and according to a determined frequency, if not at each adjustment of variables (X_i), the standard value of state variables ($X_i(t_o)^{(i=1...p)}$). It also gathers said "*smp* variational probabilistic series" (ΔX_{ij}^k) of state variations ($\Delta X_{ij}(\Delta t_k)^{(i=1...p,j=1...s,k=1...m)}$) in relation to time increment Δt_k transmitted by the central site (U). This data is memorised within the local memory bank (H_u). The local calculator (C_u) locally assesses said "*smp* probabilistic series" (X_{ij}^k) of pseudo-states ($X_{ij}(t_k)^{(i=1...p,j=1...s,k=1...m)}$) at future instants $(t_k)=(t_o+\Delta t_k)$ that correspond to the variational series by incremental numerical calculation of the type:

$$X_{ij}(t_k)=X_i(t_o)(1+\Delta X_{ij}(t_k))$$

Any other formula (addition, exponential and so forth) that implicates the "*smp* variational probabilistic series" (ΔX_{ij}^k) coming from the centralised transmitting site (U) and the standard value of state variables ($X_i(t_o)^{(i=1...p)}$).

A particular application method for this first variant is that described further above with reference

to figure 4. At a centralised transmitting site (U), an "*smp* variational probabilistic series" (ΔX_{ij}^{k}) as described above is numerically and repetitively generated at successive instants (t_o). The current value of state variables $(X_i(t_o)^{(i=1...p)})$ is repetitively collected and memorised. The "*smp* variational probabilistic series" (ΔX_{ij}^{k}) of pseudo-state variations $(\Delta X_{ij}(t_k)^{(i=1...p,j=1...s,k=1...m)})$ and the standard value of state variables $(X_i(t_o)^{(i=1...p)})$ are repetitively transmitted and in a decentralised way from the transmitting site (U) towards the various remote local systems (S_u).

A second particular combination variant for the application of the invention is described in reference to figures 1 and 4. As shown previously in figure 1, and at different points in the environment (E), a series of r captors $(\gamma_h^{(h=1...r)})$ that observe the environment (E) status transmit at each instant (t) a set of r measures of the environment (E) status $(\mu_h(t)^{(h=1...r)})$. The case described in figures 1 and 4 shows the transmitting site (U) as subscriber to environment data provided by the observable data provider (F_o) which operates the captors' network $(\gamma_h^{(h=1...r)})$. The designer site (U'), quite a distance from the majority of the n remote local industrial systems $(S_u^{(u=1...n)})$, is where a numerical model describing the environment (Φ) is previously established and defines all p state variables $(X_i(t)^{(i=1...p)}) = (\Phi(\mu_1(t),...,\mu_r(t)))$ in relation to

measures $(\mu_h(t)^{(h=1...r)})$ (where generally $p \leq r$), in such a way that all environment variables $(X_i(t)^{(i=1...p)})$ physically describe the status of the environment (E) in its entirety at each sampling instant (t_k). However, it is understood that this operation may also be performed from the transmitting site (U), or on its behalf, in particular when the designer site (U') is located within the transmitting site (U). The centralised transmitting site (U) is where the r environment measures $(\mu_h(t)^{(h=1...r)})$ are remotely collected and memorised. At each sampling instant (t_k), these r measures constitute the components of a temporal vector to assess the environment $(M(t_k)) = (\mu_h(t_k)^{(h=1...r)})$. Subsequently, at each successive sampling (t_k) period, and with the aid of a numerical model describing the environment (Φ) and the measures vector $(M(t))$, the p state variables $(X_i(t)^{(i=1...p)}) = (\Phi(\mu_1(t),...,\mu_r(t)))$ are calculated.

The invention recommends two particular methods of repetitive stochastic simulation that prioritises through probable scenario sampling in order to predict probable future behaviour and/or optimise productivity parameters of a number of remote local industrial systems (S_u).

The first method suggested by the invention of repetitive stochastic simulation that prioritises through probable scenario sampling consists in its combined use with the method known as Monte-Carlo.

According to this first method, which is described in figure 2, a history of values for p state variables $(X_i(t)^{(i=1...p)})$ of the common global environment (E) throughout time is maintained and updated at the centralised transmitting site (U). The "*smp* probabilistic series" (W_{ij}^k) with a multi-value description of probable future pseudo-states or pseudo-variations of environment (E) is numerically generated and repetitively transmitted at successive instants t_o according to the method known as "Monte-Carlo" by using the retained statistical model $(f_a(X_1,...,X_p;t;\Delta t_k))$ of joint behaviour within the time (t) of state variables (X_i) and the memorised history of values for p state variables $(X_i(t)^{(i=1...p)})$. In other words, a pseudo-random selection method of pseudo-values (W_{ij}^k) is used with the aid of a random number generator (11) located on the centralised transmitting site (U), if not the designer site (U'). Any one of the following processes can be used:

- "Pseudo-random" of an ergodic type.
- "Weak disparity" (Sobol and Hamersley series, amongst others).
- Any other method producing numbers asymptomatically shared out according to a specified distribution (for example, uniform on an interval).

Said "*smp* probabilistic series" (W_{ij}^k) with a multi-value description of probable future pseudo-states or pseudo-variations is transmitted in a decentralised way

from the transmitting site (U) towards all remote local systems (S_u). This application method is recommended by the invention.

The second method suggested by the invention of repetitive stochastic simulation that prioritises through probable scenario sampling consists in its combined use with the method known as historical analysis. It is a simplified version of the Monte-Carlo method described above. According to this historical analysis method, the sampling of probable future variations of risk factors is transmitted directly from the memorised history. A history of values for p state variables $(X_i(t)^{(i=1...p)})$ of the common global environment (E) throughout time is maintained and updated at the centralised transmitting site (U). The "*smp* probabilistic series" (W_{ij}^k) with a multi-value description of probable future pseudo-states or pseudo-variations of environment (E) is numerically generated and repetitively transmitted at successive instants t_o by using the retained statistical model $(f_\alpha(X_1,...,X_p;t;\Delta t_k))$ of joint behaviour within the time (t) of state variables (X_i) and the memorised history of values for p state variables $(X_i(t)^{(i=1...p)})$. According to the method known as "historic", the estimate of probable future states of p state variables $(X_i(t)^{(i=1...p)})$ is recreated by using the standard status $(X_i(t_o)^{(i=1...p)})$ and past historic variations $(\Delta X_i(t')^{(i=1...p)})$ for a set of past dates $(t' < t_o)$ and by affecting each recreated state

with a production probability that could depend upon the age of the corresponding historic variation. Said "*smp* probabilistic series" (W_{ij}^{k}) with a multi-value description of probable future pseudo-states or pseudo-variations is transmitted in a decentralised way from the transmitting site (U) towards all remote local systems (S_u).

A third application variant of the invention consists in introducing biased data within the transmitted stochastic simulations. The aim of the biased data is take extreme situations into account that only rarely occur and/or constitute "catastrophe scenarios". According to this method, the generated "*smp* probabilistic series" (W_{ij}^{k}) with a multi-value description of probable future pseudo-states or pseudo-variations transmitted by the transmitting site (U) towards all remote local systems (S_u) is biased in relation to the statistics for the history of state variables or variable variations. According to this variant of the invention, a history of values for p state variables $(X_i(t)^{(i=1...p)})$ of the common global environment (E) throughout time is maintained and updated at the centralised transmitting site (U). The "*smp* probabilistic series" (W_{ij}^{k}) with a multi-value description of probable future pseudo-states or pseudo-variations of the environment (E) is numerically generated and repetitively transmitted at successive instants t_o by using the retained statistical model

$(f_\alpha(X_1,...,X_p;t;\Delta t_k))$ of joint behaviour within the time (t) of state variables (X_i) and the memorised history of values for p state variables $(X_i(t)^{(i=1...p)})$.

However, joint statistic behaviour biases of state variables $(X_i(t)^{(i=1...p)})$ in relation to their historic statistic behaviour are deliberately introduced into the "*smp* probabilistic series" (W_{ij}^k). The transmitted biased series thus reproduce "catastrophe scenarios". This enables the impact of said catastrophe scenarios on remote systems (S_u) to be taken into account. Said "*smp* probabilistic series" (W_{ij}^k) with a multi-value biased description of probable future pseudo-states or pseudo-variations is then transmitted in a decentralised way from the transmitting site (U) towards all remote local systems (S_u).

According to a first sub-variant of the third variant described above, the invention recommends that the grade of "*smp* probabilistic series" (W_{ij}^k) with a multi-value biased description of probable future pseudo-states or pseudo-variations transmitted by the transmitting site (U) towards all remote local systems (S_u) in relation to selective requests made from the different remote systems (S_u) be selectively adapted. To this end, certain remote systems (S_u) send requests as numerical parameters of catastrophe scenarios according to the specific biases as defined by them to the centralised transmitting site (U). In relation to these requests and by possibly merging those that are

identical, "*smp* probabilistic series" (W_{ij}^{k}) with multi-value descriptions of probable future pseudo-states or pseudo-variations that are biased in relation to specified parameters requested by remote systems are generated at the centralised transmitting site (U). The transmitting site (U) selectively sends each remote local system (S_u) said "*smp* probabilistic series" (W_{ij}^{k}) with a multi-value biased description of probable future pseudo-states or pseudo-variations that corresponds to its request. This is sent electronically (via Internet, local network, telephone or any other method that allows the transmission of digital data).

According to a second sub-variant of the third variant described above, the invention recommends that remote systems (S_u) alter all or part of the "*smp* probabilistic series" (W_{ij}^{k}) they receive from the transmitting site (U) to take possible extreme situations that affect them into account. According to this sub-variant, certain remote systems (S_u) alter all or part of the "*smp* probabilistic series" (W_{ij}^{k}) with a multi-value description of probable future pseudo-states or pseudo-variations. This enables biased series to be created locally by reproducing catastrophe scenarios whose parameters are either specified by the main transmitting site (U) and transmitted to local systems (S_u) or defined by the local systems (S_u).

A fourth preferred application variant of the invention consists in numerically transmitting the "*smp*

probabilistic series" (W_{ij}^{k}) with a multi-value description of probable future pseudo-states or pseudo-variations from the transmitting site (U) periodically and according to a sampling frequency (φ).

According to a fifth application variant, the invention recommends three methods to transmit the "*smp* probabilistic series" (W_{ij}^{k}) with a multi-value description of probable future pseudo-states or pseudo-variations from the transmitting site (U) towards all remote local industrial systems $(S_{u}^{(u=1...n)})$.

A first sub-variant for the emission of probabilistic data is described in figure 6. At the centralised transmitting site (U), said "*smp* probabilistic series" (W_{ij}^{k}) with a multi-value description of probable future pseudo-states or pseudo-variations is transmitted in a decentralised way from the transmitting site (U) towards all remote local systems (S_{u}) as a "broadcast", notably by radio. Independently, each local system (S_{u}), the majority of which are quite a distance away from the centralised transmitting site (U), repetitively gathers said "*smp* probabilistic series" (W_{ij}^{k}) with a multi-value description of probable future pseudo-states or pseudo-variations and $s \times m \times p$ numerical values $(W_{ij}^{k} = X_{ij}^{k}$ or $\Delta X_{ij}^{k})$ through a quasi-continuous reception of this "broadcast" from the centralised transmitting site (U).

A second sub-variant of the emission of probabilistic data is described in figure 7. At the centralised transmitting site (U), said "*smp* probabilistic series" (W_{ij}^{k}) with a multi-value description of probable future pseudo-states or pseudo-variations is transmitted in a decentralised way from the transmitting site (U) towards all remote local systems (S_u) as a "below PP", i.e. emission on a network (R), notably Internet based , from the centralised transmitting site (U) to specific addresses for each remote local industrial system $(S_u^{(u=1...n)})$. To this end, it is noted that the transmitting site (U) is equipped with a main modem (20) and each remote local industrial system $(S_u^{(u=1...n)})$ with a local modem (21) through which probabilistic data passes. Independently, each local system (S_u), the majority of which are quite a distance from the centralised transmitting site (U), repetitively gathers said "*smp* probabilistic series" (W_{ij}^{k}) with a multi-value description of probable future pseudo-states or pseudo-variations and $s \times m \times p$ numerical values $(W_{ij}^{k} = X_{ij}^{k}$ or $\Delta X_{ij}^{k})$ through successive registrations at the local memory bank (H_u) of the local calculator (C_u).

A third sub-variant of the emission of probabilistic data is described in figure 8. At the centralised transmitting site (U), said "*smp* probabilistic series" (W_{ij}^{k}) with a multi-value

description of probable future pseudo-states or pseudo-variations is transmitted in a decentralised way from the transmitting site (U) towards all remote local systems (S_u) by making said multi-valued "*smp* probabilistic series" (W_{ij}^k) available on a probabilistic data server (Z). The latter is available on an emission network (R) (notably Internet type) through "PP" access of each remote local industrial system ($S_u^{(u=1...n)}$). Independently, each local system (S_u) repetitively gathers said "*smp* probabilistic series" (W_{ij}^k) with a multi-value description of probable future pseudo-states or pseudo-variations through access known as "above PP". In other words, each system accesses server (Z) of the centralised transmitting site (U) via network (R) through requests made to their specific address (notably Internet type). Subsequently, they receive the "*smp* probabilistic series" by transfer (notably "FTP" type) via network (R) and via registration at the local memory bank (H_u) of their local calculator (C_u).

According to a sixth application variant, the invention recommends three methods to organise "*smp* probabilistic series" (W_{ij}^k) transmitted from the centralised transmitting site (U) towards all remote local industrial systems ($S_u^{(u=1...n)}$) in order to compress transmitted probabilistic data and to accelerate access by all remote local industrial systems ($S_u^{(u=1...n)}$).

According to a first sub-variant for organising the emission of probabilistic data, an "*smp* probabilistic series" (W_{ij}^{k}) with its multi-value description of probable future pseudo-states or pseudo-variations of the environment (E) is numerically generated and repetitively transmitted at successive instants (t_o) from the centralised transmitting site using the retained joint behaviour statistical model $(f_\alpha(X_1,...,X_p;t;\Delta t))$ in time (t) of state variables $(X_i^{(i=1...p)})$. This series consists of s (where s is much greater than » 1) numerical pseudo-values for p components $(W_{ij}(t_k)^{(i=1...p,j=1...s)})$ for each m $(m \geq 1)$ time forecast $\left(t_k^{(k=1...m)}\right)$ as an "*smp* file" of $s \times m \times p$ successive alpha-numerical data. However, on the one hand, this "*smp* file" is sub-divided into successive m "temporal sub-files" of level 1 that groups together all pseudo-values of a same time forecast $\left(t_k^{(k=1...m)}\right)$. On the other hand, each "temporal sub-file" consists of a succession of s "selection sub-files" of level 2 each made up of a pseudo-value p-uplet.

According to a second sub-variant for organising the emission of probabilistic data, an "*smp* probabilistic series" (W_{ij}^{k}) with its multi-value description of probable future pseudo-states or pseudo-variations of the environment (E) is numerically and repetitively generated at successive instants (t_o) from the centralised transmitting site (U) by separating successive m "temporal sub-files" of level 1 and gathering together all pseudo-values of a same time

forecast $\left(t_k^{(k=1...m)}\right)$ with a corresponding time forecast indicator $(\eta_k^{k=1...m})$. At each local system (S_u), different said temporal sub-files of a same "*smp* probabilistic series" (W_{ij}^k) with its multi-value and collected data are separated from one another by identifying their specific time forecast indicators $(\eta_k^{k=1...m})$.

According to a third sub-variant for organising the emission of probabilistic data, an "*smp* probabilistic series" (W_{ij}^k) with its multi-value description of probable future pseudo-states or pseudo-variations of the environment (E) is numerically and repetitively generated at successive instants (t_o) from the centralised transmitting site (U) by separating successive s "selection sub-files" of level 2 (from a same temporal file) and each gathering together a pseudo-value p-uplet with a corresponding selection indicator $(\tau_j^{(j=1...s)})$. At each local system (S_u), different successive "selection sub-files" of level 2 (from a same temporal file) each gathering a pseudo-value p-uplet from a same "*smp* probabilistic series" (W_{ij}^k) with its multi-value and collected data are separated ones from the others by identifying their specific selection indicator $(\tau_j^{(j=1...s)})$.

According to a seventh application variant, the invention recommends three methods to selectively filter the content of the "*smp* probabilistic series" (W_{ij}^k) transmitted by the centralised transmitting site

(U) towards all remote local industrial systems $(S_u^{(u=1...n)})$. It aims to adapt their content to the needs and features of the remote local industrial systems $(S_u^{(u=1...n)})$ as well as to the hierarchical, industrial or commercial ties between the centralised transmitting site (U) and all remote local industrial systems $(S_u^{(u=1...n)})$.

A first sub-variant for filtering the emission of probabilistic data is described in figure 6. At the centralised transmitting site (U), said "*smp* probabilistic series" (W_{ij}^k) with its multi-value data is transmitted in its entirety in a decentralised way by the transmitting site (U) towards all remote local systems (S_u) as a "broadcast". Radio transmission is another process that can be used and is accessible to all local systems (S_u). Independently, a selective filter that is pre-adjusted (22) for availability at a predefined fraction $(W_{ij}'^k)$ of said collected "*smp* probabilistic series" (W_{ij}^k) from the centralised transmitting site (U) is installed and used at each local system (S_u). The data filtering characteristics of this selective filter may be acquired, in particular, through a specific subscription taken out by each local system (S_u) from the transmitting site (U). They may be altered by remote action through the network linking the centralised transmitting site (U) up to the local systems (S_u).

A second sub-variant for filtering the emission of probabilistic data is described in figure 7. At the centralised transmitting site (U), various different predefined fractions $((W_{ij}^{k})_{g}^{(g=1...v)})$ (notably acquired through specific subscription) of said "*smp* probabilistic series" (W_{ij}^{k}) are selectively transmitted (according to a predefined allocation rule). This selective transmission is performed in a decentralised way by the transmitting site (U) towards various groups $(G_{g}^{g=1...v})$ that are linked to all remote local systems (S_{u}). Each group receives a particular fraction. This is done through a "below PP" emission, i.e. via a network (R), notably Internet based, from the centralised transmitting site (U) to the specific address for each remote local industrial system $(S_{u}^{(u=1...n)})$. Independently, each group $(G_{g}^{g=1...v})$ linked to the local systems (S_{u}) repetitively gathers said predefined fraction $((W_{ij}^{k})_{g})$ of the "*smp* probabilistic series" (W_{ij}^{k}). They successively register this predefined fraction $((W_{ij}^{k})_{g})$ into the local memory bank (H_{u}) of their local calculator (C_{u}).

A third sub-variant for filtering the emission of probabilistic data is described in figure 8. At the centralised transmitting site (U), said "*smp* probabilistic series" (W_{ij}^{k}) is transmitted in a decentralised way from the transmitting site (U) towards all remote local systems (S_{u}) by making said

"*smp* probabilistic series" (W_{ij}^{k}) available on a server (Z) operated by a network (R) (notably Internet type) to which each remote local industrial system ($S_u^{(u=1...n)}$) may access as "above PP". However, various predefined restrictive fractions ($(W_{ij}^{k})_g$) (notably acquired through specific subscription) of said "*smp* probabilistic series" (W_{ij}^{k}) are selectively made available to different local system (S_u) groups ($G_g^{g=1...v}$) on a server (Z). This may in particular be operated through means of user names and passwords (23) that are transmitted by each local system (S_u) while accessing server (Z). Independently, each local system (S_u) repetitively gathers said predefined fraction ($(W_{ij}^{k})_g$) attributed to said "*smp* probabilistic series" (W_{ij}^{k}) through access known as "below PP", i.e. via a network (R) from the centralised transmitting site (U) to its specific address. They receive said predefined fraction ($(W_{ij}^{k})_g$) attributed to the multi-value "*smp* probabilistic series" by transfer. They successively register this predefined fraction ($(W_{ij}^{k})_g$) into the local memory bank (H_u) of their local calculator (C_u).

According to an eighth application variant described in figure 10, the invention recommends to carry out a grouped probabilistic optimisation of certain groups of remote local industrial systems ($S_u^{(u=1...n)}$). This relates, in particular, to cases where

industrial systems of a same optimisation group share industrial targets (of production, savings and so forth) that are worth optimising globally. First, n' $(n' \leq n)$ local industrial systems retained from amongst the n of said local industrial systems (S_u) are chosen. Also previously chosen are m' $(m' \leq m)$ time forecasts are retained from amongst the m of said time forecasts $\left(t_k^{(k=1...m)}\right)$ that are identical for all local systems.

At each n' of retained local systems (S_u) and for each m' of retained time forecast (t_k), the local systems analysis model (D_u) is numerically applied having been previously set in order to determine the productivity indicator level $(I_{uj}^{k} = D_u(\lambda_u, (X_{i,j}(t_k))))$ within each s scenario $(j = 1,...,s)$:

- For at least a particular value (λ_u) of the local action parameters vector.
- For each simulated s p-uplet state variable $(X_i(t_k)^{(i=1...p)})$ that corresponds to the said retained time forecast (t_k) of the probabilistic series of pseudo-states $(X_j(t_k)^{(j=1...s)}) = (X_{ij}(t_k)^{(i=1...p, j=1...s)})$.

The simulated s pseudo-values corresponding to the productivity indicator $(I_{uj}(t_k, \lambda_u)) = (D_u(\lambda_u, X_j(t_k))^{(j=1...s)})$ are determined. The "local simulation series" consisting of s simulated pseudo-values corresponding to the productivity indicator $(I_{uj}(t_k, \lambda_u)) = (D_u(\lambda_u, X_j(t_k))^{(j=1...s)})$ of the local system (S_u) is transmitted in a centralising way towards a centralising site (B).

At the centralising site (B), the simulated $s \times n'$ pseudo-values of the productivity indicators $(I_u(t_k, \lambda_u))^{(j=1...s)})$ are collected from each n' local system (S_u) and for each s simulation, and the global productivity indicator (J_j) of all local systems is calculated for each simulation by using a global assessment model $(J_j) = (\chi(I_{uj}(t_k, \lambda_u)^{(u=1...n', j=1...s)})$. The corresponding s values of the productivity indicator $(J_j(t_k; \lambda_1, ..., \lambda_{n'})^{(j=1...s)})$ are grouped together and arranged according to their level. The histogram (Γ) is calculated and stored as is the probability (as a number or percentage) distribution $(\Psi(J))$ of the level reached by the global productivity indicator (J) in the configuration of local action parameters vector $(\Lambda) = (\lambda_u^{(u=1...n')})$ chosen according to the retained local models (D_u) and the global assessment model (χ). A statistical calculation deduces the value of at least one chosen statistical parameter of adjustment $(V(\Lambda))$ (such as average, spread type, Value at Risk, utility and so forth) that is characteristic of the probability distribution $(\chi(\lambda_1, ..., \lambda_{n'}, J))$ for global productivity levels $(J_j(t_k; \lambda_1, ..., \lambda_{n'}))$ in relation to the multi-vector values $(\Box) = (\Box 1, ..., \Box n)$ of the vectors of local action parameters $(\Box u)$.

If necessary, a global numerical optimisation (according to predetermined criteria) of the chosen statistical parameters of adjustment $(V(\Box))$ is performed in relation to the multi-vector

$(\square) = (\square 1, \ldots, \square n)$. The corresponding level of its vector optimised from the local action parameters (λ_u) is transmitted to each local system (S_u) in order to globally anticipate the future probable behaviour and effectiveness of all local system (S_u) subjected to the environment (E) during any one retained time forecast (t_k).

According to the invention, figure 9 describes an application process in the financial industry. The invention process carries out a repetitive stochastic simulation through the sampling of probable future pseudo-states of market variables, for the probabilistic prediction of future behaviour and/or the optimisation of productivity parameters of a number n (where n is much greater than » 1) of local financial operators $(S_u^{(u=1\ldots n)})$. The invention relates to the case where local financial operators $(S_u^{(u=1\ldots n)})$ are decentralised and quite a distance from one another. Each local financial operator $(S_u^{(u=1\ldots n)})$ has a portfolio $(P_u^{(u=1\ldots n)})$ consisting of financial assets $(\theta_h^{(h=1\ldots q)})$ whose value $(I_u^{(u=1\ldots n)})$ depends upon capital market (E) fluctuations. The portfolio $(P_u^{(u=1\ldots n)})$ value $(I_u^{(u=1\ldots n)})$ may be calculated in combination with a market variables vector $(X(t)) = X_i(t)^{(i=1\ldots p)})$ and for each remote local financial operator (S_u), with a quantities vector $(\lambda_u) = (\lambda_{uh}^{(h=1\ldots q)})$ of each financial asset $(\theta_h^{(h=1\ldots q)})$ held in its portfolio (P_u). Market variables $(X_i(t)^{(i=1\ldots p)})$ are

common to the different local financial operators $(S_u^{(u=1...n)})$ and vary throughout time (t). It is possible for each remote local financial operator (S_u) to recreate, with acceptable precision, the value of all financial assets held in its portfolio (P_u) according to a local assessment model (D_u) by using the market variables vector $(X(t)) = X_i(t)^{(i=1...p)}$. Market variables may include assets or commodities prices, interest rates or coefficients of yield curbs, volatilities or coefficients of volatility surfaces, default indicators from an issuer or counter-party, or even any other number that can provide information pertaining to the state of capital markets.

For example, the value $(I_u^{(u=1...n)})$ of a portfolio $(P_u^{(u=1...n)})$ may be calculated according to the following linear combination:

$$I_u(t) = \sum_{h=1}^{q} \lambda_{uh} \pi_h(t, X(t), \theta_h) \quad (***)$$

where $\pi_h(t, X(t), \theta_h)$ is the asset price (θ_h) at instant (t) according to the local model (D_u) when the market is in state $(X(t))$, or by using any other formula that allows for a non-linearity in relation to quantities (λ_{uh}) particularly in order to take liquidity risk into account.

According to a first sub-variant of the invention's process of application to the financial

industry, the following prior choices are made at the expert site (U'):

- p market variables $(X_i(t)^{(i=1...p)})$ that describe the entire market.

- A statistical model of joint behaviour in time (t) and by time periods $(\Delta t_k^{k=1...m})$ of market variables $(X_i(t)^{(i=1...p)})$ that is described by its dense joint distribution $(f_\alpha(X_1,...,X_p;t;\Delta t_k))$.

The statistical model of joint behaviour in time (t) and by time periods $(\Delta t_k^{k=1...m})$ of market variables is determined from historical observations that may include, in particular, normal laws, normal logs and so on, or more generally, a joint statistic distribution of p environment variables $(X_i t(k)^{(i=1...p)})$ or their temporal variations $(\Delta X_i(t_k)^{i=1...p)})$. It is assessed through appropriate and classical statistic tests (averages, variances, correlations, breaks, extreme behaviours and so forth).

At the centralised transmitting site (U), and by using the statistical model $(f_\alpha(X_1,...,X_p;t;\Delta t_k))$ retained from joint distribution within the time (t) of market variables $(X_i^{(i=1...p)})$, an "*smp* probabilistic series" (W_{ij}^k) with a multi-value description of pseudo-states or pseudo-variations for the probable market future (E) is numerically generated at repetitive and successive instants (t_o).

According to a first application mode, this "*smp* probabilistic series" (W_{ij}^k) is an "*smp* probabilistic

series" (X_{ij}^{k}) of pseudo-states formed by $s \times m$ p-uplets of a multi-value sampling for future pseudo-states $(X_{ij}(t_k)^{(i=1...p,j=1...s,k=1...m)})$ that include possible $s \times m \times p$ numerical values of p market variables $(X_i(t)^{(i=1...p)})$ and constitute:

- For each m $(m \geq 1)$ time forecast $\left(t_k^{(k=1...m)}\right)$ of the simulation.

- Of s (where s is much greater than » 1) possible future pseudo-states of p market variables $(X_i(t_k)^{(i=1...p)})$.

According to a second application mode, this "*smp* probabilistic series" (W_{ij}^{k}) is an "*smp* variational probabilistic series" (ΔX_{ij}^{k}) formed by $s \times m$ p-uplets of a multi-value sampling for future pseudo-variations $(\Delta X_{ij}(t_k)^{(i=1...p,j=1...s,k=1...m)})$ from the standard state of market variables $(X_i(t_o)^{(i=1...p)})$ that include $s \times m \times p$ numerical values of probable future pseudo-variations for p state variables $(X_i(t_k)^{(i=1...p)})$ and constitutes:

- For each m $(m \geq 1)$ time forecast $\left(t_k^{(k=1...m)}\right)$ of the simulation.

- Of s (where s is much greater than » 1) possible numerical pseudo-variations for p state variables $(X_i(t_k)^{(i=1...p)})$.

Thus, the process of the invention, at the centralised transmitting site (U) that is quite a distance from the majority of n local financial operators $(S_u^{(u=1...n)})$, is to transmit at repetitive and

successive instants (t_o) said "*smp* probabilistic series" (W_{ij}^k) with a multi-value description of probable future pseudo-states or pseudo-variations that includes $s \times m \times p$ numerical pseudo-values and consists of:

- (Case 1) said "*smp* probabilistic series" (X_{ij}^k) of pseudo-values for market variables $(X_{ij}(t_k)^{(i=1...p,j=1...s,k=1...m)})$.

- (Case 2) and/or said "*smp* variational probabilistic series" (ΔX_{ij}^k) for future pseudo-variations $(\Delta X_{ij}(t_k)^{(i=1...p,j=1...s,k=1...m)})$.

This transmission of said "*smp* probabilistic series" (W_{ij}^k) is performed in a decentralised way from the transmitting site (U) towards all remote local operators (S_u).

Independently, and from each of the local operators (S_u), the majority of which are quite a distance from the centralised transmitting site (U), m' $(m' \leq m)$ time forecasts retained from amongst the m said time forecasts $\left(t_k^{(k=1...m)}\right)$ are chosen. If necessary, as in case 2 in which only said "*smp* variational probabilistic series" (ΔX_{ij}^k) of variational sampling is received, said corresponding "*smp* probabilistic series (X_{ij}^k) of pseudo-states" consisting of pseudo-samplings of future states $(X_{ij}(t_k)^{(i=1...p,j=1...s,k=1...m)})$ (at least for the retained m' time forecasts (t_k)) is locally calculated. Subsequently, for each retained m' time forecasts (t_k),

the global value $(I_{uj}^{t} = D_u(\lambda_u,(X_{ij}(t_k))$ of the portfolio (P_u) is numerically calculated according to a local assessment model (D_u) that has been previously set within each s scenarios $(j=1,...,s)$. The calculation is done for at least one particular value of the quantities vector $(\lambda_u)=(\lambda_{u1},...,\lambda_{uq})$ of held assets and for each simulated s p-uplets of state variables $(X_{ij}(t_k))$ that corresponds to said retained time forecast (t_k) for the probabilistic pseudo-state series $(X_{ij}(t_k)^{(j=1...s)})$. The corresponding simulated s pseudo-values of the portfolio $(I_{uj}(t_k,\lambda_u)) = D_u(\lambda_u,(X_{ij}(t_k)^{(i=1...p,j=1...s)})$ are then determined. These s portfolio (P_u) values are grouped together and arranged. The histogram (Γ_u) is then calculated and stored as is the probability (as a number or percentage) distribution $(\Psi_u(I_u))$ of the local portfolio (P_u) value (I_u) in the configuration (λ_u) according to the local model (D_u). A statistical calculation deduces the value of at least one chosen statistical parameter of adjustment $(V(\lambda_u))$ (such as average, spread type, Value at Risk, utility and so forth) that is characteristic of the probability distribution $(\Psi(\lambda_u,I))$ for values $(I_u(t_k,\lambda_u)$ in relation to vector variations $(\lambda_u)=(\lambda_{u1},...,\lambda_{uq})$ describing the portfolio (P_u).

If necessary, a numerical optimisation (according to predetermined criteria) of one or many chosen statistical parameters of adjustment $(V(\lambda_u))$ is

performed locally within each local operator (S_u). The portfolio composition $(\lambda_u)=(\lambda_{u1},...,\lambda_{uq})$ of each local operator (S_u) is then adjusted to a calculated optimal value in relation to predetermined criteria notably in order to anticipate the future probable behaviour and yield of each portfolio (P_u) subjected to the market (E) during any one retained time forecast (t_k).

According to a second sub-variant of the invention's process of application to the financial industry, the value $(I_{u_j}^k)$ of a financial operator's (S_u) portfolio (P_u) at a future date (t_k) according to the model (D_u) and within the state of the simulated market $(X_j(t_k))$ that corresponds to scenario j is assessed by taking the simulated market states in the same scenario j at subsequent dates $(t_l^{(l=k+1...m)})$ into account in the model (D_u) according to the following principle:

- Each financial asset $(\theta_h^{(h=1...q)})$ has a defined maximum quantity (ν_h) with which it is able to trade (to buy or to sell) within a day.

- If none of the asset (θ_h) quantities (λ_{uh}) held in the portfolios (P_u) exceeds the limit value (ν_h), then formula (***) with date and within simulation is used to assess portfolio value:

$$I_{u,j}^k=\sum_{h=1}^{q}\lambda_{uh}\pi_h(t_k,X_j(t_k),\theta_h)$$

- If one of the asset (θ_h) quantities (λ_{uh}) held in one of the portfolios (P_u) exceeds the limit value (ν_h) in absolute terms, then the quantity (λ_{uh}) is replaced by (ν_h) affected by its sign and with date, and the overhang ($\lambda_{uh} \pm \nu_h$) is reported for the following day (t_{k+1}) by using the market variables vector ($X_j(t_{k+1})$).

- If this quantity is still above the limit (ν_h) in absolute value, it is then set to the maximum value with the same sign, and the overhang ($\lambda_{uh} \pm 2\nu_h$) is again reported for the following day (t_{k+2}) by using the market variables vector ($X_j(t_{k+2})$), and so forth.

This particular arrangement allows the liquidity risk to be taken into account by imposing upper bound constraints to the quantity of each asset (θ_h) that can be rightly assessed according to the local model (D_u) at any given date (t_k), and thus leading to a possible report of the resulting virtual position within each simulation over subsequent dates.

Industrial Applications of the Invention

The invention has an industrial application in all fields, such as manufacturing, energy, food, finance, transport, public health, use of raw materials and any other industries that are subjected to a common global environment and where it is suitable to measure and/or control the impact of possible changes in global and local environment variables on the production of a number of remote industrial sites.

By way of example, the lessons of the invention may be favourably used to optimise the watering of crops, calculate road travel time or manage a fleet of cars.

Thus, a first application of the invention relates to agriculture. For this application, the remote local industrial systems $(S_u^{(u=1...n)})$ are the farms of different plots of cultivated land. State variables $(X_i(t)^{(i=1...p)})$ of the environment are air temperature, pluviometry, hygrometry, dryness of land and others at different geographical points. The local action parameters $(\lambda_u)=(\lambda_{u1},...,\lambda_{uq})$ are mainly the characteristics of plots and plantations. The aim of the invention is to limit over-consumption of water by automatically activating different watering systems only when the probability of arable lands suffering from dryness within the coming hours or days is above the acceptance threshold as defined by the farmer of each plot of land. Thus, the automatic watering systems are not activated if the probability of rain in the coming hours is high. Conversely, they could be activated one evening, for example, if the probability of extreme dryness the following day is high. Mutual cooperation between those that generate the sampling of meteorological variables and therefore, the expenses of the centralised probabilistic transmitting site (U) means that the setting-up of this automatic watering activation system is less costly.

A second application of the invention relates to optimising road travel. The target is to estimate the

probability law on time taken for a driver or a haulage contractor to reach their destination given all external random factors. For a driver needing to reach a point at a specific time, the optimisation of complex probabilistic criteria (probability of reaching a set point at a given time) is the only aspect which will allow them to truly optimise their chosen itinerary. Statistically, there could indeed be a section of the road where traffic generally moves freely, yet when it slow downs, the road may be jammed for a long time, and the view of the average (expected) travel time is therefore too simplistic. According to the invention, each vehicle of a road network consists of a remote local industrial system (S_u). The vehicles are subjected to random factors $(X_i(t)^{(i=1...p)})$ which include, for example, traffic fluidity on different sections of the road, the meteorological situation, an unexpected breakdown or accident and so forth. The local action parameters $(\lambda_u)=(\lambda_{u1},...,\lambda_{uq})$ of each vehicle represent the situation of the road network, planned route, speed of vehicle, type of vehicle and driving, and so forth. At the different remote industrial systems, the interface (Ω) for capturing parameters $(\lambda_{u1},...,\lambda_{uq})$ may be linked up to different control systems in the vehicle (notably a satellite navigation system, such as GPS, and vehicle captors) and a probabilistic data receiver (Rp_u) may be connected to a loaded Internet terminal.

A variation to this second application relates to managing a fleet of vehicles (public transport, freight transport, car hire amongst others). If each vehicle or

rolling system is fitted with a localisation system (of GPS type for example) and a transmitter, then it is possible to know the distribution of the fleet at a past or present instant. It is also possible to know "the most probable situation" (expectation) of vehicle location at any given future date. By centralising the simulated pseudo-values of the productivity indicators $(I_{uj}(t_k,\lambda_u))$ at a centralising site (E), the invention allows the manager of vehicle numbers to hone his vision on the probability of coming events. Thus, the manager of vehicle numbers may automatically control the probability of unexpected events that are rare yet laden with consequences (probability that all trucks of a freight haulage contractor simultaneously break down or probability that all vehicles of a car hire service are concentrated in one area).

A third particularly favourable application of the invention relates to the management of parameters for industrial units working on a same network and subjected to a common global random environment. By way of example, the lessons of the invention may be favourably applied to the field of electricity production within a deregulated environment where the price of electricity is set by comparing offer of n producers $(S_u^{(u=1...n)})$ and demand by a high number of consumers on a central market (the "energy pool"). The meeting of offer and demand may be done on the basis of a main planning centre that provides each producer with its working parameters. Such an approach poses the following two problems:

- The main planning centre must consider a significant amount of information, namely common information (level of demand, state of the network, prices of raw energy), local information strongly interacting with the global environment (weather) and multiple information that is specific to each producer and separate from the global environment (functioning and performance of a particular turbine, problems of discharge limits that pollute a particular river, and so on). According to classical methods, this optimisation problem has no solution under these conditions, except to grossly simplistic hypotheses of local constraints.

- Each local producer must strive to answer to requests by the main planning centre. In disregarding, by definition, the behaviour of a central optimisation model, the producer will be confronted with administrative uncertainties (which request will the main planning centre focus on?) in addition to a random global environment. This administrative uncertainty is just as difficult to model as it only imperfectly takes local operating constraints into account. The operating risk therefore becomes even more difficult to manage. Under these conditions, the global optimal value according to classical methods is illusory as it relies upon a series of remote operating states that are far from the real optimal value.

This approach, which is predominantly used in the field of electricity production, was analysed by the applicants. This study found that, in practice, the

approach led to significant industrial and energy overcapacities.

The classical alternative to relocate the optimisation problem is to establish a market where offer and demand can meet with a balanced price. The economic theory shows that searching for local optimal values relates to a global optimal value under certain very general hypotheses of convexity. The problem is technically laborious for electricity since storage is impossible. Thus, there are just as many markets as there periods during the year. The recent general move towards deregulating electricity markets has currently led to several market organisation models that it would be too long-winded to list them here. However, they more or less meet along the same lines as the model described below.

The "energy pool" is segmented into (m) sub-markets that correspond to separate time forecasts $(\Delta t_k^{(k=1...m)})$ with a "notice period". By way of example, we distinguish a very short-term market of a few minutes intended to maintain tension on the network, a short-term market of 1 hour, namely a "balancing market", intended to compensate for offer and demand uncertainties, a "normal" market of 24 hours and so on. For every sub-market, each producer $(S_u^{(u=1...n)})$ (power station) must be committed to respect a production cost curb $(C_{ku}(w))$ that provides production costs for each capacity level (w) offered on the network (this cost may be infinite beyond a maximum capacity level). For every sub-market, the "energy pool" classifies the

capacity offers according to increasing cost and matches them up with demand on the particular sub-market, where the price $(P_k^{(k=1...m)})$ of a kilowatt/hour on the sub-market is a result of this match. Producers with production costs above the price (P_k) are not called upon by the network manager. If a producer, following accidental unavailability, notices during the time (Δt_k) before delivery that it is unable to respect its commitment on the sub-market (l) (with $\Delta t_k < \Delta t_l$) then it must buy back the corresponding quantities on the sub-market (k) (or any other sub-market with a shorter notice period). Within this application framework of the invention, the producer's productivity indicator is its gross margin. A producer's $(S_u^{(u=1...n)})$ order parameters $(\lambda_u = (\lambda_{u1},...,\lambda_{uq}))$ are specifically the following:

- Allocation of its available capacity (Cap_u) between (m) sub-markets and a specific sub-market that is programmed to be maintained by the power station.
- Choice of primary energy use if this resource is available (for example, gas/carbon, fuel/carbon).

The choice of parameters is subjected to local operating constraints such as time and minimum start-up costs for a unit, change of fuel type, minima and maxima techniques, problems of discharge limits that pollute air and water, and so forth. The local optimisation problem is complex, insofar as its calls upon a forecast based on random variables that are relevant to both an environment specific to the installation (availability of production installations)

and a global environment common to all producers, including the following:

- Weather, and, in particular, temperature for a thermal power station (that affects thermodynamic productivity of power station) pluviometry for a hydraulic power station (that affects output and reserves) and so on.

- Prices of (m) electricity sub-markets.

- Prices of fuel used by a producer and so on.

This global environment is very familiar to all producers where prices are the same for everyone and climatic variables not only strongly correlate between different sites but also interact with price booms (for example, we expect a very cold day predicted within 24 hours would reflect a surge in electricity prices on the market within 24 hours).

The global optimisation problem by a main planning system is replaced by n local optimisation problems, in order to maximise the expected gross margin for example and to guarantee a minimal gross margin of x% to bear the debt charge (typically, a Value-at-Risk calculation), thereby entailing complex calculations. According to the previous work, the three possible solutions are as follows:

- Following trading, each producer enters into agreement with a body, such as an "asset manager", equipped with global environment analysis tools that will dictate parameter choices in exchange for guaranteeing a predetermined gross margin ("tolling agreement"). This solution eliminates, through trading, a possible inefficient main planning system, albeit

fundamentally posing the same type of problem in that such agreements may never perfectly take local operating constraints into account. Further, it entails relaying confidential information about the site's functioning constraints to the "asset manager".

- Each producer carries out its optimisation on the basis of an analytical modelling of the global environment and its impact on their productivity equation. This is done after very simplistic hypotheses that, when not respected, lead to crisis situations (extremely high losses for the producer, global production deficit, and so on).

- Each producer simulates all possible environment states (global and specific to each time forecast) that correspond to electricity sub-markets. It calculates its gross margin for each state and parameter trajectory, and chooses the parameters vector thereby optimising the "expectation/VaR" pair on its gross margin. The simulation of possible global environment states entails the application of complex calculations, thereby requiring costly computing systems and resources, obviously identical for all producers.

The application of the invention's lessons allows each electricity producer to choose the third approach, i.e. the only one that allows an exact search for a local optimal value all the while mutualising the complex side of calculations. According to the invention:

- It repetitively gathers (with a frequency that corresponds to the price quotation frequency on the

pool) said "*smp* probabilistic series" (W_{ij}^{k}) with a multi-value description of probable future pseudo-states at $s \times m \times p$ numerical values ($W_{ij}^{k} = X_{ij}^{k}$ global) that is provided by the centralised transmitting site (U).

- For each "*smp* probabilistic series" and for each possible orders parameter vector, it selects a default random function that reflects the probability of a technical fault in the installation. It then deduces a gross margin ($MB_u(W_{ij}^{k}, \lambda_u)$) for each state and orders parameter vector that is calculated using a simple arithmetic calculation.

- Subsequently, a simple sorting action that classifies gross margin (MB_u) selections for each vector (λ_u) is deduced for a function $VaR_u(\lambda_u)$ and an expected gross margin function $Emb_u(\lambda_u)$.

The complex optimisation problem in a random environment is reduced to a simple optimisation problem that is to seek the maximum of $Emb_u(\lambda_u)$ under the constraint $VaR_u(\lambda_u) < V_{max}$ for each power station ($S_u^{(u=1...n)}$).

Advantages of the Invention

The invention allows for computing systems and human resources necessary for the application of probabilistic simulations on a set of remote industrial sites that are subjected to a common random environment to be minimised with the notable end results being:

- To optimise production while respecting regulation constraints.

- To optimise production costs by controlling unfavourable unexpected events.

- To control and minimise rare and unfavourable unexpected events.

Another advantage of the invention is to simplify the global risk calculation of a group of remote local industrial systems.

A third advantage of the invention is to perform local statistical simulation calculations at a number of industrial sites by using mutualised random selections without any local system having to transmit information to the centralised transmitting site on its situation or having to adjust its industrial parameters. This ensures an improved industrial and commercial confidentiality.

In addition, the application example in the electric energy field given above allows the following advantages for an industrial producer to be outlined:

- The producer may draw nearer to the local optimal value by using the most sophisticated optimisation techniques in a simple way and with few local resources. This will reflect a faster turnover on investment or a price drop for the benefit of consumers.

- There is no need to invest in expensive modelling and global environment simulation systems. The producer may focus on the simulation of specific local parameters that are separate from the global environment.

- There is no need for the producer to relay its working parameters to a central body. Within a

competitive environment, the consumer may therefore preserve its strategic confidentiality.

The applicants reserve themselves the sole right to the invention, its description and relevance now justified through detailed examples, throughout the duration of the patent, with no limitation other than that contained in the terms of the claims hereinafter.

CLAIMS

1. Process of repetitive stochastic simulation that is prioritised and mutualised by a sampling of probable scenarios for the probabilistic prediction of future behaviour and/or the optimisation of productivity parameters for a number remote local industrial systems $(S_u^{(u=1...n)})$:

- a great distance from one another,
- subjected to a common and evolutionary global environment (E) that may be numerically described with p state variables $(X_i(t)^{(i=1...p)})$, which are effectively the components of a state vector $(X(t)=X_i(t)^{(i=1...p)})$,
- where the effectiveness of each local system $(S_u^{(u=1...n)})$ may be further described with a numerical productivity indicator $(I_u^{(u=1...n)})$ according to a local numerical systems analysis model with parameters (D_u) that has been previously determined $(I_u = D_u^{(u=1...n)}(\lambda u, X(t)))$ and is dependent upon each system (S_u) and for each instant (t):

• of all or some $(X_i(t)^{(i=1...p)})$ state variables of the state vector $(X(t))$,

• a vector of local q action parameters (that may be adjusted) $(\lambda_u = (\lambda_{u1},...,\lambda_{uq}))$,

this process characterised in that, in combination:

– at a centralised transmitting site (U) a great distance (of several kilometres, if not a few hundred kilometres) from a majority of n remote local industrial systems $(S_u^{(u=1...n)})$:

• in that an "*smp* series of probabilistic simulations" $(W_{ij}^{k(i=1...p,j=1...s,k=1...m)})$ with a multi-value description of environment (E) variables $(X_i(t)^{(i=1...p)})$ is repetitively generated at successive instants (t_o) and consisting of:

♦ either future probable pseudo-states of environment (E) variables $(X_i(t)^{(i=1...p)})$,

♦ either future probable pseudo-variations of these environment (E) variables $(X_i(t)^{(i=1...p)})$,

common to the number of decentralised n (where n is much greater than » 1) remote local industrial systems $(S_u^{(u=1...n)})$ and simulated at one (or several m where $m \geq 1$) time forecast $\left(t_k^{(k=1...m)} > t_o\right)$,

• in that this "*smp* series of probabilistic simulations" (W_{ij}^k) with a multi-value description of probable future pseudo-states or pseudo-variations of environment variables is distributed in a decentralised way:

- from the transmitting site (U),
- towards a number of remote local systems (S_u),

– independently, at each local system (S_u) the majority of which are a great distance from the centralised transmitting site (U), and repetitively:

- in that said "*smp* series of probabilistic simulations" (W_{ij}^k) with a multi-value description of probable future pseudo-states or pseudo-variations are collected,
- in that specific local statistical and numerical processing is performed on said series of probabilistic simulations (W_{ij}^k) received in order to predict future probabilistic behaviour of local industrial systems (S_u),
- if necessary, in that the vector level of the local action parameters $(\lambda_u)=(\lambda_{u1},\ldots,\lambda_{uq})$ for each local system (S_u) is adjusted to an optimal value that is calculated in relation to predetermined criteria in order to anticipate, in particular, the probable future behaviour and effectiveness of each system (S_u) subjected to the environment (E) during any one retained time forecast (t_k).

2. Process in accordance with claim 1 above of repetitive stochastic simulation that is prioritised and mutualised by a sampling of probable scenarios for the probabilistic prediction of future behaviour and/or the optimisation of productivity parameters for a number remote local industrial systems (S_u), this process being of the specific type that consists of:

- at an expert site (U') a great distance (of several kilometres, if not several hundred kilometres) from the majority of n remote local industrial systems ($S_u^{(u=1...n)}$) where the preliminary choice is made on:

  • p environment (E) variables ($X_i^{(i=1...p)}$),

  • a statistical joint behaviour model at time (t) and by time periods ($\Delta t_k^{k=1...m}$) of state variables ($X_i(t)^{(i=1...p)}$) described in its dense joint distribution ($f_\alpha(X_1,...,X_p;t;\Delta t_k)$):

    ♦ determined by historical observations that may, in particular, entail normal laws, normal logs and so on, or more generally, a joint statistical distribution of p environment variables ($X_i t(k)^{(i=1...p)}$) or their temporal variations ($\Delta X_i(t_k)^{i=1...p)}$),

    ♦ assessed through appropriate and classical statistic tests (averages, variances, correlations, breaks, extreme behaviours and so forth),

- at a centralised transmitting site (U) a great distance (of several kilometres, if not several hundred kilometres) from a majority of n remote local industrial systems ($S_u^{(u=1...n)}$):

  • in that an "*smp* probabilistic series" ($W_{ij}^{k(i=1...p,j=1...s,k=1...m)}$) with a multi-value description of probable future pseudo-states or pseudo-variations for the environment (E) is numerically and repetitively generated at successive instants (t_o) and consisting of:

♦ case 1: an "*smp* probabilistic series" (X_{ij}^{k}) of pseudo-states formed by $s \times m$ p-uplets with a multi-value sampling of future pseudo-states $(X_{ij}(t_k)^{(i=1...p,j=1...s,k=1...m)})$ that include possible $s \times m \times p$ numerical values of probable future pseudo-values for p state variables $(X_i(t)^{(i=1...p)})$ and constitute:

▪ for each m $(m \geq 1)$ time forecast $\left(t_k^{(k=1...m)}\right)$ of the simulation,

▪ of s (where s is much greater than » 1) possible future pseudo-states $(X_j^{k(j=1...s)}) = (X_{ij}(t_k)^{(i=1...p,j=1...s)})$ for each p state variable $(X_i(t_k)^{(i=1...p)})$,

♦ case 2: and/or, if necessary, an "*smp* variational probabilistic series" (ΔX_{ij}^{k}) formed by $s \times m$ p-uplets with a multi-value sampling of future pseudo-variations $(\Delta X_{ij}(t_k)^{(i=1...p,j=1...s,k=1...m)})$ using the standard value of state variables $(X_i(t_o)^{(i=1...p)})$ that include $s \times m \times p$ numerical values of probable future pseudo-variations for p state variables $(X_i(t_k)^{(i=1...p)})$ and constitute:

▪ for each m $(m \geq 1)$ time forecast $\left(t_k^{(k=1...m)}\right)$ of the simulation,

▪ of s (where s is much greater than » 1) possible future numerical pseudo-variations $(\Delta X_{ij}(t_k)^{(j=1...s)})$ of each p state variable $(X_i(t_k)^{(i=1...p)})$,

the process characterised in that, in combination:

- at the centralised transmitting site (U) a great distance (of several kilometres, if not several hundred kilometres) from the majority of n remote

local industrial systems $(S_u^{(u=1...n)})$ repetitively and at successive instants (t_o):

• in that said *smp* probabilistic series (W_{ij}^k) with a multi-value description of probable future pseudo-states or pseudo-variations including the $s \times m \times p$ numerical pseudo-values that consist of:

♦ case 1: said "*smp* probabilistic series" (W_{ij}^k) of pseudo-values for state variables $(X_{ij}(t_k)^{(i=1...p,j=1...s,k=1...m)})$,

♦ case 2: and/or said "*smp* variational probabilistic series" (ΔX_{ij}^k) of pseudo-variations $(\Delta X_{ij}(t_k)^{(i=1...p,j=1...s,k=1...m)})$,

in a decentralised way:

♦ from the transmitting site (U),

♦ towards a number of remote local systems (S_u),

- independently, at each local system (S_u) the majority of which are a great distance from the centralised transmitting site (U), and repetitively:

• in that said "*smp* probabilistic series" (W_{ij}^k) with a multi-value description of probable future pseudo-states or pseudo-variations including $s \times m \times p$ numerical values $(W_{ij}^k = X_{ij}^k$ or $\Delta X_{ij}^k)$ is collected,

• in that m' $(m' \leq m)$ time forecasts, retained from amongst said m time forecasts $\left(t_k^{(k=1...m)}\right)$ are chosen,

• if necessary, as in case 2 in which only said "*smp* variational probabilistic series" (ΔX_{ij}^k) of variational samplings $(X_{ij}(t_k)^{(i=1...p,j=1...s,k=1...m)})$ is received, in that corresponding said "*smp* probabilistic series"

(X_{ij}^k) of pseudo-states consisting of pseudo-samplings of future states $(X_{ij}(t_k)^{(i=1...p,j=1...s,k=1...m)})$ (at least for the retained m' time forecasts (t_k)),

• for each retained m' time forecasts (t_k):

♦ in that the local systems analysis model (D_u) is numerically applied, having been previously set in order to determine for each s scenarios $j=1,...,s$ the productivity indicator:

$$(I_{uj}^k = D_u(\lambda_u, (X_j(t_k))$$

♦ for at least a particular value $(\lambda_u)=(\lambda_{u1},...,\lambda_{uq})$ of the vector (λ_u) of local action parameters,

♦ for each simulated s p-uplets of state variables $(X_{ij}(t_k)^{(i=1...p)})$ that corresponds to said retained time forecast (t_k) of the probabilistic pseudo-state series $(X_{ij}(t_k)^{(j=1...s)})$,

♦ in that the corresponding simulated s pseudo-values of the productivity indicator $(I_{uj}(t_k,\lambda_u))=D_u(\lambda_u,(X_j(t_k)^{(i=1...p,j=1...s)})$ are determined,

♦ in that the corresponding s values of the productivity indicator $(I_{uj}(t_k,\lambda_u)^{(j=1...s)})$ are grouped together and arranged according to the productivity level (I_{uj}),

♦ in that the histogram (Γ_u) is calculated and memorised as is the probability (as a number or percentage) distribution $(\Psi_u(I_u))$ of the level reached

by the local productivity indicator (I_u) in the configuration (λ_u) according to the local model (D_u),

• in that a statistical calculation deduces the value of at least one chosen statistical parameter of adjustment $(V(\lambda_u))$ (such as average, spread type, Value at Risk, utility and so forth) that is characteristic of:

♦ the probability distribution $(\Psi(\lambda_u, I))$ for productivity levels $(I_u(t_k, \lambda_u))$,

♦ in relation to variations of the vector of local action parameters $(\lambda_u) = (\lambda_{u1}, \ldots, \lambda_{uq})$,

• if necessary, in that a numerical optimisation (according to predetermined criteria) is performed locally within each local system (S_u) of one or many chosen statistical parameters of adjustment $(V(\lambda_u))$, and in that the vector level of local action parameters $(\lambda_u) = (\lambda_{u1}, \ldots, \lambda_{uq})$ for each local system (S_u) is adjusted to a calculated optimal value in relation to predetermined criteria in order to anticipate the future probable behaviour and effectiveness of each system (S_u) subjected to the environment (E) during any one retained time forecast (t_k).

3. Process in accordance with claim 2 of repetitive stochastic simulation that is prioritised and mutualised by sampling of probable scenarios, characterised in that, in combination:

- at the expert site (U'):

• in that each local action parameter $(\lambda_{uh}^{(h=1...q)})$ is assigned a generic code (L_h) (that is not dependent upon the local system (S_u)),

• in that a "productivity evaluator" (Π_h) is set up and regularly updated for each code (L_h), i.e. a programme (produced as a digital file) that is able to calculate, in relation to the p-uplet of state variables $(X)=(X_i^{(i=1...p)})$ and the local action parameter (λ_{uh}), the corresponding productivity component $(I_{uh})=(\Pi_h(\lambda_{uh},X))$,

• in such a way that, for each local system (S_u), said local systems analysis model (D_u) consists simply in adding up the components (I_{uh}) of the productivity assessment system corresponding to each local action parameter (λ_{uh}):

$$D_u(\lambda_u,X)=\sum_{h=1}^{q}\Pi_h(\lambda_{uh},X) \quad (*)$$

- at the centralised transmitting site (U):

• in that the "*smp* probabilistic series" (W_{ij}^k) with its multi-value description of probable future pseudo-states or pseudo-variations is numerically generated and repetitively transmitted at successive instants (t_o) by using the retained joint behaviour statistical model $(f_\alpha(X_1,...,X_p;t;\Delta t))$ in time (t) of state variables (X_i),

• in that, as each new code (L_h) appears or adjustment to the productivity evaluator (Π_h) is made, the pair (L_h,Π_h) is transmitted as a digital file,

- at each remote and local industrial system (S_u):

• in that the productivity component $(I_{uhj}^{k})=(\Pi_h(\lambda_{uh},X_j^k))$ is calculated:

♦ for each m' $(m'\leq m)$ retained time forecast (t_k) of the simulation at the local level (S_u),

♦ for each $j=1,...,s$ (where s is much greater than » 1) of possible numerical pseudo-states $(X_j^{k(j=1...s)})$ received or recreated using the pseudo-variation series (ΔX_{ij}^{k}),

♦ for each $h=1,...,q$ of local action parameters (λ_{uh}),

♦ the productivity component $(I_{uhj}{}^{k})=(\Pi_h(\lambda_{uh},X_j^k))$,

♦ subsequently, in summation and according to formula (*), the productivity indicator $(I_{uj}{}^{k})$,

♦ the retained statistical parameter $(V(\lambda_u))$ is calculated,

• in that the vector of local action parameters (λ_u) is applied in order to optimise the value of the statistical parameter (V).

4. Process in accordance with claim 2 of repetitive stochastic simulation that is prioritised by sampling of probable scenarios, characterised in that, in combination:

- at the expert site (U'):

• in that each local action parameter $(\lambda_{uh}^{(h=1...q)})$ is assigned a generic code (L_h) (that is not dependent upon the local system (S_u)),

• in that a "marginal productivity evaluator" (π_h) is set up and regularly updated for each code (L_h), i.e. a programme (produced as a digital file) that is able to calculate, in relation to the p-uplet of state variables $(X)=(X_i^{(i=1...p)})$ the corresponding marginal productivity component $(I'_{uh})=(\pi_h(X))$,

• in such a way that, for each local system (S_u), said local systems analysis model (D_u) consists simply in performing a scalar product between the vector of local action parameters $(\lambda_u)=(\lambda_{uh}^{(h=1...q)})$ and the vector of marginal productivity (I'):

$$D_u(\lambda_u)=(\lambda_u|I') \quad (**)$$

- at the centralised transmitting site (U):

• in that the "*smp* probabilistic series" (W_{ij}^k) with a multi-value description of probable future pseudo-states or pseudo-variations is numerically generated and repetitively transmitted at successive instants (t_o) by using the retained joint behaviour statistical model $(f_\alpha(X_1,...,X_p;t;\Delta t))$ in time (t) of state variables (X_i),

• in that, as each new code (L_h) appears or adjustment to the productivity evaluator (Π_h) is made, the pair (L_h,Π_h) is transmitted as a digital file,

• in that the marginal productivity component $(I'^{k}_{hj}) = (\pi_h(X^k_j))$ is calculated:

♦ for each m retained time forecast (t_k),

♦ for each $j = 1,...,s$ (where s is much greater than » 1) of possible numerical pseudo-states $(X^{k(j=1...s)}_j)$,

♦ for each $h=1,...,q$ of local action parameters (λ_{uh}),

♦ the marginal productivity component $(I'^{k}_{hj}) = (\pi_h(X^k_j))$,

• in that the "*smq* probabilistic series" (W'^{k}_{hj}) with a multi-value description of probable future pseudo-states (I'^{k}_{hj}) or pseudo-variations $(\Delta I'^{k}_{hj})$ is transmitted.

- at each remote and local industrial system (S_u):

• in that the "*smq* probabilistic series" (W'^{k}_{hj}) with a multi-value description of probable future pseudo-states (I'^{k}_{hj}) or pseudo-variations $(\Delta I'^{k}_{hj})$ is collected,

• in that, subsequently, in summary and according to formula (**), the productivity indicator series (I^{k}_{uj}) and the retained statistical parameter $(V(\lambda_u))$ are calculated,

• in that, subsequently, the vector of local action parameters (λ_u) is applied in order to optimise the value of the statistical parameter (V).

5. Process in accordance with claim 2 of repetitive stochastic simulation that is prioritised by

sampling of probable scenarios, characterised in that, in combination:

- at a centralised transmitting site (U):

• in that a variational probabilistic series (ΔX_{ij}^{k}) formed by $s \times m$ p-uplets of a multi-value sampling of pseudo-variations $(\Delta X_{ij}(t_k)^{(i=1\ldots p, j=1\ldots s, k=1\ldots m)})$ for future states by using the standard state of state variables $(X_i(t_o)^{(i=1\ldots p)})$ and including $s \times m \times p$ numerical values of probable future pseudo-variations for p state variables $(X_i(t_k)^{(i=1\ldots p)})$ is numerically and repetitively generated at successive instants (t_o) and constitutes:

♦ for each m $(m \geq 1)$ time forecast $\left(t_k^{(k=1\ldots m)}\right)$ of the simulation,

♦ of s (where s is much greater than » 1) possible future numerical pseudo-variations $(\Delta X_{ij}(t_k)^{(j=1\ldots s)})$ of each p state variable $(X_i(t_k)^{(i=1\ldots p)})$,

• in that said variational probabilistic series (ΔX_{ij}^{k}) of pseudo-variation states $(\Delta X_{ij}(t_k)^{(i=1\ldots p, j=1\ldots s, k=1\ldots m)})$ is repetitively transmitted in a decentralised way:

♦ from the transmitting site (U),

♦ towards the number of remote local systems (S_u),

- independently, and at each local system (S_u):

• in that the standard value of state variables $(X_i(t_o)^{(i=1\ldots p)})$ is repetitively collected and memorised at each instant (t_o) and according to a determined frequency, if not at each adjustment of variables (X_i),

• in that said "*smp* variational probabilistic series" (ΔX_{ij}^{k}) of state variations $(\Delta X_{ij}(\Delta t_k)^{(i=1\ldots p,j=1\ldots s,k=1\ldots m)})$ in relation to time increment Δt_k transmitted by the central site (U) is collected,

• in that said "*smp* probabilistic series" (X_{ij}^{k}) of pseudo-states $(X_{ij}(t_k)^{(i=1\ldots p,j=1\ldots s,k=1\ldots m)})$ is calculated at future instants $(t_k)=(t_o+\Delta t_k)$ that correspond to the variational series by an incremental numerical calculation of the type:

$$X_{ij}(t_k)=X_i(t_o)(1+\Delta X_{ij}(t_k))$$

or any other formula (addition, exponential and so forth) that implicates:

♦ the "*smp* variational probabilistic series" (ΔX_{ij}^{k}) transmitted by the centralised transmitting site (U),

♦ the standard value of state variables $(X_i(t_o)^{(i=1\ldots p)})$,

6. Process in accordance with claim 2 of repetitive stochastic simulation that is prioritised by sampling of probable scenarios, characterised in that, in combination:

- at the centralised transmitting site (U):

• in that an "*smp* variational probabilistic series" (ΔX_{ij}^{k}) formed by $s\times m$ p-uplets of a multi-value sampling of pseudo-variations $(\Delta X_{ij}(t_k)^{(i=1\ldots p,j=1\ldots s,k=1\ldots m)})$ for future states by using the standard value of state

variables $(X_i(t_o)^{(i=1...p)})$ and including $s \times m \times p$ numerical values of probable future pseudo-variations for p state variables $(X_i(t_k)^{(i=1...p)})$ is numerically and repetitively generated at successive instants (t_o) by using the retained joint behaviour statistical model $(f_\alpha(X_1,...,X_p;t;\Delta t))$ in time (t) of state variables (X_i), and constitutes:

- for each m $(m \geq 1)$ time forecast $\left(t_k^{(k=1...m)}\right)$ of the simulation,
- of s (where s is much greater than » 1) possible numerical pseudo-variations $(\Delta X_{ij}(t_k)^{(j=1...s)})$ of p state variables $(X_i(t_k)^{(i=1...p)})$,
- in that the standard value of state variables $(X_i(t_o)^{(i=1...p)})$ is repetitively collected and memorised,
- in that, at the transmitting site (U) and towards the number of remote local systems (S_u), the following are repetitively transmitted in a decentralised way:
- the "*smp* variational probabilistic series" (ΔX_{ij}^k) of pseudo-variations $(\Delta X_{ij}(t_k)^{(i=1...p,j=1...s,k=1...m)})$.
- the standard value of state variables $(X_i(t_o)^{(i=1...p)})$.

7. Process in accordance with claim 2 of repetitive stochastic simulation that is prioritised by sampling of probable scenarios, characterised in that, in combination:

- in that, previously and at different points in the environment (E), a series of r captors $(\gamma_h^{(h=1...r)})$ that

observe the environment (E) status transmit at each instant (t) a set of r measures of the environment (E) status $(\mu_h(t)^{(h=1...r)})$,

- in that, at the designer site (U'), a numerical model describing the environment (Φ) is previously established and defines all p state variables $(X_i(t)^{(i=1...p)}) = (\Phi(\mu_1(t),...,\mu_r(t)))$ in relation to measures $(\mu_h(t)^{(h=1...r)})$ (where generally $p \leq r$), in such a way that all environment variables $(X_i(t)^{(i=1...p)})$ physically describe with acceptable precision the status of the environment (E) in its entirety at each sampling instant (t_k),

- at the transmitting site (U):

• in that r environment measures $(\mu_h(t)^{(h=1...r)})$ are remotely collected and memorised, and constitute at each sampling instant (t_k) the components of a temporal vector to assess the environment $(M(t_k)) = (\mu_h(t_k)^{(h=1...r)})$,

• in that, at each successive sampling (t_k) period, and with the aid of a numerical model describing the environment (Φ) and the measures vector $(M(t))$, the p state variables $(X_i(t)^{(i=1...p)}) = (\Phi(\mu_1(t),...,\mu_r(t)))$ are calculated.

8. Process in accordance with claim 2 of repetitive stochastic simulation that is prioritised by sampling of probable scenarios, characterised in that, in combination:

- at the centralised transmitting site (U):

• in that a history of values for p state variables $(X_i(t)^{(i=1...p)})$ of the common global environment (E) throughout time is maintained and updated,

• in that said "*smp* probabilistic series" (W_{ij}^k) with a multi-value description of probable future pseudo-states or pseudo-variations of the environment (E) is numerically and repetitively generated at successive instants (t_o) by using:

♦ the retained statistical model $(f_\alpha(X_1,...,X_p;t;\Delta t_k))$ of joint behaviour within the time (t) of state variables $(X_i^{(i=1...p)})$,

♦ the memorised history of values for p state variables $(X_i(t)^{(i=1...p)})$,

♦ in that said "*smp* probabilistic series" (W_{ij}^k) with a multi-value description of probable future pseudo-states or pseudo-variations is transmitted in a decentralised way from the transmitting site (U) towards a number of local systems (S_u).

9. Process in accordance with claim 8 above of repetitive stochastic simulation that is prioritised by sampling of probable scenarios, characterised in that, in combination:

- at the centralised transmitting site (U):

• in that a history of values for p state variables $(X_i(t)^{(i=1...p)})$ of the common global environment (E) throughout time is maintained and updated,

• in that the "*smp* probabilistic series" (W_{ij}^k) with a multi-value description of probable future pseudo-

states or pseudo-variations of the environment (E) is numerically and repetitively generated at successive instants (t_o) by using:

- the retained statistical model $(f_a(X_1,...,X_p;t;\Delta t_k))$ of joint behaviour within the time (t) of state variables (X_i),
- the memorised history of values for p state variables $(X_i(t)^{(i=1...p)})$,

the method known as "Monte-Carlo", a pseudo-random selection of pseudo-values (W_{ij}^k) with the aid of a random number generator located on the centralised transmitting site (U), if not the designer site (U'), and relying on any one of the following processes:

- "Pseudo-random" of an ergodic type,
- "Weak disparity" (Sobol and Hamersley series, amongst others),
- any other method producing numbers asymptomatically shared out according to a specified distribution (for example, uniform on an interval),
- in that said "*smp* probabilistic series" (W_{ij}^k) with a multi-value description of probable future pseudo-states or pseudo-variations is transmitted in a decentralised way from the transmitting site (U) towards all remote local systems (S_u).

10. Process in accordance with claim 8 of repetitive stochastic simulation that is prioritised by sampling of probable scenarios, characterised in that, in combination:

- at the centralised transmitting site (U):

• in that a history of values for p state variables $(X_i(t)^{(i=1...p)})$ of the common global environment (E) throughout time is maintained and updated,

• in that the "*smp* probabilistic series" (W_{ij}^k) with a multi-value description of probable future pseudo-states or pseudo-variations of the environment (E) is numerically and repetitively generated at successive instants (t_o) by using:

♦ the retained statistical model $(f_\alpha(X_1,...,X_p;t;\Delta t))$ of joint behaviour within the time (t) of state variables $(X_i^{(i=1...p)})$,

♦ the memorised history of values for p state variables $(X_i(t)^{(i=1...p)})$,

the method known as "historical", the estimate of probable future states of p state variables $(X_i(t)^{(i=1...p)})$ that are recreated by using the standard state $(X_i(t_o)^{(i=1...p)})$ and past historic variations $(\Delta X_i(t'_j)^{(i=1...p,j=1...v)})$ for a set of past dates $(t'_1,...t'_v < t_o)$ and by modifying each recreated state with a production probability that could depend upon the age of the corresponding historic variation,

• in that said "*smp* probabilistic series" (W_{ij}^k) with a multi-value description of probable future pseudo-states or pseudo-variations is transmitted in a decentralised way from the transmitting site (U) towards all remote local systems (S_u).

11. Process in accordance with claim 8 of repetitive stochastic simulation that is prioritised by

sampling of probable scenarios, characterised in that, in combination:

- at the centralised transmitting site (U):

• in that a history of values for p state variables $(X_i(t)^{(i=1...p)})$ of the common global environment (E) throughout time is maintained and updated,

• in that the "*smp* probabilistic series" (W_{ij}^k) with a multi-value description of probable future pseudo-states or pseudo-variations of the environment (E) is numerically and repetitively generated at successive instants (t_o) by using:

♦ the retained statistical model $(f_\alpha(X_1,...,X_p;t;\Delta t))$ of joint behaviour within the time (t) of state variables $(X_i^{(i=1...p)})$,

♦ the memorised history of values for p state variables $(X_i(t)^{(i=1...p)})$,

♦ and deliberately introducing joint statistic behaviour biases of state variables $(X_i(t)^{(i=1...p)})$ in relation to their historic statistic behaviour into the "*smp* probabilistic series" (W_{ij}^k), whereby the biased series reproduce "catastrophe scenarios" in order to take the impact of said catastrophe scenarios on remote systems (S_u) into account,

• in that said "*smp* probabilistic series" (W_{ij}^k) with a biased multi-value description of probable future pseudo-states or pseudo-variations is transmitted in a decentralised way from the

transmitting site (U) towards all remote local systems (S_u).

12. Process in accordance with claim 2 of repetitive stochastic simulation that is prioritised by sampling of probable scenarios, characterised in that, in combination:

- in that certain remote systems (S_u) send requests of catastrophe scenarios as numerical parameters according to the specific biases as defined by them to the centralised transmitting site (U),

- at the centralised transmitting site (U):

• in that, in relation to these requests and by possibly merging those that are identical, "*smp* probabilistic series" (W_{ij}^k) with multi-value descriptions of probable future pseudo-states or pseudo-variations, and biased in relation to parameters specified by remote systems are generated,

• in that the transmitting site (U) sends each remote local system (S_u) said "*smp* probabilistic series" (W_{ij}^k) with a multi-value biased description of probable future pseudo-states or pseudo-variations that corresponds to its request.

13. Process in accordance with claim 2 of repetitive stochastic simulation that is prioritised by sampling of probable scenarios, characterised in that, in combination:

- in that each remote system (S_u) alters all or part of the "*smp* probabilistic series" (W_{ij}^k) with a multi-value description of probable future pseudo-

states or pseudo-variations themselves so as to create biased series reproducing catastrophe scenarios whose parameters are:

• either specified by the main transmitting site (U) and transmitted to local systems (S_u),

• either defined by the local systems (S_u).

14. Process in accordance with claim 2 of repetitive stochastic simulation that is prioritised by sampling of probable scenarios, characterised in that, in combination:

- in that, at the transmitting site (U), the "*smp* probabilistic series" (W_{ij}^k) with a multi-value description of probable future pseudo-states or pseudo-variations of the environment (E) is numerically and periodically generated according to a sampling frequency (φ).

15. Process in accordance with claim 2 of repetitive stochastic simulation that is prioritised by sampling of probable scenarios, characterised in that, in combination:

- at the centralised transmitting site (U):

• in that said "*smp* probabilistic series" (W_{ij}^k) with a multi-value description of probable future pseudo-states or pseudo-variations is transmitted in a decentralised way from the transmitting site (U) towards all remote local systems (S_u) as a "broadcast", notably by radio,

- independently, and repetitively, at each local system (S_u), the majority of which are a great distance from the centralised transmitting site (U):

• in that said "*smp* probabilistic series" (W_{ij}^k) with a multi-value description of probable future pseudo-states or pseudo-variations and $s \times m \times p$ numerical values ($W_{ij}^k = X_{ij}^k$ or ΔX_{ij}^k) is collected through a quasi-continuous reception of this "broadcast" from the centralised transmitting site (U).

16. Process in accordance with claim 2 of repetitive stochastic simulation that is prioritised by sampling of probable scenarios, characterised in that, in combination:

- at the centralised transmitting site (U):

• said "*smp* probabilistic series" (W_{ij}^k) with a multi-value description of probable future pseudo-states or pseudo-variations is transmitted in a decentralised way from the transmitting site (U) towards all remote local systems (S_u) as a "below PP", i.e. by emission on a network (R), notably Internet based, from the centralised transmitting site (U) to specific addresses of each remote local industrial system ($S_u^{(u=1...n)}$),

- independently, and repetitively, at each local system (S_u), the majority of which are a great distance from the centralised transmitting site (U):

• said "*smp* probabilistic series" (W_{ij}^k) with a multi-value description of probable future pseudo-

states or pseudo-variations and $s \times m \times p$ numerical values ($W_{ij}^{k} = X_{ij}^{k}$ or ΔX_{ij}^{k}) is collected through successive registrations at the local memory bank (H_u) of the local calculator (C_u).

17. Process in accordance with claim 2 of repetitive stochastic simulation that is prioritised by sampling of probable scenarios, characterised in that, in combination:

- at the centralised transmitting site (U):

• said "*smp* probabilistic series" (W_{ij}^{k}) with a multi-value description of probable future pseudo-states or pseudo-variations is transmitted in a decentralised way from the transmitting site (U) towards all remote local systems (S_u) by making said multi-valued "*smp* probabilistic series" (W_{ij}^{k}) accessible on a server (Z) itself available:

♦ on an emission network (R) (notably Internet type),

♦ through "PP" access for each remote local industrial system ($S_u^{(u=1...n)}$),

- independently, and repetitively, at each local system (S_u):

• said "*smp* probabilistic series" (W_{ij}^{k}) with a multi-value description of probable future pseudo-states or pseudo-variations and $s \times m \times p$ numerical values ($W_{ij}^{k} = X_{ij}^{k}$ or ΔX_{ij}^{k}) is collected through access known as "above PP", i.e. via network (R) access

(notably Internet based) to the centralised transmitting site with their own specific address to retrieve said multi-valued "*smp* probabilistic series" by transfer (notably "FTP" type) and via registration at the local memory bank (H_u) of their local calculator (C_u).

18. Process in accordance with claim 2 of repetitive stochastic simulation that is prioritised by sampling of probable scenarios, characterised in that, in combination:

- at the centralised transmitting site (U), by using the retained joint behaviour statistical model $(f_\alpha(X_1,...,X_p;t;\Delta t))$ in time (t) of state variables $(X_i^{(i=1...p)})$, an "*smp* probabilistic series" (W_{ij}^k) with a multi-value description of probable future pseudo-states or pseudo-variations of the environment (E) is numerically and repetitively generated at successive instants, and consisting of s (where s is much greater than » 1) numerical pseudo-values for p components $(S_{ij}(t_k)^{(i=1...p,j=1...s)})$ for each m $(m \geq 1)$ time forecast $\left(t_k^{(k=1...m)}\right)$, as a file of $s \times m \times p$ successive alpha-numerical data sub-divided as follows:

• into successive m "temporal sub-files" of level 1 that groups together all pseudo-values of a same time forecast $\left(t_k^{(k=1...m)}\right)$,

• each "temporal sub-file" includes a succession of s "selection sub-files" of level 2 each consisting of a pseudo-value p-uplet.

19. Process in accordance with claim 2 of repetitive stochastic simulation that is prioritised by sampling of probable scenarios, characterised in that, in combination:

- at the centralised transmitting site (U), an "*smp* probabilistic series" (W_{ij}^{k}) with a multi-value description of probable future pseudo-states or pseudo-variations of the environment (E) is numerically and repetitively generated at successive instants (t_o) by separating successive m "temporal sub-files" of level 1 and gathering together the pseudo-values of a same time forecast $\left(t_k^{(k=1...m)}\right)$ with a corresponding time forecast indicator $(\eta_k^{k=1...m})$,

- at each local system (S_u), different said temporal sub-files of a same collected multi-value "*smp* probabilistic series" (W_{ij}^{k}) are separated from one another by identifying their specific time forecast indicators $(\eta_k^{k=1...m})$.

20. Process in accordance with claim 2 of repetitive stochastic simulation that is prioritised by sampling of probable scenarios, characterised in that, in combination:

- at the centralised transmitting site (U), an "*smp* probabilistic series" (W_{ij}^{k}) with a multi-value description of probable future pseudo-states or pseudo-variations of the environment (E) is numerically and repetitively generated at successive instants (t_o) by separating successive s "selection sub-files" of level

2 (from a same temporal file) and each gathering together a pseudo-value p-uplet with a corresponding selection indicator $(\tau_j^{(j=1...s)})$,

- at each local system (S_u), the majority of which are a great distance from the centralised transmitting site (U), different successive "selection sub-files" of level 2 (from a same temporal file) are separated from one another and each gathering together a pseudo-value p-uplet from a same collected multi-value "*smp* probabilistic series" (W_{ij}^k) by identifying their specific selection indicator $(\tau_j^{(j=1...s)})$.

21. Process in accordance with claim 2 of repetitive stochastic simulation that is prioritised by sampling of probable scenarios, characterised in that, in combination:

- at the centralised transmitting site (U):

• said "*smp* probabilistic series" (W_{ij}^k) with a multi-value description of probable future pseudo-states or pseudo-variations is transmitted in its entirety in a decentralised way from the transmitting site (U) towards all remote local systems (S_u) as a "broadcast" transmission, notably by radio transmission, to all local systems (S_u),

• independently, at each local system (S_u), a selective filter that is pre-adjusted for availability of a predefined (acquired through a specific subscription) fraction $(W_{ij}'^k)$ of said collected "*smp* probabilistic series" (W_{ij}^k) with a multi-value

description of probable future pseudo-states or pseudo-variations is installed and used to collect and receive from the centralised transmitting site (U).

22. Process in accordance with claim 2 of repetitive stochastic simulation that is prioritised by sampling of probable scenarios, characterised in that, in combination:

- at the centralised transmitting site (U):

• various different predefined fractions $((W_{ij}^k)_g^{(g=1...v)})$ (notably acquired through specific subscription) of said "*smp* probabilistic series" (W_{ij}^k) are selectively transmitted (according to a predefined allocation rule),

• this selective transmission is performed in a decentralised way towards various groups $(G_g^{g=1...v})$ that are linked to all remote local systems (S_u), with each group receiving a particular fraction,

• this is done through a "below PP" emission, i.e. via a network (R), notably Internet based, from the centralised transmitting site (U) to the specific address of each remote local industrial system's $(S_u^{(u=1...n)})$,

- independently, each group $(G_g^{g=1...v})$ linked to a local system (S_u), the majority of which are a great distance from the centralised transmitting site (U), repetitively collects:

• said predefined fraction $((W_{ij}^k)_g)$ of the "*smp* probabilistic series" (W_{ij}^k) with a multi-value

description of probable future pseudo-states or pseudo-variations through successive registrations at the local memory bank (H_u) of their local calculator (C_u).

23. Process in accordance with claim 2 of repetitive stochastic simulation that is prioritised by sampling of probable scenarios, characterised in that, in combination:

- at the centralised transmitting site (U):

• said "*smp* probabilistic series" (W_{ij}^k) is transmitted in a decentralised way from the transmitting site (U) towards all remote local systems (S_u) by making said "*smp* probabilistic series" (W_{ij}^k) accessible on a server (Z) available on a network (R) (notably Internet type) to which each remote local industrial system $(S_u^{(u=1...n)})$ has PP access;

• various predefined restrictive fractions $((W_{ij}^k)_g)$ (notably acquired through a specific subscription) of said "*smp* probabilistic series" (W_{ij}^k) with a multi-value description of probably future pseudo-states are selectively made available to different local system (S_u) groups $(G_g^{g=1...v})$ on a server (Z), in particular, through a system of usernames and passwords (23) that are transmitted by each local system $(S_u^{(u=1...n)})$,

- independently, and repetitively, at each local system (S_u):

• Said predefined fraction $((W_{ij}^k)_g)$ attributed to said "*smp* probabilistic series" (W_{ij}^k) with a multi-value

description of probably future pseudo-states or pseudo-variations is collected by access known as "below PP", i.e. via a network (R) (notably Internet type) from the centralised transmitting site (U) to its specific address, receiving said predefined fraction $((W_{ij}^{k})_{g})$ attributed to the multi-value "*smp* probabilistic series" by transfer and registration at the memory bank (H_u) of the local calculator (C_u).

24. Process in accordance with claim 2 of repetitive stochastic simulation that is prioritised by sampling of probable scenarios, characterised in that, in combination:

- n' $(n' \leq n)$ local industrial systems retained from the n of said local industrial systems $(S_u^{(u=1...n)})$ are previously chosen,

- m' $(m' \leq m)$ time forecasts are retained from the m of said time forecasts $\left(t_k^{(k=1...m)}\right)$ that are identical for all local systems,

- at each n' of retained local systems (S_u) and for each m' of retained time forecast (t_k):

• the local systems analysis model (D_u) is numerically applied having been previously set in order to determine the productivity indicator $(I_{uj}^{k} = D_u(\lambda_u, (X_{i,j}(t_k))))$ within each s scenario $(j = 1,...,s)$:

♦ for at least a particular value (λ_u) of the local action parameters vector,

♦ for each simulated s p-uplet of state variables $(X_i(t_k)^{(i=1...p)})$ that corresponds to said retained

time forecast (t_k) of the probabilistic series of pseudo-states $(X_j(t_k)^{(j=1...s)})$,

• the corresponding simulated s pseudo-values of the productivity indicator $(I_{uj}(t_k,\lambda_u))=(D_u(\lambda_u,X_j(t_k))^{(j=1...s)})$ are determined,

• the "local simulation series" consisting of the corresponding simulated s pseudo-values of the productivity indicator $(I_{uj}(t_k,\lambda_u))=(D_u(\lambda_u,X_j(t_k))^{(j=1...s)})$ belonging to the local system (S_u) is transmitted in a centralising way towards a centralising site (B);

- at the centralising site (B):

• the simulated $s\times n'$ pseudo-values of the productivity indicators $(I_u(t_k,\lambda_u))^{(j=1...s)})$ from each n' local system (S_u) and for each s simulation are collected,

• the global productivity indicator (J_j) of all local systems is calculated for each simulation $(j=1,...,s)$ by using a global evaluation model $(J_j)=(\chi(I_{uj}(t_k,\lambda_u)^{(u=1...n')})$. The corresponding s values of the productivity indicator $(J_j(t_k;\lambda_1,...,\lambda_{n'})^{(j=1...s)})$ are grouped together and arranged according to their level,

• the histogram (Γ) is calculated and memorised as is the probability distribution (as a number or percentage) $(\Psi(J))$ level reached by the global productivity indicator (J) in the chosen configuration of local action parameters vector $(\Lambda)=(\lambda_u{}^{(u=1...n')})$

according to the retained local models (D_u) and the global evaluation model (χ),

• a statistical calculation deduces the value of at least one chosen statistical parameter of adjustment $(V(\Lambda))$ (such as average, spread type, Value at Risk, utility and so forth) that is characteristic:

♦ of the probability distribution $(\chi(\lambda_1,...,\lambda_{n'},J))$ for global productivity levels $(J_j(t_k;\lambda_1,...,\lambda_{n'}))$,

♦ in relation to the multi-vector values $(\Delta)=(\lambda_1,...,\lambda_n)$ of the local action parameters vector (λ_u),

• (if necessary), a global numerical optimisation (according to predetermined criteria) of the chosen statistical parameters of adjustment $(V(\Lambda))$ is performed in relation to the multi-vector $(\Delta)=(\lambda_1,...,\lambda_n)$, and for each local system, the corresponding level of its vector is optimised from the local action parameters (λ_u) and duly transmitted to each local system (S_u) in order to globally anticipate the future probable behaviour and effectiveness of all local systems (S_u) subjected to the environment (E) during any one retained time forecast (t_k).

25. Process in accordance with claim 2 of repetitive stochastic simulation that is prioritised by the sampling of probable future pseudo-states of market variables for the probabilistic prediction of future behaviour and/or the optimisation of productivity parameters of a number n (where n is much greater than » 1) of local financial operators $(S_u^{(u=1...n)})$:

- in that they are decentralised and a great distance from one another,

- in that each has a portfolio $(P_u^{(u=1...n)})$:

• consisting of financial assets $(\theta_h^{(h=1...q)})$,

• whose value $(I_u^{(u=1...n)})$ depends upon capital market (E) fluctuations,

• whose value $(I_u^{(u=1...n)})$ may be calculated by combination:

♦ of a common market variables vector $(X(t)) = X_i(t)^{(i=1...p)})$ that varies throughout time (t) and from which it is possible for each remote local financial operator (S_u) to recreate, with acceptable precision, the value of all financial assets held in its portfolio (P_u) according to a local evaluation model (D_u) (these market variables may include assets or commodities prices, interest rates or coefficients of yield curbs, volatilities or coefficients of volatility surfaces, default indicators from an issuer or counter-party, or any other number that can provide information pertaining to the state of capital markets),

♦ for each remote local financial operator, of a quantities vector of each financial asset held in its portfolio, in that, for example, according to the following linear combination:

$$I_u(t) = \sum_{h=1}^{q} \lambda_{uh} \pi_u(t, X(t), \theta_h) \quad (***)$$

where $\pi_u(t,X(t),\theta_h)$ is the asset price (θ_h) at instant (t) according to the local model (D_u) when the market is in state $(X(t))$, or another formula that allows for a non-linearity in relation to quantities (λ_{uh}) particularly in order to take liquidity risk into account,

this process being of the type that consists of:

- at the expert site (U'), a great distance (of several kilometres, if not several hundred kilometres) from the majority of n local financial operators $(S_u^{(u=1...n)})$, the following previous choices are made:

• p market variables $((X_i)^{(i=1...p)})$ that describe the entire market (E),

• a statistical model of joint behaviour in time (t) and by time periods $(\Delta t_k^{(k=1...m)})$ of market variables $(X_i(t)^{(i=1...p)})$ that is described by its dense joint distribution $(f_a(X_1,...,X_p;t;\Delta t_k))$:

♦ determined from historical observations that may include, in particular, normal laws, normal logs and so on, or more generally, a joint statistic distribution of p environment variables $(X_i(t_k)^{(i=1...p)})$ or their temporal variations $(\Delta X_i(t_k)^{(i=1...p)})$,

♦ validated through appropriate and classical statistic tests (averages, variances, correlations, breaks, extreme behaviours and so forth),

- at the centralised transmitting site (U), a great distance (of several kilometres, if not several

hundred kilometres) from the majority of n local financial operators $(S_u^{(u=1...n)})$:

• an "*smp* probabilistic series" (W_{ij}^k) with a multi-value description of pseudo-states or pseudo-variations for the probable market future (E) is numerically and repetitively generated successive instants (t_o) by using the statistical model $(f_\alpha(X_1,...,X_p;t;\Delta t_k))$ retained from the joint distribution within the time (t) of market variables $(X_i^{(i=1...p)})$, and consisting of:

♦ case 1: an "*smp* probabilistic series" (X_{ij}^k) of pseudo-states formed by $s\times m$ p-uplets of a multi-value sampling for future pseudo-states $(X_{ij}(t_k)^{(i=1...p,j=1...s,k=1...m)})$ that include possible $s\times m\times p$ numerical values of p market variables $(X_i(t)^{(i=1...p)})$ and constitute:

▪ for each m $(m\geq 1)$ time forecast $\left(t_k^{(k=1...m)}\right)$ of the simulation,

▪ of s (where s is much greater than » 1) possible future pseudo-states of p market variables $(X_i(t_k)^{(i=1...p)})$,

♦ case 2: and/or possibly, an "*smp* variational probabilistic series" (ΔX_{ij}^k) formed by $s\times m$ p-uplets of a multi-value sampling for future pseudo-variations $(\Delta X_{ij}(t_k)^{(i=1...p,j=1...s,k=1...m)})$ from the standard state of market variables $(X_i(t_o)^{(i=1...p)})$ that include $s\times m\times p$ numerical values of probable future pseudo-variations for p state variables $(X_i(t_k)^{(i=1...p)})$ and constitutes:

▪ for each m $(m \geq 1)$ time forecast $\left(t_k^{(k=1\ldots m)}\right)$ of the simulation,

▪ of s (where s is much greater than » 1) possible numerical pseudo-variations for p state variables $(X_i(t_k)^{(i=1\ldots p)})$,

the process being characterised in that, in combination:

- at the centralised transmitting site (U), a great distance from the majority of n local financial operators $(S_u^{(u=1\ldots n)})$, repetitively and at successive instants (t_o):

• said "*smp* probabilistic series" (W_{ij}^k) with a multi-value description of probable future pseudo-states or pseudo-variations that includes $s \times m \times p$ numerical pseudo-values is transmitted and consists of:

♦ case 1: said "*smp* probabilistic series" (X_{ij}^k) of pseudo-values of market variables $(X_{ij}(t_k)^{(i=1\ldots p, j=1\ldots s, k=1\ldots m)})$,

♦ case 2: and/or said "*smp* variational probabilistic series" (ΔX_{ij}^k) of pseudo-variations $(\Delta X_{ij}(t_k)^{(i=1\ldots p, j=1\ldots s, k=1\ldots m)})$,

in a decentralised way:

• from the transmitting site (U),

• towards all remote local operators (S_u).

- independently, and repetitively, at each of the local operators (S_u), the majority of which are a great distance from the centralised transmitting site (U):

• said "*smp* probabilistic series" (W_{ij}^k) with a multi-value description of probable future pseudo-states or pseudo-variations including $s \times m \times p$ numerical values $(W_{ij}^k = X_{ij}^k$ or $\Delta X_{ij}^k)$ is collected,

• m' $(m' \leq m)$ time forecasts retained from the m said time forecasts $\left(t_k^{(k=1...m)}\right)$ are chosen,

• if necessary, as in case 2 in which only said "*smp* variational probabilistic series" (ΔX_{ij}^k) of variational sampling is received, said corresponding "*smp* probabilistic series" (X_{ij}^k) of pseudo-states consisting of pseudo-samplings of future states $(X_{ij}(t_k)^{(i=1...p,j=1...s,k=1...m)})$ (at least for the retained m' time forecasts (t_k)) is locally calculated,

• for each retained m' time forecast (t_k):

♦ according to the previously set local evaluation model (D_u), and for each s scenarios $(j = 1,...,s)$, the global value $(I_{uj}^k = D_u(\lambda_u, (X_{ij}(t_k))$ of the portfolio (P_u) is numerically calculated:

▪ for at least one particular value $(\lambda_u) = (\lambda_{u1},...,\lambda_{uq})$ of the quantities vector (λ_u) of held assets,

▪ for each simulated s p-uplets of state variables $(X_{ij}(t_k))$ that corresponds to said retained time forecast (t_k) of the probabilistic pseudo-state series $(X_{ij}(t_k)^{(j=1...s)})$,

▪ the corresponding simulated s pseudo-values of the portfolio $(I_{uj}(t_k, \lambda_u)) = D_u(\lambda_u, (X_j(t_k)^{(j=1...s)})$ are determined,

- the corresponding s values $(I_{uj}(t_k,\lambda_u)^{(j=1...s)})$ of the portfolio (P_u) are grouped together and arranged,
- the probability distribution (as a number or percentage) $(\Psi_u(I_u))$ of the local portfolio (P_u) value (I_u) in the configuration (λ_u) according to the local model (D_u) is calculated and memorised,
- a statistical calculation deduces the value of at least one chosen statistical parameter of adjustment $(V(\lambda_u))$ (such as average, spread type, Value at Risk, utility and so forth) that is characteristic of:
- the probability distribution $(\Psi(\lambda_u,I))$ for values $(I_u(t_k,\lambda_u)$,
- the vector $(\lambda_u)=(\lambda_{u1},...,\lambda_{uq})$ describing the portfolio (P_u),
- if necessary, at each local operator (S_u), a numerical optimisation (according to predetermined criteria) of one or many chosen statistical parameters of adjustment $(V(\lambda_u))$ is performed locally and the portfolio composition $(\lambda_u)=(\lambda_{u1},...,\lambda_{uq})$ of each local operator (S_u) is adjusted to a calculated optimal value in relation to predetermined criteria, notably in order to anticipate the future probable behaviour and yield of each portfolio (P_u) subjected to the market (E) during any one retained time forecast (t_k).

26. Process in accordance with claim 2 of repetitive stochastic simulation that is prioritised by the sampling of probable future pseudo-states of market variables for the probabilistic prediction of future

behaviour and/or the optimisation of productivity parameters of a number n (where n is much greater than » 1) of local financial operators $(S_u^{(u=1...n)})$:

- in that they are decentralised and a great distance from one another,

- in that each has a portfolio $(P_u^{(u=1...n)})$:

• consisting of financial assets $(\theta_h^{(h=1...q)})$,

• whose unit value $(I_h'^{(h=1...q)})$ depends upon capital market (E) fluctuations and is a function of a common market variables vector $(X(t)) = X_i(t)^{(i=1...p)})$ that varies throughout time (t) and from which it is possible for each remote local financial operator (S_u) to recreate, with acceptable precision, the value of all financial assets held in portfolios (P_u) of local players, according to a local evaluation model (D_u) (these market variables may include assets or commodities prices, interest rates or coefficients of yield curbs, volatilities or coefficients of volatility surfaces, default indicators from an issuer or counter-party, or any other number that can provide information pertaining to the state of capital markets),

• whose value $(I_u^{(u=1...n)})$ may be calculated with a scalar product between:

♦ the vector of unit values $(I') = (I_h'^{(h=1...q)})$.

♦ and for each remote local financial operator (S_u), a quantities vector $(\lambda_u) = (\lambda_{uh}{}^{(h=1...q)})$ of each financial asset $(\theta_h^{(h=1...q)})$ held in its portfolio (P_u):

$$D_u(\lambda_u, X) = (\lambda_u | I') \quad (***)$$

where $(I'_h) = (\pi_h(t, X(t), \theta_h))$ is the asset price (θ_h) at instant (t) according to the local model (D_u) when the market is in state $(X(t))$,

this process being of the type that consists of:

- at the expert site (U'), a great distance (of several kilometres, if not several hundred kilometres) from the majority of n local financial operators $(S_u^{(u=1...n)})$, the following previous choices are made:

• p market variables $((X_i)^{(i=1...p)})$ that describe the entire market (E),

• a statistical model of joint behaviour in time (t) and by time periods $(\Delta t_k^{(k=1...m)})$ of market variables $(X_i(t)^{(i=1...p)})$ that is described by its dense joint distribution $(f_\alpha(X_1,...,X_p;t;\Delta t_k))$:

♦ determined from historical observations that may include, in particular, normal laws, normal logs and so on, or more generally, a joint statistic distribution of p environment variables $(X_i(t_k)^{(i=1...p)})$ or their temporal variations $(\Delta X_i(t_k)^{(i=1...p)})$,

♦ validated through appropriate and classical statistic tests (averages, variances, correlations, breaks, extreme behaviours and so forth).

- at the centralised transmitting site (U), a great distance (of several kilometres, if not several hundred kilometres) from the majority of n remote local industrial systems $(S_u^{(u=1...n)})$:

• an "*smp* probabilistic series" (W_{ij}^{k}) with a multi-value description of probable future pseudo-states or pseudo-variations market (E) is numerically and repetitively generated at successive instants (t_o) by using the statistical model $(f_\alpha(X_1,...,X_p;t;\Delta t_k))$ retained from the joint statistical distribution model within the time (t) of market variables $(X_i^{(i=1...p)})$, and consisting of:

♦ case 1: an "*smp* probabilistic series" (X_{ij}^{k}) of pseudo-states formed by $s\times m$ p-uplets of a multi-value sampling for future pseudo-states $(X_{ij}(t_k)^{(i=1...p,j=1...s,k=1...m)})$ including $s\times m\times p$ numerical values and constitutes:

▪ for each m $(m\geq 1)$ time forecast $\left(t_k^{(k=1...m)}\right)$ of the simulation,

▪ s (where s is much greater than » 1) possible future pseudo-states of p market variables $(X_i(t_k)^{(i=1...p)})$.

♦ case 2: an "*smp* variational probabilistic series" (ΔX_{ij}^{k}) of pseduo-states formed by $s\times m$ p-uplets of a multi-value sampling for future pseudo-variations $(\Delta X_{ij}(t_k)^{(i=1...p,j=1...s,k=1...m)})$ including $s\times m\times p$ numerical values and constitutes:

▪ for each m $(m\geq 1)$ time forecast $\left(t_k^{(k=1...m)}\right)$ of the simulation,

▪ of s (where s is much greater than » 1) possible future pseudo-variations for p market variables $(X_i(t_k)^{(i=1...p)})$,

• for each pseudo-state market variables vector (X_j^k) an "*smq* probabilistic series" $(W_{hj}'^k)$ is calculated with a multi-value description of:

♦ case 1: probable future pseudo-prices of an asset

$$(I_{hj}'^{k(h=1\ldots q,j=1\ldots s,k=1\ldots m)}) = D(t_k, X_j(t_k), \theta_h)$$

♦ case 2: and/or resulting pseudo-variations $(\Delta I_{hj}'(t_k)^{(h=1\ldots q,j=1\ldots s,k=1\ldots m)})$,

the process being characterised in that, in combination:

- at the centralised transmitting site (U), a great distance from the majority of n remote local financial operators $(S_u^{(u=1\ldots n)})$, repetitively and at successive instants (t_o):

• said "*smq* probabilistic series" $(W_{hj}'^k)$ with a multi-value description of probable future pseudo-states or pseudo-variations including $s \times m \times p$ numerical pseudo-values is transmitted and consists of:

♦ case 1: said "*smq* probabilistic series" (I_{hj}') of pseudo-value asset prices $(I_{hj}'^{k(h=1\ldots q,j=1\ldots s,k=1\ldots m)})$,

♦ case 2: and/or said "*smq* variational probabilistic series" of pseudo-variations $(\Delta I_{hj}'^{k(h=1\ldots q,j=1\ldots s,k=1\ldots m)})$,

in a decentralised way:

♦ from the transmitting site (U),

♦ towards all remote local operators (S_u),

- independently, and repetitively, at each of the local operators (S_u), the majority of which are a great distance from the centralised transmitting site (U):

• said "*smq* probabilistic series" (W'^{k}_{hj}) with a multi-value description of probable future pseudo-states or pseudo-variations including $s \times m \times p$ numerical values $(W'^{k}_{hj} = I'^{k}_{hj}$ or $\Delta I'^{k}_{hj})$ is collected,

• m' $(m' \leq m)$ time forecasts retained from the m said time forecasts $\left(t_k^{(k=1...m)}\right)$ are chosen,

• if necessary, as in case 2 in which only said "*smq* variational probabilistic series" $(\Delta I'^{k}_{hj})$ of variational sampling $(\Delta I'_{hj}(t_k))$ is received, said corresponding "*smq* probabilistic series" (I'^{k}_{hj}) of pseudo-states consisting of pseudo-samplings of future states $(I'_{hj}(t_k)^{(h=1...q,j=1...s,k=1...m)})$ (at least for the retained m' time forecasts (t_k)) is locally calculated,

• for each retained m' time forecast (t_k):

♦ according to the previously set local evaluation model (D_u), and for each s scenarios $(j=1,...,s)$, the global value $(I^{k}_{uj}) = (\lambda_u | I'^{k}_{j})$ of the portfolio (P_u) is numerically calculated:

▪ for at least one particular value $(\lambda_u) = (\lambda_{u1},...,\lambda_{uq})$ of the quantities vector of held assets,

▪ for each simulated s p-uplets of price assets $(I'_{hj}(t_k))$ that corresponds to said retained time forecast

(t_k) of the probabilistic pseudo-state series $(I'_{hj}(t_k)^{(j=1...s)})$,

the corresponding simulated s pseudo-values of the portfolio $(I_{uj}(t_k,\lambda_u))=(\lambda_u|I'^{k}_{j}{}^{(j=1...s)})$ are determined,

- for value $(\lambda_u)=(\lambda_{u1},...,\lambda_{uq})$ of the retained local actions parameter:
- the corresponding s values $(I_{uj}(t_k,\lambda_u)^{(j=1...s)})$ of the portfolio (P_u) are grouped together and arranged,
- the histogram (Γ_u) and probability distribution (as a number or percentage) $(\Psi_u(I_u))$ of the local portfolio (P_u) value (I_u) in the configuration (λ_u) according to the local model (D_u) are calculated and memorised,
- a statistical calculation deduces the value of at least one chosen statistical parameter of adjustment $(V(\lambda_u))$ (such as average, spread type, Value at Risk, utility and so forth) that is characteristic of:
- the probability distribution $(\Psi(\lambda_u,I_u))$ for values $(I_u(t_k,\lambda_u)$,
- in relation to the vector $(\lambda_u)=(\lambda_{u1},...,\lambda_{uq})$ describing the portfolio (P_u),
- if necessary, at each local operator (S_u), a numerical optimisation (according to predetermined criteria) of one or many chosen statistical parameters of adjustment $(V(\lambda_u))$ is performed locally and the portfolio composition $(\lambda_u)=(\lambda_{u1},...,\lambda_{uq})$ of each local operator (S_u) is adjusted to a calculated optimal value

in relation to predetermined criteria, notably in order to anticipate the future probable behaviour and yield of each portfolio (P_u) subjected to the market (E) during any one retained time forecast (t_k).

27. Process in accordance with claim 25 of repetitive stochastic simulation that is prioritised by the sampling of probable future pseudo-states of market variables for the probabilistic prediction of future behaviour and/or the optimisation of productivity parameters of a number n (where n is much greater than » 1) of local financial operators $(S_u^{(u=1...n)})$, this process being characterised in that:

- the value (I_{uj}^{k}) of a financial operator's (S_u) portfolio (P_u) at a future date (t_k) according to the model (D_u) and within the state of the simulated market $(X_j(t_k))$ that corresponds to scenario j is evaluated by taking the simulated market states in the same scenario j at subsequent dates $(t_l^{(l=k+1...m)})$ into account in the model (D_u) according to the following principle:

• each financial asset $(\theta_h^{(h=1...q)})$ has a defined maximum quantity (ν_h) with which it is able to trade (to buy or to sell) within a day,

• if none of the asset (θ_h) quantities (λ_{uh}) held in the portfolios (P_u) exceeds the limit value (ν_h) in absolute terms, then formula (***) with date and within simulation is used to assess portfolio (P_u) value (I_{uj}^{k}):

$$I^{k}_{u,j}=\sum_{h=1}^{q}\lambda_{uh}\pi_{h}(t_k,X_j(t_k),\theta_h)$$

• if one of the asset (θ_h) quantities (λ_{uh}) held in one of the portfolios (P_u) exceeds the limit value (ν_h) in absolute terms, then the quantity (λ_{uh}) is replaced by (ν_h) modified by its sign, at date (t_k), and the overhang $(\lambda_{uh} \pm \nu_h)$ is reported for the following day (t_{k+1}) by using the market variables vector $(X_j(t_{k+1}))$,

• if this quantity is still above the limit (ν_h) in absolute terms, it is then set to the maximum value with the same sign, and the overhang $(\lambda_{uh} \pm 2\nu_h)$ is again reported for the following day (t_{k+2}) by using the market variables vector $(X_j(t_{k+2}))$, and so on and so forth,

this particular arrangement allows the liquidity risk to be taken into account by imposing upper bound constraints to the quantity of each asset (θ_h) that can be rightly assessed according to the local model (D_u) at any given date (t_k), and thus leading to a possible carrying over of the resulting virtual position within each simulation over subsequent dates.