MAINTENANCE OF A TRAFFIC SIGNAL LIGHTS BASED ON PORTFOLIO MODEL

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Abstract: Traffic signals have been considered a way to improve traffic safety and traffic operations at intersections. This research deals with a significant and effective method to decide the investment for intersection to implement light emitting diodes (LED) signals retrofit. Structural learning method is proposed for a mutual connective neural network in this research. The proposed method enables us to solve problems defined in terms of mixed integer quadratic programming. In this research, an analysis is performed using the concepts of reliability and risks of units evaluated with a variance-covariance matrix and also the effect and expenses of replacement are measured. Mean-variance analysis is formulated as a mathematical programming with the following multiple objectives: (i) to minimize the risk and (ii) to maximize the expected return. Finally, we employ a meta-controlled Boltzmann machine to solve the mean-variance analysis efficiently. The application of the proposed method is illustrated using a LED signal retrofit in Hiroshima Prefecture. The proposed method enables us to obtain a more effective selection of results and enhance the effectiveness of decision making. As conclusions, decision makers can select the investment rate and risk of each intersection within a given total budget.

Keywords: Boltzmann machine, Mean-variance analysis, Structural learning.

1. INTRODUCTION

Traffic crashes bring out tragic loss of lives, cost many countries tremendous amount of money, and produce substantial congestion to a nation's transportation system. Large percentage of traffic accidents occurs at or near intersections [Yong-Kul and Dong-Young, 2007]. Pernia indicates that intersections-related crashes make up a very high percentage of the total number of crashes in the roadway system. For example, in the United States, the national statistics shows that 22.87 percent of all fatal crashes occurred at intersections or intersection-related locations. Traffic signals have been a way to improve traffic safety and traffic operations at intersections [Pernia et al, 2004].

In order to improve traffic safety and traffic operations at intersections, due to the many advantages of operation and energy consumption, Light Emitting Diode (LED) traffic light is preferred [Traffic Eng. Div., Dept. of Public Works City of Little Rock, Arkansas, US, 2003]. LED traffic lights, whose advantages - compared to conventional light bulb traffic lights - include the significantly reduction of electric power consumption, the dramatic saving of lower maintenance costs and the improvement of safety due to greater brightness, were so impressive even after a short time that soon further junctions were equipped with LED traffic lights.

Despite their excellent performance, several barriers hinder more rapid retrofit such as high retrofit cost and capital constraints. Thus, one of the most significant challenges in retrofit strategy is to decide which intersection to signalize with LEDs, which to keep on the table. We provide a method for selecting intersections not through traditional effectiveness measures like cost and performance, but instead through a quantitative analysis of the embedded uncertainty in each potential intersection. Cost and performance in this approach remain central themes in decision making, but uncertainty serves as the focal point to identify potentially powerful combinations of intersections to explore concurrently in decision phases. Presented is a method to identify and quantify uncertainty in intersections, as well as a means to manage it using mean-variance analysis (portfolio theory) and optimization. Perhaps best known to economists and investors, portfolio theory is based on the objective of minimizing risk subject to a decision maker's sufficient return considering his or her risk aversion. This simple concept, as well as the theoretical accuracy that has evolved the theory to practice, is presented as one means of exploring the retrofit strategy of potential intersections around the central theme of uncertainty.

A mean-variance approach is proposed to change the situation of investing a large amount of money on maintenance and repair based on accident rates. We intend to invest using the frequency of accidents under the consideration of past data.

Portfolio theory treats a mathematical allocation problem of a given amount of money among several different available investments, such as stocks, bonds and securities. This is named the portfolio selection problem. Markowitz originally proposed and formulated the mean-variance approach on the basis of the portfolio selection problem [Markowitz, 1978; Jiang et al, 2006]. That is, on the basis of the time series of return rates, the theoretical method enables us to determine the highest investment rate, which minimizes the risk or variance of profit, affirming the highest rate of the expected return which a decision maker expects. This method is formulated as a quadratic programming. In this paper, a portfolio selection problem is formulated as a mathematical programming with two objectives to minimize risk and maximize the expected return, since the efficient frontier should be considered in the discussion of a portfolio selection. Yang et al. 2004 proposed the multi-objective programming model of portfolio and compute the optimal solution with some methods by neural network.

A Hopfield network and a Boltzmann machine are used to find an optimal solution [Jurado and Penas, 2007]. In this paper, we applied the concepts of a Boltzmann machine to solve the portfolio selection problem efficiently. The Boltzmann machine [Ackley, 1985] is an interconnected neural network proposed by G. E. Hinton. The Boltzmann machine is a model that improves a Hopfield network using probability rule to update the state of a neuron and its energy function. Thus, the energy function of the Boltzmann machine hardly falls into a local minimum. For that reason, if we transform the objective function of a portfolio selection problem into an energy function of the Boltzmann machine, it enables us to solve the portfolio selection problem as its highly approximate solution. And then, the output value of each unit represents the investing rate to each stock. In the conventional method to solve portfolio selections, the investing rate to each stock is decided to realize the minimum risk under the constraints that the goal rate of an expected return given by a decision maker should be guaranteed. But in this proposed method, the objective of solving a portfolio selection problem is not only to minimize its risk but also to maximize the expected return rate. Therefore, the Boltzmann machine can provide the investment rate for each intersection using the output of each unit of the neural network. Retrofit traffic signals investment problems are presented in order to demonstrate the effectiveness of our proposal.

The rest of this paper is organized as follows: Section 2 is an overview on retrofit traffic signals with LED lamps and Section 3 describes mean-variance analysis. Section 4 present structural learning and Section 5 shows an examples. Finally, concluding remarks are shown in Section 6.

2. OVERVIEW ON RETROFIT TRAFFIC SIGNALS WITH LED LAMPS

Traffic signals have been considered a way to improve traffic safety and traffic operations at intersections. Intersections induce more attention for safety analyses than other roadway elements due to the fact many intersections are found to be relatively crash-prone spots from safety point of view. Each year, the number of traffic crashes occurred has been increased. According to the Traffic Safety Facts 2002, in United States, there were 6,316,000 estimated traffic crashes in 2002 [Pernia et al, 2004].

LED lamps have been developed to replace conventional incandescent or fluorescent lamps for increasing reliability and reducing electrical and maintenance costs. The new traffic lights are made out off arrays of LED signals. These are tiny, purely electronic light that are extremely energy efficient and have a very long life. Each LED is about size of a pencil eraser, so hundreds of them are used together in an array. The LED signals are replacing the conventional incandescent halogen bulbs rated at between 50 and 150 watts. Three main advantages of LED signals:

- LED signals are brighter than conventional signals, which enhances intersection safety.
- Due to their low wattage, LED signals consume significantly less power, which results in lower energy bills.
- LED signals can be expected to run for at least 10 years.

In Japan, there are roughly 2 million traffic signal systems. Japan government supports 50 percent of changing expenditure for each regional government. Now 10 percent of all systems was already changed to LED type, but the cost of LED type is 1.5 times more expensive than conventional tube type. Japan Economy Newspaper (NIKKEI) on November 21 2007 reported that the traffic accidents were reduced about 30 percent from 2001 to 2005 due to the usage of LED type that has an advantage to eliminate phantom effect during morning and evening hours. In the same report also indicates that Japan National Police Agency decided to change gradually conventional type traffic signal to LED type for major highway from 2007.

There appears to be growing acceptance of LED signals as viable light sources for traffic signals, and a growing awareness of the potential maintenance and energy savings achievable with LED signals, but many self-governing bodies face significant capital constrains. And huge numbers of intersections could not be replaced simultaneously. These are disincentives within local governments to perform LED retrofits despite their potential lifecycle cost benefits. Thus, jurisdictions have to selectively implement LED signals retrofit to enhance traffic security and operate more cost-effectively.

3. MEAN-VARIANCE ANALYSIS

Mean Variance Analysis deals with a problem to decide for a given collection of assets an investment with desirable features. A variety of different asset characteristics can be taken into consideration, such as the amount of value, on average, an asset returns on over a period of time and the riskiness of reaping returns comparable to the average. The financial objectives of an investor and tolerance of risk determine what types of portfolios are to considered desirable [Markowitz, 1987], [Watanabe, 1999], [Konno and Suzuki, 1992]. In this section we shall introduce the methods of constrained optimization to construct portfolios for a given collection of assets with desirable features as quantified by an appropriate utility function and constraints.

3.1. Characterizing the Return Rates of Assets and Portfolios

We shall mainly concern with the following two basic characteristics of an asset: (i) the average return of an asset over a period of time and (ii) how risky it is to obtain similar returns comparable to the average over the investment period. The return rate ρ for an asset with value S(0) at time 0 and value S(T) at time T, is defined by

$$S(T) = (1+\rho)S(0) \quad \textbf{(1)}$$

The rate of return can be thought of as an "effective interest rate" which would be required for a deposit of *S*(0) into account at a bank to obtain the same change in value as the asset over the period [0, *T*]. As the outcome of an investment in an asset has some level of uncertainty, the value *S(T)* is unknown exactly at time 0. In order to model the uncertainty we shall take the value of the asset at time T for a random variable. In the same way, return rate ρ defined by equation (1) is also a random variable. To characterize the asset we shall consider the average rate of return, μ , defined by

$$\mu = E(\rho), \quad \textbf{(2)}$$

where $E(\rho)$ denotes the expectation of a random variable. In order to capture the riskiness of the asset and to quantify how much the rate of return deviates from the expected return, the variance is defined

$$\sigma^2 = Var(\rho) = E(|\rho - \mu|^2). \quad \textbf{(3)}$$

The return rate of the i^{th} asset denoted by ρ^i and the variance by σ_i^2 for a given collection of n assets $\{S_1, S_2, ..., S_n\}$. In addition, it is useful to consider how the random rates of return are coupled for a collection of assets. To measure this for random rates of return we shall use the covariance for the returns defined by

$$\sigma_{i,j} = E\big((\rho_i - \mu_i)(\rho_j - \mu_j)\big). \quad \textbf{(4)}$$

It is noted that $\sigma_{i,j} = \sigma_{j,i}$ and that when $i = j$, $\sigma_{i,i} = \sigma_i^2$. To describe the coupling of all n assets, a covariance matrix is defined by

$$V = \begin{pmatrix} \sigma_{1,1} & \sigma_{1,2} & \dots & \sigma_{1,n} \\ . & . & & . \\ . & . & & . \\ \sigma_{n,1} & \sigma_{n,2} & \dots & \sigma_{n,n} \end{pmatrix}. \quad \textbf{(5)}$$

V is a symmetric matrix and positive definite.

A portfolio is an investment made in n assets using some amount of wealth W. Let W_i denote the amount of money invested to the i^{th} asset. Negative values of W_i, can be interpreted as short selling an asset. Since the total wealth invested is W

$$\sum_{i=1}^{n} W_i = W. \quad \textbf{(6)}$$

In order to avoid dealing with absolute magnitudes of the assets and portfolios, it is convenient to instead describe the investments in terms of relative values such as the rates of return of the assets and the relative portion of wealth invested in a given asset. The fraction of wealth invested to the i^{th} asset is defined as

$$w_i = \frac{W_i}{W}\ . \tag{7}$$

Equation (6) then implies

$$\sum_{i=1}^{n} w_i = 1. \tag{8}$$

The value Q_p of the portfolio at time t can be expressed as

$$Q_p(t) = \sum_{i=1}^{n} \frac{W_i}{S_i(0)} S_i(t), \tag{9}$$

where the portfolio has the value $Q_p(0)$ = W from equation (6). The rate of return of the portfolio ρ_p at time t is given by

$$\begin{aligned}\rho_p(t) &= \frac{Q_p(t) - Q_p(0)}{Q_p(0)} \\ &= \frac{\sum_{i=1}^{n} \frac{W_i}{S_i(0)} S_i(t) - W}{W} \\ &= \sum_{i=1}^{n} \frac{W_i}{W} \frac{S_i(t)}{S_i(0)} - \sum_{i=1}^{n} \frac{W_i}{W} \\ &= \sum_{i=1}^{n} w_i \frac{(S_i(t) - S_i(0))}{S_i(0)} \\ &= \sum_{i=1}^{n} w_i \rho_i\ .\end{aligned} \tag{10}$$

In other words, return rate for a portfolio is the weighted average of the rates of return of the assets. The weights are determined by the fraction of wealth invested in each asset.

The expected rate of return μ_p of the portfolio is given by

$$\begin{aligned}\mu_p &= E\left(\sum_{i=1}^{n} w_i \rho_i\right) \\ &= \sum_{i=1}^{n} w_i \mu_i;\end{aligned} \tag{11}$$

where the linearity property of expectations has been used. The variance σ_p^2 for the rate of return of the portfolio is given by

$$\begin{aligned}\sigma_p^2 &= E(|\rho_p - \mu_p|^2)\ldots \\ &= E\left(|\sum_{i=1}^{n} w_i(\rho_i - \mu_i)|^2\right) \\ &= E\left(\left(|\sum_{i=1}^{n} w_i(\rho_i - \mu_i)|\right)\left(|\sum_{j=1}^{n} w_j(\rho_j - \mu_j)|\right)\right) \\ &= \sum_{i,j=1}^{n} w_i w_j E\big((\rho_i - \mu_i)(\rho_j - \mu_j)\big) \\ &= \sum_{i,j=1}^{n} w_i w_j \sigma_{i,j} \\ &= \mathbf{w}^T V \mathbf{w},\end{aligned} \tag{12}$$

where $\mathbf{w}^T = [w_1, \ldots, w_N]$ and V is defined in equation (5). In case where portfolios a and b, the coupling between two portfolios is quantitatively described by the covariance of the random rates of returns of the two portfolios $\rho_p^{(a)}$ and $\rho_p^{(b)}$. This is given by

$$\begin{aligned}\sigma^{(a,b)} &= E\left(\left(\rho_p^{(a)} - \mu_p^{(a)}\right)\left(\rho_p^{(b)} - \mu_p^{(b)}\right)\right) \\ &= E\left(\left(|\sum_{i=1}^{n} w_i^{(a)}(\rho_i - \mu_i)|\right)\left(|\sum_{j=1}^{n} w_j^{(b)}(\rho_j - \mu_j)|\right)\right) \\ &= \sum_{i,j=1}^{n} w_i^{(a)} w_j^{(b)} E\big((\rho_i - \mu_i)(\rho_j - \mu_j)\big) \\ &= \sum_{i,j=1}^{n} w_i^{(a)} w_j^{(b)} \sigma_{i,j} \\ &= \left(\mathbf{w}_p^{(a)}\right)^{\mathbf{T}} V \mathbf{w}_p^{(b)}.\end{aligned} \tag{13}$$

To summarize, the average return rate, riskiness in obtaining comparable returns to the average, and coupling among the returns for both portfolios and individual assets are characterized. This will be done quantitatively by using, respectively, the expected rate of return, variance of the return, and covariance of the returns.

3.2. Portfolio Theory

Determining what constitutes a desirable portfolio depends on various factors. The main factors we shall consider are the financial objectives of the investor and his or her tolerance for risk in achieving these objectives. If an investor is presented with two assets, the investor would choose the one that having the larger variance only if this also entails having a larger expected return. This larger expected return acts as an incentive for the investor; this is referred to as a "risk premium" which compensates the investor for taking the larger risk. Another way to think about these preferences in our theory is that if the two assets had the same expected rate of return, then an investor would choose the one with the smallest variance (least risk). Through this understanding about the preferences of the investor, we shall consider a portfolio to be desirable if for a given expected rate of return μ_p the portfolio has the least variance ρ_p^2. Finding such a portfolio is referred to as the Markowitz problem and can be stated mathematically as the constrained optimization problem

$$\text{minimize}(w_i,\ldots,w_n) = \frac{1}{2}\sum_{i,j=1}^{n} w_i w_j \sigma_{i,j}$$

$$\text{subject to}(w_i,\ldots,w_n) = \sum_{i=1}^{n} w_i \mu_i - \mu_p = 0 \qquad \textbf{(14)}$$

$$(w_i,\ldots,w_n) = \sum_{i-1}^{n} \mathrm{w_i} - 1 = 0$$

The objective function is the variance of the portfolio, as computed in equation (12). The first constraint specifies that the constructed portfolio is to have expected rate of return μ_p while the second constraint arises from equation (8) defining the portfolio. In order to solve the constrained optimization problem analytically, we can employ the method of structure learning. Many numerical methods can also exist for these types of optimization problems.

4. STRUCTURAL LEARNING

4.1. Mean-variance Analysis

A mean-variance analysis is widely used as investment theory proposed by H. Markowitz in the early 1950s as mentioned in Section 3. In the formulation of mean-variance analysis, H. Markowitz started his discussion with the assumption that almost all decision makers have aversion to risk even if its return may be obtained less. However, it should be difficult to identify a utility function because they have a different utility structure of their own. So, H. Markowitz has formulated a mean-variance analysis as the following quadratic programming problem under the restriction that the expected return rate must be more than certain amount.

[Formulation 1]

$$\text{minimize} \sum_{i=1}^{n}\sum_{j=1}^{n} \sigma_{ij} x_i x_j \qquad \textbf{(15)}$$

$$\text{subject to} \sum_{i=1}^{n} \mu_i x_i \geq R \qquad \textbf{(16)}$$

$$\sum_{i=1}^{n} x_i = 1 \qquad \textbf{(17)}$$

$$x_i \geq 0 \ (i=1, 2, \ldots, n) \qquad \textbf{(18)}$$

where R denotes an acceptable least rate of the expected return, σ_{ij} a covariance between stock i and stock j, μ_i an expected return rate of stock i, and x_i an investing rate to stock i, respectively. In Formulation 1, the optimal solution with the least risk is searched under the constraint that the expected return rate should be more than the value a decision-maker arbitrarily gives. The investing rate to each of the stocks is decided for the solution with the least risk to the given expected return rate. Since the risk is estimated under the condition of fixing the rate of the expected return, the decision-maker cannot be fully satisfied of its solution. Therefore, the following Formulation 2 is much more proper and reasonable rather than Formulation 1.

[Formulation 2]

$$\text{maximize} \sum_{i=1}^{n} \mu_i x_i \qquad \textbf{(19)}$$

$$\text{minimize} \sum_{i=1}^{n}\sum_{j=1}^{n} \sigma_{ij} x_i x_j \qquad \textbf{(20)}$$

$$\text{subject to} \sum_{i=1}^{n} x_i = 1 \qquad \textbf{(21)}$$

$$x_i \geq 0 \ (i=1, 2, \ldots, n). \qquad \textbf{(22)}$$

Formulation 2 is a quadratic programming problem with two objective functions of an expected return rate and a degree of risk.

4.2. Boltzmann Machine

A Boltzmann machine is an interconnected neural network proposed by G. E. Hinton in 1984 [Ackley, 1985]. This model is based on a Hopfield network. The Boltzmann machine is a model that improves a Hopfield network by means of probability rules which are employed to update its state of the neuron and the energy function.

If $V_i(t+1)$ is an output value of neuron i in next time $t+1$, $V_i(t+1)$is 1 according to probability P which is shown in the following. On the other hand, $V_i(t+1)$ is 0 according to probability $1 - P$

$$P[V_i(t+1)] = f(\frac{u_i(t)}{T}), \qquad \textbf{(23)}$$

where $f(\cdot)$ is a sigmoid function, $u_i(t)$ is the total of input values to neuron i shown in equation (24) and T is a parameter which is called temperature of the network.

$$u_i(t) = \sum_{j=1} w_{ij} V_i(t) + \theta_i \quad , \qquad \textbf{(24)}$$

where w_{ij} is a weight between neurons i and j, θ_i is a threshold of neuron i.

The energy function E, which is proposed by J. J. Hopfield, is written in the following equation:

$$E = \frac{1}{2}\sum_{ij=1}^{n} w_{ij} V_i V_j - \sum_{i=1}^{n} \theta_i V_i \quad . \qquad \textbf{(25)}$$

J. J. Hopfield has shown that this energy function simply decreases as the neural network works [Hopfield, 1982]. There is possibility that this energy function converges to a local minimum. But in the case of the Boltzmann machine, the energy function can increase with minute probability. Therefore, the energy function hardly falls into a local minimum.

4.3. Boltzmann Approach to Mean-Variance Analysis

In this section, we explain how to solve a mean-variance analysis using a Boltzmann machine [Watada, 1997], [Watanabe, 1999], [Watada and Oda, 2000]. We transform the mean-variance model shown by Formulation 1 or 2 into its energy function of the Boltzmann machine. So, we describe how to transform the mean-variance analysis into the energy function as mentioned below.

First, we transform the objective function which is shown as equation (15) or (20) into the energy function in the following equation (25).

$$E = -\frac{1}{2}(\sum_{i=1}^{n}\sum_{j=1}^{n} \sigma_{ij} x_i x_j) . \qquad \textbf{(26)}$$

In the next step, we show a condition that the total of investment rates of all stocks is 1 (Note that the investment rate of each stock is not less than 0). The condition can be expressed as follows

$$(\sum_{i=1}^{n} x_i - 1)^2 . \qquad \textbf{(27)}$$

And equation (27) can be rewritten as follows

$$\sum_{i=1}^{n}\sum_{j=1}^{n} x_i x_j - 2\sum_{i=1}^{n} x_i + 1 . \qquad \textbf{(28)}$$

Then as we can transform this equation into equation (26), equation (26) is rewritten as follows

$$E = -\frac{1}{2}(\sum_{i=1}^{n}\sum_{j=1}^{n} \sigma_{ij} x_i x_j - \sum_{i=1}^{n}\sum_{j=1}^{n} x_i x_j) - \sum_{i=1}^{n} x_i . \qquad \textbf{(29)}$$

Finally, we consider about the expected return. The equation of the expected return is shown as equation (16) or (19). Therefore, we can transform equation (16) or (19) into equation (29):

$$E = -\frac{1}{2}(\sum_{i=1}^{n}\sum_{j=1}^{n} \sigma_{ij} x_i x_j - \sum_{i=1}^{n}\sum_{j=1}^{n} x_i x_j) \qquad \textbf{(30)}$$

$$-\sum_{i=1}^{n} x_i + K\sum_{i=1}^{n} \mu_i x_i ,$$

where K is a real number which is not less than 0. If value K is set to a larger number, the expected return is evaluated much more than the risk. And then, if we determine K=1.0, then the Boltzmann machine converges into a problem of minimizing its risk. When the energy function of the Boltzmann machine described in this section converges into the global minimum, we can obtain the investing rate to stocks by the output value of each unit.

The algorithm of the Boltzmann machine is executed as shown in Fig.1.

Step 1. Give the initial value of all units optionally.
Step 2. Choose a certain unit (i) out of all units at random.
Step 3. Compute a total of the input $u_i(t)$ into the chosen unit i ($1 \le i$).
Step 4. Add a sufficiently small value to the output value $V_i(t+1)$ of unit i according to the probability P shown in equation (9). And subtract a sufficiently small value from the output value with probability $1-P$. But the output value isn't varied in the case $u_i(t)=0$.
Step 5. The output value of units j except i aren't varied.
Step 6. After iterating from Steps 2 to 5, compute the probability of each unit for all units.

Fig.1 Boltzmann machines' algorithm

4.4. Meta-controlled Boltzmann Machine

The meta-controlled Boltzmann machine is a neural network model, which is proposed by T. Watanabe and J. Watada [Watanabe, 2004]. This model deletes the units of the lower layer, which are not selected in the meta-controlling layer in its execution. Then the lower layer is restructured using the selected units. Because of this feature, the meta-controlled Boltzmann machine converges more efficiently than a conventional Boltzmann machine. This is an efficient method for solving a portfolio selection problem by transforming its objective function into the energy function since the Hopfield and Boltzmann machines converge at the minimum point of the energy function.

The meta-controlled Boltzmann machine mentioned above converted the objective function into the energy functions of the two components that are Meta-controlling layer (Hopfield network) E_u and the Lower-layer (Boltzmann machine) E_l as described below:

Meta-Controlling Layer (Hopfield network)

$$E_u = -\frac{1}{2}\sum_{i=j}^{n}\sum_{j=1}^{n}\sigma_{ij}s_i s_j + K_u\sum_{i=1}^{n}\mu_i s_i \qquad \textbf{(31)}$$

Lower Layer (Boltzmann machine)

$$E_l = -\frac{1}{2}\left(\sum_{i=1}^{n}\sum_{j=1}^{n}\sigma_{ij}x_i x_j + 2\sum_{i=1}^{n}\sum_{j=1}^{n}x_i x_j\right) \qquad \textbf{(32)}$$

$$+2\sum_{i=1}^{n}x_i + K_l\sum_{i=1}^{n}\mu_i x_i \,,$$

where K_u and K_l are weights of the expected return rate for each layer and s_i is the output value of the i^{th} unit of the meta-controlling layer. The algorithm of meta-controlled Boltzmann machine is described as in Fig. 2, and is shown in Fig. 3.

Step 1. Set each parameter to its initial value.
Step 2. Input the values of K_u and K_l.
Step 3. Execute the meta-controlling layer.
Step 4. If the output value of a unit in the meta-controlling layer is 1, add some amount of value to the corresponding unit in the lower layer. Execute the lower layer.
Step 5. After executing the lower layer the constant number of times, decreases the temperature.
Step 6. If the output value is sufficiently large, add a certain amount of value to the corresponding unit in the meta-controlling layer.
Step 7. Iterate from Step 3 to Step 6 until the temperature reaches the restructuring temperature.
Step 8. Restructure the lower layer using the selected units of the meta-controlling layer.
Step 9. Execute the lower layer until reaching at the termination.

Fig.2 Meta-controlled Boltzmann machines' algorithm

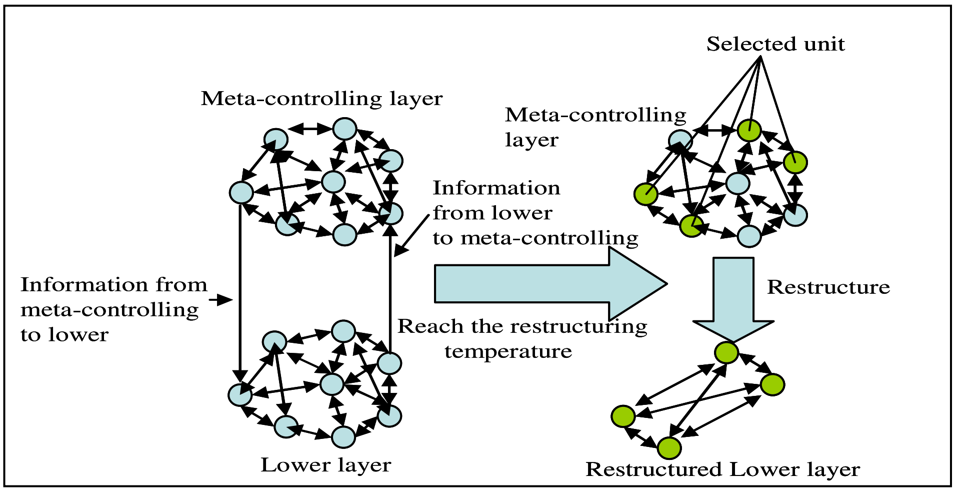

Fig. 3. Meta-controlled Boltzmann machine

5. EXAMPLES

We take 10 intersections in Hiroshima with their 8 years accident numbers into account, in which portfolios of retrofit can be analyzed and optimized. Proposed is an effective retrofit strategy where risk, measured by the variance in accident numbers, is considered together with accident mean. Our analysis of trade-off between accident numbers mean and variance employs mean-variance analysis and meta-controlled Boltzmann machine which is considerably efficient as the number of intersections dramatically increases. It seemed obviously that investors are concerned with risk and return, and that these should be measured for the portfolio as a whole. Variance (or, equivalently, standard deviation), came to mind as a measure of risk of the portfolio. The fact that the variance of the portfolio, that is the variance of a weighted sum, involved all covariance terms added to the plausibility of the approach. Since there were two criteria - expected return and risk - the natural approach for an economics program was to imagine the investor selecting a point from the set of optimal expected return, variance of return combinations, now known as the efficient frontier. In this section we employ meta-controlled Boltzmann machine as an efficient model to solve this trade-off.

The simulation parameters employed are in the following step:

1. The temperature T of the Boltzmann machine is changed from 100 ^{0}C to 0.00001 ^{0}C. The change in temperature is performed every Y performances to set the temperature. Nevertheless, Y is also changed each 10,000.
2. The modification interval per one performance is 0.0001.
3. The initial setting for each unit is to 0.1. The $K = K_u = K_l$ values are determined for 0.3, 0.5, 0.7 and 1.0 where K_u is weight of the expected return rate for the meta-controlling layer and K_l is weight of the expected return rate for lower layer.

The implementation procedure of the proposed method is described as in the following five steps:

Step 1. Identifying the Right Uncertainty

Identifying the right uncertainties is the first step in mean-variance analysis. The right uncertainty will have the following characteristics. The characteristic of an uncertainty that should be included in the analysis is one that differentiates one asset from another. An example of this characteristic can be found in a set of intersections that they don't rely on the same security. For example, accidents occurred in Intersection1 by a mean number of 21, but Intersection 9 by a number of 12. Security is just one source of differentiating uncertainty, policy, market conditions or manufacturing capability are others. In our case, we select 10 intersections around Fukuyama station as shown in Fig. 4.

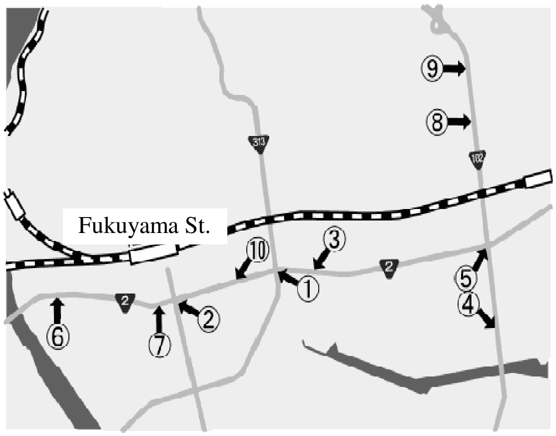

Fig. 4. Location of intersections

Step 2. Quantifying Individual Uncertainties

Once the relevant sources of uncertainty have been identified, the next step is to apply some level of probability and impact to them. Some individual uncertainties can be very straightforward to quantify. For example, if the security model being used is based on the historical data, this model typically have standard deviations that can be included as security modeling uncertainty. Uncertainty identified by security is quantified based on 8 years accident numbers. Table 1 shows historical accident numbers of 10 intersections as shown in Fig. 4. Other uncertainties might not be so straightforward to quantify. These could arise from market conditions, policy uncertainty, new technology or novel architectural concepts.

Table 1. Accident numbers in intersections

	1998	1999	2000	2001	2002	2003	2004	2005	Mean
Int.1	18	28	21	17	18	22	20	24	21.0000
Int.2	20	14	17	20	15	24	18	22	18.7500
Int.3	13	19	20	13	20	14	17	14	16.2500
Int.4	19	20	17	12	16	18	16	13	16.3750
Int.5	19	12	11	19	17	13	10	12	14.1250
Int.6	11	19	10	9	14	11	16	10	12.5000
Int.7	10	14	8	12	10	4	7	9	9.2500
Int.8	15	17	16	7	11	17	15	13	13.8750
Int.9	13	15	7	9	15	14	11	12	12.0000
Int.10	10	6	13	11	9	10	15	12	10.7500

Note: Int. represents Intersection

Step 3. Post-processing the Uncertainties

Once the uncertainties have been quantified for each alternative, it is necessary to post-process and feed the data to the next step in the approach, mean-variance analysis. At this point statistics of each distribution should be calculated. This includes standard measures of expected value and standard deviation or variance.

Once individual distributions have been investigated, the set of distributions also needs to be post processed to develop the covariance matrices for use in implementing the portfolio optimization. The covariance matrix represents the relative independence of the assets, as well as the uncertainty of the assets. The matrix is created, as shown in Fig. 5, by placing the variance of assets on the diagonal and using pair-wise covariance, as calculated in (33), on the off-diagonals.

$$\sigma_{x_1,x_2} = \rho_{x_1,x_2}\sigma_{x_1}\sigma_{x_2}. \qquad \textbf{(33)}$$

$$\begin{array}{ccccccc}
Assets & X_1 & X_2 & X_3 & \bullet & \bullet & X_n \\
X_1 & \sigma_1^2 & \rho_{12}\sigma_1\sigma_2 & \rho_{13}\sigma_1\sigma_3 & \bullet & \bullet & \bullet \\
X_2 & \rho_{12}\sigma_1\sigma_2 & \sigma_2^2 & \rho_{23}\sigma_2\sigma_3 & \bullet & \bullet & \bullet \\
X_3 & \rho_{13}\sigma_1\sigma_3 & \rho_{23}\sigma_2\sigma_3 & \sigma_3^2 & \bullet & \bullet & \bullet \\
\bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet \\
\bullet & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet \\
X_n & \bullet & \bullet & \bullet & \bullet & \bullet & \bullet
\end{array}$$

Fig. 5. Covariance matrix Q

Table 2 shows the covariance matrix of 10 intersections that used in this case study.

Step 4. Applied Portfolio Theory

In order to enable the decision maker implement LED signals retrofit at an optimal set of assets to pursue that maximize return while at the same time consider his aversion to risk. The specific class of optimization is quadratic optimization based on an appropriate balance of risk and returns. These risks and returns are typically derived from historical accident numbers in intersections historically. The quadratic programming problem can be solved by a method named mean-variance analysis employed meta-controlled Boltzmann machine efficiently.

Table2. Covariance Matrix of 10 intersections

	Int.1	Int.2	Int.3	Int.4	Int.5	Int.6	Int.7	Int.8	Int.9	Int.10
Int.1	11.750	-1.875	2.625	3.500	-7.625	5.875	1.750	6.750	3.000	-3.500
Int.2	-1.875	10.188	-7.688	-2.656	0.906	-7.125	-5.688	-0.281	-1.000	2.688
Int.3	2.625	-7.688	8.438	2.531	-4.281	5.250	1.313	2.531	0.250	-0.938
Int.4	3.500	-2.656	2.531	6.734	-1.547	4.688	-0.094	6.797	3.250	-3.156
Int.5	-7.625	0.906	-4.281	-1.547	11.609	-4.188	3.594	-6.984	1.250	-2.969
Int.6	5.875	-7.125	5.250	4.688	-4.188	10.750	3.125	4.313	4.875	-3.250
Int.7	1.750	-5.688	1.313	-0.094	3.594	3.125	8.188	-3.344	0.875	-4.063
Int.8	6.750	-0.281	2.531	6.797	-6.984	4.313	-3.344	10.359	2.125	-0.781
Int.9	3.000	-1.000	0.250	3.250	1.250	4.875	0.875	2.125	7.250	-4.750
Int.10	-3.500	2.688	-0.938	-3.156	-2.969	-3.250	-4.063	-0.781	-4.750	6.438

Note: Int. represents Intersection

Table 3. Result of simulation in investment rate for each intersection

	K=0.3	K=0.5	K=0.7	K=1.0
Int.1	0.281	0.287	0.289	0.289
Int.2	0.224	0.244	0.245	0.251
Int.3	0.237	0.239	0.242	0.245
Int.4	-	-	0.017	0.045
Int.5	0.255	0.197	0.155	0.041
Int.6	-	-	-	0.027
Int.7	-	-	-	-
Int.8	-	-	-	-
Int.9	-	-	-	-
Int.10	-	0.031	0.051	0.101

Note: Int. represents Intersection

As shown in Table 3, in case of K = 0.3, from the total budget allocated, Intersection1 should be invested in by 28.1 percent, Intersection2 25.8 percent, Intersection3 23.7 percent and Intersection5 25.5 percent. Other intersections which are not included in the list of units after restructuring will not get any investment. So in the case of K = 0.3, we can select Intersection1, Intersection2, Intersection3, and Intersection5 in order to invest maintenance cost in by 28.1 percent, percent, 22.4 percent, 23.7 percent and 25.5 percent. In case of K = 0.5, five intersections were selected in the list of units after restructuring. There were Intersection1, Intersection2, Intersection3, Intersection5 and Intersection10 with investment maintenance cost percentage 28.7 percent, 24.4 percent, 23.9 percent, 19.7 percent and 3.1 percent. In case of K = 0.7, six intersections was selected and in case of K = 1.0, seven intersections were selected in the list of units after restructuring. From that, we can conclude that

Table 4. Expected invest rate and risk

K	Return Rate	Risk
0.3	16.163	0.036
0.5	16.261	0.046
0.7	16.311	0.051
1.0	16.353	0.059

the number of selected wards in restructured list is directly proportional to K.

Step 5. Determining the Optimal Maintenance Strategy

In Step 4, the portfolio theory algorithm is developed and a mean-variance analysis employed neural network is designed that shows the set of solutions on the efficient frontier from which an optimal solution should be chosen. In order to determine where a decision maker's optimal strategy lies, their level of aversion to uncertainty must be quantified. The most straightforward method of calculating a decision maker's aversion is to find an indifferent curve between the value and uncertainty that accurately reflects his/her interests.

The expected investment rate and risk are calculated, as shown in Table 4 and also indicates four different levels of risk aversion, value of K, reflect decision maker's different preference. When K is set at a larger

Table 5. Comparison of conventional Boltzmann machine and meta-controlled Boltzmann machine

	Computational Times (sec)	
No. of Intersection	Conventional Boltzmann Machine	Meta-controlled Boltzmann Machine
10	7.21	6.42
40	12.11	8.52
160	43.41	12.61
640	219.12	31.90

value, the solution is obtained with high investment rates and high risk.

Table 5 compares meta-controlled Boltzmann machine and conventional Boltzmann machine, employing various sizes from 10 intersections to 640 intersections. The computing time of the meta-controlled Boltzmann machine is drastically shorter than a conventional Boltzmann machine. The reason for this is because the meta-controlled Boltzmann machine deletes useless units during the restructuring step. By contrast, a conventional Boltzmann machine computes all units until the termination condition reached.

6. CONCLUDING REMARKS

This paper demonstrates that proposed method has various advantages. Mean-variance analysis and structural learning is employed to solve the problem on how to choose intersections to implement LED signal retrofit, and its appropriateness has been verified. As a result, it was shown that the proposed method in this paper can successfully determine the optimal intersection solution, as illustrated in the numerical example. The simulation also showed that computational times are significantly decreased compared with a conventional Boltzmann machine.

Mean-variance analysis, which employs the portfolio method using a meta-controlled Boltzmann machine, can deal much more effectively with these types of problems. The results obtained show that the selection, investment expense rate of intersections, and reduced computation time can be prolonged to increase cost savings. The results also demonstrate that our proposal for incorporating structural learning into the Boltzmann machine is effective and can enhance the decision making process.

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