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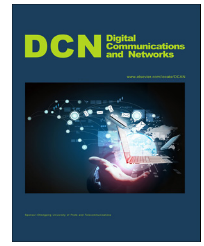

Production and inventory control of auto parts based on predicted probabilistic distribution of inventory☆

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Abstract
Bayesian networks are probabilistic models used for prediction and decision making under uncertainty. The delivery quantity, the production quantity, and the inventory are changing according to various unexpected events. Then the prediction of a production inventory is required to cope with such irregular fluctuations. This paper considers a production adjustment method for an automobile parts production process by using a dynamic Bayesian network. All factors that may influence the production quantity, the delivery quantity, and the inventory quantity will be handled. This study also provides a production schedule algorithm that sequentially adjusts the production schedule in order to guarantee that all deadlines are met. Furthermore, an adjusting rule for the production quantities is provided in order to maintain guaranteed delivery.
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1. Introduction

In the production system generally termed FA (Factory Automation), purchased parts or materials that go through each process of manufacturing, subassembly, and final assembly are both sent to the client and stored in the inventory for the next shipment. In the workplace utilizing such a system, production attributes such as production rate are subject to irregular changes according to the operating capabilities of the facilities and number and quality of the day's labor force. Product orders themselves also randomly change [1-3]. As such, the managers of each process needs to make an estimation based on their know-how and experience and tactfully decide the output in such a production system.

Regarding the inventory, according to a 'Kanban' production management way of thinking, the inventory itself is a cost.

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Kanban is a scheduling system for lean and just-in-time (JIT) production. Kanban is a system to control the logistical chain from a production point of view, and is an inventory control system [4]. This system controls the logistical chain from a production point of view, and is an inventory control system.

The general purpose of inventory management is to efficiently compress stock and maintain the standard amount of stock. Inventory of final goods resulting from production is the origin of profit and necessary to guarantee the due date of orders. However, over-stocking increases company costs through interest, rent, and outdated products. On the other hand, under-stocking hinders companies from guaranteeing the due date for large or urgent orders and could decrease the customer service quality or company credibility. As such, production inventory problems become the discerning matter for a trade-off between decreased cost by inventory and increased customer satisfaction and company credibility with respect to due date guarantees and urgent orders.

This research aims to suggest an approach for a trade-off such that delivered goods are seen as demand and production and inventory as supply regarding the demand. The irregular changes of various factors bringing demand and supply cause the problem [5,6]. The research describes the irregularly varied supply and demand, its various causes and corresponding changes in production, and the causal relationship by using dynamic Bayesian network (DBN) [7-14]. A method is proposed to estimate the supply and demand probability distribution and accordingly adjust production and inventory plans [14-23].

With the rapidly changing socioeconomic environment surrounding the automobile parts manufacturing industry, one of the basic industries with a strict deadline schedule is selected as the subject for this study. We will analyze various factors influencing production and delivery viewed as supply and demand, and will construct a probability model by DBN. Based on real data obtained from an automobile parts manufacturing company, we will estimate the supply and demand probability distribution and describe the production inventory plan in order to control the overflow and underflow inventory probability, maintains the optimum inventory to guarantee even large or urgent orders.

2. Construction of the DBN model regarding the production inventory management

2.1. Dynamic Bayesian networks

Bayesian networks, a type of graphical model, are suitable for discovering neural interactions due to their graphical nature and rigorous underlying theory. First, the structural similarity between Bayesian networks and the nervous systems makes the former promising tools for modeling the latter. The nervous system is a network of connected neurons that transmit electrochemical signals between each other through nerve fibers. The topology of this complicated system can be naturally abstracted as a graph, that is, nodes connected with edges. Second, the edges of a Bayesian network are directional, which is suitable for modeling the transmission path of neural signals. Third, the node variables of a Bayesian network only locally depend on their parent nodes, which is similar to a neuron network with direct interactions with neighbor neurons through nerve fibers. Fourth, Bayesian networks are modular and flexible, which can be used to describe the dependence relationships between nodes and their parent nodes. Fifth, plenty of model-learning and computation methods have been developed for Bayesian networks by researchers in the field of artificial intelligence. A dynamic Bayesian network (DBN) is an extension of a Bayesian network (also called a belief network) for stochastic processes [9-11].

A Bayesian network employs a directed and acyclic graph (DAG) to encode conditional independence among random variables. The essential concept in the encoding is D-separation, which we will introduce after defining related concepts in graph theory. A DAG G is a pair (U, E) where U is a set of vertices and $E \subseteq U \times U$ is a set of arrows without cycles.

A chain between two vertices α and β is a sequence $\alpha=\alpha_0, \ldots, \alpha_n=\beta$ of distinct vertices such that (α_{i-1}, α_i) or $(\alpha_i, \alpha_{i-1}) \in E$ for all $i=1,\ldots, n$. Vertex β is a descendant of vertex a if and only if there is a sequence $\alpha=\alpha_0,\ldots, \alpha_n=\beta$ of distinct vertices such that $(\alpha_{i-1}, \alpha_i) \in E$ for all $i=1,\ldots, n$. If three disjoint subsets A, B and $S \subseteq U$ satisfy the condition that any chain between $\forall\alpha \in A$ and $\forall\beta \in B$ contains a vertex $\gamma \in \pi$ such that either

- arrows of π do not meet head-to-head at γ and $\gamma \in S$,
- arrows of π meet head-to-head at γ and γ is neither in S nor has any descendants in S,

then S is a D-division of A and B. The same set of conditional independence can be encoded by different DAGs, and a DAG can be converted to an essential graph that uniquely encodes the set of conditional independencies [10-13].

A multi-channel stochastic process can be modeled with a Bayesian network of $C \times T$ vertices, where C is the number of channels and T is the number of time points and each vertex represents the signal of a channel at a time point. In this case, DAG is subject to an additional constraint, that vertices at time t cannot have vertices after t as their parents, since the future cannot influence either the present or the past. If the same dependence relationships repeat time after time and the signals at t only depend on the signals from $t-\mathrm{N}$ to t, then the whole network can be rolled up as its DBN representation, a DAG is composed of only vertices from $t-\mathrm{N}$ to t.

For example, $Z_t=[U_t, X_t, Y_t]^{\mathrm{T}}$ is a first-order Markov process with dependence relationships specified as in Fig. 1. X_t is a Markov process whose transition distribution $P(X_t|X_{t-1},U_t)$ varies according to the input U_t. Arrows from X_{t-1} and U_t to X_t are associated with the transition distribution. Y_t is the output observation at time t. The arrow from X_t to Y_t is associated with the distribution $P(Y_t|X_t)$. Such a process can be represented by the first two time-slices circled by the dots [13].

2.2. Formularization of the production inventory control problem and probability distribution of inventory

For a production system with three volumes: the planned production volume, the delivery product volume, and the inventory volume, it is necessary to consider situations

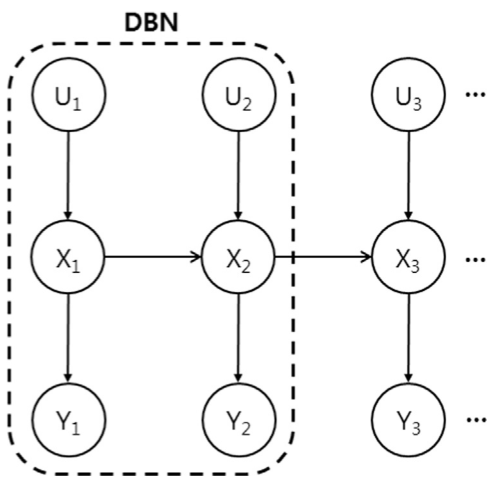

Fig. 1 Manufacturing process.

where the three volumes would probabilistically change due to diverse factors. For instance, although the delivery product volume during m period is already set, it can be changed due to production facility breakdown, sudden change in order volume according to customer needs, and abrupt faulty occurrences. With this in consideration, the DBN model for production inventory control problem can be constructed as below.

- Production quantities: A_t
- Delivered product quantities: D_t
- Inventory quantities: S_t
- The production plans will be carried out for m months (t=1,2, ,...,l l : forecast adjustment months)
- Factors for the production quantities
  $RA\alpha_t$: (α=$A,B,\ldots,Z$ α; factors)
  $RA\alpha\beta_t$: (β=$A,B,\ldots,Z$ β; factors)
  $RA\alpha\beta\gamma_t$: (γ=$A,B,\ldots,Z$ γ; factors)
  $RA\alpha\beta\gamma\delta_t$: (δ=$A,B,\ldots,Z$ δ; factors)
  $RA\alpha\beta\gamma\delta_t^i$: ($i$=1,2,...,$m$ m; the number of factors)
- Probabilistic change factors for the delivery quantities
  $RD\kappa\mu\nu\sigma_{\ t}$: (κ=$A,B,\ldots,Z$ κ; factors)
  $RD\kappa\mu\nu\sigma_{\ t}$: (μ=$A,B,\ldots,Z$ μ; factors)
  $RD\kappa\mu\nu\sigma_{\ t}$: (ν=$A,B,\ldots,Z$ ν; factors)
  $RD\kappa\mu\nu\sigma_{\ t}$: (σ=$A,B,\ldots,Z$ σ; factors)
  $RD\kappa\mu\nu\sigma_{\ t}$: (j=1,2,...,n n; the number of factors)
- Production quantity of every month: $A_t \leq A_{\max}$

Thus, the total stock of the product S_t for the tth month can be expressed as Eq. (1).

$$S_t = S_{t-1} + A_t - D_t \tag{1}$$

Also, considering all these factors, the probability distribution for product S_t of the tth month can be expressed as Eq. (2).

$$P\left(S_t^i\right) = \sum_{S_{t-1}^i}\sum_{A_t^i}\sum_{D_t^i}\sum_{RA\alpha_t}^{C}\sum_{RD\kappa_t}^{B}\sum_{RA\alpha\beta_t}^{E}\sum_{RD\kappa\mu_t}^{C}\sum_{RA\alpha\beta\gamma_t}^{U}\sum_{RA\alpha\beta\gamma\delta_t}^{G}$$
$$P\left(S_t^i, S_{t-1}^i, A_t^i, D_t^i, RA\alpha_t, RD\kappa_t, RA\alpha\beta_t, RD\kappa\mu_t, RA\alpha A\alpha_t, RA\alpha RA\delta_t\right) \tag{2}$$

Here, the combination probability distribution is developed further by a conditional probability distribution as below.

$$\begin{aligned}
&P(S_t^i, S_{t-1}^i, A_t^i, D_t^i, RA\alpha_t, RD\kappa_t, RA\alpha\beta_t, RD\kappa\mu_t,\\
&\quad RA\alpha\beta\gamma_t, , RA\alpha\beta\gamma\delta_t)\\
&= P(S_t^i|S_{t-1}^i, A_t^i, D_t)P(S_{t-1}^i)P(A_t^i)P(D_t^i)\\
&\quad \times P(A_t^i|RA\alpha_t, RA\alpha\beta_t, RA\alpha\beta\gamma_t, RA\alpha\beta\gamma\delta_t)\\
&\quad \times P(D_t^i|RD\kappa_t, RD\kappa\mu_t)\\
&\quad \times P(RA\alpha_t|RA\alpha\beta_t, RA\alpha\beta\gamma_t, RA\alpha\beta\gamma\delta_t)P(RA\alpha_t)\\
&\quad \times P(RD\kappa_t|RD\kappa\mu_t)P(RD\kappa_t)\\
&\quad \times P(RA\alpha\beta_t|RA\alpha\beta\gamma_t, RA\alpha\beta\gamma\delta_t)\\
&\quad \times P(RA\alpha\beta_t)P(RD\kappa\mu_t)\\
&\quad \times P(RA\alpha\beta\gamma_t|RA\alpha\beta\gamma\delta_t)P(RA\alpha\beta\gamma_t)P(RA\alpha\beta\gamma\delta_t)
\end{aligned} \tag{3}$$

Here, $\sum_{X_i} P(\cdots, X_i, \cdots)$means $\sum_{x_i \in \Omega_{X_i}} P(\cdots, X_i = x_i, \cdots)$. Due to the D-division [9-13], a characteristic of the DBN, Eq. (3)'s joint probability distribution can be simplified like Eq. (4), and acquires the probability distribution of inventory like Eq. (5).

$$\begin{aligned}
&P(S_t^i, S_{t-1}^i, A_t^i, D_t^i, RA\alpha_t, RD\kappa_t, RA\alpha\beta_t, RD\kappa\mu_t,\\
&\quad RA\alpha\beta\gamma_t, , RA\alpha\beta\gamma\delta_t)\\
&= P(S_t^i|S_{t-1}^i, A_t^i, D_t)\\
&\quad \times P(A_t^i|RA\alpha_t, RA\alpha\beta_t, RA\alpha\beta\gamma_t, RA\alpha\beta\gamma\delta_t)\\
&\quad \times P(D_t^i|RD\kappa_t, RD\kappa\mu_t)\\
&\quad \times P(RA\alpha_t|RA\alpha\beta_t, RA\alpha\beta\gamma_t, RA\alpha\beta\gamma\delta_t)\\
&\quad \times P(RA\alpha\beta_t|RA\alpha\beta\gamma_t, RA\alpha\beta\gamma\delta_t)\\
&\times P(RA\alpha\beta\gamma_t|RA\alpha\beta\gamma\delta_t)P(RD\kappa_t|RD\kappa\mu_t)
\end{aligned} \tag{4}$$

$$\begin{aligned}
P(S_t^i) =& \sum_{S_{t-1}^i}\sum_{A_t^i}\sum_{D_t^i}\sum_{RA\alpha_t}^{C}\sum_{RD\kappa_t}^{B}\sum_{RA\alpha\beta RD\kappa\delta_t}^{E}\sum^{C}\sum_{RA\alpha\beta\gamma_t}^{U}\sum_{RA\alpha\beta\gamma\delta_t}^{G}\\
&P(S_t^i, S_{t-1}^i, A_t^i, D_t^i, RA\alpha_t, RD\kappa_t, RA\alpha\beta_t,\\
&RD\kappa\mu_t, RA\alpha\beta\gamma_t, RA\alpha\beta\gamma\delta_t)\\
=& \sum_{S_{t-1}^i}\sum_{A_t^i}\sum_{D_t^i}\sum_{RA\alpha_t}^{C}\sum_{RD\kappa_t}^{B}\sum_{RA\alpha\beta RD\kappa\mu_t}^{E}\sum^{C}\sum_{RA\alpha\beta\gamma_t}^{U}\sum_{RA\alpha\beta\gamma\delta_t}^{G}\\
&P(S_t^i|S_{t-1}^i, A_t^i, D_t)\\
&\times P(A_t^i|RA\alpha_t, RA\alpha\beta_t, RA\alpha\beta\gamma_t, RA\alpha\beta\gamma\delta_t)\\
&\times P(D_t^i|RD\kappa_t, RD\kappa\mu_t)\\
&\times P(RA\alpha_t|RA\alpha\beta_t, RA\alpha\beta\gamma_t, RA\alpha\beta\gamma\delta_t)\\
&\times P(RA\alpha\beta_t|RA\alpha\beta\gamma_t, RA\alpha\beta\gamma\delta_t)\\
&\times P(RA\alpha\beta\gamma_t|RA\alpha\beta\gamma\delta_t)P(RD\kappa_t|RD\kappa\mu_t)
\end{aligned} \tag{5}$$

2.3. Production inventory control for auto parts production

This research will study the production system of an automobile parts processing line that produces four types of products under a situation where the set production volume and the delivered product volume are probabilistically changed.

For a production system with three volumes: the planned production volume, the delivery product volume, and the inventory volume, it is necessary to consider situations where the three volumes would probabilistically change due to diverse factors. For instance, although the delivery product volume during *m* period is already set, it can be changed due to a production facility breakdown, a sudden change in order volume according to customer needs, and abrupt faulty occurrences. Therefore, four products of the automobile parts of manufacturing lines of production systems are defined as below.

- Production item: auto parts engine valve lifter (four types)
- Production capacity: 1.5 million units per month
- Product composition: comprised of ten parts across eight processing lines
- Actual data acquisition period: Jan. 2003–Dec. 2005 (36 months)

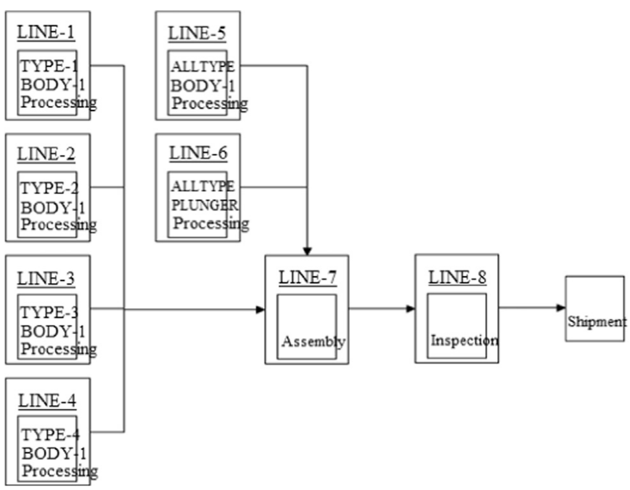

Fig. 2 Manufacturing process.

The auto parts production line producing singular product varieties are composed of eight manufacturing processing lines such as manufacturing, subassembly, final assembly, inspection of the final product as shown in Fig. 2. It assembles 10 varieties of parts that are separately produced on different processing lines according to the final destination of products.

It should be noticed that this study calculates the factors that influence production and delivery in each assembly for actual auto parts processing lines from January 2003 to December 2005 (36 months). Tab. 1 shows the statistical variables of delivered goods and production volumes.

Fig. 3 presents the statistical model of production and inventory by a dynamic Bayesian network in which S_t is inventory volume, A_t is the production volume, and D_t is the delivered product volume. They are probability variables and are represented as nodes.

2.4. Probability distribution of inventory volume according to conditional probability

The initial production schedule can probabilistically change due to production facility faulty, shipment inspection mistake, strikes, or sudden changes in orders. In fact, even the daily production volume, set according to the inventory volume and delivered products volume of the previous day, can probabilistically change due to factors such as the change of production plans or faulty assembly lines. Therefore, the prior probability for changed delivered product volume and production volume will be obtained by utilizing the data of the previous 36 months for each related cause of change.

Fig. 4 presents the early prior probability of order change (*RAAA*), representing the node of changed production plans of the assembling company and other companies in LINE-1. Fig. 5 shows the early prior probability of production change caused by manufacturing trouble (RAAB).

Tab. 1 The stochastic variables of delivered goods and production.

S_t	Inventory quantities	$RACAF_t$	An external diameter processing
D_t	Delivered goods	$RACB_t$	Inferior of B2
RDA_t	The cause of external	$RACBA_t$	Lathe processing
$RDAA_t$	A poor outbreak process	$RACBB_t$	Dimensional check
$RDAB_t$	A poor delivery inspection	$RACBC_t$	An external diameter processing
RDB_t	The cause of in-company	$RACBD_t$	The inside diameter processing
$RDBA_t$	Strike of customer	$RACC_t$	Inferior of DPL
$RDBB_t$	Order-change of A/S products	$RACCA_t$	DPL-lathe processing
$RDBC_t$	Change of production schedule	$RACCB^t$	Crowning
A_t	Production quantities	$RACCC_t$	Hole-processing
RAA_t	The cause of external	$RACCD_t$	An external diameter processing
$RAAA_t$	Order-change	$RACCE_t$	Hole polishing
RAB_t	The cause of in-company	$RACCF_t$	An external diameter processing
$RABA_t$	Control of inventory quantity (+)	$RACD_t$	Inferior of assembling
$RABB_t$	Control of Inventory quantity (-)	$RACDA_t$	HOLE-CHECK
RAC_t	Inferior of a manufacturing process	$RACDB_t$	CLIP Insertion
$RACA_t$	Inferior of B 1	$RACDC_t$	DPL-assembling
$RACAA_t$	Body-lathe processing	$RACDD_t$	Stratification
$RACAB_t$	Hole-processing	$RACDE_t$	Stratification

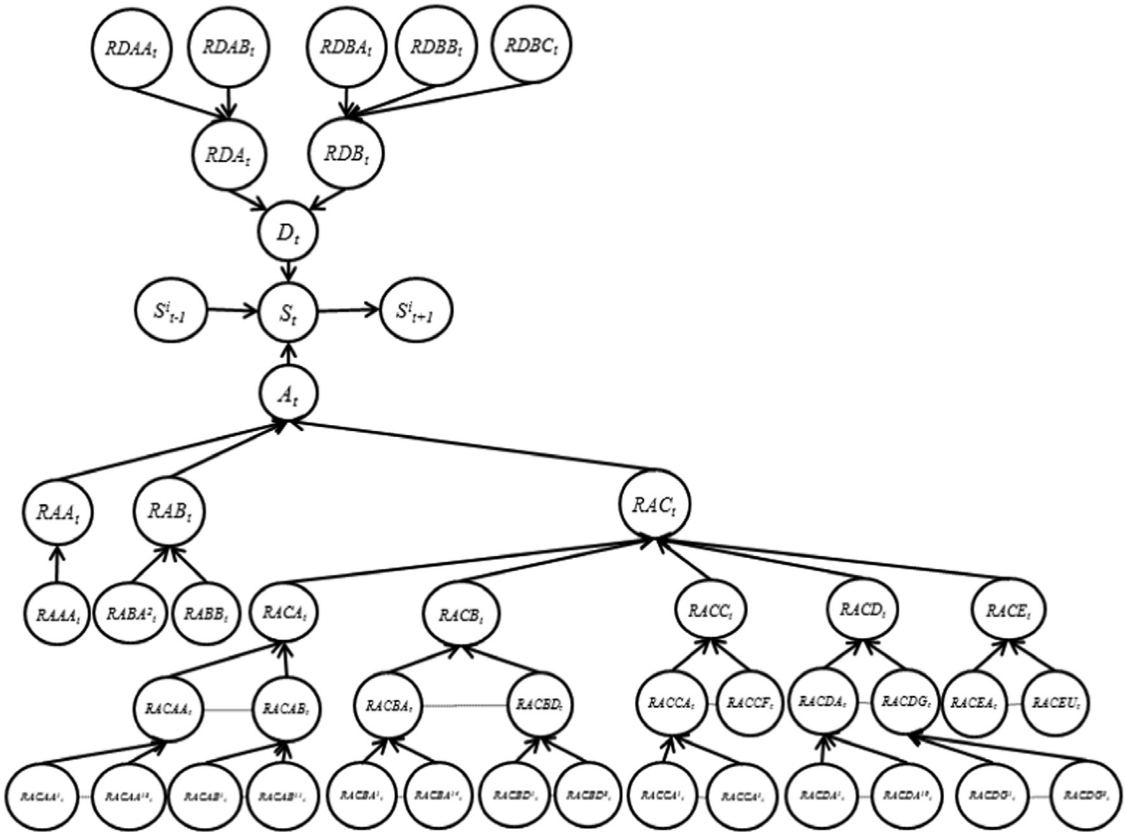

Fig. 3 Stochastic model of production and inventory by a dynamic Bayesian network.

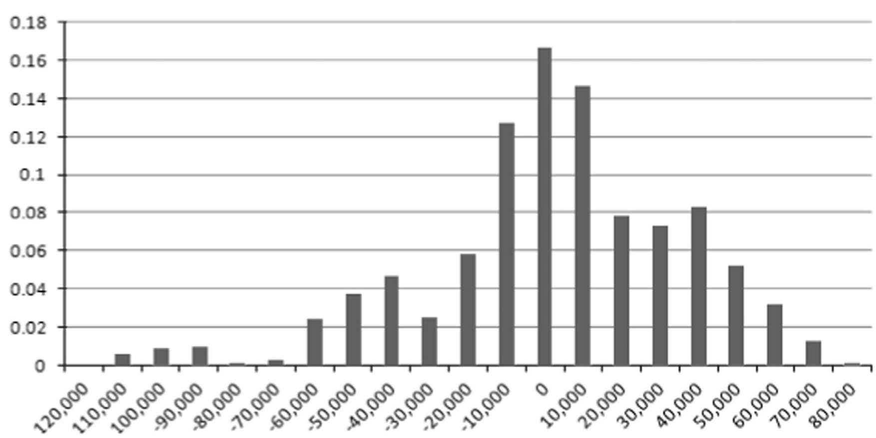

Fig. 4 Prior probability of order change (*RAAA*).

Fig. 6 presents the early prior probability of internal trouble (*RDBA)*, representing the node of causes in the assembling company such as faulty production facilities or faulty shipment inspections for delivering company B. Fig. 7 shows the early prior probability of external factors (*RDBB)*, representing the node for causes outside the assembling company such as strikes or sudden changes in orders.

Considering these factors, the probability distribution for inventory S_t can be obtained by Eq. (5). Fig. 8 presents the probability distribution for inventory volume estimated from prior probability distribution between January 2003 and December 2005, as well as the production plan of 2006.

3. Maintaining optimum inventory according to a production adjustment algorithm

3.1. Production adjustment algorithm

While inventory volume is decided by the inventory volume of the previous month, delivery and production volume of that month, there can be over or under inventory due to various causes after that month. With that, defective products or increased inventory management costs occur. The plan is to adjust a production plan that restricts to a certain limit when the probability of each inventory volume goes under the lowest or over the highest limit due to changes in production volume and delivered products volume.

The targeted inventory is set to 20–30% of the maximum production volume (300,000–450,000 units), the lowest limit is set to 10% of the maximum production volume (150,000 units), and the highest limit is set to 80% of the maximum production volume (1,200,000 units). The production plan is adjusted so that the probability of each situation is lower than 5%. The focal point of the adjustment algorithm is to intervene in the situation that the probability of the inventory volume decreasing more than the lowest limit is more than 5%.

Also, in the scenario that the probability of the inventory volume increasing more than the highest limit is more than 5% as the production volume is increased, the algorithm will

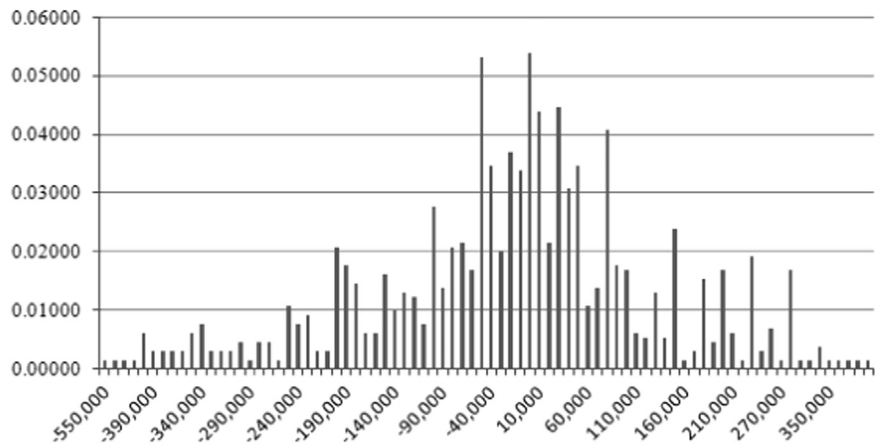

Fig. 5 Prior probability of production change by manufacturing trouble (*RAAB*).

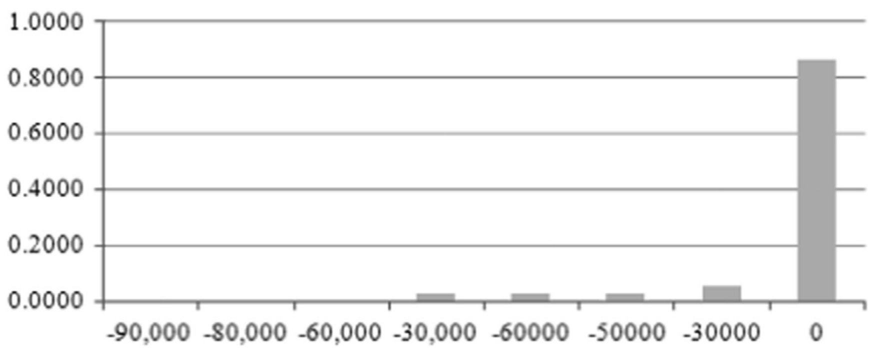

Fig. 6 Prior probability of internal trouble (*RDBA*).

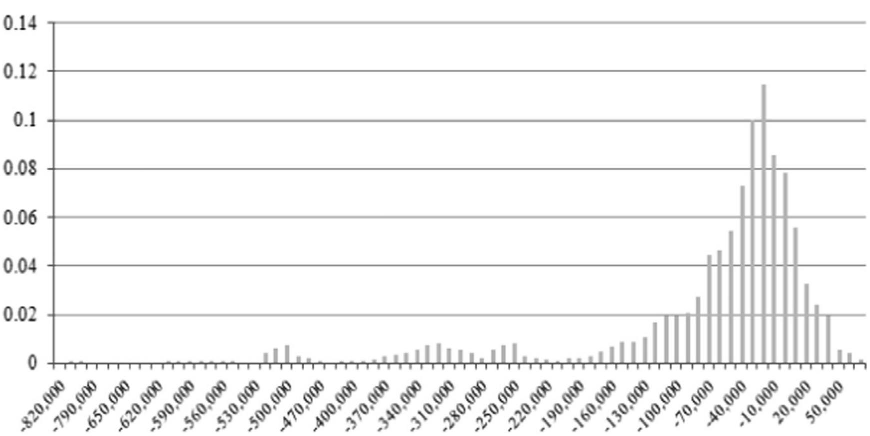

Fig. 7 Prior probability of external factors (*RDBB*).

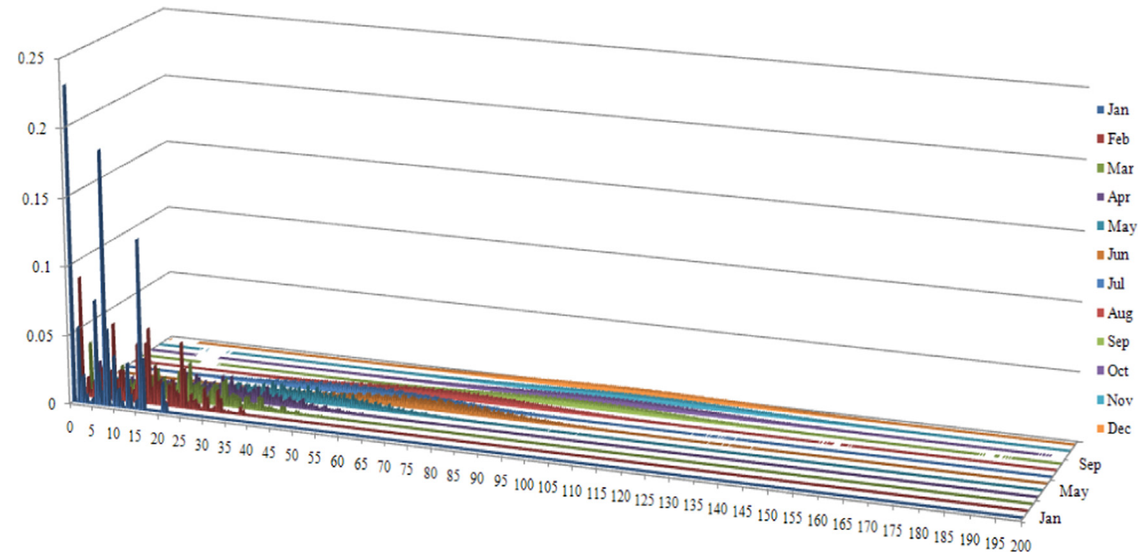

Fig. 8 Probability distribution of the production schedule.

intervene to decrease the production volume while considering the probability of having less than the lowest limit as seen in Fig. 9.

3.2. Update of conditional probability

While the prior probability of the production volume and delivered products volume has been determined based on data accumulated for the past 36 months, this prior probability can be updated when the data of the 37th month has been measured. The DBN model for the production inventory control assigns each prior probability to the number of times as new nodes of the delivered product volume and production volume occur. Here, the probability distribution of inventory volume of a set time period based upon prior probability of a time period before the set term is estimated. Adjustment of production plans are carried out per period.

Regarding the set time period, we will hold it to six months for the auto parts production plan problem. A conceptual diagram will update the conditional probability for each cause of delivered product volume and production volume based upon determined volume of inventory at the end of the month and factors that occurred during that month. It will also obtain the predicted probability distribution of a set period according to the expected delivery product volume and production volume. The conceptual diagram is presented in Fig. 10.

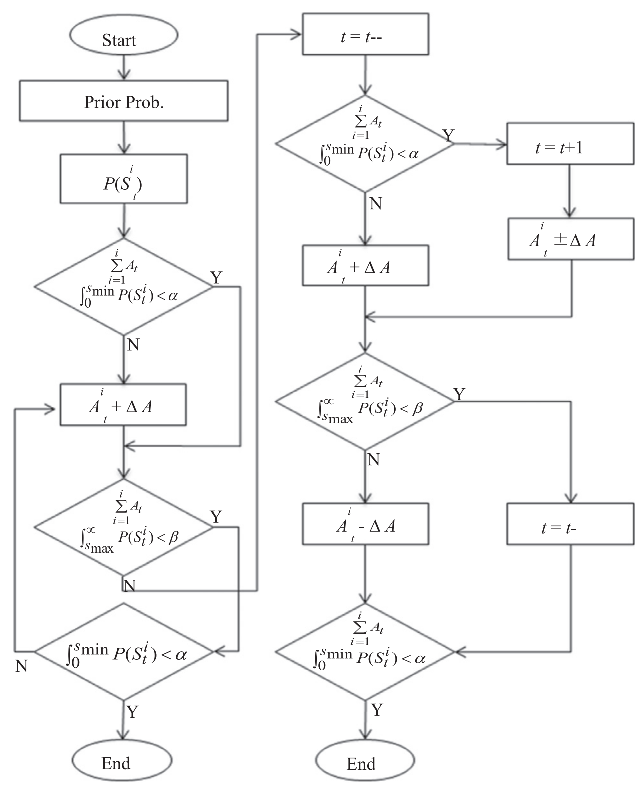

Fig. 9 Flowchart of adjusting rule.

3.3. Predicted probability distribution of inventory volume

In practice, the adjustment of production plan and the update of inventory probability distribution are necessary. As can be seen in Fig. 8, which predicts the inventory probability distribution from initial production plans, the months from January to April have more than 5% probability that production volume falls short of the lowest limit (150,000 units) and the months from September to December have more than 5% probability that production volume will exceed the highest limit (1,200,000 units). The adjusted production plan via the adjustment algorithm is presented in Tab. 2.

Fig. 11 presents the change in probability distribution for inventory volume S_t by the adjusted production plan. In contrast, Fig. 12 shows the predicted inventory volume by the adjusted production plan, the predicted inventory volume by the initial production plan, and the real inventory volume of that year (2006). The subject, an assembly

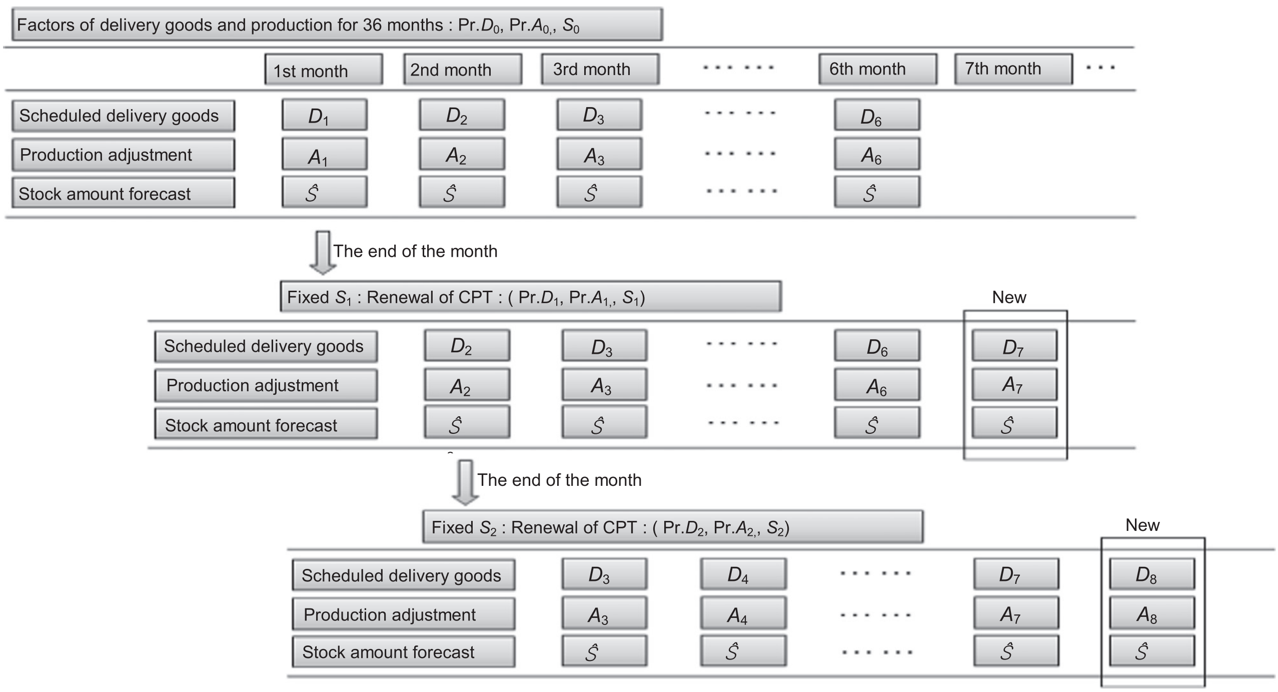

Fig. 10 Delivery goods, production and stock forecasting flow by the adjusting rule.

Tab. 2 Adjustment of the production schedule.

Month	Initial production schedule	The production schedule updated
Jun	960,000	960,000
Jul	1,140,000	1,140,000
Aug	1,060,000	910,000
Oct	1,230,000	1,130,000
Nov	1,210,000	1,160,000
Dec	1,130,000	880,000

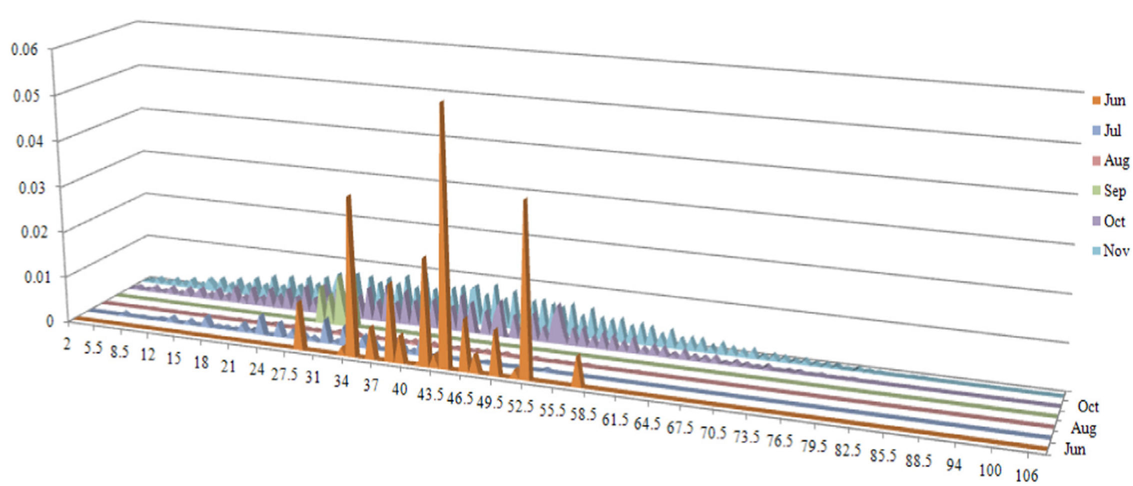

Fig. 11 The adjustment of the probability distribution of the production shedule.

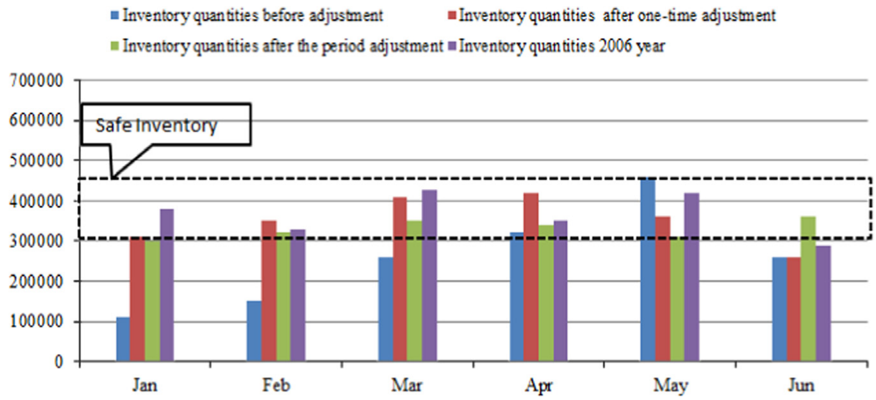

Fig. 12 Inventory quantities of adjusted production and actual production.

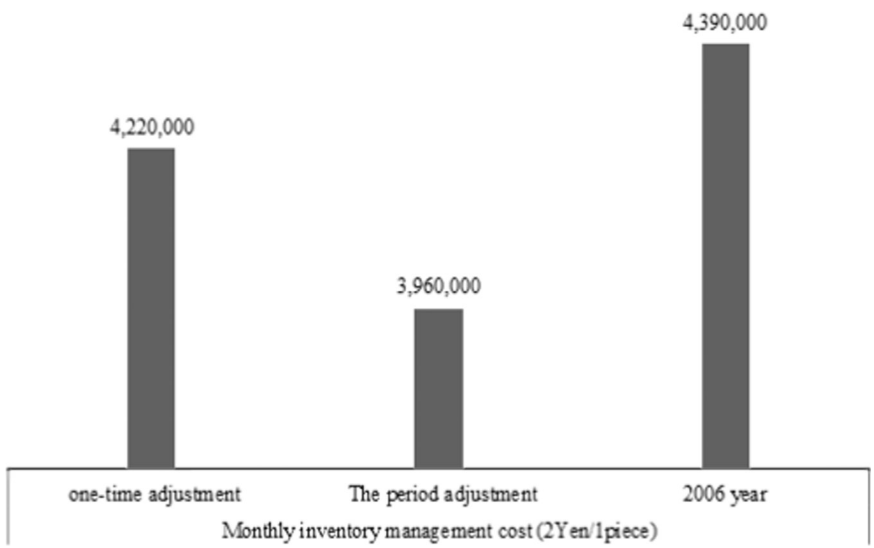

Fig. 13 Inventory management cost during year.

line, has a safe production volume as 20–30% (300,000–450,000 units) of the monthly maximum production volume. This safety inventory range is presented as a dotted line. The predicted inventory volume of the adjusted production plan is close to the predicted inventory volume by the initial production plan and actual inventory volume.

Note that the assembly line calculates the inventory management cost at 2 Yen per product due to the labor cost and facilitation management cost, the company has saved 1,120,000 yen via the production plan adjustment and 890,000 yen over the real inventory volume in 2006. This is presented in Fig. 13.

4. Conclusion

The DBN model is constructed for a production inventory management of an auto parts assembly line to handle the irregularly changing delivered product volume, production volume, and inventory volume. We determine the causes of change for probabilistically changing delivered product volume and production volume through factor analysis, and convert these causes into nodes to denote a probabilistic dependent relation that is presented through a graph. Also, in order to develop a production plan reflecting such efforts, we suggest a production inventory management method that would accordingly adjust production plans to each coming period and optimally guarantee delivery deadlines. Production plans themselves would maintain optimal inventory volume by calculating the predicted probability distribution based upon accumulative data. Finally, we present a reduced cost of inventory management by comparing them prior and after adjusted production plans, and comparing the real cost of that year.

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References

[1] T. Shiina, J.R. Birge., Multistage stochastic programming model for electric power capacity expansion problem, Jpn. J. Ind. Appl. Math. 20 (2003) 379–397.

[2] G.B. Dantzig., Linear programming under uncertainty, Manag. Sci. 1 (1955) 197–206.

[3] A. Charnes, W.W. Cooper, Chance constrained programming, Manag. Sci. 6 (1959) 73–79.

[4] Ronald G. Askin, M. George Mistwasi, Jeffry B. Goldberg, Determining the number of kanbans in multi-item just-in-time systems, IIE Trans. 25 (1) (1993) 89–98.

[5] J.K. Delson, S.M. Shahidehpour, Linear programming applications to power system economics planning and operations, IEEE Trans. Power Syst. 7 (1992) 1155–1163.

[6] Peter Kall, Janos Mayer, Linear Programming Models, Theory, and Computation, International Series in Operations Research & Management Science, Springer, 2005.

[7] R. Wollmer, Two stage linear program under uncertain with 0-1 integer first stage variables, Math. Program. 19 (1980) 279–288.

[8] J.D. Schaffer, Multiple objective optimization with vector evaluated genetic algorithms, in: Proceedings of the First International Conference of Genetic Algorithms and their Applications, 1985, pp. 93–100.

[9] Kevin Patrick Murphy, Dynamic Bayesian Networks: Representation, Inference and Learning (Ph.D. thesis), University of California, Berkeley, 2002.

[10] J. Pearl, Fusion, propagation, and structuring in belief networks, Artif. Intell. 29 (3) (1986) 241–288.

[11] J. Pearl, Probabilistic Reasoning in Intelligent Systems, 1988.

[12] Stuart Russell, Peter Norvig, Artificial Intelligence: A Modern Approach, Prentice Hall559 (Chapter15.5).

[13] Junning Li, Dynamic Bayesian Networks Modeling and Analysis of Neural Signals, The university of British Columbia, 2009.

[14] E. Richard, Neapolitan, Learning Bayesian Networks, Prentice Hall, 2003.

[15] Y. Motomura, S. Akaho, H. Aso, Application of Bayesian network to intelligent system, J. SICE 38 (7) (1999) 468–473.

[16] A. Biedermann, F. Taron, Bayesian networks and probabilistic reasoning about scientific evidence when there is a lack of data, Forensic Sci. Int. 157 (2006) 163–167.

[17] S. Lauritzen, D. Spiegelhalter, Local computations with probabilities on graphical structure and their application to expert systems, J. R. Stat. Soc. B 50 (1988) 157–224.

[18] E. Solpmpn, Carmel Domshlak Shimony, Complexity of probabilistic reasoning in directed-path singly-connected Bayesian networks, Artif. Intell. 151 (2003) 213–225.

[19] Han-Ying Kao, Shia-Hui Huang, Han-Lin Li, Supply chain diagnostics with dynamic Bayesian networks, Comput. Ind. Eng. 49 (2005) 339–347.

[20] J.R. Birge, Stochastic programming computation & applications, INFORMS J. Comput. 9 (1997) 111–133.

[21] A. Biedermann, F. Taron, Bayesian networks and probabilistic reasoning about scientific evidence when there is a lack of data, Forensic Sci. Int. 157 (2006) 163–167.

[22] Edward A. Siver, et al., Inventory Management and Production Planning and Scheduling, John Wiley & Sons Inc, 1998.

[23] F. Catherine, M. Evans, et al., Statistical Distributions, 4 edition, John Wiley & Sons Inc, 2010.

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