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Future Penetration of Advanced Industrial Robots in the Japanese Manufacturing Industry: An Econometric Forecasting Model

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WORKING PAPER

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FOREWORD

Analysis and forecasting of industrial robot (IR) penetration constitute one of the main activities of the IIASA Project "Computer Integrated Manufacturing" (CIM). Advanced Industrial Robots are important components of CIM systems.

The author has analyzed past penetration data of I.R. in the Japanese manufacturing industry in detail and he developed a macroeconometric model forecasting the future penetration of advanced industrial robots. This model integrates the approaches of two earlier CIM Working Papers, namely the production function appproach [Mori 87] and the learning curve approach [Ayres & Funk 87].

It is hoped that this model will also be applied to other countries, and that international comparisons will be made.

Prof. Jukka Ranta
Project Leader
Computer Integrated Manufacturing

SUMMARY

A new econometric model to forecast industrial robot penetration is proposed. This model consists of the following three components:

a) Application of a "learning curve" for industrial robot prices [Ayres & Funk 87];

b) Application of an extended production function taking account of industrial robot population effects [Mori 87];

c) Introduction of a demand function for "augmented equivalent labor force", in order to integrate the above two components.

The validation of the proposed model was made for the penetration of advanced industrial robots in the Japanese manufacturing industry.

The forecasts of I.R. penetration by this model were compared with the simple logistic curve model and also with the forecasts by JIRA (Japan Industrial Robot Association).

ACKNOWLEDGEMENT

The author wishes to express his gratitude to Prof. R.U. Ayres, Dr. S. Mori and Prof. J. Ranta for their helpful suggestions and advice. The author alone is, however, responsible for any remaining errors.

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I. Introduction

It is one of the key issues to forecast the diffusion of CIM technologies in order to ascertain the economic and social impacts of the introduction of CIM. However, forecasting has the following two major problems.

The first one is caused by the concept of CIM itself. Data of definite CIM are not available, because CIM is a system which integrates many components of factory automation. All we can obtain is limited to the data on the penetration of components, such as industrial robots, numerical control machine tools, CAD/CAM systems, etc.

The second problem is related to the methodology of forecasting the penetration of CIM. As described in the section on CIM of the IIASA Activity Plan, there are two ways to approach the "penetration" question. One is essentially empirical, i.e., to extrapolate the historical trends forward in time. A logistic curve model is often applied to forecast the diffusion of new goods. Although this is the only feasible approach in some cases, it provides minimal insight to decision-makers.

Therefore it is highly desirable to supplement straightforward empiricism with a more sophisticated theory-based model.

The purpose of this paper is to develop such a kind of model by introducing "learning curve" effects into the production function model, which was developed by S. Mori [Mori 87]. Some necessary modifications are made to integrate the two models. According to the data availability on diffusion statistics, we focus in this paper on the penetration model of industrial robots.

II. **Logistic Curve Model**

As a starting point, we apply the logistic curve to the trend of the industrial robot population in the Japanese manufacturing industry. In order to study the penetration of I.R., we should select the country with the highest diffusion level. This is the reason why Japan was chosen [Yonemoto 87, and Edquist & Jacobsson 86].

According to the Japanese classification, industrial robots are classified into the following six types [JIRA-a 85]:

Type A: manual manipulator

Type B: fixed sequence robot

Type C: variable sequence robot

Type D: playback robot

Type E: numerical control robot

Type F: intelligent robot

Based on the diffusion patterns and the price levels, these six types can be grouped into two, namely conventional type (A+B+C), and advanced type (D+E+F).

The data of the industrial robot population in the Japanese manufacturing industry are estimated from the domestic shipment data [JIRA 75-86], assuming the replacement time of I.R. to be seven years [JIRA 84] and imports of robots to be relatively negligible. A standard logistic curve is shown below.

$$U(t) = 1/(a+b.e^{-ct}) \qquad (1)$$

where U(t) denotes the population of I.R. at time t.

In order to clarify the meaning of the parameters, we can transform the above function into the following form:

$$U(t) = U\infty/[1 + e^{-c.(t-tm)}] \qquad (2)$$

where $U\infty$ and tm denote the saturation population, and the time when the population reaches half the saturation level, respectively. The logistic curve function shown in (2) is the solution of the following well-known equation:

$$\frac{dU}{dt} = c.U(t)[U\infty - U(t)] \qquad (3)$$

According to the above equation, the parameter c is proportional to the speed of diffusion.

The results of logistic curve fittings to I.R. populations in the Japanese manufacturing industry are shown in Table 1 and Figure 1.

We employed the non-linear least squares method named Marquardt for logistic curve fitting.

The results show very good fittings to the logistic curve for both the conventional type and the advanced type. In case of the conventional type (A+B+C), the population has been saturating recently.

According to the above results, the penetration of I.R. in Japan will proceed mainly in the advanced type (D+E+F) after the year of 1985.

Therefore we will, in the following chapters of this paper, focus on an advanced robot type (D+E+F), with special emphasis on the aspect of subsystems in computer integrated manufacturing systems.

Figure 1

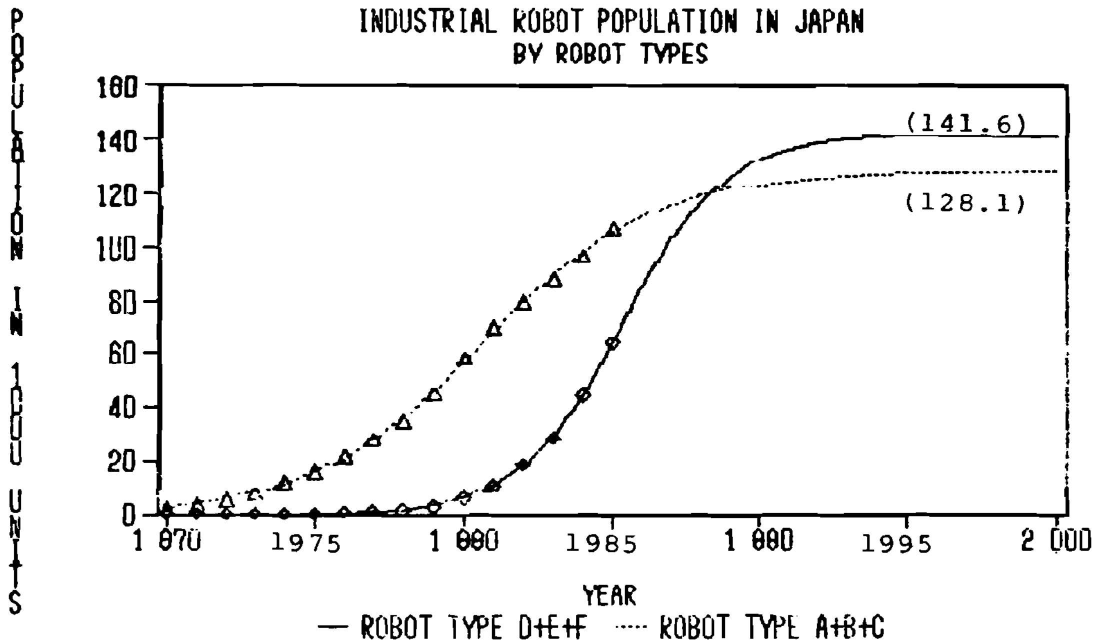

INDUSTRIAL ROBOT POPULATION IN JAPAN
BY ROBOT TYPES
POPULATION IN 1000 UNITS
180
140
120
100
80
60
40
20
0
1 970
1975
1 980
1985
1 990
1995
2 000
(141.6)
(128.1)
YEAR
— ROBOT TYPE D+E+F ···· ROBOT TYPE A+B+C

Table 1

Logistic curve fittings to I.R. population in the manufacturing sector of Japan (Non-linear least squares method)

Robot type (D+E+F)*	Robot type (A+B+C)*
$f=1/[a+b*EXP(-c*t)]$	$f=1/[a+b*EXP(-c*t)]$
PARAMETERS (IT= 13)	PARAMETERS (IT= 11)
a= 7.06115E-03	a= 7.80954E-03
b= 53.7394	b= .340363
c= .582438	c= .354198
$f=141.6/[1+e^{-0.5824(t-1985.3)}]$	$f=128.1/[1+e^{-0.3542(t-1980.7)}]$
*R2 = .999717	*R2 = .999144
R S S = 1.31354	R S S = 14.5068
D.W.= 1.5816	D.W. = 1.53659

YEAR	ESTIMATED		OBSERVED	
	(E+E+F)	(A+B+C)	(D+E+F)	(A+B+C)
1970	0.019	2.872	0.000	2.300
1971	0.033	4.054	0.000	3.600
1972	0.060	5.701	0.000	5.300
1973	0.107	7.973	0.000	7.800
1974	0.191	11.069	0.140	11.640
1975	0.342	15.215	0.260	15.340
1976	0.610	20.640	0.500	21.550
1977	1.089	27.527	1.020	27.580
1978	1.938	35.943	1.680	34.390
1979	3.433	45.761	2.850	45.010
1980	6.030	56.612	5.710	57.810
1981	10.445	67.913	10.510	69.420
1982	17.671	78.975	18.470	78.850
1983	28.799	89.168	28.570	88.010
1984	44.422	98.048	44.180	96.530
1985	63.732	105.415	63.830	106.920

(in 1000 units)

*A: Manual Manipulator; B: Fixed Sequence; C: Variable Sequence; D: Playback Robots; E: NC Robots; F: Intelligent Robots

III. **Formulation of the Penetration Model**

Production Function Model

At first we review the production function model developed by S. Mori [Mori 87]. The function depends upon the three heterogeneous production factors, namely Y(K,L,U), where Y,K,L and U represent output in real terms, non-IR capital stock, labor in terms of total employment and I.R. population in the manufacturing industry, respectively. It is postulated that L and U are separable from K, namely

$$Y = Y\,[K,\ F(L,U)] \tag{4}$$

F(L,U) can be interpreted as augmented equivalent labor force. According to the model developed by S. Mori, the following function form is assumed:

$$F(L,U) = (L^{a} + A.U^{a})^{(1/a)} \tag{5}$$

Equation (5) is a special form of the well-known CES production function.

The optimal strategy of equation (5) is formulated as follows:

$$\begin{aligned} &\max\ F(L,U) \\ &\text{subject to } W.L + P_R.U = M \end{aligned} \tag{6}$$

where M, W and P_R denote the total annual cost of labor and robots, annual wage and annual cost per robot, respectively.

The equilibrium condition of (6) yields a well-known equation

$$A.(U/L)^{a-1} = (P_R/W) \qquad (7)$$

Annual cost per robot (P_R) is considered to be proportional to industrial robot price (P). Therefore, P_R is assumed as follows:

$$R_R = r.\ d.\ P \qquad (8)$$

where d and r denote the ratio of initial system cost to the price of industrial robots, and annual cost rate. They are assumed to be constant. According to the assumption described above, equation (7) can be represented as follows:

$$\left(\frac{A}{r.d}\right) .\ (U/L)^{a-1} = (P/W) \qquad (9)$$

Therefore we can estimate the parameter (A/r.d) and a by employing a log-linear regression analysis method. The parameter r is assumed to be 25% (Low case) and 33% (High case), according to the results of S. Mori. The value of d is assumed to be 2.07, based upon the survey data of JIRA.

Based on the set-up of these parameters, we can estimate the augmented equivalent labor force F(l,U) by using equation (5). Let L_R and E_R denote labor force augmentation, and equivalent labor force per unit industrial robot, respectively. They are defined as follows:

$$L_R = F(L,U) - L \qquad (10)$$

$$E_R = \{ F(L,U) - L \}/U \qquad (11)$$

<u>Equivalent labor force demand model</u>

In order to forecast the population of I.R., we formulate the equivalent labor force F as a function of value added in real terms (V).

$$F = C.V^{c} \qquad (12)$$

Learning curve model for industrial robot prices

As shown in equation (9), the ratio of robot price to annual wage is a key factor in promoting the penetration of industrial robots. Therefore, we introudce a "learning curve" or "experience curve"[1] for robot prices, where the price at time t is a function of the cumulative number N produced to time t.

A simple dynamic theoretical model based on the "experience curve" for estimating private benefits (to the farm) has been briefly discussed, as well as an application of the model to predicting penetration rates [Ayres & Funk 87]. In this paper, we estimate the learning curve for industrial robots based on empirical data.

We assume the following equation as a learning curve:

$$P_t = B.Nt^{b} \qquad (13)$$

Based upon the observed data on P and N, we can estimate the parameters B and b.

The cumulative number of robots N produced to time t is defined as follows:

$$Nt = Nt-1 + Xt \qquad (14)$$

where Xt denotes the number of robots produced at time t.

$$Xt = (1 + \alpha).\ Dt \qquad (15)$$

---

[1]For a recent survey of the micro-economic literature, relating "experience curves" and cost functions, see [Gulledge and Womer 86].

where Dt and α denote the domestic shipments to the manufacturing industry and the ratio of non-manufacturing use including exports at time t.

Assuming that the life time of industrial robots, i.e. the replacement time, is distributed during m-1 to m+1, Dt is represented as follows:

$$Dt = Ut - Ut-1 + \frac{1}{3} \sum_{i=-1}^{1} Dt-m-i \tag{16}$$

Structure of the penetration model

The whole structure and diagram of the I.R. penetration mechanism is shown in Figure 2. This model includes non-linear simultaneous equations. Therefore, an iteration method is employed to solve the equations. If exogeneous variables Vt, Wt and α at future time t are given, our model can forecast the future population of I.R.

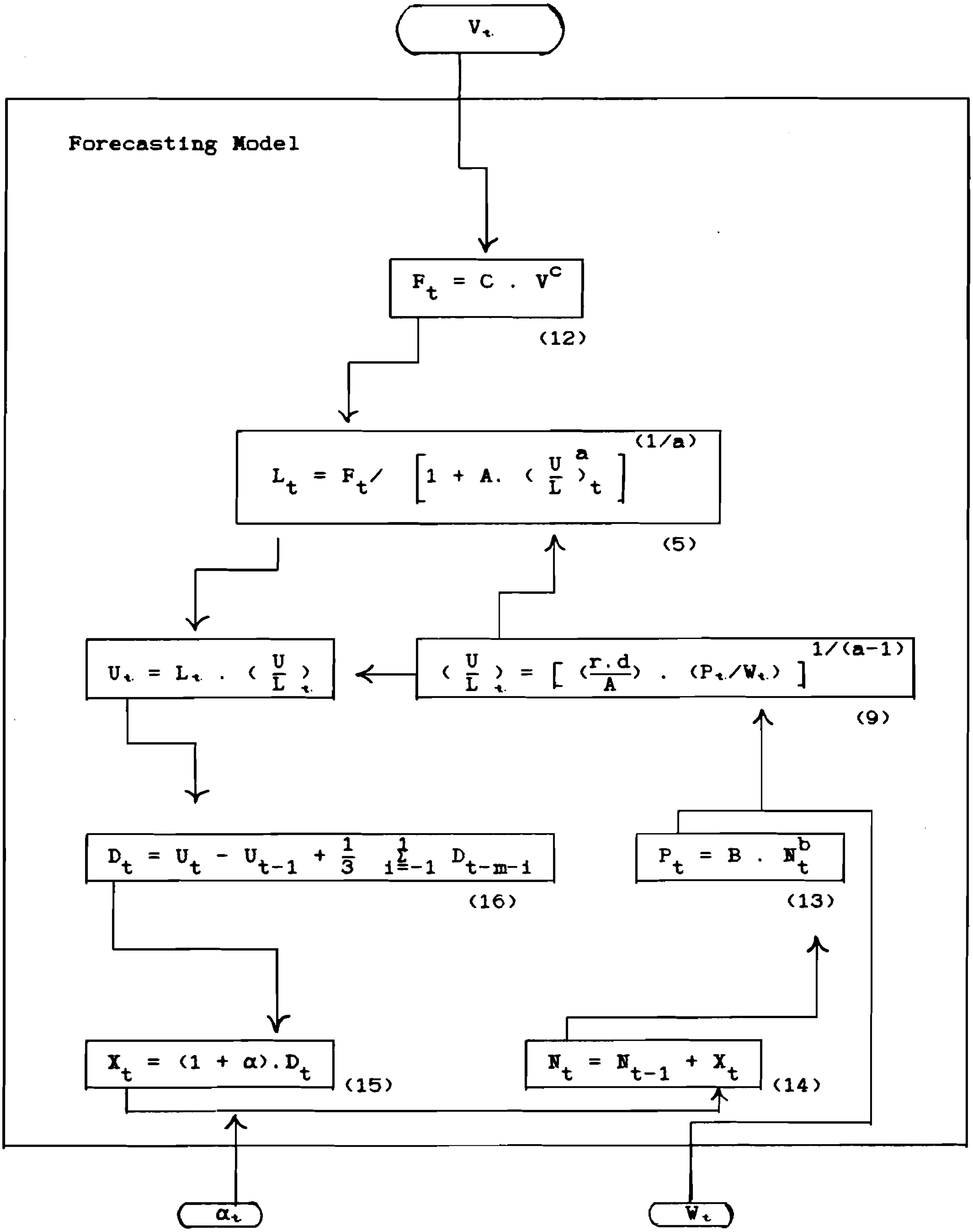


Figure 2: Diagram of Penetration Model

IV. **Forecasting Future Penetration of I.R.**

Based upon the formulation described before, we will forecast the future population of advanced industrial robots in the Japanese manufacturing industry in this chapter.

Regression analyses give us the following estimations of the equations in our penetration model:

<u>Production function</u> (see Table 2)

$$\log (Pt/Wt) = \underset{(0.0160)}{-0.2829} \log (Ut/Lt) - \underset{(0.0317)}{0.7718} \quad (9')$$

$$R^2 = 0.9874 \qquad \bar{R}^2 = 0.9843$$

$$F_t = (L_t^a + A.U_t^a)^{1/a} \quad (5')$$

$$a = 0.7171$$

$$A = 0.4621 \ .r.d$$

where d = 2.07 and r = 0.25 (Case 1) or

r = 0.33 (Case 2).

<u>Equivalent labor force demand</u> (see Table 3)

Case 1 (r = 0.25)

$$\log (F_t) = \underset{(0.0102)}{0.1297} \log (V_t) + \underset{(0.0033)}{8.9411} \quad (12\text{-}1')$$

$$R^2 = 0.9758 \qquad \bar{R}^2 = 0.9698$$

Case 2 (r = 0.33)

$$\log (F_t) = \underset{(0.0101)}{0.1345} .\log (V_t) + \underset{(0.0032)}{8.9210} \quad (12\text{-}2')$$

$$R^2 = 0.9778 \qquad \bar{R}^2 = 0.9723$$

<u>Learning curve for industrial robot prices</u> (see Table 4)

$$\log (P_t) = \underset{(0.0081)}{-0.1462} .\log (N_t) + \underset{(0.0218)}{9.6014} \quad (13)$$

$$R^2 = 0.9880 \qquad \bar{R}^2 = 0.9850$$

Table 2

Social Benefits of Industrial Robots in Japan
(PBR+MCR+ITR)

YEAR	POP(U)	LABOR(L)	PIR(P)	WAGE(W)	LN(P/W)	LN(U/L)	EST(P/W)	P/W
1980	5.71	13246	12616	2935	1.45825	-7.7492	4.13914	4.29846
1981	10.51	13364	10549	3116	1.21948	-7.1479	3.49170	3.38543
1982	18.47	13331	9285	3235	1.05437	-6.5816	2.97480	2.87017
1983	28.57	13502	8869	3349	0.97390	-6.1582	2.63893	2.64825
1984	44.18	13712	8346	3508	0.86673	-5.7377	2.34295	2.37913
1985	63.83	13811	7685	3596	0.75944	-5.3769	2.11562	2.13709

Based upon Dr. MORI's Model
Manufacturing Sector
RESULT OF REGRESSION ANALYSIS: LN(P/W)=LN(A/rd)+(a-1)*LN(U/L)

LN(A/rd)=	-0.7718	P/W=	0.46214 *(U/L)^ -0.2829
STD OF ESTIMATION	0.03167	a=	0.71708
R^2=	0.98742	*R^2=	0.98427
NUMBER OF SAMPLES	6		
DEGREE OF FREEDOM	4		F(L,U)=(L^a+A*U^a)^(1/a)
			A= 0.46214 * rd
COEF (a-1)=	-0.2829		d= 2.07
STD OF COEF=	0.01596		r= 0.25 OR 0.33

Data Source: W (Wage in manufacturing industry) [MOL 87]
U (Population of advanced industrial robots in manufacturing industry [JIRA 75-86]
P (Price of advanced industrial robots) [JIRA 75-86]
L (Labor force in manufacturing industry)*

---

*We use the Population Census data of 1980 and 1985 [MCA 86] because of reliability and interpolate the figures from 1981 to 1984 by using MCA annual data [MCA 87], instead of using the data of MITI which don't cover the whole manufacturing companies [MITI 86].

Table 3
Equivalent Labor Demand Estimation in Manufacturing Sector in Japan

YEAR	POP(U)	LABOR(L)	F(L,U)	R.VA(V)	LN(F)	LN(V)	EST(F)
1980	5.71	13246	13263.0	70.273	9.49273	4.25238	13261.7
1981	10.51	13364	13390.4	73.416	9.50230	4.29614	13337.2
1982	18.47	13331	13370.6	77.653	9.50081	4.35225	13434.6
1983	28.57	13502	13556.4	83.872	9.51461	4.42929	13569.5
1984	44.18	13712	13786.7	93.568	9.53146	4.53868	13763.5
1985	63.83	13811	13908.5	101.465	9.54025	4.61971	13908.9

EQUIV.LABOR vs. VALUE ADDED
Manufacturing Sector
R.VA:IN 10^12 YEN OF 1980
Case 1 (25%)
RESULT OF REGRESSION ANALYSIS:LN(C)+c*LN(V)

LN(c)=	8.94108	F= 7639.46 * (V)^0.12970
STD OF ESTIMATION	0.00325	
R^2=	0.97582	*R^2= 0.96978
NUMBER OF SAMPLES	6	
DEGREE OF FREEDOM	4	F(L,U)= (L^a+A*U^a)^(1/a)
COEF c=	0.12970	A= 0.46214 * rd
STD OF COEF=	0.01020	rd= 0.5175
		a= 0.71708

Table 3 (Continuation)

YEAR	POP(U)	LABOR(L)	F(L,U)	R.VA(V)	LN(F)	LN(V)	EST(F)
1980	5.71	13246	13268.5	70.273	9.49314	4.25238	13267.4
1981	10.51	13364	13398.9	73.416	9.50293	4.29614	13345.7
1982	18.47	13331	13383.3	77.653	9.50176	4.35225	13446.8
1983	28.57	13502	13573.8	83.872	9.51590	4.42929	13586.9
1984	44.18	13712	13810.7	93.568	9.53319	4.53868	13788.4
1985	63.83	13811	13939.8	101.465	9.54250	4.61971	13939.5

EQUIV. LABOR vs. VALUE ADDED
Manufacturing Sector
R.VA:IN 10^12 YEN OF 1980
Case 2 (33%)
RESULT OF REGRESSION ANALYSIS:LN(F)=LN(C)+c*LN(V)

LN(C)=	8.92095	F=	7487.21 *(V)^ 0.13453
STD OF ESTIMATION	0.00323		
R^2=	0.97784	*R^2=	0.97230
NUMBER OF SAMPLES	6		
DEGREE OF FREEDOM	4	F(L,U)=	(L^a+A*U^a)^(1/a)
		A=	0.46214 * rd
COEF c=	0.13453	rd=	0.6831
STD OF COEF=	0.01012	a=	0.71708

Data Source: V (Value added in manufacturing industry)
[EPA 87]

Table 4

Recent Trend of Advanced Industrial Robot Price (PBR+NCR+ITR)

YEAR	PRC(P)	PRODUNT	CUM(N)*	LN(P)	LN(N)	EST(P)
1980	12616.4	3.329	3.329	9.443	1.203	12401.0
1981	10548.7	5.883	9.212	9.264	2.221	10686.3
1982	9285.0	10.503	19.715	9.136	2.981	9561.3
1983	8869.4	15.210	34.925	9.090	3.553	8794.5
1984	8346.1	23.056	57.981	9.030	4.060	8166.3
1985	7684.8	26.816	84.797	8.947	4.440	7724.8

P: IN 1000 YEN/UNI
N:IN UNITS

LEARNING CURVE OF RECENT INDUSTRIAL ROBOT PRICE IN JAPAN
RESULT OF REGRESSION ANALYSIS: LN(P)=LN(B)+b*LN(N)

LN(B)= 9.60136
STD OF ESTIMATION ERROR 0.02178
R^2= 0.98799
NUMBER OF SAMPLES= 6
DEGREE OF FREEDOM= 4

COEFFICIENT b= -0.1462
STD OF b= 0.00805

p= 14784.8 * N ^ (-0.1462)

*R^2= 0.98499

P(2N)/P(N)= 0.90362
LEARNING COEF= 9.64%

*The cumulative number of advanced industrial robot production before 1979 is small and its prices are unstable and lower than those after 1980. Therefore, we consider the data before 1979 as a primitive kind of advanced type robots, and neglect such data for estimating "learning curve".

The regression analyses shown above are carried out for the data from 1980 to 1985, because an advanced type of industrial robots has begun to diffuse in the Japanese manufacturing industry since 1980, as shown in Table 1.

Other equations in our model

$$N_t = N_{t-1} + X_t \qquad (14')$$

$$X_t = (1 + \alpha) \, . D_t \qquad (15')$$

$$D_t = U_t - U_{t-1} + \frac{1}{3} (D_{t-6} + D_{t-7} + D_{t-8}) \qquad (16')$$

It is necessary for our forecasting efforts to assume the future trends of exogenous variables, V_t, W_t and α in our penetration model, as shown in Figure 2.

We set the following trends in these variables, as a base case of forecasts based upon recent trends:

Annual growth rate of real Value Added [V] in the Japanese manufacturing industry: $\Gamma = 5\%$

Annual increase rate of annual wage [W] in the Japanese manufacturing industry: $\beta = 2\%$

Ratio of non-manufacturing use: $\alpha = 0.35$ (average of 1984 and 1985)

The results of the forecasts according to our model are shown in Table 5.

We also estimated the industrial robot population from 1981 to 1985 with our model and obtained a good fitting to the observed data as shown in Figure 3.

Table 5

Simulation of IR Penetration
(Base Case)

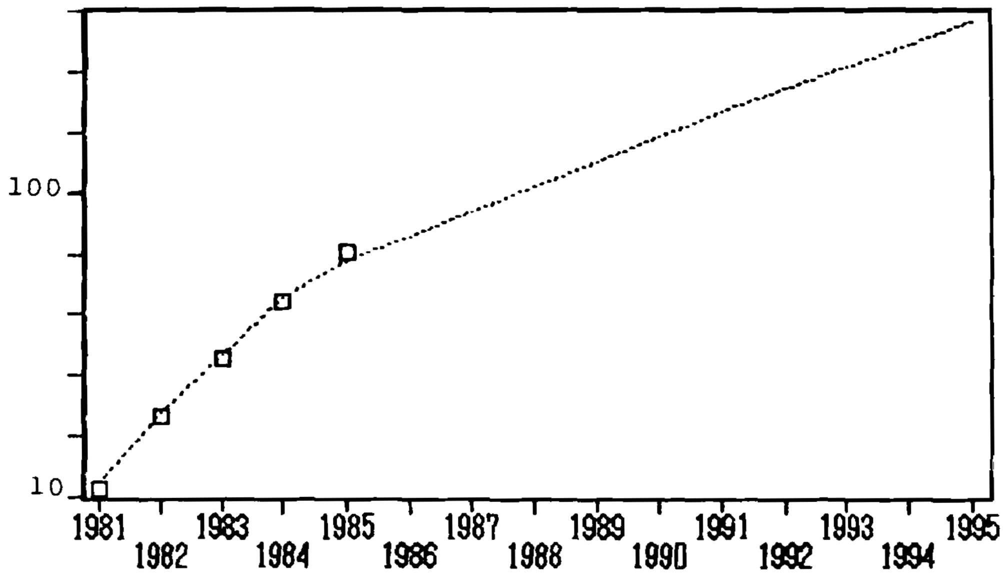
ALPHA(α)	BETA(β)	GM(Γ)	r
0.350	0.020	0.050	0.330

YEAR	U(T)	P(T)	W(T)	L(T)	F(T)	LR (F-L)	ER (F-L)/U	P/W	
1981	11.2	10686	3116	13309	13345	36	3.268	3.429	
1982	19.0	9560	3235	13393	13446	54	2.817	2.955	
1983	29.1	8794	3349	13514	13586	73	2.503	2.626	
1984	45.1	8166	3508	13688	13788	100	2.220	2.328	Estimating
1985	60.5	7725	3596	13815	13939	124	2.049	2.148	
1986	71.9	7516	3668	13890	14031	141	1.955	2.049	
1987	86.3	7290	3741	13963	14123	160	1.859	1.949	Forecasting
1988	104.5	7054	3816	14032	14216	184	1.764	1.848	
1989	126.7	6822	3892	14098	14310	212	1.673	1.753	
1990	154.1	6593	3970	14160	14404	244	1.586	1.661	
1991	186.1	6382	4050	14219	14499	280	1.506	1.576	
1992	222.1	6199	4131	14276	14594	318	1.434	1.501	
1993	262.4	6038	4213	14331	14690	360	1.370	1.433	
1994	309.2	5885	4298	14382	14787	405	1.310	1.369	
1995	365.2	5732	4384	14428	14885	457	1.251	1.308	

Figure 3

Past and Future Population of I.R.
(Base-case Forecast)

Population of I.R. (U)
(Log scale)



V. Sensitivity Analysis and Discussion

There are four parameters, namely α, β, Γ and r, in our model. The results of the forecasts are dependent on the setting of these parameters. Therefore, we will carry out the sensitivity analysis of the impacts by the above parameters in this chapter.

The base case is set to be α=0.35, β=0.02, Γ=0.05 and r=0.33, as described in the previous chapter.

In order to estimate the degree of impact by each parameter, we set the following extreme cases of sensitivity analysis:

Base case (r=0.33, Γ=0.05, α=0.35 and β=0.02)

Case R (r=0.25)

Case G (Γ=0.10) Case G (Γ=0.0)	impact by the annual growth rate of value added in manufacturing
Case A (α=0.7) Case A (α=0.0)	impact by the ratio of non-manufacturing use
Case B (β=0.04) Case B (β=0.0)	impact by the annual wage increase rate

The forecast results in the industrial robot population in 1990 and 1995, as shown for each case in Table 6.

According to the results of the sensitivity analysis from our penetration model, the conclusions are summarized as follows:

a) There is little difference between r=0.25 and r=0.33. We can obtain almost the same forecast for the industrial robot population, whichever we chose as an annual cost ratio to the initial system cost.

b) The impact of the annual growth rate of value added in the manufacturing industry on the population of I.R. within ten percentage points of the forecasts is not a major factor deciding the degree of penentration.

c) The ratio of exporting and non-manufacturing sector use seems relatively important compared to the above two parameters. However, the degree of the impact is limited within a range of 20%.

d) The most important factor in our penetration model is considered to be the annual wage increase rate. This parameter greatly influences the future population of industrial robots as shown in Table 6. The forecast population in 1995 ranges between 1184.0 in case of a 4% increase and 117.5 in case of a 0% increase.

The reason why the wage increase is so important can be seen from Equation (9). The robot population is mainly influenced by the relative price of robots to wage (P/W). In our model, robot price P decreases according to a learning curve. The higher the wage, the more robots are produced and a cheaper price of robots can be achieved. The higher wage and the cheaper price will increase the demand for industrial robots according to Equation (9). There is a positive feed-back in our penetration model as shown in Figure 4.

Finally, we compared our forecasts to other forecasts. As shown in the second Chapter, the forecast by a logistic curve fitting method shows the saturation level of an advanced industrial robot population, namely 141.6. This is a considerably small population compared to the results of our penetration model described in the previous chapter.

Table 6

Results of Sensitivity Analysis

Case	Industrial Robot Population (in 1000 units)	
	1990	1995
Base case*	154.1	365.2
Case R ($r=0.25$)	154.3 (+ 1.3%)	366.9 (+ 0.5%)
Case G ($\Gamma=0.10$)	162.7 (+ 5.6%)	406.8 (+ 11.4%)
Case G ($\Gamma=0.0$)	145.6 (- 5.5%)	326.3 (- 10.7%)
Case A ($\alpha=0.7$)	178.8 (+16.0%)	442.1 (+ 21.1%)
Case A ($\alpha=0.0$)	132.2 (-14.2%)	293.0 (- 19.8%)
Case B ($\beta=0.04$)	282.1 (+83.1%)	1184.0 (+224.2%)
Case B ($\beta=0.0$)	86.4 (-43.9%)	117.5 (- 67.8%)

* $r=0.33$, $\Gamma=0.05$, $\alpha=0.35$ and $\beta=0.02$

Figures in ( ) show the degrees of difference to the results of the base case.

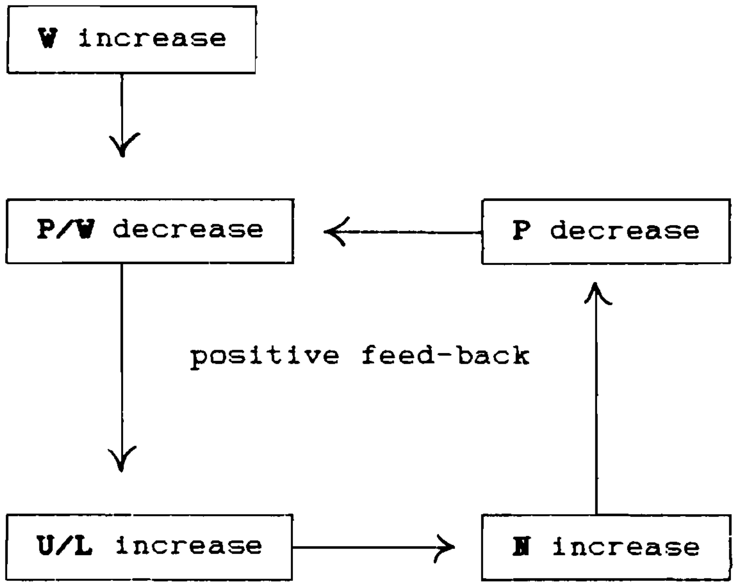


Figure 4: Positive Feed-back in Penetration Model

On the other hand, JIRA carried out forecasts of industrial robot population by types for the manufacturing industry [JIRA 85b], based upon the survey data on robot users. According to the results of the forecasts, the population of advanced industrial robots is projected to be 161.6 in 1990, and 327.4 in 1995, which is similar to our forecasts of the base case.

Our penetration model is considered to be too sensitive with respect to parameter β (annual wage increase rate) to forecast the future population of industrial robots. In order to narrow down the range of uncertainty in our model, some modifications would have to be made to part of the learning curve in further investigations, because the robot price in current values has the tendency to increase in the long term, as the wage increases.

One of the modifications in our model is shown in Appendix B.

Nevertheless, it is possible to draw some conclusions from the foregoing analysis. The penetration of industrial robots greatly depends on the decrease of the robot price and on the wage increase. In particular, the learning curve for the robot price plays an important role as a driving force mechanism -- through a positive feed-back loop -- to a wide diffusion of industrial robot technologies in the manufacturing industry.

It may be concluded that the model proposed here can be regarded as a useful step towards further investigations on the penetration mechanism of new technologies such as CIM.

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Appendix A

Notation of Variables in the Penetration Model

Variable	Definition
L	total employment in manufacturing industry (for 1000 persons)
U	population of industrial robots (in 1000 units)
F	augmented labor force (for 1000 persons)
W	annual wage (in 1000 yen/person)
P	price of industrial robots (in 1000 yen/unit)
L_R	labor force augmentation $L_R = F - L$
E_R	equivalent labor force per unit of robot $E_R = \frac{F-L}{U}$
V	value added in manufacturing industry (in 1980, trillion yen)
N_t	cumulative number of industrial robots produced to time t (in 1000 units)
X_t	number of industrial robot production at time t (1000 units)
D_t	domestic shipment of industrial robots to manufacturing industry (in 1000 units)
a	parameter of labor augmentation subproduction function
A	parameter of labor augmentation subproduction function
d	ratio of initial system cost to robot price
r	annual cost ratio to initial system cost
c	parameter of equivalent labor force function
C	parameter of equivalent labor force function
b	parameter of learning curve function
B	parameter of learning curve function
α	non-manufacturing use ratio
β	annual wage increase rate
Γ	annual growth rate of value added in manufacturing

Appendix B

An Alternative Model for Penetration Forecasting (Model II)

This model is different from the model (Model I) described in the previous chapters from the point of employing a learning curve for P/W (relative price of robots to wage) instead of P in Model I. In addition, we suppose that (P/N)t depends upon N_{t-1} instead of N_t. Assuming equation (17) as a kind of learning curve, we can forecast the population of industrial robots without a simultaneous equation problem.

$$(P/W)t = B.\ N_{t-1}^{b} \qquad (17)$$

In this model, variables P and W are eliminated by substituting (17) into (9) as shown below.

$$(U_t/L_t) = \left(\frac{r.d.B}{A}\right)^{1/a-1}.\ N_{t-1}^{b/a-1} \qquad (18)$$

Therefore, this model does not need the assumption on β (annual wage increase rate). The results of the regression analysis, the forecasting and sensitivity analysis are shown in Table 7, Table 8 and Table 9, respectively.

Model II yields the lower future population of industrial robots with a narrower range of forecasts than that of Model I, though the estimate errors between 1981 and 1985 are larger than in Model I. The result of Case G (Γ=0.0) is similar to that of the logistic curve model. Compared with the forecast by JIRA, the forecast population of I.R. in 1995 by this model is half of the former. It is necessary to carry out further investigations which would make this model more realistic.

Table 7

Learning Curve for P/W (Model II)

Recent Trend of Advanced Industrial Robot Price
(PBR+NCR+ITR); N[T-1]

YEAR	PRC(P)	WAGE(W)	CUM(N)	LN(P/W)	LN(N)	EST(P/W)	P/W
1981	10548.7	3116	3.329	1.219	1.203	3.401	3.385
1982	9285.0	3235	9.212	1.054	2.221	2.902	2.870
1983	8869.4	3349	19.715	0.974	2.981	2.578	2.648
1984	8346.1	3508	34.925	0.867	3.553	2.359	2.379
1985	7684.8	3596	57.981	0.759	4.060	2.180	2.137

Learning Curve of Recent Industrial Robot Price in Japan
Result of Regression Analysis: LN(P/W)= LN(B)+b*LN(N)

LN(B)=	1.41108	P/W= 4.10041 * N_{t-1} (-0.1556)
Std of Estimation Error	0.02106	
R^2=	0.98928	*R^2= 0.98571
Number of Samples=	5	
Degree of Freedom=	3	P/W(2N)/P/W(N)= 0.89774
		Learning Coef= 10.23%

Coefficient b= -0.1556
Std of b= 0.00935

Table 8

Results of Forecasting (Model II)

SIMULATION OF IR PENETRATION (r=33%)

ALPHA(α)	r	GM(Γ)
0.350	0.330	0.050

YEAR	U(T)	L(T)	F(T)	F-T	(F-L)/U	P/W	
1981	11.5	13307.9	13345.2	37.2	3.241	3.401	
1982	20.2	13390.3	13446.3	56.0	2.767	2.903	
1983	31.0	13510.1	13586.4	76.3	2.458	2.578	
1984	43.1	13690.9	13787.8	96.9	2.249	2.359	
1985	57.5	13819.5	13938.9	119.5	2.079	2.180	Estimation
1986	71.2	13891.2	14030.7	139.5	1.960	2.055	
1987	80.7	13970.2	14123.1	152.9	1.895	1.986	Forecasting
1988	88.2	14052.8	14216.1	163.3	1.851	1.940	
1989	95.7	14136.3	14309.8	173.4	1.812	1.899	
1990	104.1	14219.5	14404.0	184.5	1.773	1.858	
1991	113.5	14302.2	14498.8	196.7	1.733	1.816	
1992	123.8	14384.7	14594.3	209.7	1.694	1.774	
1993	134.6	14467.4	14690.4	223.0	1.657	1.736	
1994	145.1	14551.4	14787.2	235.8	1.625	1.702	
1995	155.0	14636.9	14884.5	247.7	1.598	1.673	

Table 9

Results of Sensitivity Analysis (Model II)

Case	Population of Industrial Robots (in 1000 units)	
	1990	1995
Base case*	104.1	155.0
Case R (r=0.25)	104.1 (0.05)	154.9 (0.1%)
Case G (Γ=0.10)	109.1 (+ 4.8%)	170.3 (+ 9.9%)
Case G (Γ=0.0)	99.0 (- 4.9%)	140.6 (- 9.3%)
Case A (α=0.7)	115.5 (+11.0%)	180.6 (+16.5%)
Case A (α=0.0)	94.1 (- 9.6%)	131.3 (-15.3%)

* $r= 0.33$, $\Gamma= 0.05$ and $\alpha= 0.35$