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Quantifying the Technology Level of Production System for Technology Transfer

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Abstract. This paper develops a technology level quantification (TLQ) model by utilizing a learning curve. Original learning curve shows the relationship between cumulative number of units and the required time for the unit. On the other hand, in our developed model, the technology level, such as speed of production and quality of the produced items, is expressed as a function of not cumulative number of units but time, for increasing generality. Furthermore, for expressing each learning that consists of conceptual learning and operational learning, S-curve is utilized in our developed model. By fitting the S-curve and/or decomposing into some activities, our TQL model can be applied to approximate organizational and complicated process. Some variations in time and levels, parameters of our developed model are shown. By using the parameters, the procedure to identify our developed model is proposed. Also, the influential factors for the parameters of our developed model are discussed with classifying the factors into technoware, infoware, humanware, and orgaware. The expected technology level is utilized for expecting the capacity of production system, and the expected capacity can be utilized in predicting various changes in the organization and deciding managerial decision about TT. A case study in manufacturing industry shows the effectiveness of the developed model.

Keywords: Technology Transfer, Technology Level, Learning Curve, S-curve, Case Study.

1. INTRODUCTION

Technology transfer (TT) is the process of transferring skills, knowledge, technologies, methods of manufacturing, and facilities. Usually, the technology transferred is not a technology itself but an integrated embodiment of skills, knowledge, technologies, methods of manufacturing, and facilities. Unsuccessful cases in TT frequently occurred due to failure in recognizing correctly technology embodiment, phases, and hierarchies involved in the transfer process of technology. Successful TT demands integrated approach to plan, implement, evaluate and improve the transfer process comprehensively. Therefore, the main objective of our research is developing integrated TT model towards technology self-sufficiency and sustainable growth. Especially in this paper, we develop a model to quantify the technology level of production system.

For quantifying the technology level, various models have been developed. Large increases in productivity are typically realized as organizations gain experience in production. These "learning curves" have been found in many organizations (Wright, 1936). More recently, the concept was broadened and the term "experience curve" was adopted. An experience curve relates total cost per unit, or alternatively, value added per unit, to the cumulative number of units produced. Anyway, the learning curve is utilized to express not only operational learning but also conceptual learning and other organizational learning. Corbett *et al*. (1999) applied learning curve to cases of partnerships to improve supply chains. Lapré and Van Wassenhove (2001) applied learning curves in order to create and transfer knowledge for productivity improvement in factories. Furthermore, Kim (1993)

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proposed the link between individual and organizational learning. Mukherjee *et al*. (1998) applies the idea of Kim (1993) to the activities of quality improvement. Lapré *et al*. (2000) analyzed the relationship behind the learning curve by linking leaning activities to waste reduction. Also, Lapré and Van Wassenhove (2003) considered managing learning curves in factories by creating and transferring knowledge. Based on the literature, this paper develops a technology

level quantification (TLQ) model by utilizing a learning curve. Original learning curve shows the relationship between cumulative number of units and the required time for the unit. On the other hand, in our TLQ model, the technology level, such as speed of production and quality of the produced items, is expressed as a function of not cumulative number of units but time, for increasing generality. Furthermore, for expressing each learning that consists of conceptual learning and operational learning, S-curve is utilized in our developed model. By fitting the S-curve and/or decomposing into some activities, our developed model can be applied to approximate organizational and complicated process. After discussing variations in time and levels, parameters of our developed model are shown. Based on the parameters, the procedure to identify our developed model is proposed. Also, the influential factors for the parameters of our developed model are discussed with classifying the factors into *technoware*, *infoware*, *humanware*, and *orgaware* (Kahen, 1995).

With the learning curve, the technology level, such as production speed of workers, will be quantified. Once the TLQ model is developed, the expected capacity of production system can be calculated. Then, the expected capacity of production system will be utilized in predicting various changes in the organization and deciding managerial decision about TT, such as whether the TT should be introduced or not, when the TT should be started, or others. A case study in manufacturing industry shows the effectiveness of the developed model.

2. LITERATURE REVIEW

After the conventional learning curve of log-linear model was proposed by Wright (1936), various kinds of learning curves have been proposed, and there is a lot of literature on learning curve. In the literature, Carr (1946) proposed S-curve, and Badiru (1992) surveyed various univariate and multivariate learning curves. Vigil and Sarper (1994) investigated effects of parameter variability on learning curve predictions, and Li and Rajagopalan (1998) proposed a learning curve with knowledge depreciation, that is a decreasing rate of learning. For more practical situations, Jaber and Kher (2002) proposed a dual-phase learning-forgetting model that consists of learning as a combination of cognitive and motor skills learning and forgetting based on the worker's learning rate, prior experience, as well as the length of the interruption interval. Jaber and Sikström (2004) analyzed comparatively three models of learning and forgetting. Also, Plaza *et al*. (2010) analyzed learning curves comparatively and discussed implications for new technology implementation management.

Various learning curves have not only been developed, the effects of learning curve in production systems or enterprises have also been investigated. Andrade *et al*. (1999) considered Activity Based Costing for learning. Anderson (2001) analyzed the impact of high market growth and learning on productivity and service quality, and Terwiesch and Bohn (2001) considered learning in production ramp-up. Ngwenyama *et al*. (2007) used learning curve to maximize IT productivity. Lieven *et al*. (2005) con-sidered managing learning resources for consecutive product generations. Plaza and Rohlf (2008) considered learning and performance in ERP implementation projects. Armbruster *et al*. (2007) dealt with bucket brigates production line with worker learning. Tarakci *et al*. (2009) considered learning effects on maintenance outsourcing. Jaber and Bonney (2003), Jaber *et al*. (2009), and Jaber and Khan (2010) considered lot sizing or lot splitting problem with learning. Jaber *et al*. (2010) coordinated a three-level supply chain with learning-based continuous improvement.

Various learning curves have been developed, and the developed curves have been applied to analyze various activity-related technologies. However, there is still room for researching general learning curve for general activity- related technology transfer.

3. PROPOSAL OF TLQ MODEL

Based on the literature review, a TLQ model will be proposed in this section. After explaining issues to quantify technology level a TLQ model is proposed, and variations, parameters of the model are shown. Then, a procedure to identify the proposed model is proposed.

3.1 Issues to Quantify Technology Level

Technologies are some kind of knowledge, and it has been classified into explicit knowledge and tacit knowledge. Explicit knowledge, or explicit technology can be learned at once by TT, however, tacit knowledge, or tacit technology, can not be learned at once but learned gradually. Complicated technologies need different learning with different characteristics such as conceptual learning and operational learning, and the total learning can be regarded as heterogeneous learning. Also, macro-view of TT needs to discuss long-term organizational learning.

Not for short-term individual learning but long-term organizational learning of complicated organization with many components, simple learning curves are not sufficient. Mixed and more general model is necessary even if the complicated organization can be identified by white-box model as much as possible.

3.2 Proposed TLQ Model

As our fundamental idea for the technology level quantification model, a learning curve can be utilized. For expressing various kinds of learning, not a simple learning curve but a S-curve originally developed by Carr (1999) is applied in our proposed model. As shown in Figure 1, the proposed TLQ model with S-curve has three stages, i.e., early, middle, and final stage. The early stage corresponds to time as a beginner to amateur. The middle and final stage corresponds to amateur to expert, and expert to specialist, respectively. The learning speed at the early stage is slow and the technology level will not be improved fast. After finishing the early stage and in the middle stage, the learning speed will increase and the technology level be improved rapidly. Then, at the final stage, as the technology level approaches to its highest level, the learning speed will decrease, and finally the level reaches the highest level.

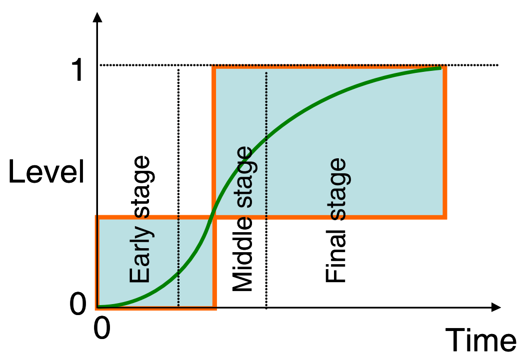

Figure 1. The concept of the proposed TLQ model.

The proposed and previous models have the following relationship. Original learning curve developed by Wright (1936) shows the relationship between cumulative number of units and the required time for the unit. For expressing the technology level, such as speed of production and quality of the produced items, vertical axis shows a reciprocal of the original axis. Also, for increasing generality, horizontal axis shows not cumulative number of units but time, and revised learning curve can be expressed.

For expressing each learning that consists of conceptual learning and operational learning, S-curve is utilized in the proposed technology quantification model. By fitting the S-curve and/or decomposing into some activities, the proposed TLQ model can be applied to approximate organizational and complicated process.

As special cases of the proposed model, we can point out the following cases. At first, the learning of explicit knowledge can be pointed out as a special case of the proposed model. As explicit knowledge can be learned immediately, technology level after learning can be improved just after TT. No further improvement will be expected.

As the next special case, operational learning with constant rate can be pointed out. Operational learning with constant rate can be expressed by original learning curve.

Next, conceptual and operational learning can be pointed out. Conceptual learning as well as operational learning can be expressed by original learning curve. However, the two kinds of learning with different learning rate leads to S-shape learning curve, that is, the proposed model.

Then, general cases of conceptual and operational learning with innovation can be considered. Final technology level will be improved by any innovation much more than that without innovation after operational learning.

3.3 Variation of the Proposed Model

As stated before, in usual TT, the technology to be transferred is not a technology itself but an integrated embodiment of skills, knowledge, technology, methods of manufacturing, and facilities, or various factors should be considered in TT. Then, various factors affects upon the shape of TLQ model, and the type of factors affect the type of influence. At first, the following factors affects upon variation in time of the proposed model. *Infoware*, such as manual or training system for beginners, affects conceptual learning and time at early stage. Also, *humanware*, such as fundamental knowledge, affects the learning and the time. These factors affect only upon the time at the early stage as shown in Figure 2(a).

Orgaware, such as wage system or incentive plan for workers, affects operational learning and time at middle stage. Also, *humanware*, such as individual variation, affects the time. These factors affect only upon the time at middle stage as shown in Figure 2(b). Furthermore, *orgaware*, such as incentive plan for workers, especially experts, affects time at final stage. Also, *humanware*, such as individual variation, affects the time at the final stage as shown in Figure 2(c).

Next, the factors affects upon variation in technology level of the proposed model are discussed. *Infoware*, such as manual or training system for beginners, affects conceptual learning and technology level at early stage. Also, *humanware*, such as fundamental knowledge, affects the learning and the technology level at the early stage. The factors affect only upon the technology level at early stage as shown in Figure 3(a).

Orgaware, such as wage system or incentive plan for workers, affects operational learning and technology level at middle stage. Also, *humanware*, such as individual variation, affects the level as shown in Figure 3(b).

Orgaware, such as incentive plan for workers, especially experts, affects technology level at final stage. Also, *humanware*, such as individual variation, affects the level as shown in Figure 3(c).

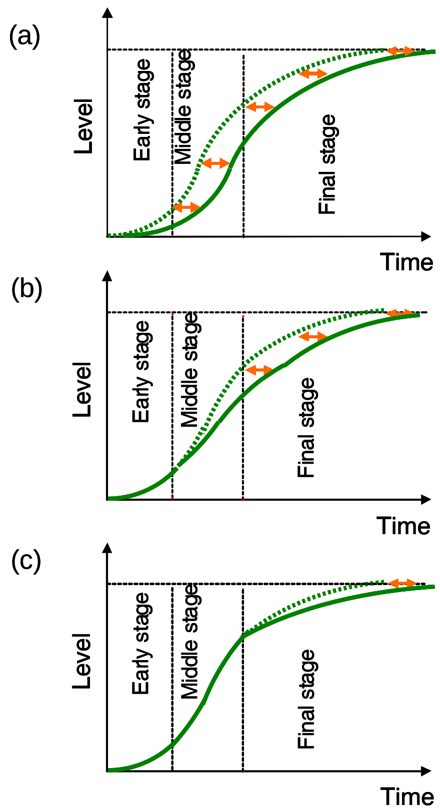

Figure 2. Influence of factors upon time at each stage.

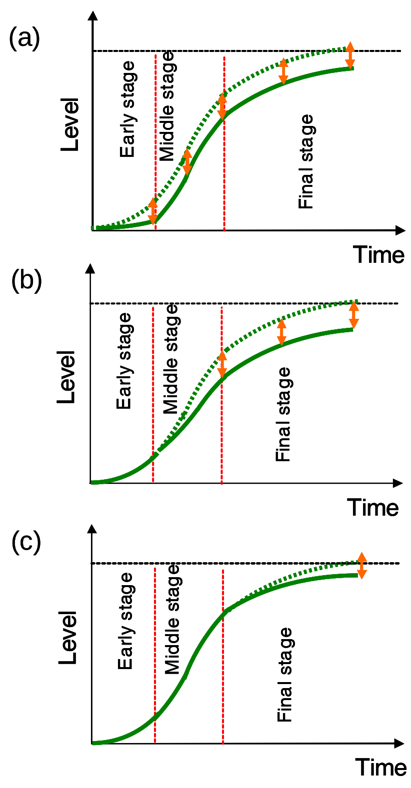

Figure 3. Influence of factors upon level at each stage.

3.4 Parameters of the Proposed Model

For identifying the learning curve, some parameters have to be identified. In this paper, for identifying the learning curve for production speed, such as the number of items produced in unit time, four values of production speed, Y_{min}, Y_1, Y_2, Y_{max}, and three values of time, X_1, X_2, X_{max}, are considered as characteristic parameters as shown in Figure 4. The value of Y_{min} indicates the technology level of the beginner, and Y_{max}, the maximum technology level to be realized by the specialist. Surveying the values and utilizing the surveyed values will identify the learning curve.

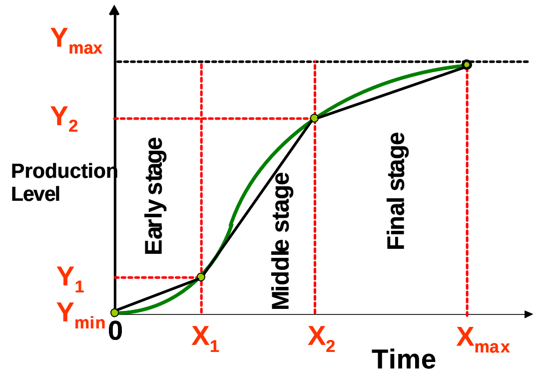

Figure 4. Parameters for the proposed model.

As influential factors for the parameters of the proposed model, factors of *technoware*, *infoware*, *orgaware*, and *humanware* are assumed as shown in Figure 5. *Technoware* affects determining all of seven parameters. Under the condition of *technoware*, *infoware* affects X_1 and X_2, that is, *infoware* is valuable to improve the learning time at early and middle stages. Also, *orgaware* affects (X_2, Y_2) and X_{max}, that is, *orgaware* is valuable to improve not only the leaning time but also the level at middle stage and the leaning time at final stage. Finally, *humanware* affects the variation of Y_2 and the downward variation of Y_{max}.

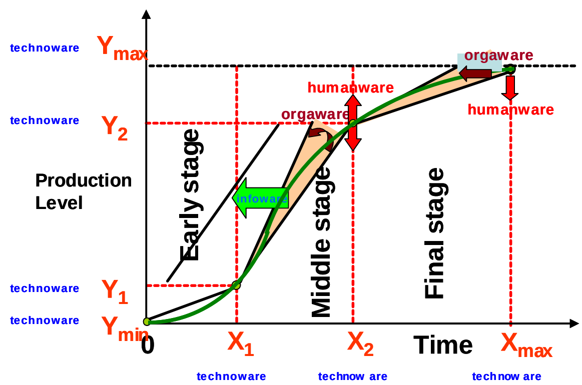

Figure 5. Influence of factors upon the parameters of the proposed model.

3.5 Identification of the Proposed Model

For identifying the proposed model, we propose the following procedure, and some of the steps are shown in Figure 6.

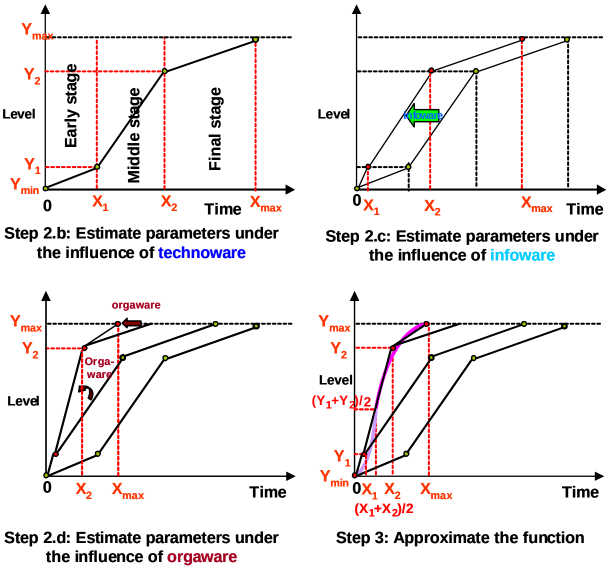

Figure 6. Some steps in the procedure to identify the proposed model.

1. Specify the activity in TT.
2. Identify the parameters.
   a. Identify the related *technoware*, *infoware*, *orgaware*, and *humanware*.
   b. Predict the influence of *technoware* in TT, and estimate the parameters (0, Y_{min}), (X_1, Y_1), (X_2, Y_2), and (X_{max}, Y_{max})
   c. Predict the influence of *infoware*, and estimate the difference of X_1, X_2, and X_{max} from the values estimated in step 2b.
   d. Predict the influence of *orgaware*, and estimate the difference of (X_2, Y_2) and/or (X_{max}, Y_{max}) from the values estimated in steps 2b and 2c.
   e. Predict the influence of *humanware*, and estimate the variance of X_2 and/or X_{max} around the values estimated above.
3. Approximate the function.
   a. Fit a monotonically increasing convex function for (0, Y_{min}), (X_1, Y_1), and ((X_1, $+X_2$)/2, (Y_1, $+Y_2$)/2).
   b. Fit a monotonically increasing concave function for ((X_1, $+X_2$)/2, (Y_1, $+Y_2$)/2), (X_2, Y_2), and (X_{max}, Y_{max}).

4. CASE STUDY

For investigating the effectiveness of the proposed TLQ model, the developed model is applied to a case.

Nishikawa Rubber, Co. Ltd. (NR) produces many kinds of automotives-related products. Recently, NR introduces a *technoware* to change from production line to production cell. The work is not so complicated even in production cell as well as in production line, and the support for training the work has been prepared. The learning of the work is not so tough, and there is no difference between the beginner and the amateur, that means $X_1 = 0$ and $Y_{min} = Y_1$. As a result, the learning curve for explaining the relationship between the working days and the normalized production speed shows not S-curve but ordinary curve, and the learning curves have been identified by the proposed procedure with approximating the actual data with logarithmic functions as shown in Figure 7. All of the coefficients of determination for production line and production cell are more than 0.912, and the approximated learning curve can be considered as highly fitted to the actual data.

Figure 7 shows that, with the *technoware* to change from production line to production cell, the beginner's technology level (normalized production speed) Y_{min} and the amateur level Y_1 may be lower than those under production line. However, the expert level Y_2 and the specialist level Y_{max} will be higher. Also, the time to expert X_2 and the time to specialist X_{max} are longer than those under production line. However, under production cell, the influence of *humanware*, that is, individual variations is much more than that under production line. The difference of the normalized production speed between the best and worst workers is more than 50%, and any kind of *orgaware*, for example, incentive or quota for achievement should be considered.

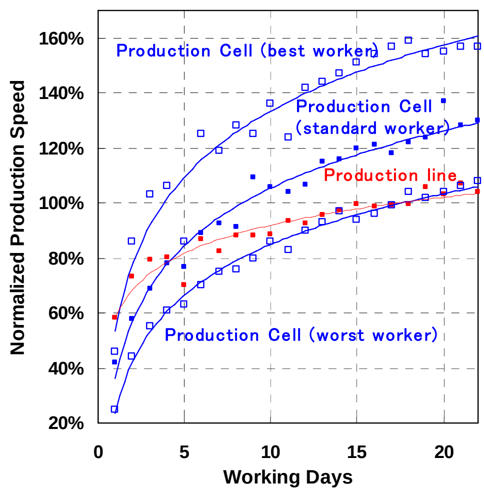

Figure 7. The relationship between working days and normalized production speed.

5. CONCLUSION

This paper developed a technology level quantification model by utilizing a learning curve. In our developed model, the technology level, such as speed of production and quality of the produced items, was expressed as a function of not cumulative number of units but time, for increasing generality. Furthermore, for expressing each learning that consists of conceptual learning and operational learning, S-curve was utilized in our developed model. By fitting the S-curve and/or decomposing into some activities, our developed model can be applied to approximate organizational and complicated process. Some variations in time and levels, parameters of our developed model were shown. Based on the parameters, the procedure to identify our developed model was proposed. Also, the influential factors for the parameters of our developed model were discussed with classifying the factors into *technoware*, *infoware*, *humanware*, and *orgaware*. A case study in manufacturing industry showed the effectiveness of the developed model.

Further additional work should be carried out to strengthen the proposed model. Deciding the suitable time point between stages and estimating the value of parameters is a demanded task. Qualitative discussions about the influence of factors upon time and level should be enhanced by quantitative analysis and relevant case studies.

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