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Towards a learning curve for electric motors production under organizational learning via shop floor data

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Abstract: Due to the fierce market competition, organizations should respond quickly to customers' needs by reducing lead times, or/and lowering operating costs. These objectives can be reached by effectively assessing the workforce capacities. Manufacturing progress function or organizational learning is considered as one of the most important factors that affect workforce capacity. The current paper introduces an examination research that uses factory data to introduce the most appropriate organizational learning model for the manufacture of electric motors. The data used was collected for a period of 42 months for 110 manufacturing processes and 10 different styles of electric motors. By using regression analysis the significant parameters were obtained for 10 learning models. And in order to select the most reliable one, the analytical hierarchy process (AHP) was used after defining the selection criteria. Among most of monovariate learning models listed in literature the model of Wright (1936) is found to be the best one to fit the data, and then comes the model of Knecht (1974). The failure of the other models in fitting the data was also shown.

Keywords: Learning curve, Continuous improvement, manufacturing of electric motors, non linear regression, analytical hierarchy process (AHP).

1. INTRODUCTION

For the previous decades the modelling of the manufacturing progress function, also known as work-based-learning or learning curve, and according to which the productivity improvement can be modelled as a function of the work replication, aroused great interest from researchers and practitioners. The pioneer in this subject is Theodore P. Wright (1936) who discovered that, in aircraft manufacturing, a 20 percent productivity improvement is achieved each time the production quantity is doubled. This phenomenon has a great importance in operations planning and control by which the required human resources can be accurately estimated. As stated by Badiru (1991) learning curves are essential for setting production goals, monitoring progress, reducing waste, and improving efficiency. The learning curve concept was considered in many applications including cost estimation (Yelle, 1976), identification of production lines' bottlenecks (Finch and Luebbe, 1995), lot sizing (Jaber et al., 2009), implementation of ERP (Plaza et al., 2010), production planning (Glock et al., 2012), manpower assignment (Attia et al., 2014), inventory management (Teng et al. 2014), construction (Srouf et al. 2015), and recently in machine scheduling (Ji et al. 2016) and construction costs of nuclear power reactors (Lovering et al. 2016). In addition, its existence was validated across a wide range of products' manufacturing e.g. aircraft (Wright, 1936), fuel cells

(Tsuchiya and Kobayashi, 2004), washing machines, laundry dryers, and dishwashers (Weiss et al., 2010).

According to Levin and Globerson (1993) learning curves can be divided into two major types: individual and organizational. The individual learning curve considers the person's performance evolution versus work replications. According to DeJong (1957) skills development process includes not only the under-skilled workmen but also the skilled and experienced operators. Organizational learning curves are used when the evolution of the desired output (e.g. a specified product) is a function of the performance of the whole organization elements rather than that of a specified individual. Ellstrom (2001) defined it as changes in organizational practices (including routines and procedures, structures, technologies, systems, and so on) that are mediated through individual learning or problem-solving processes. For more details on organizational learning, see the work of Levitt and March (1988).

In industrial applications the representation of learning effect on an individual basis is a very complex task where the industrial setup requires a wide range of different processes that are integrated to form the final products. To overcome this complexity the consideration of the skill evolution is represented in a batch basis. In other words, one can represent the number of required man-hours to manufacture a specified number of good parts, semi-finished products or even the whole products. But this aggregated consideration

represents the organizational learning as well for a specified firm, where organizational learning refers to the total learning accumulated in an organization that depends on the continuous improvement (Kim and Seo, 2009), and distinguishing between individual learning and the organizational one is a hard task. In reasons of this difficulty many works propose to represent the organizational learning relying on the traditional learning models (e.g. Saraswat and Gorgone, 1990; Epple et al., 1991; Chatzimichali and Tourassis, 2008).

In the current investigation learning is the process of making, retaining, and transferring knowledge within the factory for all workforces. The performance is improved as the firm gains experience; from this experience, it is able to build/accumulate knowledge. This knowledge is wide, covering any topic that could enhance the organization's performance. Examples may include ways to increase production efficiency or to develop beneficial relations among different groups. Knowledge is created at three interrelated levels: individuals, groups, and organizational aspects. The three levels can be combined to form the organizational continuous learning. An organization learns successfully when it is able to keep this knowledge and transfer it to several divisions. Organizational learning can be measured in different ways; however one common measurement used is the learning curve: it measures the relation between an improvement in labour skills and the practice of a given job. In other words, learning effect leads to reduce the unit production cost with an increased involvement of labour and managers in the production process: this leads to improvement in their efficiency. Here 'efficiency' means greater amount of output generated per process/product over a specified period. The current paper investigates the most used monovariate learning models in order to introduce the best one. The investigation relies on shop floor data collected from a factory that is dedicated to produce electric motors for a large home appliance manufacturing company.

The remainder of this paper is organized as follows: in Section 2 the most common monovariate learning models will be presented. Then Section 3 describes the manufacturing process of electric motors as a case study in one of the Egyptian manufacturing companies. Section 4 introduces the research methodology. Section 5 discusses the results. And finally section 6 introduces the conclusions and future work.

2. LEARNING CURVES

In literature there are many works that provide several formulations of the learning curve, starting from the model of Wright (1936). According to the review paper of Yelle (1979), the reason for searching more advanced models than the log-linear one of Wright (1936) is that the log-linear model does not always provide the best fit in all simulations. But on the other side, it is the most used model in reasons of its simplicity and generality of applications. Nembhard and Uzumeri, (2000) classified the learning curves according to two attributes depending on the originated bases: aggregated

models or individual models, where Badiru (1992) classified them according to monovariate or multivariate models. Multivariate models were proposed to accommodate numerous factors that can influence how fast, how far, and how well a worker learns within a specified horizon. Depending on the work of Badiru (1992), Nembhard and Uzumeri (2000), the monovariate models can be listed by the following.

Aggregated models:

- The log-linear model (Wright, 1936);
- The S-curve (Carr, 1946);
- The Stanford-B model (Asher, 1956);
- DeJong's learning formula (DeJong, 1957);
- Levy's adaptation function (Levy, 1965);

Individual models of (Mazur and Hastie, 1978):

- Exponential models with 2 and 3 parameters;
- Hyperbolic models with 2 and 3 parameters;

Combined models:

- Pegel's exponential function (Pegels, 1969);
- Knecht's upturn model (Knecht, 1974);

3. MANUFACTURING OF ELECTRIC MOTORS

The current real case study was conducted at an Egyptian manufacturing firm that is specialized in the manufacturing of electric home appliances. The study only considers the electric motors workshop. The production of electric motors has started to grow up in the current firm since 1992. The factory under consideration manufactures four types of electric motors with their different characteristics: 1- ceiling fans, 2- vacuum cleaning machines, 3- ventilators and 4- disk fans. Motors of types 1, 2 and 3 are completely produced in the factory, but the factory contributes to 95% of processes operations for type 4. Manufacturing these four families of products involve 110 production processes that must be performed to shape the required parts. The production processes can be classified into six main categories as shown by the simplified flow diagram shown by Fig. 1.

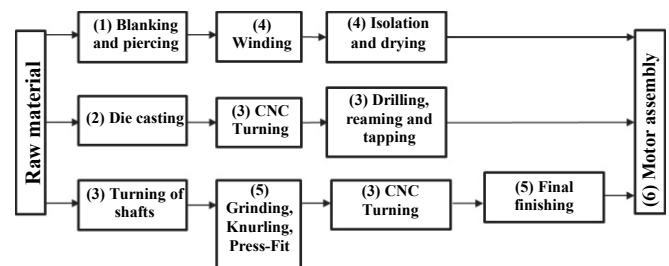


Fig. 1 illustration of motor production processes

The first category is the blanking and piercing operations of the steel strips that produce the steel laminations which form the stator of the electric motors. The second group is the die casting operations, producing some different parts such as the front and rear covers of the motors, and the cover of transmission gears for some models. Following the casting process, there is a need for metal cutting processes such as turning, drilling, reaming and tapping operations that form the third category. The fourth kind gathers the wiring operations that integrate the stator with the required electric

coils, then isolation and treatment of coils. There are some other processes such as pressing, grinding, knurling, shaft threading etc. These processes, simply known in this company as finishing, characterises the fifth category. Finally, the sixth category is the assembly process that gathers all the parts together so as to form the final product. Following the production steps, we find the inspection and testing operations, but they are not considered in this study.

4. RESEARCH METHODOLOGY

4.1 Data collection

In order to figure out the best model of productivity evolution, the actual production quantities are taken into consideration. The current study considers a production period of 42 months, with an average monthly production rate of over 17,000 units of end products. It starts from June 2011 to the end of December 2014 and is split into 6 months long production periods. The use of such an aggregated level of data is practically valid, according to the empirical analysis based on the work of Smunt and Watts (2003): the aggregated data provide confidence to incorporate the learning curve effect into both short-and medium-term manufacturing horizons. And the data aggregation reduces the high variation that can be found in the detailed level - another reason is the confidentiality of firms' detailed information. In order to compute the labour required for manufacturing a specified number of parts or end products the term "man-day" is used. Throughout this work, it can be represented as the number of workers required to produce a number of 1000 units from a specified part/product during only one working day. At the end of each period two types of data are collected for the 110 processes. The first is AN_{pj} : it represents the actual number of parts produced at each process p during production period j ; the second is TW_{pj} : it denotes the total number of workers required during this period j to produce the corresponding number of units at process p . Afterwards the man-day for each process is computed as: $man-day_{pj} = (1000 \times TW_{pj}) / AN_{pj}$. Additionally to the processes-based data, the final products data are also collected for all of 10 final products' models. For each product the corresponding man-day is also computed by the same manner.

4.2 Selected learning models

In this study the learning models presented in section 2 were considered in the investigation. In each model the independent variable χ represents the accumulated production duration in months. The learning model dependent variable represents the developed man-day. It will be used to represent the evolution of the required manpower capacity to produce a number of 1000 units of a given part at the associated production process or kind of product. We propose to introduce another mathematical model to represent the relation between man-day and the worked production period χ . The proposed model is a 3rd degree polynomial ($man-day = c_1 + c_2\chi + c_3\chi^2 + c_4\chi^3$) where c_1 to c_4 are constants that can be found by data regression. We call it cubic function model.

Regardless the inapplicability of this function to represent a learning model, it was proven to fit all types of data. The drawback of this function is its cyclic nature (cycles of decreasing and increasing); accordingly it cannot be used to represent the evolution of manufacturing productivity in long run bases. However it can be used efficiently to forecast the improvement in productivity evolution for short terms.

4.3 Data analysis

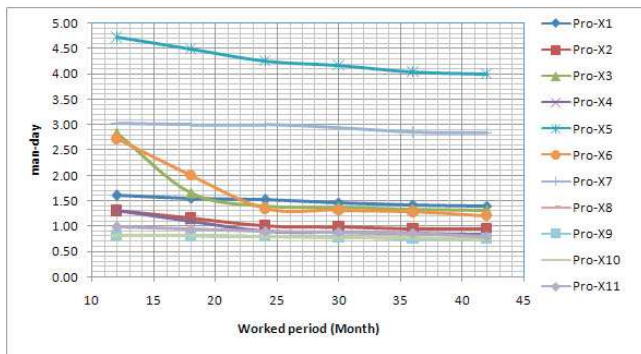
The data analysis is conducted relying on two methods: the scatter plot with line of fit, and the regression analysis. The scatter plot is performed between the worked period (in months) and the required man-day to produce a number of 1000 units either for processes and products. As it well known the scatter plot is used to show visually the trend of data. Regression analysis is mainly used to get the mathematical representation of this trend. Accordingly and in order to get the most appropriate learning model that can significantly fit the collected data, all of the previous learning models are regressed using the statistical software (XLSTAT). The fitness was measured by three criteria: the visual inspection of the scatter plot with the line of fit, the regression coefficient R^2 and the sum of squares of the errors (SSE). All of these criteria express the relevance of the model to represent the real data. The regression analysis was performed for each of the 110 processes in addition to the final 10 products.

5. RESULTS AND DISCUSSIONS

First, according to the data plots (Fig. 2), the learning effect was proven for processes as well as for products: the required capacity (man-day) decreases as the number of worked periods grows. Due to the aggregation of many processes or products in one chart, one can figure out that the amount of reduction is small. But the percentage of reduction varies from 6% to 56% for the 110 operations, and from 6% to 11% for products. The reduction percentage of products is smaller than that of processes where the full product is simply an aggregation of many processes. These reductions in the required capacity cannot be neglected in manufacturing management, e.g. capacity planning, productivity analysis etc. This reduction depends on many factors that form the organizational learning. These factors include: personal learning, mastering of tools and fixtures, manufacturing improvement initiatives (e.g. lean manufacturing, advanced maintenance philosophies and total quality management), and/or managers experience development (better use of resources, development of behavioural skills, increased cooperation between work groups, and standardization of processes in order to prevent defects). These factors formulate the final productivity improvement.

As previously mentioned, the regression analysis is used to define the best-fitting learning model(s). The R^2 and SSE are represented using the interval plot at confidence level of 95%: results are displayed in Fig. 3, 4 and 5. In these figures, the confidence intervals of R^2 are presented in a descending average R^2 order. The confidence intervals of SSE are presented in growing average SSE order. Amongst the

models listed in section 2, seven models proved to fit the process data. These seven models are: Levy (1965), Knecht (1974), hyperbolic models with 3 parameters (named Mazur-3P) or with 2 parameters (Mazur-2P) (Mazur and Hastie, 1978), Pegels (1969), Wright (1936), and DeJong, (1957). All the other models show inability to fit the data. And only three models are likely to fit the data concerning products, these models being Knecht (1974), Wright, (1936), and DeJong (1957). In the following, the investigations of the different learning models for each process and each product will be presented.



(a)



(b)

Fig. 2 Sample of: (a) processes data (b) products data

Relying on the data analysis and as shown in the sample Fig. 3, 4, and 5 one can observe that the best model to fit the data is the cubic function we propose. It provides the highest values of R^2 (average of 0.986 for operations and 0.926 for products) with low variance (shortest interval). It also provides smallest values of SSE (0.096 for operations and 2.38 for products). It looks relevant for all kinds of data. Regarding learning models listed in literature, the performance of each model varies according to the data investigated. Referring only to the average R^2 of the operations data one can rank them as: Levy (1965) with average $R^2 = 0.96$ and average SSE= 0.05; Knecht (1974) with $R^2 = 0.96$ / SSE= 0.19; Mazur 3P with $R^2 = 0.923$ / SSE = 0.878; Pegels (1969) with $R^2 = 0.912$ / SSE= 0.255; DeJong (1957) with $R^2 = 0.86$ / SSE = 0.503; Wright (1936) with $R^2 = 0.856$ / SSE= 0.485; Mazur 2P ($R^2 = 0.755$ / SSE= 0.354). But it isn't correct to rank them according to the average R^2 only. As shown in Fig. 4 and 5, there are instable models e.g. some models unable to fit the data of assembly operations and data of full products. Also there are variations in the obtained R^2 and SSE. In order to rank these

models correctly the results of the different measuring criteria (R^2 , Stability, SSE, Variation of R^2 , and Variation of SSE) are computed. The analytical hierarchy process (AHP) could be adopted to sort the models according to their results.

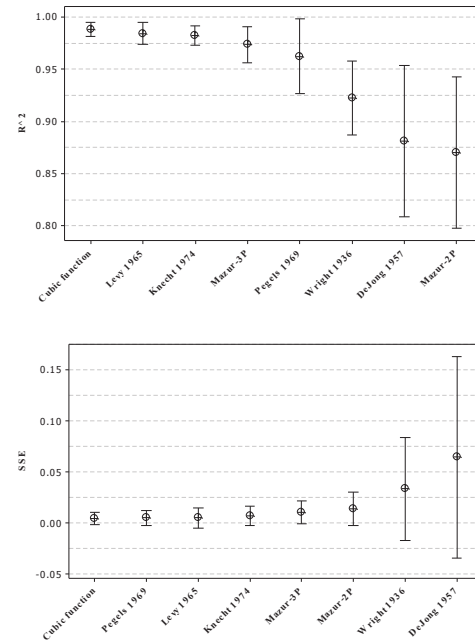


Fig. 3 interval plots of R^2 and SSE for blanking and piercing

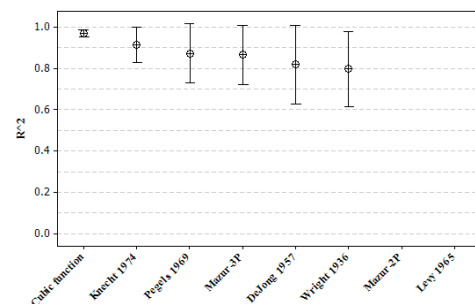


Fig. 4 interval plots of R^2 and SSE for assembly

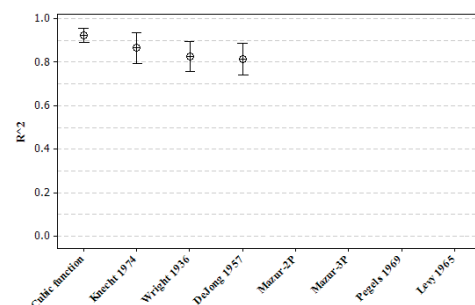


Fig. 5 interval plot of R^2 for products' data

The current problem can be rearranged as a three levels hierarchy in which the alternatives are the learning models, the criteria are R^2 , Stability, SSE, Variation of R^2 , and Variation of SSE, and the goal is to find the best model to fit the manufacturing data. According to Saaty and Vargas (2012) the AHP can be performed as following. First, pair-

wise comparisons are performed between the results of each pair of models. Regarding pair-wise comparison of R^2 : for each instance, the obtained R^2 of the first model was divided by that of the second one. After that, the sum of these ratios of all instances was computed. After computing all the pair-wise comparisons of models, the obtained values were then normalized over the interval [1, 9] where 1 indicates equal importance of the two models and 9 extreme superiority of the first model on the second one. The obtained preference matrix is presented in table 1 where the models are coded as [1] Mazur-2P (1978); [2] Mazur-3P (1978); [3] Pegels (1969); [4] DeJong (1957); [5] Knecht (1974); [6] Levy (1965); [7] Wright (1936); [8] Cubic Function. For a given model, its comparisons with all the others are read on the corresponding line: thus, the model of Knecht (1974) [5] is preferable to that of DeJong (1957) [4] by a factor of 5.25. But the model [4] is better than the [5] by a preference factor of $1/5.25 = 0.19$, which means that it is not preferable at all. Relying on this preference matrix the priority of each model, computed via the principal eigenvector of the preference matrix is presented in the last column of table 1.

Regarding the models' stability, for each model the number of instances (operations, products) where a specified model fits the corresponding data was computed. Then the pair-wise comparisons were determined, after that results were normalized over the interval [1, 9] where 9 indicates the highest stability of the model. Table 2 displays these results and here again the priority of each model according to this criterion was defined by computing the principal eigenvector of the stability preference matrix and provided in the last column. By the same manner, the preference matrices for the other criteria were computed. In these results, regarding R^2 and stability, the maximum values are preferred, whereas for SSE, variation of R^2 and variation of SSE, the minimum values are preferred. In each case of SSE, variation of R^2 and variation of SSE, the data were first transformed to "the maximum is the best" by subtracting each element of the matrix from the highest value in the whole matrix.

The second step consists in prioritizing the sorting criteria with respect to the desired goal. Each of the criteria was compared to each other, according to a qualitative scale of (1, 3, 5, 7, 9) to represent respectively equal, moderate, strong, very strong and extreme importance. Results of these pair-wise comparisons are listed in table 3. After that the principle eigenvector was computed to represent the priority vector.

Table 1 Models comparisons according to R^2

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	Model priority
[1]	1.00	0.22	0.22	0.16	0.12	0.45	0.15	0.11	0.018
[2]	4.65	1.00	0.58	0.28	0.19	4.53	0.25	0.17	0.058
[3]	4.64	1.72	1.00	0.29	0.19	2.68	0.24	0.17	0.055
[4]	6.15	3.57	3.45	1.00	0.19	0.72	0.25	0.17	0.080
[5]	8.30	5.20	5.33	5.25	1.00	1.41	0.43	0.24	0.165
[6]	2.22	0.22	0.37	1.38	0.71	1.00	0.19	0.14	0.046
[7]	6.78	4.02	4.18	3.98	2.32	5.37	1.00	0.18	0.188
[8]	9.00	5.86	6.02	6.03	4.09	6.97	5.43	1.00	0.391

Table 2 Models comparisons according to stability

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	Model priority
[1]	1.00	0.19	0.19	0.15	0.13	0.36	0.13	0.13	0.017
[2]	5.18	1.00	0.27	0.20	0.17	0.64	0.17	0.17	0.032
[3]	5.30	3.75	1.00	0.21	0.18	0.68	0.18	0.17	0.046
[4]	6.60	4.89	4.78	1.00	0.22	1.57	0.23	0.22	0.084
[5]	7.66	5.83	5.71	4.49	1.00	16.85	0.28	0.27	0.200
[6]	2.81	1.56	1.47	0.64	0.06	1.00	0.11	0.11	0.035
[7]	7.54	5.72	5.60	4.39	3.55	8.74	1.00	0.26	0.240
[8]	7.78	5.93	5.81	4.58	3.73	9.00	3.82	1.00	0.347

Table 3 Pairwise comparison of the sorting criteria

	R^2	Stability	SSE	Var. of R^2	Var. of SSE	Model priority
R^2	1	9/7	7/3	9/3	7/1	0.329
Stability	7/9	1	7/1	5/1	9/1	0.431
SSE	3/7	1/7	1	3/5	9/3	0.094
Var. of R^2	3/9	1/5	5/3	1	3/2	0.100
Var. of SSE	1/7	1/9	3/9	2/3	1	0.046

Once we have evaluated the priority of each learning model according to the different criteria, and the priority of each of these criteria with respect to the goal, one can compute the consistency of the different models with respect to the final goal. The obtained priorities of learning models can be synthesized as shown by figure 6. As shown the best model to fit the data is the cubic function then the model of Wright (1936), then the model of Knecht (1974). And the worst models are that of Mazur and Hastie, (1978) with 2 parameters and 3 parameters. The poor performances of these two last models may relate to the fact that they both represent individual learning and not an aggregated betterment.

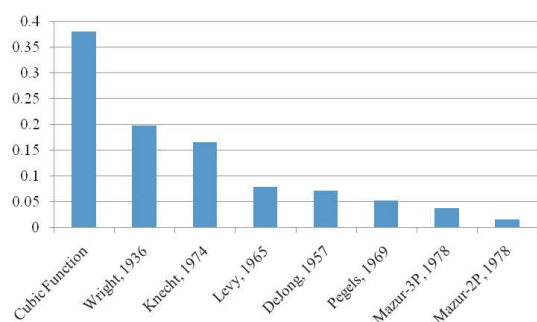


Fig. 6 Priority of learning models in fitting database

CONCLUSIONS

Due to the greatest importance of the organizational learning in operations management, the current paper introduces an investigation study to determine the most reliable monovariate learning model according to a set of shop floor data. A total of ten learning models have been considered. The data base considers 110 manufacturing operations and 10 final products. The regression analysis has been used to

determine the significance of models to fit the data. In order to introduce the most significant and stable model to present the organizational learning phenomenon, the AHP process has been used to prioritize the associated performance of each model. Amongst all the monovariate learning models listed in literature the model of Wright (1936) was proven to be the best one to fit the collected data of electric motors manufacturing. The model of Wright (1936) can be used efficiently to represent the organizational learning of the firm relying on the aggregated data. As a future work, the best model will be used for the capacity planning. Moreover, the factors affect the development of organizational learning can be investigated to introduce the principal causes.

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