A BEST-MATCHING PROTOCOL FOR SUPPLIER SELECTION IN E-WORK NETWORKS

Juan D. Velásquez, S.Y. Nof
School of Industrial Engineering, Purdue University, 315 N Grant Street, West Lafayette, IN, USA

Abstract
A Best-Matching Protocol can give a company an upper hand in the supplier selection process by determining which one best satisfies the pre-defined quality and cost requirements. The Best-Matching Protocol developed enables better matches for geometrical specifications (e.g., physical components) as compared to random matches based on the evaluation of a new performance measure, Best-Fit Index [1], for which a small value is desired. Two statistical distributions, normal and uniform, were used for the generation of part specifications of physical components. A statistical analysis corroborated that the performance of the Best-Matching Protocol in yielding better matches for geometrical specifications, within allowed tolerance ranges, was consistent across both distributions. A double-match was also implemented using as input the normally-distributed matching results from the manufacturing scenario and the cost of different suppliers to produce and deliver the components. Finally, the Economic Value of a Match (EVM) enables the selection of the supplier(s) that better meet the quality and cost requirements.

Keywords:
Distributed operations, selective assembly, supply networks.

1 INTRODUCTION

Large industrial systems are often geographically distributed. A geographically distributed system has great advantages such as increased technical specialty; however, there are drawbacks to such distributed facilities; sub-assembly parts can be manufactured without always considering the counterparts' machined dimensions. In order to satisfy customer demand and ensure better quality products, it is critical to verify the dimensions of the parts being assembled and as such, it is recommended to select best matching sub-assembled components that yield the finished part with the desired functionality and performance.

It is assumed that within specified tolerance limits, better products can be produced by better matching of individual components. Within the context of modern-day integration of business processes, dimensional integration of manufactured parts remains a challenge to assembly and manufacturing processes. For example, integration and assembly of power generators and engines require coordinated supplies of machined components, control and power wiring, hydraulic and pneumatic piping, large variety of fasteners and lubricants, and more. This research focuses on two areas of integration, dimensional, and business partners' collaboration, both enabled via a Best-Matching Protocol (BMP). BMP enables better assemblies while procuring the parts from the suppliers that better meet part requirements and manufacturing costs. Such best matching is particularly beneficial when sub-assembled parts from widely dispersed suppliers have to be combined or assembled. A key benefit of incorporating the Best-Matching Protocol is that detailed information gathered locally from distributed enterprises can be further leveraged for purposes of product quality and customer service satisfaction.

2 RESEARCH BACKGROUND

2.1 Background

Manufacturers face tremendous competition from one another to produce parts of higher quality at lower costs. Selective assembly, the process by which high precision assemblies are obtained from low precision components has enabled companies to remain competitive by reducing surplus costs of components. The number of groups and range of each group, into which to divide the population of components, still remains a challenge as their selection has significant effects in the accuracy of the process and the number of surplus parts. As the number of groups increase, the accuracy of the assembly does too; unfortunately, parts in some of the groups will remain surplus due to the imbalance of mating parts [2] and the biased dimensional distribution of the components. On the work by Fang and Zhang [3], the authors employ an algorithm that groups the components based on balanced probability and unequal tolerance range in each group in order to reduce the number of surplus components. The work by Kannan and Jayabalan [4] enables the design of the required mean for selective assembly. The authors expanded their work to include the selective assembly process for linearly assembled components [5] [6]. Multiple parameter selective assembly has been explored using a multiple regression quality model and compensating for product deviations [7]. Genetic algorithms [8] are just some of the methods authors have tried in recent years to address the challenges of selective assembly and particularly the best combination of groups.

The selection of business partners based on various criteria (i.e., costs, efficiencies, trust, precision, etc.) have become of increasing importance [9] [10]. In order to select the appropriate suppliers (or customers), cost and quality requirements need to be matched. Because of the intricate relationship among the members of a supply network, a proper match that considers both the quality of the parts and the costs to procure the parts is difficult to achieve and therefore, a harmonized communication and matching system is required to ensure desired performance and effective collaboration. Among the integration, coordination and collaboration theory and models of e-Work and e-Manufacturing are computer-supported collaborative work tools that enable information exchange among distributed team members (e.g., suppliers, manufacturers and assemblers) and the integration and management of the entire product life-cycle [11] which support the effective selection of suppliers for a dynamic supply chain.

3 BEST-MATCHING PROTOCOL DEFINITION

Best-Matching for assembly matching was initially researched [1] with the development of a best-matching protocol for geometrical components on a one-dimensional level and with the further development of a double-match which identifies the supplier that can better meet quality demands and costs requirements. A new performance measure, Best-Fit Index (BFI), enabled the comparison of using random matches compared to those obtained with BMP by minimizing the Best-Fit Index of two sub-assembled components. A study of matching parts on one dimension following normal and uniform statistical distributions, the most common found ones in industrial environments, compared to random matches in order to identify the performance improvements of matching 8 and 100 parts are presented in Table 1 [12]

3.1 Geometrical best-matching

In assembly operations, individual components are often manufactured in independent lines with the components later being assembled together with limited consideration for better matching the different components. The Best-Matching Protocol (BMP) for geometric components seeks to match individual components and sub-assemblies based on their current measured attributes, in an effort to yield a better assembled product. Consider a one-dimensional measurement of two components, a bolt A_i and a washer B_j, for matching under the BMP.

Definition #1: Dimensional definition of components

$\delta(A_i)$: dimensional measurement of bolt i

$\delta(B_j)$: dimensional measurement of washer j

Definition #2: For an equal number of bolts and washers, m, that have to be pair-wise matched, define a Best-Fit Index (*BFI*) that represents the relative quality of a match among components to be assembled or joined.

BFI of bolt (A_i) = min $(|\delta(B_j)-\delta(A_i)|/\delta(A_i))= \beta(A_i)\ \forall j \in m$

BFI of washer (B_j) = min $(|\delta(A_i)-\delta(B_j)|/\delta(B_j)) = \beta(B_j)\ \forall i \in m$

Definition #3: Define a joint Best-Fit Index (*BFI*) for matching bolt A_i with washer B_j as $\beta(A_i, B_j)$

Definition #3A: Define the joint Random Fit Index (*RFI*) for matching bolt A_i with washer B_j as $\varphi(A_i, B_j)$

Definition #3B: Define an overall best joint *BFI* for a match as

$$\mathrm{OBM}(\beta(A_i, B_j)) = \min \sum_{i,j=1}^{m} \beta\left(A_i, B_j\right)$$

Definition #4: Tie breaking rules for matches that yield identical *BFI* values.

For instances when washer B_j can be matched equally well to multiple A_i bolts, tie-breaking rules are applied to select the bolt that yields the lowest $(\beta(A_i, B_j))$. The following geometric tie-breaking rules are applied:

Tie-breaking rule 1 (TB_1):

If B_j is the "best" washer match for both bolts A_i and A_l

Compute the next best-match for B_{j+1} and A_i : $(|\delta(B_{j+1})-\delta(A_i)|/\delta(A_i)) = x$

Compute the next best-match for B_{j+1} and A_l : $(|\delta(B_{j+1})-\delta(A_l)|/\delta(A_l)) = y$

If $x < y$ match washer B_j with bolt A_i, otherwise, match with bolt A_l

Tie-breaking rule 2 (TB_2):

If washers, B_j and B_{j+1}, are "best" matches for bolt A_i then:

If neither washer matches another bolt, arbitrarily pick either washer

If either of the washers matches another bolt $A_.$, pick the washer that does not have another match.

Definition #5: The Best-Matching Protocol (BMP) for geometrical matches is defined as:

$\Omega_{MG} = \{A_i, B_j, MP, TB_s\}$ where

A_i: Bolt i, $i = 1, \ldots, m$.

B_j: Washer j, $j = 1, \ldots, m$.

MP: Matching process by (a) BMP (single attribute), or (b) by random matching

TB_s: Tie-breaking rule(s), $s = 1, \ldots, 2$

The Best-Matching Protocol for geometrical matches can be expanded for multiple geometric attributes and further enhanced to incorporate additional non-geometric attributes, e.g., suppliers' cost information and customer requirements as presented in the next section.

3.2 Supplier best-matching

The matching of suppliers and customers in a supply network can be facilitated by applying the Best-Matching Protocol (BMP) to non-geometrical attributes in a distributed environment. To apply the BMP to a supply network environment, it is initially assumed that both the supplier of bolts and washers are integral participants in the network being investigated. Customers in this industry are not only concerned with the quality of the component manufactured but they are also concerned with other attributes, such as the price, service-ability, shipping cost, purchasing conditions, etc. Due to the cost considerations of the matching process, a double-match process has also been developed. In the following discussion, price (cost) is considered as the attribute of matching concern.

Definition #6: Supplier and customer price information.

Ps_k : Supplier k's floor price, minimum price suppliers are willing to accept when selling a part.

P_{Bc} : Customer c's ceiling price, maximum price customers are willing to pay for a part they buy.

Definition #7: Economic Cost of a Match (*ECM*).

Individual gains for the supplier: $GS_{(k,c)} = ([P_{Bc} - Ps_k]/P_{Bc})\ \forall k, c \in K, C$

A best match is obtained when $GS_{(k,c)}$ is maximized while minimizing the Economic Cost of a Match (*ECM*) defined as

$$ECM = \sum_{k \in K}\left(PC_k + VC_k + CC_k + LC_k\right)$$

where

PC_k = Production cost of supplier k;

VC_k = Vulnerability cost (penalty cost when supplier k cannot fulfill an order in time);

CC_k = Communication cost a customer needs to pay to communicate with supplier k;

LC_k = Logistics Cost incurred for ordering and receiving supplies from supplier k.

Definition #8: A Double-Match ($\psi_{(k,c)}$) is defined as a match combination of sub-assembled parts and cost criteria defined by both the suppliers and the customers.

$$\Psi_{(k,c)} = GS_{(k,c)} \frac{1}{\left(\beta\left(A_i, B_j\right)\right)}$$

$\psi_{(k,c)}$ is computed for a given customer, for all suppliers and every possible pair-wise joint Best-Fit Index $\beta(A_i, B_j)$. The maximum of all ψ's for a given customer is chosen as the optimum.

Definition #9: Best Matching Protocol (BMP) for non-geometrical matches is defined as:

$\Omega_{MNG} = \{S_k, c, MP, TB_s\}$ where

S_k: Supplier k of bolts A_i

c: Customer (or buyer), already having washers B_j

MP: Matching process by (a) BMP(single attribute), (b) BMP(double attribute), or (c) random matching

TB_s: Tie-breaking rule(s), $s = 1, \ldots, 2$

Definition #10: The Economic Value of a Match (*EVM*) is defined as the total economic gains for supplier $_k$ ($GS_{(k,c)}$) minus the cost of a match (*ECM*) multiplied by the Overall Best Match (*OBM*) of a component for a specific customer (c).

4 BEST-MATCHING PROTOCOL: CASE STUDY

Single-dimensional matches performed with BMP resulted in statistically significantly better matching at 95% when comparing the Best-Fit Index (*BFI*) and the Random Fit Index (*RFI*) of the matches (Table 1). The statistically generated dimensions for the two parts represent low precision and high precision components. By restricting the generation of parts to a pre-determined tolerance range for all distributions, extremely low precision parts are not e-manufactured.

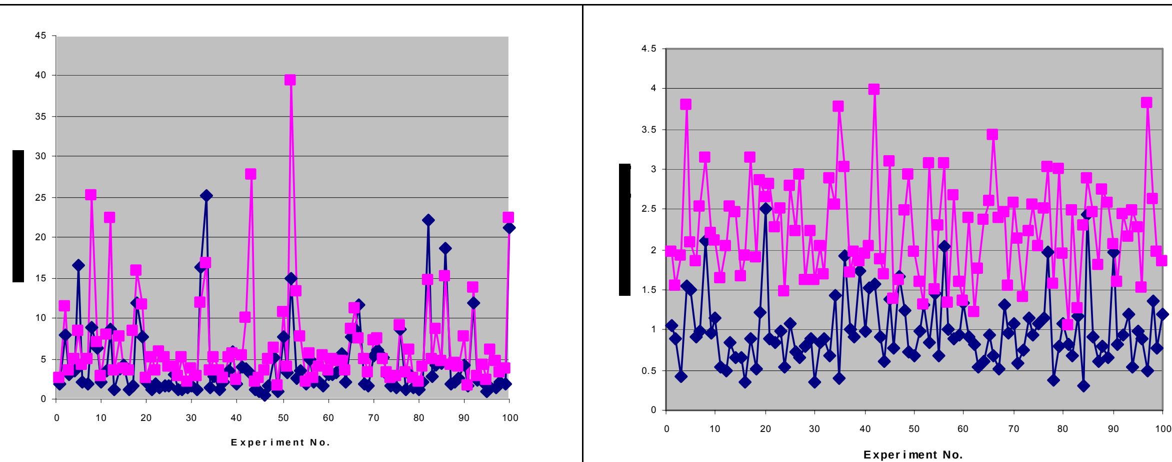
Graphical comparisons between the two matching methods for normal and uniform are illustrated in figure 1 for the matching of eight parts, a small data set. After analyzing the smaller sets results, an analysis of one-hundred normally and uniformly distributed parts was conducted (Figure 2). The results corroborate that BMP-enabled matching performs better than random matching (i.e., in the uniform distribution BMP outperformed random matching in all cases).

Best-Fit Index (BFI) values from single geometrical cases, and different cost combinations defined for the Economic Cost of a Match (*ECM*) along with different gains from a supplier $GS_{(k,c)}$ are combined to determine the Economic Value of a Match (*EVM*) for six suppliers manufacturing normally distributed washers and bolts. As shown in figure 3, a decision maker can quickly identify, based on unit costs, whether a match is worth undertaking or not. If the cost to perform a match is 1 or 2 cost units all suppliers can provide the parts economically. However, different suppliers provide a greater value than others (i.e., if the cost of a match is 2 cost units, supplier's 2, 4 and 6 provide the best *EVM*). Once the cost to perform a match exceeds 3 cost units, matching is no longer economically feasible for a number of the suppliers (i.e., supplier 2, 3 and 5).

Table 1. Experimental results and significance of results of BMP for both normal and uniform statistical distributions (#)

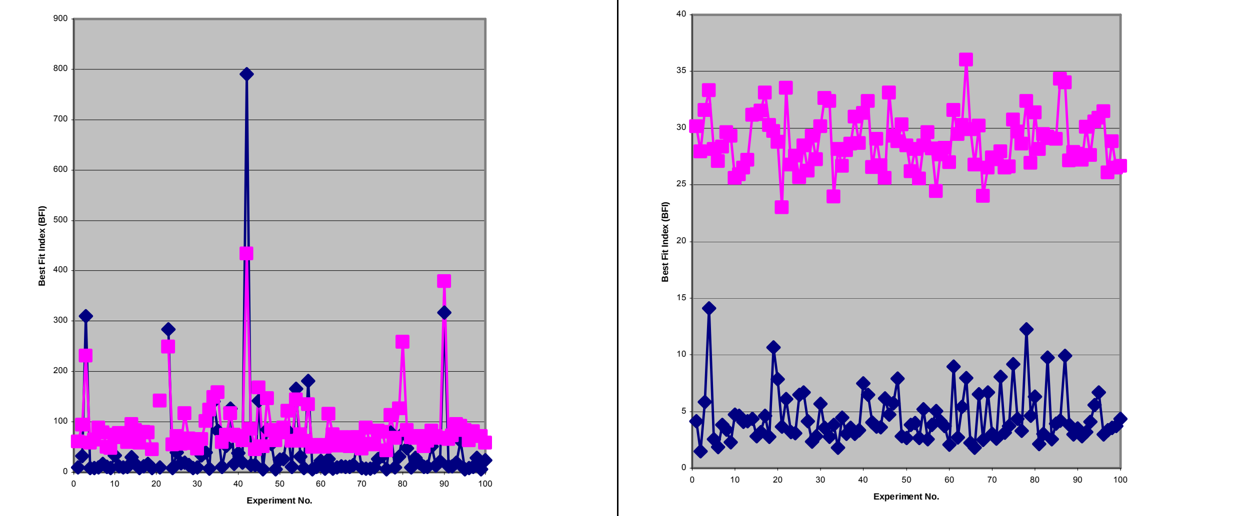
Distribution	Number of items Matched ($_i = _j$)	Best Fit Index (BFI) BMP $\beta A_i,B_j)$	Random Fit Index (RFI) $\varphi(A_i,B_j)$	BFI(BMP) vs. RFI	# observations BFI(BMP) ≤ Random Fit Index [%]	Paired *t*-test *Ho* value	*t* test statistic at 0.025
Normal	8:8*	4.4	6.6	104.7%	90.00%	4.96	1.90
	100:100*	44.9	89.8	386. 8%	93.00%	8.62	1.90
Uniform	8:8*	0.9	2.2	168.0%	98.00%	18.69	1.90
	100:100*	4.4	28.8	673.2%	100.00%	92.06	1.90

Pre-specified tolerance limits (ranges) for BMP were identical across all experiments (0,1000) units. Samples falling out of pre-specified tolerance range were discarded. *statistically significant advantage for BMP at 95%



(a) (b)

Figure 1. (a) Best-Fit Index, β, for BMP (Blue) vs. Random Matching (Red) for a small data set of (a) Normally*; (b) Uniformly* distributed parts (*statistically significantly different at 95%)



(a) (b)

Figure 2. (a) Best-Fit Index, β, for BMP (Blue) vs. Random Matching (Red) for a large data set of (a) Normally*; (b) Uniformly* distributed parts (* statistically significantly different at 95%)

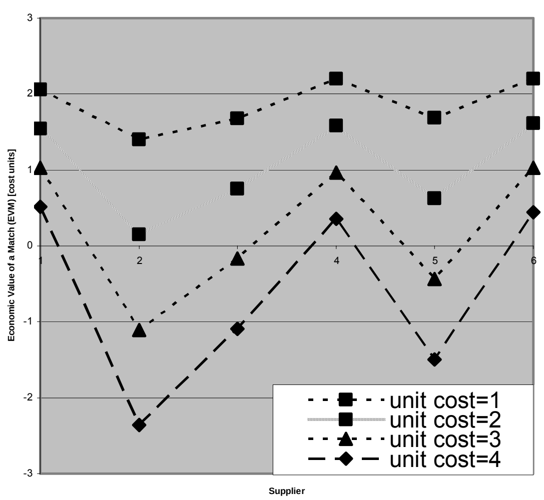


Figure 3. Economic Value of a Match, *EVM*, for six suppliers manufacturing normally distributed bolts and washers

5 CONCLUSIONS

A Best-Matching Protocol for geometrical as well as supplier matching is defined and developed in this research. The findings demonstrate the advantages of implementing a Best-Matching Protocol for supplier selection by better leveraging component quality and the costs to supply the parts. For all experiments, the Best-Matching Protocol (BMP) matches yielded a better Best-Fit Index (BFI), within the acceptable tolerance limits, than matches performed randomly. The best-matching of suppliers and customers may not always yield the best price, or provide the best possible quality products, but the combination of price and quality will always yield better decisions on quality and costs.

Research questions involving matching based on multiple dimensions needs to be addressed. It is clear that the information gathered extensively at local e-Work and e-Manufacturing locations can be highly useful for management decisions seeking to improve the benefits of integrated suppliers

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