EXPLICIT PRODUCT FAMILY INDICATORS BASED ON ACONSTRAINT PROGRAMMING SIMULATION OF USAGE COVERAGE

Jiliang Wang[a] and Bernard Yannou[b]

Laboratoire Génie Industriel, Ecole Centrale Pairs, Grande Voie des Vignes, 92290, Châtenay-Malabry, France.
Email: [a]ji-liang.wang@ecp.fr, [b]bernard.yannou@ecp.fr

In this paper, we apply usage context model to model jigsaw product family usages. Then constraint programming technique is employed to measure the feasible usages under consumers' usage constraints. Adequacy indicators for different users and the given product family are invented and simulated. Users can make appropriate choice decision for choosing products in a family, while designers can evaluate appealing product family composition and configurations.

Keywords: Usage context model, Scale-based product family, Constraint programming technique, Usage coverage indicators.

1. INTRODUCTION

The main objective of product family design is to allow a particular standardization degree which forms the platforms, and still leave product flexibility to adapt to various usages. Scale-based product family development process has a strong practicability in development cost and is widely used in the industrial domain. Many relative researches exist also in design engineering [1]. In daily life, consumers encounter often the products which may be reused several times. Consumer durable products are these do not quickly wear out and may be applied for different service situation during life cycle. Thus the adequacy between durable products and supposed usage conditions is not a trivial question for product family development as well as its assessment. Consumers come across various usages and they usually prefer to choose the product that completes most of their diverse expected usages with a lower expense. We found here our analysis onto a Usage Context description model that we apply on a set of representative users of jigsaws. We also use a physics-based simulation platform to result in performance predictions that we map onto the set of expected usages to finally calculate a degree of usage coverage of a given user for a given product. This paper has extended this approach to a scale-based product family of increasing performances in terms of power and size. Following the two heuristics that a user should prefer, within the family, the product that maximizes its usage coverage degree and that no product must be dominated by another one, we propose new indicators for expressing the quality of a scale-based product family. As they are obtained by a clear modeling of the market usage demand and after performance simulations, they are much less questionable than those of the literature which are more or less heuristic-based.

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2. LITERATURE REVIEW AND OBJECTIVE OF RESEARCH

We have recently proposed in [2] a Usage Coverage Model (UCM) so as to get a more thorough marketing model based on sets of permitted usages for a product-service instead of the conventional perceived marketing attributes, in which a taxonomy of variables is suggested to setup the link between the design parameters of a product-service and the part of a set of expected usages that may be covered. In fact, the formal study of usage context permeated the field of marketing years ago, it has only just begun to be applied directly to the design and engineering of new products. Green *et al*. [3, 4, 5] have published three successive papers on the subject, with the goal of forming a comprehensive product design methodology that includes contextual factors. When a durable product family, such as a power tool line, is delivered for the users, product designer must consider not only the product features, but also measure the adequacy in a variety of usage environments. In the design of a product line, such marketing and engineering considerations are often highly interdependent, as revealed in works [6, 7]. When users choose to buy a product, they may imagine different situations in which the product may be applied and would like to know whether it fulfills his requirements and expectations. During the course of the studies, users were found to have distinct product preferences under different usage contexts [8]. Luo *et al*. [9] have remarked partially such preference distinction by a "robust criteria" analysis way; while a more precise market-engineering combined way is always absent in the research field. However, a quantitative measurement of usage coverage between usage requirement and usage satisfied is helpful for user's preference analysis. A more explicit process, presented in the work [10], implements therefore a physics-based model to provide a performance prediction for each usage context that also depends on the user skill. The physics describing the behavior, usage context and consequently the performances of a jigsaw is established. Based on such a process, the primary goal of this research is to extent the measurement to a scale-based product family and to propose several new relative usage coverage indicators for consumers' choice.

Several heuristic Product Family Indexes have been invented in academic field and applied for industries. Most engineering researches focus on the comparison of component and process: Thevenot and Simpson in [11] did a thorough comparison for these heuristic indicators since last decades, and then based on the Commonality vs. Diversity Index [12], they proposed a comprehensive metrics for evaluating commonality [13]. In the evaluation of consumer preference for products, market research methods such as conjoint analysis and discrete choice analysis are utilized [14, 15]. Heuristic and statistic-based conjoint data is always indispensable for the near-optimal product family selecting level of consumer attributes [16]. These pre-studied data work relatively well will meta-heuristic algorithms, such as G.A. [17, 18], and others [19], in which several heuristic and A.I. algorithms are compared.

Despite the prosperous research concerning usage context models and consumer preference analysis, rare research gives explicit and objective indicators for product family evaluation regarding to target usage contexts. In this work, we apply usage context model to model jigsaw product family usages. Then a set-based comparison between simulated performances and usage satisfied is employed to measure the feasible usages under consumers' usage constraints. Adequacy indicators for different users and the given product family are proposed and simulated. Users can make economic or efficient choice decision for choosing products in a family based on proposed usage coverage criteria, while designers can deduce appealing product family composition and configurations.

3. MODEL AND METHODS

3.1. Nomenclature

As shown in the literature review section, previous works have defined list of variables of Usage Context Based Design framework [2, 8, 10]. Following illustrates the principal notation in this paper and a jigsaw product family evaluation problem is used as example throughout the section.

U-Usage context scenario
k-index for the kth product in the family, $k = 1, \ldots, K$
i-index for the ith user, $i = 1, \ldots, M$

j-index for the jth usage context scenario, $j = 1, \ldots, N_i$
N_i*-total usage context scenario for user i*
E_{ij}*-jth usage context attributes for user i*
$w_i j$*-jth usage relatvie weight for user i*
C_s*-Performance related customer attributes*
X*-Product design variables*
Y*-Engineering performance*

3.2. Usage Context Model and Usage Coverage

As mentioned in the Usage Coverage Model, a usage needed is a set of expected service contexts E_j associated with a usage relative weight

$$U_{\text{needed}} = \left\{(E_j, w_j)\right\} \quad \text{with} \sum w_j = 1 \tag{1}$$

Given a product design X and a user with certain expertise C_s, we figure out that only a subset of this "usage needed" set may be fulfilled by a given product and use, as shown in Figure 1, this part is called the "feasible usage" and is defined by equation below:

$$U_{\text{feasible}}(X, U_{\text{needed}}, C_s) = \left\{ \begin{array}{c} (E_j^*, w_j) \ \textit{such that} \\ (E_j, w_j) \epsilon U_{\text{needed}} \ \textit{and} \ E_j^* \subseteq E_j \\ \textit{and} \ Y_j = f(X, E_j^*, C_s) \ \textit{is feasible}) \end{array} \right\} \tag{2}$$

In formula (2), the performances of the service are explicitly affected by the user and his experience with the product. So performance estimation formulas are required:

$$Y = (X, E, C_s) \tag{3}$$

Here, a physics-based performance estimation model for jigsaw is used as shown in [10]. Constraint Satisfaction Problem method is applied to solve the usage context needed reduction process, with the physical constraints and user's usage context constraint for the performances.

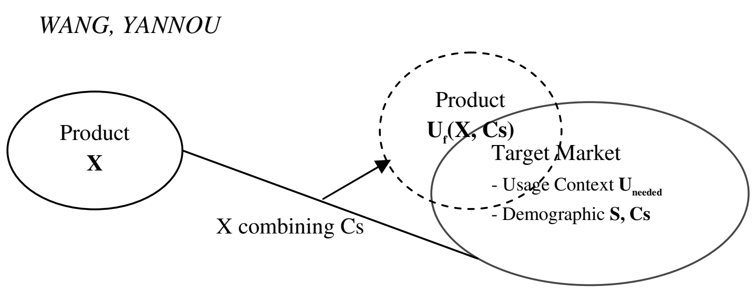

Figure 1. Usage Coverage Mechanism.

3.3. Definition of Degree of Usage Coverage(DC) for Single Usage

In our work [10], different categories of variables and detailed list of intermediate variables for jigsaw design problem are illustrated. Below certain important variables for cutting wood board usage are cited for simplicity:

$$U_{\text{need}}(E, w) = \left\{ \begin{array}{l} T_c - \text{Thickness of the wood board} \\ \text{Type}_{\text{wood}} \ - \text{Type of wood} \end{array} \right\}$$

$$C_s = \left\{ \begin{array}{l} \text{Gender} - \text{Gender of the saw user} \\ \text{Skill-Skill of the user for cutting wood with a tool X} \end{array} \right\}$$

$$Y = \left\{ \begin{array}{l} S_a - \text{Mean advance speed} \\ P_{\text{comfort}} - \text{Degree of comfort in the user wrist} \end{array} \right\}$$

A possible illustrating typological value for the variables is given below and will be used in the simulation example section:

$Type_{\text{wood}}$: 5 type of ordinary wood are listed (0–4):

0-fir,	1-oak,	2-pine,	3-plywood,	4-teak

C_s: 6 gender and skill combination user typed are listed (0-5):

0-female basic,	1-female medium,	2-female professional user;
3-male basic,	4-male medium,	5-male professional user.

Correspondent tables exist for translating typological variables to intermediate variables.For the usage context aspect, when we collect usage context and user information through a questionnaire [8] or when interpreting intermediate variable, uncertainties are generated. Set-based modeling method is used to model the uncertainties of usage context and user. For example, to interpret the semantic typological answers to uniform distributed intervals, we have

Ex. Wood type: fir→ density $\rho = [480, 608]\text{kg/m}^3$

User type: female basic user → application forces

$$F_{\text{t}} = [0, 35]\text{N};\ F_{\text{p}} = [0, 15]\text{N};$$

After using Constraint Programming technique to shrink these intervals, a possibledegree of given usage context coverage DC is defined as:

$$\begin{aligned} DC_{\text{single--usage}} &= Cut_{ok} \times \frac{|E_{\text{Final}}|}{|E_{\text{Initial}}|} 100\% \\ &= Cut_{ok} \times \frac{|T_C|_{Final} \times |\rho|_{\text{Final}}}{|T_C|_{\text{Final}} \times |\rho|_{\text{Final}}} \times 100\% \end{aligned} \tag{4}$$

In the experimental section 4, anillustrative user choosing jigsaws example is shown.

3.4. Usage Coverage Indicators for Product Family

When it comes to a penal of users with different usage context scenarios, facing K products in a family which sever the same service with certain distinction, the predefined degree of usage coverage forms a matrix.

The typical usages in the market are represented as a structure of usage context map. Each user is defined by a set of usage context scenarios. The users are supposed to be representative of the market. The usages for each user are weighed with a relative importance w_{ij}.

Table 1. Consumers' Usage Context Scenario Map.

User Id	$\text{Usage}_{i,1}$	$\text{Usage}_{i,2}$	…	$\text{Usage}_{i,Ni}$
User 1	E_{11} (w_{11})	E_{12} (w_{12})	…	E_{1N1} (w_{1N1})
User 2	E_{21} (w_{21})	E_{22} (w_{22})	…	E_{2N2} (w_{2N2})
User 3	E_{31} (w_{31})	E_{32} (w_{32})	…	E_{3N3}(w_{3N3})
…				
User M	E_{M1} (w_{M1})	E_{M2} (w_{M2})	…	E_{MNM} (w_{MNM})

The numbers of different usages N_i for a use $i = 1, \ldots, M$ may vary for the different users i. And the relative weights of each usage context should be:

$$\sum_{j=1}^{Ni} w_{ij} = 1, with\ i = 1, \ldots, M \tag{5}$$

Then for each Product P_k and user i, a series of N_i degrees of usage coverage is calculated, e.g. for product P_k:

Table 2. Degree of Usage Coverage Map for a Given Product.

User Id	$DC_{i1,k}$	$DC_{i2,k}$	…	$DC_{iNi,k}$
User 1	DC_{11k}	DC_{12k}	…	DC_{1N1k}
User 2	DC_{21k}	DC_{22k}	…	DC_{2N2k}
User 3	DC_{31k}	DC_{32k}	…	DC_{3N3k}
…				
User M	DC_{M1k}	DC_{M2k}	…	DC_{MNMk}

And a total degree of coverage for user i's multi-usages N_i by a product P_k can be calculated by formula below:

$$DC_{ik} = \sum_{j=1}^{N_i} (DC_{ijk} \cdot w_{ij}), with\ i = 1, \ldots, M \tag{6}$$

Here $i = 1, \ldots, M$ is the number of representative users; $k = 1, \ldots, K$ is the number of products in a family. Thus an $M \times K$ indicator matrix is formed (see Table 3).

Table 3. Product Family Degree of Usage Coverage Matrix.

User Id	DC_1 Product 1	DC_2 Product 2	…	DC_K Product K
User 1	DC_{11}	DC_{12}	…	DC_{1K}
User 2	DC_{21}	DC_{22}	…	DC_{2K}
User 3	DC_{31}	DC_{32}	…	DC_{3K}
…				
User M	DC_{M1}	DC_{M2}	…	DC_{MK}
Total	DC_1	DC_2	…	DC_K

3.5. Consumer Decision

Based on the metric of adequacy between usage and product, consumer can make coverage — economical choice with index as:

$$C1 : EconomicalCh\ (User) = max_{pi} \left(\frac{Degree\ Usage\ Coverage}{Price} \right) \tag{7}$$

Or a coverage — efficient choice with index as:

$$C2 : EfficientCh\ (User) = max_{p_i} \left(\frac{Degree\ Usage\ Coverage \times \overline{Performance}}{Price} \right) \tag{8}$$

4. EXPERIMENTATION AND RESULTS

4.1. Power Tool — Jigsaw Product Family

We start with the issue of an existing scale-based family of 4 Bosch jigsaws (from P1 i.e. PST 650 to P4 i.e. Bosch PST900 in Table 5), with different output power, size and weight.

4.2. Decision of User with Composite Usage Context Scenarios

For a single person with composite usages expectation, this is a real usage context instance.

For example: A Female Basic User wants to cut Fir wood of 0.035 m thickness, Pine of 0.050m thickness, and Oak of 0.015 m thickness. She has 4 jigsaws Bosch listed in Table 4 to choose from.

Table 4. Bosch Jigsaw Product Family.

	PST 650	PST 700 PE	PST 800 PEL	PST 900 PEL
				
Power:	120W	180 W	200 W	250 W
Weight:	1.5 kg	1.8 kg	2 kg	2.2 kg
Price:	50 €	80 €	100 €	130 €
Parameters:	Stroke rate: 500–3000 min-1 Stroke: 18 mm			

Table 5. Usage Coverage and Performance Domains.

Usage 1	P1	P2	P3	P4
ρ_I	[480, 608]	[480, 608]	[480, 608]	[480, 608]
ρ_F	[480,507.46]	[480, 608]	[480, 608]	[480, 608]
Sa	[0, 0.0004]	[0, 0.00055]	[0, 0.00059]	[0, 0.00069]
Pcom	[0.728, 1]	[0.687, 1]	[0.688, 1]	[0.689, 1]
DC	0.209	1	1	1

Table 6. Indicators based on Given Usage.

Indicators	P1	P2	P3	P4
$C_1 = \frac{DC}{\text{Price}}$	0.0043	0.0125	0.0100	0.0077
$C_2 = \frac{DC \times Sa_{ub} \times P_{com_l}\mathrm{b}}{\text{Price}}$	1.25E-06	4.72E-06	4.06E-06	3.66E-06

With this information given, we use correspondent table to interpret the typological words to operational value. This process generates uncertainty.

In these intervals, there exists a point (F_t, F_p, ρ, f) that makes (S_a, P_{com}) optimal, while the DC on this point is maximal. This problem may be further studied in future work.

Under this scenario and with the concept of formula (6), (7), the user' decision can be based on a ratio adequacy — price or a ratio efficiency — price. In the second indicator, Sa_{ub} is the upper bound of advance speed interval; $P_{com_{ib}}$ is the lower bound of wrist comfort degree interval. Since lower bound of *Sa* is always 0–no advancement without applying forces and the same reason for P_{com} upper bound. These indicators are listed and calculated as in Table 6. A Figure 2 with the curves for comparison is shown below:

Similarly, for the composite usages for given *Female Basic User*, the values of indicators are listed below:

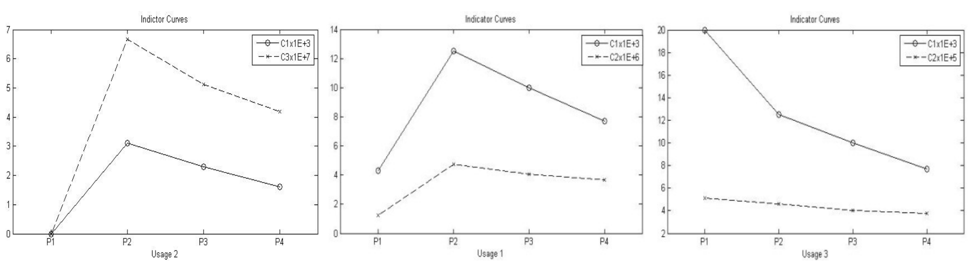

Figure 2. Indicator Curves for Composite Usages 1, 2, 3.

Table 7. Indicators for Composite Usage.

Product	Indicators	Usage 1 (Fir, 0.035)	Usage 2 (Pine, 0.050)	Usage 3 (Oak, 0.015)
P1	C_1	0.0043	0.0000	0.0200
P2	C_1	0.0125	0.0031	0.0125
P3	C_1	0.0100	0.0023	0.0100
P4	C_1	0.0077	0.0016	0.0077
Economical Choice		P2	P2	P1
P1	C_2	1.25E-06	0	5.14E-05
P2	C_2	4.72E-06	6.68E-07	4.59E-05
P3	C_2	4.06E-06	5.12E-07	4.04E-05
P4	C_2	3.66E-06	4.2E-07	3.78E-05
Efficient Choice		P2	P2	P1

Table 8. Weighted Composite Usage Context Scenarios.

	Usage 1 (w_1)	Usage 2 (w_2)	Usage 3 (w_3)	
Economical Choice	P2	P2	P1	$\max(C_1^*(P_1), C_1^*(P_2))$
Efficient Choice	P2	P2	P1	$\max(C_2^*(P_1), C_2^*(P_2))$

Firstly, we suppose the 3 usage scenarios are equally important to the user. So, as we can see from Table 7, under economical choice criteria, the user would prefer product 1 and 2 from the given product family; and the same choice under efficient criteria. The product P2 is dominant among the 4 products in a family.

If we consider the 3 usage scenarios with relative importance w_1, w_2, w_3, then the transformed composite criteria, C_1^*, C_2^*, defined as formula below:

$$C_1^*(P_k) = \delta_1(P_k) \cdot w_1 + \delta_2(P_k) \cdot w_2 + \delta_3(P_k) \cdot w_3 \quad with\ k = 1, 2, 3, 4 \tag{9}$$

Here $\delta_1(P_k) = 1$, when the economical choice is P_k for the jth usage scenario, 0 otherwise. Similarly we have the weighted efficient choice criteria:

$$C_2^*(P_k) = \delta_1(P_k) \cdot w_1 + \delta_2(P_k) \cdot w_2 + \delta_3(P_k) \cdot w_3 \quad with\ k = 1, 2, 3, 4 \tag{10}$$

The final decision for weighted composite usages can be decided by the maximum C_1^*, C_2^* value for the products as shown in Table 8.

4.3. Evaluation of Product Family with a Panel of Target Users

For experimental illustration, we randomly generate 30 users of 6 different types, combination of gender and skill in C_s variables as listed in Sec. 3.3.

Each of the 30 users has at most 6 usages with different weights. The usages are also generated with 5 types of wood and with a thickness uniformly distributed in the interval [0.010, 0.060] meter. A user-usages map is formed as shown in the Appendix Table. Each user has at most 6 different usages requirements, and every usage has a relative weight with a total sum of 1 for its user.

The usage coverage indicator can be calculated for each user and each product, a 30×4 usage coverage degree matrix is constructed. The two weighted decision criteria are also calculated and compared to obtain final preference estimation.

Under the two criteria $C1$, $C2$ and the indicators C_1^*, C_2^* values, the most adequate products regarding to target weighted composite usage context scenarios are listed at the right in above Table 8. means that no product among given product family is appropriate for the target usages.

The occurrence in the table reflects the most adequate product been chosen, in regard to target panel users. This reveals the well formation of given product family. Table 9 below shows that, for this panel of 30 user, product 1 and 2 are qualified for most (more than 2/3) of the usage context scenarios. Since the user type is mostly skillful user and the wood objects are relatively easy for given jigsaws.

Table 9. Usage Coverage and Decision IndicatorsMatrix.

ID	PST 650			PST 700			PST 800			PST 900			C1	C2
	DC	C_1^*	C_2^*	DC	C_1^*	C_2^*	DC	C_1^*	C_2^*	DC	C_1^*	C_2^*		
1	0.610	0.0122	1.58E−04	0.610	0.0076	1.46E−04	0.610	0.0061	1.29E−04	0.610	0.0047	1.23E−04	P1	P1
2	0.040	0.0008	7.60E−07	0.915	0.0114	9.47E−06	0.930	0.0093	8.29E−06	0.930	0.0072	7.81E−06	P2	P2
3	0.940	0.0188	4.37E−05	1.000	0.0125	4.14E−05	1.000	0.0100	3.64E−05	1.000	0.0077	3.47E−05	P1	P1
4	0.000	0.0000	0.00E+00	0.000	0.0000	0.00E+00	0.000	0.0000	0.00E+00	0.000	0.0000	0.00E+00	X	X
5	0.217	0.0043	3.21E−05	0.936	0.0117	4.54E−05	0.974	0.0097	4.07E−05	0.980	0.0075	3.90E−05	P2	P2
6	0.184	0.0037	7.39E−06	0.621	0.0078	1.25E−05	0.660	0.0066	1.13E−05	0.660	0.0051	1.07E−05	P2	P2
7	0.336	0.0067	2.66E−05	0.990	0.0124	5.18E−05	0.990	0.0099	4.57E−05	0.990	0.0076	4.36E−05	P2	P2
8	0.060	0.0012	5.29E−06	0.075	0.0009	5.26E−06	0.091	0.0009	4.95E−06	0.130	0.0010	5.31E−06	P1	P4
9	0.000	0.0000	0.00E+00	0.598	0.0075	5.94E−06	0.878	0.0088	7.33E−06	1.000	0.0077	7.96E−06	P3	P4
10	0.030	0.0006	7.98E−06	0.041	0.0005	7.80E−06	0.056	0.0006	7.11E−06	1.000	0.0077	1.53E−05	P4	P4
11	0.990	0.0198	2.29E−04	0.990	0.0124	2.12E−04	0.990	0.0099	1.88E−04	0.990	0.0076	1.80E−04	P1	P1
12	0.000	0.0000	0.00E+00	0.000	0.0000	0.00E+00	0.000	0.0000	0.00E+00	0.000	0.0000	0.00E+00	X	X
13	0.049	0.0010	4.23E−06	0.070	0.0009	5.62E−06	0.070	0.0007	4.96E−06	0.070	0.0005	4.74E−06	P1	P2
14	0.530	0.0106	1.50E−04	0.530	0.0066	1.40E−04	0.530	0.0053	1.24E−04	0.530	0.0041	1.18E−04	P1	P1
15	0.680	0.0136	9.02E−05	0.680	0.0085	8.38E−05	0.680	0.0068	7.40E−05	0.680	0.0052	7.07E−05	P1	P1
16	0.009	0.0002	1.51E−07	0.149	0.0019	1.54E−06	0.293	0.0029	1.85E−06	0.304	0.0023	1.78E−06	P3	P3
17	0.570	0.0114	6.63E−05	0.767	0.0096	6.82E−05	0.850	0.0085	6.26E−05	1.000	0.0077	6.34E−05	P1	P2
18	0.000	0.0000	0.00E+00	0.009	0.0001	7.61E−08	0.013	0.0001	8.97E−08	0.029	0.0002	1.09E−07	P4	P4
19	1.000	0.0200	1.29E−05	1.000	0.0125	1.15E−05	1.000	0.0100	9.85E−06	1.000	0.0077	9.15E−06	P1	P1
20	0.270	0.0054	2.21E−05	0.789	0.0099	2.59E−05	0.880	0.0088	2.34E−05	0.880	0.0068	2.22E−05	P2	P2
21	0.000	0.0000	0.00E+00	0.713	0.0089	2.64E−05	0.985	0.0099	3.15E−05	1.000	0.0077	2.97E−05	P3	P3
22	0.200	0.0040	7.30E−06	0.200	0.0025	6.62E−06	0.200	0.0020	5.75E−06	0.200	0.0015	5.40E−06	P1	P1
23	0.650	0.0130	1.41E−04	0.972	0.0121	1.32E−04	0.997	0.0100	1.16E−04	1.000	0.0077	1.11E−04	P1	P1
24	0.000	0.0000	0.00E+00	0.000	0.0000	0.00E+00	0.000	0.0000	0.00E+00	0.000	0.0000	0.00E+00	X	X
25	0.040	0.0008	9.13E−06	0.270	0.0034	1.36E−05	0.270	0.0027	1.20E−05	0.561	0.0043	1.30E−05	P4	P2
26	0.301	0.0060	1.40E−05	0.778	0.0097	2.94E−05	0.853	0.0085	2.70E−05	1.000	0.0077	2.74E−05	P2	P2
27	0.305	0.0061	1.67E−05	1.000	0.0125	4.28E−05	1.000	0.0100	3.78E−05	1.000	0.0077	3.60E−05	P2	P2
28	0.000	0.0000	0.00E+00	0.279	0.0035	5.08E−07	0.246	0.0025	3.66E−07	0.214	0.0016	2.79E−07	P2	P2
29	0.130	0.0026	1.26E−05	0.130	0.0016	1.16E−05	0.220	0.0022	1.03E−05	0.400	0.0031	9.96E−06	P4	P1
30	0.430	0.0086	1.63E−05	0.430	0.0054	1.48E−05	0.430	0.0043	1.28E−05	0.430	0.0033	1.21E−05	P1	P1

Table 10. Occurrence of Selection under two Criteria.

	P1	P2	P3	P4	X
C1	12	8	3	4	3
C2	10	11	2	4	3

5. CONCLUSION AND PERSPECTIVES

In this work, the concept of Degree of usage Coverage indicator is applied to weighted composite usage scenarios. A consumer usage context scenarios map is built to represent usage variety in target market. DC metric is then extended to a given product family in form of a matrix. Under user's two decision criteria — economical and efficient, a concrete form of indicators is introduced for jigsaw cutting wood service. Constraint programming technique is applied in the process of DC calculation and performance estimation. Simulations with a jigsaw family for cutting wood usages are implemented. The proposed indicators help to evaluate the adaptability for a given scale-basedproduct family towards diverse usages context scenarios in a target market. Designers can eliminate unnecessary products which have no domination in all users with their usage context scenarios.

The perspectives of this research work will mainly lie in three directions. First, the complement of jigsaw family model. In this work, only scalable variations in the product family are under consideration in the model. More dimensional variations and functional variation are appealing and convincing, even the introducing of competing product family is preferred. Second, adding estimation index of uncertainty or possibility for the model and process. Constraint programming technique is based on a set-based concept. During the variable interpretation and estimation process, diverse uncertainties are pulled in. Finally, a user interactive product selection system platform is very appealing in assistant buying service in stores.

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