TECHNICKÁ UNIVERZITA V LIBERCI

FAKULTA TEXTILNÍ

PREDIKCE OMAKU TKANIN

Habilitační práce

Obor: Textilní technika a materiálové inženýrství

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PODĚKOVÁNÍ

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Obsah

Seznam použitých symbolů a zkratek

Symbol, zkratka	**Význam**
2HB	Moment hystereze na jednotku délky [Ncm/cm]
2HG	Hystereze při úhlu smyku Φ=0,5° [N.cm]
2HG5	Hystereze při úhlu smyku Φ=5° [N.cm]
ACF(h)	Autokorelační funkce
AIC	Akaikovo informační kriterium
b	Tepelná jímavost [W/ (m^2 K^1 $s^{-0,5}$)]
B	Tuhost v ohybu na jednotku délky [Ncm^2/cm]
BIC	Bayesovo informační kriterium
BM	Nově navržený postup pro objektivní predikci omaku
BM11	Označení navrhovaného modelu
C(h)	Kovariance
CL_k	Model proporcionálních šancí
CV	Variační koeficient
d_j	Měřené body povrchu
d_s	Vzorkovací vzdálenost
D	Fraktální dimenze
D_F	Průměrná fraktální dimenze
D_{Fp}	Fraktální dimenze spočtená ze 12 bodů
f_{Me}	Relativní četnost v mediánové třídě
F_{Me}	Kumulativní relativní četnost v mediánové třídě
G	Tuhost ve smyku [N/cm.stupeň]
G^2	Deviance
G(h)	Odhad variogramu
h	Velikost posunu
H	Hurstův exponent
KES	Kawabata evaluation system
KES11	Model vytvářený logistickou regresí na základě vlastností ze systému KES
L	Délka proměřovaného povrchu vzorku
L_0	Maximální věrohodnost modelu, který obsahuje pouze absolutní člen
LC	Linearita [-], při deformaci v tlaku
L_M	Maximální věrohodnost modelu
LT	Linearita [-], při deformaci v tahu
M	Počet tkanin
M	Plošná měrná hmotnost [kg/m^2]
Me	Mediánová kategorie
MAD	Průměrná absolutní odchylka [µm]
MIU	Koeficient tření [-]
MMD	Průměrná odchylka *MIU* [-]
MS	Průměrný sklon profilu

MV	Průměrná hloubka údolí
MP	Průměrná výška píků
N	Odhad regresního koeficientu je statisticky nevýznamný
P(.)	Pravděpodobnost jevu (.)
PC	Směrodatná odchylka křivosti profilu
PS	Směrodatná odchylka sklonu profilu
Q	Počet zaznamenaných bodů na délce *L*
r_S	Spearmanův pořadový korelační koeficient
$\bar{R}$	Průměrná hodnota z R_j, (j=1,2,…Q)
R^2_F	Nagelkerkeova statistika
R^2_{MF}	McFadenův koeficient determinace
RC	Pružnost v tlaku [%]
$R(d_j)$, R_j	Záznam řady bodů na délce *L*
RT	Pružnost v tahu [%]
S	Stlačitelnost [-]
S	Odhad regresního koeficientu je statisticky významný
SD	Směrodatná odchylka
SFV	Variabilita průběhu síly
SHV	Variabilita výšky povrchu
SMD	Povrchová drsnost [μm]
t	Tloušťka [mm], postup BM
T	Tuhost [mN.cm]
T0	Tloušťka [mm], systém KES
THV	Celkový omak (hodnocení pomocí panelu respondentů)
THV(O)	Celkový omak - objektivní predikce
TP	Průměr deseti bodů
W	Plošná měrná hmotnost [mg/cm^2], systém KES
$W_{a,i}$	Waldovo testační kriterium, *i*-tý regresní koeficient
WC	Energie potřebná ke stlačení [N.cm/cm^2]
WT	Deformační energie [N.cm/cm^2], při namáhání v tahu
x_R	Medián ordinální škály
$\bar{x}_R$	Průměr z mediánů
Y	Modul pružnosti [MPa]
Y45	Modul pružnosti po diagonále [MPa]
α	Hladina významnosti
$\Gamma(h)$	Variogram

Seznam přiložených publikací

Jedná se o zahraniční a tuzemské recenzované časopisecké publikace, které mají vztah k předkládané habilitační práci.

[B1] Bajzík, V., Hes., L. The Effect of Finishing Treatment on Thermal Insulation and Thermal Contact Properties of Wet Fabrics. *Tekstil ve Konfeksiyon*. 2012, roč. 22, č. 1, s. 26-31. ISSN 1300-3356.

[B2] Mangat, M. M., Hussain, T., Bajzík, V. Impact of Different Weft Materials and Washing Treatments On Moisture Management Characteristics. *Journal of Engineered Fibres and Fabrics*. 2012, roč. 7, č. 1, s. 38-49. ISSN 1558-9250.

[B3] Bajzík V. A New Way To The Objective Hand Evaluation. *Vlákna a Textil*. 2012, roč. 19, č. 1, s. 8-13. ISSN 1335-0617.

[B4] Bajzík, V., Mangat, M. M., Hes, L. Effect of Two Types of Softenetrs and Weft Composition on Thermal Comfort Characteristics of Denim Fabrics. *Vlákna a Textil*. 2011, roč. 18, č. 4, s. 3-8. ISSN 1335-0617.

[B5] Bajzík, V. Alternativní přístup k predikci omaku s využitím ordinální logistické regrese. *Informační Bulletin*. 2011, roč. 22, č. 2. s. 3-10. ISSN 1210-8022 (tištěný), ISSN 1804-8617 (on-line).

[B6] Militký, J., Bajzík, V. Surface Roughness of Heat Protective Clothing Textiles. *International Journal of Clothing Science and Technology*. 2003, roč. 15, č. 3/4, s. 258-267. ISSN 0955-6222.

[B7] Militký, J., Bajzík, V. Surface Roughness of Protective Clothing. *Vlákna a textil*. 2003, roč. 10, č. 3, s. 118-125. ISSN 1335-0617.

[B8] Militký, J., Bajzík, V. Long Term Cyclic Deformation of Fabrics with Improved Elasticity. *Vlákna a textil*. 2003, roč. 10, č. 2, s. 91-94. ISSN 1335-0617.

[B9] Militký, J., Bajzík, V. Surface Roughness and Fractal Dimension. *The Journal of The Textile Institute*. 2001, roč. 92, č 3, s. 91-113. ISSN 0400-5000.

[B10] Militký, J., Bajzík, V. Some Open Problems of Hand Evaluation. *Vlákna a textil*. 2000, roč. 7, č. 3, s. 141-145. ISSN 1335-0617.

[B11] Militký, J., Trávníčková, M., Bajzík, V. Air Permeability and Light Transmission of Weaves. *International Journal of Clothing Science and Technology*. 1999, roč. 11, č. 2/3, s. 116-124. ISSN 0955-6222.

[B12] Militký, J., Bajzík, V. Influence of Wool Content on Properties of Blended Fabrics. *International Journal of Clothing Science and Technology*. 1994, roč. 6, č. 2/3, s. 32-36. ISSN 0955-6222.

1. Úvod

Subjektivní hodnocení omaku patří mezi metody, které nazýváme organoleptické, tj., jsou to metody, které hodnotí danou vlastnost smysly, v případě omaku hmatem. I když jednoznačná definice pojmu omak není dána, je omak obecně chápán jako pocit, který je vyvolán při kontaktu textilie s pokožkou, specielně, při hodnocení omaku prsty a dlaní ruky. V posledních 40 až 50 letech bylo věnováno velké úsilí snaze porozumět vnímání omaku textilií, aby ho bylo možno predikovat z objektivně měřitelných vlastností, které souvisejí s omakem. To je dáno tím, že textilie určené pro oděvní účely jsou nejdříve hodnoceny v souvislosti s módností (vzhled textilie) a příjemností při kontaktu (omak). Tento způsob hodnocení odpovídá lidské psychice. Ta je uzpůsobena tak, že se nejprve hodnotí přijatelnost a příjemnost vjemu [1]. Z hlediska vnímání vlastností běžným uživatelem lze vlastnosti rozdělit na:

a) vlastnosti hodnocené při nákupu textilie – mezi tyto vlastnosti patří především vzhled, omak a komfort – jsou to vlastnosti špatně měřitelné – jsou subjektivně vnímány zákazníkem, souvisí s psychickým stavem spotřebitele

b) spotřebitelem nezjišťované ale dobře měřitelné vlastnosti – pevnost, tažnost, prodyšnost, oděr – pro běžné oděvní účely mají menší význam, ale korelují s vlastnostmi, které jsou uvedeny v bodě a)

c) vlastnosti související s chováním textilie v procesu spotřeby – trvanlivost, životnost, opotřebení – patří mezi praktické zkoušky (nošení), simulují se pomocí umělého stárnutí

d) vlastnosti charakterizující zpracovatelnost – spřadatelnost, vhodnost pro konfekcionování, atd.

Význam predikce omaku pomocí objektivních metod roste i s rozvojem nových druhů syntetických vláken, nových technologií a nových textilních výrobků, kde se omak dostává na přední místo při hodnocení jakosti textilií.

V neposlední řadě hraje důležitou roli i rychlý rozvoj obchodování přes internet, kdy se spotřebitel rozhoduje o koupi pouze na základě vizuálního kontaktu bez možnosti si textilii osahat, a tak potřebuje získat jiným způsobem představu o kvalitě textilie z hlediska omaku. Lze namítnout, že v dnešním světě módy tyto informace rychle zastarají, stejně rychle jak se mění móda, která vzhled významně ovlivňuje. Nejen vlastní zkušenosti však ukazují, že hodnocení omaku nepodléhá změnám tak rychle jako vzhled (barevnost, vzorování, atd.).

V předložené habilitační práci jsou uvedeny stěžejní postupy mnou navržené a realizované, popř., na kterých jsem se podílel. Většina návrhů a výsledků byla časopisecky publikována. Tyto publikace jsou uvedeny jako přílohy a označené B1 až B12. V habilitační práci je uveden mnou navržený postup hodnocení omaku s využitím panelu respondentů, který je založen na mediánové kategorii ordinální škály [B10] – celá kapitola 2 kromě části kapitoly 2.4, na jejichž výsledcích jsem se spolupodílel [B6, B7, B9]. V kapitole 3 je uvedena mnou navržená metodika pro konstrukci predikční rovnice, která je vybudována na ordinální logistické regresi (BM technika) [B3, B5].

Ke kapitole 2 (kromě části 2.4). – V příspěvku [B10] jsou diskutovány tři významné aspekty spojené se subjektivním hodnocením omaku popř. senzorickou analýzou a jeho predikce s využitím lineární regrese. Jsou zde uvedena východiska k výběru hodnotitelů, škály a sémantiky. Jsou zde uvedeny výsledky reprodukovatelnosti a vlivu vizuálního stimulu na hodnocení omaku. V tomto příspěvku jsem vytvořil metodiku hodnocení omaku a postup při realizaci experimentu. Vytvořil jsem výchozí návrh na konstrukci techniky BM – výběr vlastností. V pozdějších modelech jsem koeficient tření nahradil průměrnou absolutní odchylkou. Toto nahrazení bylo dáno především problémem jeho přesnosti měření na nakloněné rovině. Podílel jsem se na vytvoření predikčních rovnic vycházejících z lineární regrese. Na základě vlastních zkušeností jsem později lineární regresní modely nahradil logistickými (ordinální logistickou regresí). V kapitolách 2.1, 2.2 a 2.3 jsou uvedeny původní výsledky autora, které zatím nebyly publikovány, avšak vycházejí z přílohy [B10]. Postup byl využit při vývoji „nového" denimu [B2, B4].

Ke kapitole 2.4 - Vedle výběru vlastností, které jsou použity pro konstrukci predikční rovnice, je důležité stanovit, jaký parametr popisující danou vlastnost nejlépe koresponduje s omakem. Jelikož jsem zjistil, že drsnost povrchu patří ke klíčovým vlastnostem při subjektivním hodnocení omaku, navrhl jsem, aby byla věnována této vlastnosti zvláštní pozornost. Výsledkem byly tři publikace, na kterých jsem se podílel [B6, B7, B9]. Kromě popisu drsnosti povrchu s využitím fraktální dimenze jsem navrhl použití všech ostatních parametrů. Navrhl jsem pro popis fraktální dimenze využití autokorelační funkce a variogramu. Navrhl jsem kompletní experimentální část, která se týká získání profilu povrchu ať už *SHV* nebo *SFV*.

Ke kapitole 3 - Postup uvedený v kapitole 3 je zcela původní a byl publikován v [B3, B5]. Východislo lze nalézt v [B10].

Výsledky návrhu postupu subjektivního hodnocení omaku byly využity při vývoji nové konstrukce denimu, kde bylo v útku nahrazeno bavlněné vlákno polypropylénovým – zde jsem navrhl celý experiment a podílel se na vyhodnocení a interpretaci výsledků [B4]. Vlastnosti nové konstrukce denimu jsou uvedeny v práci [B2]. Zde jsem se podílel na přípravě experimentu, jeho vyhodnocení a interpretaci výsledků.

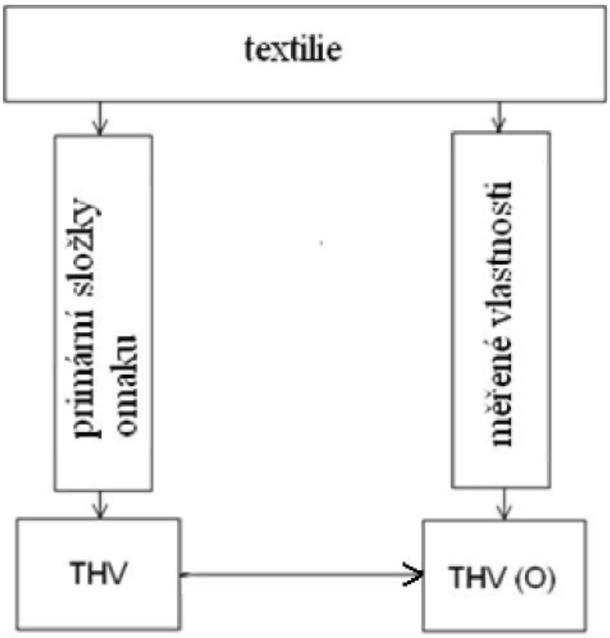
Obsahy příloh [B1, B2 a B12] mají nepřímý vztah k predikci omaku, která je stěžejním obsahem předkládané habilitační práce. Jelikož však výsledný omak a jeho složky jsou ovlivněny finálními úpravami a materiálovým složením jsou tyto práce přiloženy.

Jednou ze složek komfortu je senzorická část, která zahrnuje vjemy a pocity člověka, které vznikají, při přímém styku pokožky s první vrstvou oděvu. Je tvořena mechanickým (např. vratné změny tvaru při pohybu těla) a tepelným kontaktem mezi lidskou kůží a textilií. Je zřejmé, že omak může být chápán jako jedna z částí senzorické složky komfortu. Pocity vznikající při styku pokožky a textilie mohou být příjemné či nepříjemné. Mezi příjemné pocity patří pocit měkkosti, splývavosti a naopak mezi nepříjemné patří pocity vlhkosti, dráždění pokožky způsobené mechanickým kontaktem textilie s pokožkou. Senzorický komfort je dán i tepelnými vlastnostmi, které vyvolávají pocity tepla, chladu a vlhkosti. Tyto vlastnosti lze ovlivnit různými finálními úpravami. Vliv úprav na termofyziologické vlastnosti je uveden v příloze [B1]. Zde jsem se podílel na přípravě experimentu a jeho vyhodnocení.

V příloze [B11] je porovnáván vztah mezi teoreticky odvozenou porozitou a experimentálně měřenou prodyšností. Zároveň je zde porovnání s propustností světla tkanin. Zde jsem se podílel na vytvoření metodiky pro měření propustnosti světla a vyhodnocení. Příloha [B12] obsahuje vliv složení materiálu na různé vlastnosti tkanin. Zde jsem navrhl experiment, modely a relizoval experiment.

2. Subjektivní hodnocení omaku textilií

Omak textilií je chápán jako komplexní psychofyzikální vlastnost, což znamená, že subjektivní vnímání omaku je váženým průměrem jednotlivých primárních stimulů a osobní zkušenosti hodnotitele. Vedle konstrukce textilií, finálních úprav, vzhledu atd., rozhodnutí o tom, zda je textilie vnímána na omak jako příjemná či nikoliv, je současně ovlivněno aktuálním psychickým stavem hodnotitele, jeho zkušeností, citlivostí kontaktního místa (nejčastěji prsty a dlaň dominantní ruky). Velké množství faktorů tak vede k rozdílnému subjektivnímu hodnocení. Proto se při hodnocení a tvorbě predikčních rovnic musí dodržovat zásady senzorické analýzy. Důležitost je dána tím, že výsledky z hodnocení pomocí panelu respondentů tvoří základ pro tvorbu predikční rovnice (obrázek 1). Pokud je cílem získat důvěryhodné a významné informace o omaku tkanin, je zapotřebí mít vhodné informace řádově alespoň od 100 hodnotitelů.



Obrázek 1. Vztah mezi *THV* a jeho predikcí *THV(O)*

Hodnocení omaku je vždy zatíženo určitými odchylkami, i když jsou dodržovány zásady pro dosažení stabilního hodnocení. Opakovatelnost a reprodukovatelnost jsou klíčovým faktorem pro možnost konstrukce predikční rovnice, protože rozšiřují platnost rovnice pro delší časové období (řádově roky). Při přípravě a pro následnou analýzu hodnocení omaku je zapotřebí definovat tyto dílčí složky celého procesu [B10, 2]:

1) hodnotitele,
2) vlastnosti,
3) škálu,
4) průběh hodnocení,
5) podmínky hodnocení,
6) analýzu výsledků.

Určení a dodržování nastavených parametrů těchto složek je nutnou podmínkou pro stanovení opakovatelnosti a reprodukovatelnosti. Jedním z velmi důležitých faktorů (součást bodu 5), který ovlivňuje výsledné hodnocení, je působení vizuálního kontaktu při hodnocení. Prakticky to znamená vybrat, zda bude hodnocen omak s vizuálním kontaktem nebo bez něho.

2.1 Materiál

Pro ověření opakovatelnosti, reprodukovatelnosti a zjištění vlivu vizuálního stimulu na hodnocení celkového omaku bylo použito 28 vlnařských tkanin, které se používají na výrobu pánských oblekových tkanin. Jednalo se o standardní komerčně vyráběné tkaniny, které pocházely z českých výrobních podniků. Rozměr hodnocených vzorků byl 0,7x0,7 m. Rozmezí základních parametrů je uvedeno v tabulce 1.

2.2 Opakovatelnost a reprodukovatelnost

Opakovatelnost a reprodukovatelnost hrají důležitou roli při predikci omaku. Opakovatelnost ukazuje, zda jsou titíž hodnotitelé schopni dosahovat shodných výsledků při opakovaném hodnocení. Reprodukovatelnost ukazuje na míru shody hodnocení mezi různými skupinami hodnotitelů. To následně umožňuje činit závěry pro celou populaci, ze které hodnotitelé pocházejí.

Tabulka 1. Rozsah základních parametrů hodnocených tkanin

Hmotnost	g/m^2	140 - 370
dostava - osnovy - útku	nití/10 cm	170 - 560 150 - 370
základní typy složení	100% vlna, 45/55 vlna/polyester, vlna/polyester/polyamid	
základní typy vazeb	převážně různé typy keprů, plátno	

Pro ověření opakovatelnosti, reprodukovatelnosti a stability hodnocení v čase byly použity tři skupiny hodnotitelů, kteří hodnotili omak v průběhu přibližně 8 let. Současně s tím byl sledován vliv vizuálního kontaktu na hodnocení omaku.

Respondenti ve všech hodnotících panelech mají vzdělání v textilu, avšak s malými zkušenostmi, co se týče profesionálního hodnocení omaku tkanin.

Tabulka 2. Použitá ordinální škála

jedenáctistupňová ordinální škála		
1	nevyhovující	
2	špatný	horší
3		střední
4		lepší
5	průměrný	horší
6		střední
7		lepší
8	dobrý	horší
9		střední
10		lepší
11	vynikající	

První skupina - byla složena z 30 hodnotitelů ve věku 20-26 let. Hodnotila celkový omak (THV) bez a s vizuálním kontaktem. Jako první hodnotila omak bez vizuálního kontaktu. Hodnocení omaku s vizuálním kontaktem bylo realizováno o týden později. Druhé, opakované hodnocení se uskutečnilo po 4 měsících. Byla hodnocena celá skupina 28 tkanin.

Druhá skupina – byla tvořena 40 hodnotiteli ve věku od 20 do 28 let. Hodnotila celkový omak pouze s vizuálním kontaktem přibližně 3 roky po první skupině. Hodnocení prováděla 2x s periodou mezi hodnoceními rovněž 4 měsíce a hodnotila všech 28 tkanin.

Třetí skupina - byla složena z 21 hodnotitelů ve věku 20 až 27 let. Prováděla hodnocení celkového omaku s a bez vizuálního kontaktu pouze jednou. Časová perioda mezi hodnoceními byla 1 týden. Hodnocení se uskutečnilo přibližně 5 let po druhé skupině, tj. asi 8 let po první skupině. Tato skupina měla k dispozici 10 tkanin, které byly vybrány na základě hodnocení realizovaných skupinami 1 a 2. Výběr byl proveden tak, aby pokrýval co nejpravidelněji celý rozsah úrovně omaku.

Hodnocení omaku pomocí panelu respondentů patří mezi senzorické metody, kdy je analyzován výsledný vjem smyslových orgánů. Aby mohlo být výsledné hodnocení snáze interpretováno, byla použita pro hodnocení ordinální škála, která byla rozdělena do K kategorií. Všechny skupiny pro své hodnocení používaly jedenáctistupňovou (K=11) ordinální škálu (tabulka 2).

Při hodnocení omaku pomocí panelu N hodnotitelů (n=1, 2, 3,…. N) se třídí M tkanin (m=1, 2, 3,…. M) do K kategorií (k=1, 2,….K). Kategorie jsou seřazeny vzestupně od nejhorší kategorie C_1 po nejlepší C_K (tabulka 2). Použití číselných hodnot u stupnicových metod může vést k tomu, že se s nimi zachází jako s běžnými daty, a tudíž se počítají aritmetické průměry a rozptyly. Je však zapotřebí vzít v úvahu, že nejde o lineární stupnice a kardinální data. Čísla mají tedy význam symbolů, a tudíž rozdíly mezi sousedními třídami nejsou konstantní, takže speciálně aritmetický průměr nelze korektně použít. Zároveň při individuálním hodnocení je spekulativní předpokládat, že stejné hodnocení (přiřazení do téže třídy) je opravdu číselně shodné. Proto byl použit pro odhad parametru polohy z výsledků subjektivního hodnocení omaku textilií medián ordinální škály x_R [3], který je definován vztahem

$$x_R = Me + 0{,}5 - \frac{F_{Me} - 0{,}5}{f_{Me}} \qquad (1),$$

kde mediánová třída *Me* je definována nerovnostmi

$$F_{Me-1} < 0{,}5,\ F_{Me} \geq 0{,}5\ , \qquad (2).$$

Pro *m*-tou tkaninu je x_{Rm} dáno vztahem

$$x_{R\,m} = Me_m + 0{,}5 - \frac{F_{Me\,m} - 0{,}5}{f_{Me\,m}}\ ,$$

kde $F_{Me\,m}$ je kumulativní relativní četnost až do třídy *Me* a $f_{Me\,m}$ je relativní četnost ve třídě *Me*. V tabulce 3 jsou uvedeny základní výsledky hodnocení omaku tkanin - minimální, maximální a průměrná hodnota mediánů ordinální škály x_R. Celkové průměrné hodnoty mediánů $\bar{x}_R$ pro hodnocení bez vizuálního stimulu ($\bar{x}_R = \frac{1}{M}\sum_{m=1}^{M} x_{Rm}$) jsou v rozsahu od 5,7 do 5,9, což ukazuje, že „průměrné“ hodnocení se v čase neměnilo. Na druhou stranu je odlišnost v minimální hodnotě. Skupina 3 nehodnotila omak vyloženě jako špatný, ale pouze na rozmezí špatný-průměrný. Určité rozdíly v hodnocení u skupiny 3, vzhledem ke zbývajícím dvěma skupinám, lze také nalézt v případě hodnocení omaku s vizuálním kontaktem. Celková průměrná hodnota mediánu $\bar{x}_R$ je přibližně o 0,8 bodu nižší, tzn., že tato skupina v průměru hodnotila omak jako horší. Toto indikuje určitý možný vliv vizuálního kontaktu při hodnocení omaku. Nelze opominout také fakt, že mezi výrobou tkanin a jejich hodnocením v případě skupiny 3 uplynulo více než 8 let, takže hodnotitelé mohli být ovlivněni trendy (barevností).

Tabulka 3. Základní charakteristiky median ordinální škály x_R

	skupina 1				skupina 2		skupina 3	
	bez vizuálního stimulu		s vizuálním stimulem		s vizuálním stimulem		bez vizuálního stimulu	s vizuálním stimulem
	1. hodn.	2. hodn.	1. hodn.	2. hodn.	1. hodn.	2. hodn.		
$\bar{x}_R$	5,7	5,7	5,8	6,0	6,3	6,0	5,9	4,9
minimum	1,9	2,3	2,9	3,0	3,7	3,4	3,5	2,6
maximum	9,1	9,2	9,1	8,8	10,1	9,2	9,0	7,9

K porovnání výsledků mezi jednotlivými skupinami hodnocení byl použit Spearmanův pořadový korelační koeficient r_S a lineární regresní model. Teoreticky, při shodnosti hodnocení, porovnávaná hodnocení leží na přímce $y = \beta_0 + \beta_1 x$, kde pro regresní koeficienty platí nulový úsek β_0=0 a jednotková směrnice β_1=1. Proto pro porovnání dvou hodnocení byla testována hypotéza H_0: β_0=0 a β_1=1 proti alternativní hypotéze H_1: $\beta_0 \neq 0$ a $\beta_1 \neq 1$. Veškeré realizované testy hypotéz byly řešeny na hladině významnosti α=0,05.

Opakovatelnost celkového omaku (THV)

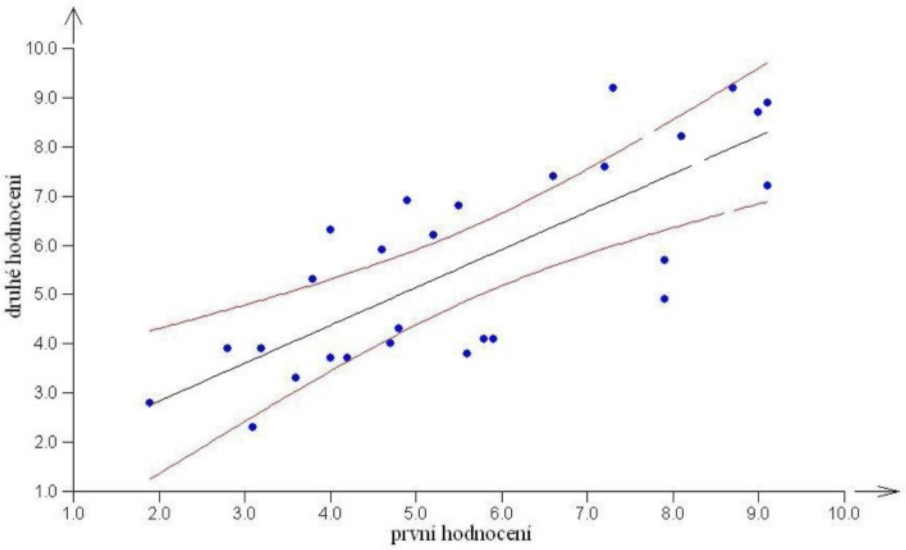
Aby mohla být ověřena opakovatelnost hodnocení, posuzovatelé hodnotili omak za stejných podmínek dvakrát. Experiment byl rozdělen do dvou částí:

a) bez vizuálního stimulu – byl ověřován na skupině 1,
b) s vizuálním stimulem – byl ověřován na skupině 1 a 2.

V tabulkách 4 až 8 *S* značí, že odhad regresního koeficientu je statisticky významný ($\beta_i \neq 0$) a *N* znamená, že odhad regresního koeficientu je statisticky nevýznamný (β_i= 0).

a) bez vizuálního stimulu

Výsledky jsou uvedeny v tabulce 4**.** Ukazují, že lze tato dvě hodnocení považovat za shodná. Regresní koeficient β_0 je statisticky nevýznamný a pro koeficient β_1 platí, že jeho 95%-ní interval spolehlivosti pokrývá hodnotu 1. Korelační koeficient r_S má hodnotu 0,77, což ukazuje na vysoký soulad v hodnocení jednotlivých tkanin (obrázek 2).



Obrázek 2. Opakovatelnost – porovnání prvního a druhého hodnocení x_R bez vizuálního kontaktu – skupina 1

Tabulka 4. Opakovatelnost hodnocení celkového omaku bez vizuálního stimulu

	skupina 1	
odhady regresních koeficientů	b_0	b_1
odhad	1,3	0,77
směrodatná odchylka	0,73	0,12
závěr – významnost	*N*	*S*
hladina významnosti	0,087	0,000
95%-ní int. spol. – spodní mez	-0,2	0,52
horní mez	2,79	1,02
r_S	0,77	

b) s vizuálním stimulem

Ověření opakovatelnosti hodnocení omaku bylo realizováno pomocí dvou panelů respondentů – skupiny 1 a skupiny 2, kde každá skupina hodnotila omak dvakrát. Výsledky uvedené v tabulce 5 ukazují, že 95%-ní interval spolehlivosti pro β_0 nepokrývá 0 a tedy $\beta_0 \neq 0$. Ačkoli odhad regresního koeficientu β_1 nemůže být striktně chápán jako rovný hodnotě 1 pro skupinu 2 (95%-ní interval spolehlivosti nepokrývá hodnotu 1), tak jako v případě skupiny 1, je v obou případech poblíž této hodnoty. Výsledky vedou u obou skupin ke shodnému závěru. Druhá hodnocení se liší od prvních, jelikož odhady regresních koeficintů $b_0 \neq 0$. Výsledky naznačují, že v případě druhých hodnocení byly tkaniny oběma skupinami hodnoceny blíže k sobě. Korelační koeficienty r_S dosáhly hodnoty kolem 0,7, což ukazuje, také jako v případě hodnocení bez vizuálního stimulu, že tkaniny, které byly při prvním testování oceňovány jako tkaniny s lepším omakem, byly takto hodnoceny i při druhém testování.

Jak výsledky hodnocení omaku bez vizuálního kontaktu, tak i výsledky s vizuálním kontaktem naznačují, že hodnotitelé jsou schopni opakovaně hodnotit tkaniny s obdobným výsledkem.

Tabulka 5. Opakovatelnost hodnocení celkového omaku bez vizuálního stimulu

	skupina 1		skupina 2	
odhady regresních koeficientů	b_0	b_1	b_0	b_1
odhad	1,55	0,77	1.39	0.73
směrodatná odchylka	0,69	0,11	0.68	0.10
závěr - významnost	S	S	S	S
hladina významnosti	0,033	0,000	0.050	0.000
95%-ní int. spol. – spodní mez	0,14	0,53	0.002	0.52
horní mez	2,95	1,00	2.78	0.95
r_S	0,71		0,70	

Reprodukovatelnost celkového omaku

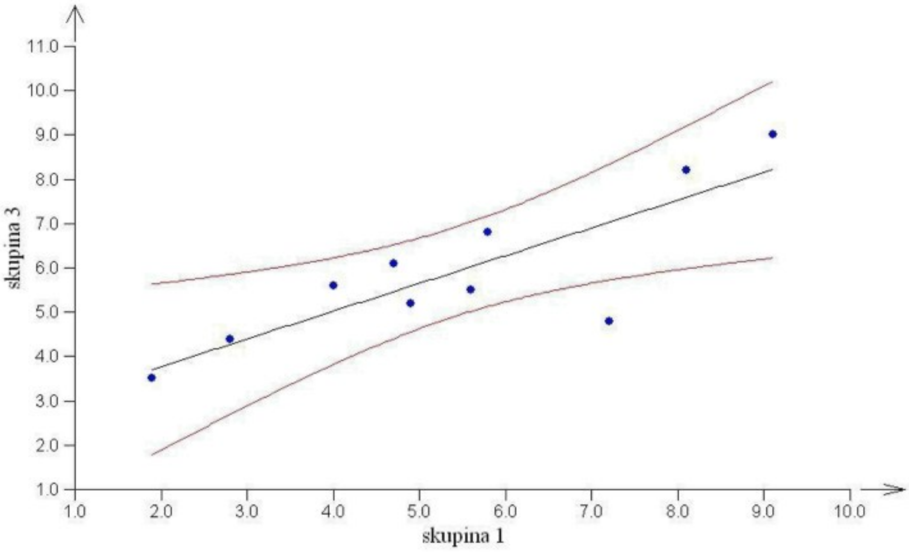
Pro ověření reprodukovatelnosti hodnocení celkového omaku bylo využito tří panelů respondentů. Podmínky a průběh hodnocení byly u všech skupin zachovány. Rovněž bylo realizováno hodnocení bez a s vizuálním kontaktem. Porovnávané skupiny:

a) bez vizuálního stimulu – skupina 1 a skupina 3
b) s vizuálním kontaktem – všechny tři skupiny.

V případech, kdy skupiny realizovaly hodnocení 2x (skupiny 1 a 2), byly porovnávány mezi sebou první a druhá hodnocení, jelikož v případě druhých hodnocení již respondenti měli s hodnocením tkanin určité zkušenosti vzhledem k úvodním hodnocením. Z tohoto důvodu byly porovnávány výsledky prvních hodnocení skupiny 1 s výsledky skupiny 3.

a) bez vizuálního stimulu

Regresní koeficient r_s=0,72 ukazuje vysoký soulad v hodnocení mezi skupinami 1 a 3 (tabulka 6 a obrázek 3). Na základě výsledků regrese lze přijmout hypotézy, že $\beta_0 \neq 0$ a $\beta_1 \neq 1$. Tyto výsledky indikují určitou odlišnost v hodnocení. Skupina 3 při svém hodnocení nevyužívala zcela celý rozsah stupnice tak často jako první skupina, hlavně v oblasti pro hodnocení špatného omaku (tabulka 3). Lze tak konstatovat, že skupina 3 byla méně kritická.



Obrázek 3. Reprodukovatelnost - porovnání prvních hodnocení x_R bez vizuálního kontaktu – mezi skupinami 1 a 3

Tabulka 6. Reprodukovatelnost hodnocení celkového omaku bez vizuálního stimulu

	mezi skupinami 1 a 3	
odhady regresních koeficientů	b_0	b_1
odhad	2,52	0.63
směrodatná odchylka	0,83	0.14
závěr - významnost	S	S
hladina významnosti	0,017	0.002
95%-ní int. spol. – spodní mez	0,59	0.30
horní mez	4,44	0.96
r_S	0,72	

b) s vizuálním stimulem

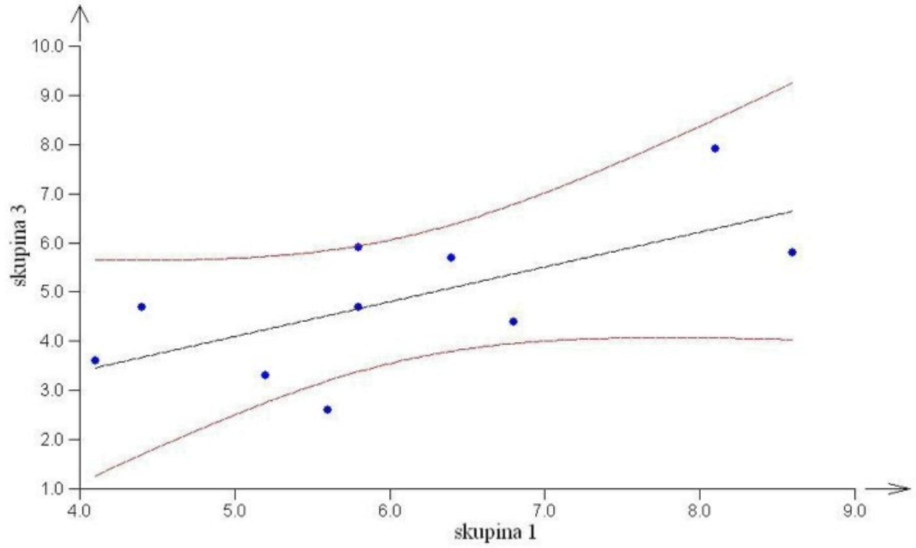
Stanovení reprodukovatelnosti hodnocení celkového omaku s vizuálním kontaktem bylo uskutečněno za pomoci tří skupin respondentů. Skupiny 1 a 2 hodnotily omak dvakrát. Tento způsob hodnocení se nejvíce přibližuje reálné situaci, kdy hodnotitel textilii hodnotí na omak vždy s vizuálním kontaktem. Výsledky jsou uvedeny v tabulce 7.

Tabulka 7. Reprodukovatelnost hodnocení celkového omaku s vizuálního stimulu

	mezi skupinami 1 a 2 - 1. Hodnocení		mezi skupinami 1 a 2 - 2. hodnocení		mezi skupinami 1 a 3		mezi skupinami 2 a 3	
odhady regresních koeficientů	b_0	b_1	b_0	b_1	b_0	b_1	b_0	b_1
odhad	1,97	0.75	3.34	0.48	0,55	0,71	0,31	0.74
směrodatná odchylka	0,83	0.14	0.74	0.12	1,74	0,28	1,46	0.23
závěr - významnost	S	S	S	S	N	S	N	S
hladina významnosti	0.025	0.000	0.000	0,001	0,758	0,034	0.837	0.013
95%-ní int. spol. – spodní mez	0,26	0.47	1.83	0.23	-3.46	0,064	-3,06	0.21
horní mez	3,67	1.04	4.85	0.73	4,56	1,35	3,68	1.28
r_S	0,67		0,58		0,64		0,71	

Výsledky neposkytují zcela jednoznačný závěr. Podle hodnot odhadů regresních koeficientů existuje soulad v hodnocení mezi skupinami 1 – 3 a 2 - 3. Avšak výsledky v tabulce 3 ukazují, skupina 3 hodnotila omak tkanin v průměru o 0,8 stupně hůře než skupiny 1 a 2. Tento nesoulad lze vysvětlit tím, že směrodatná odchylka odhadu regresního koeficientu b_0 je příliš vysoká a tak 95%-ní interval spolehlivosti je schopen snadno pokrýt hodnotu 0. Nižší hodnoty Spearmanova pořadového korelačního koeficientu (<0,7) ukazují na nižší soulad v hodnocení než v případě opakovatelnosti. Respondenti jsou tak více ovlivněni vzhledem hodnocených tkanin.

Přes ne zcela jednoznačné výsledky lze konstatovat, že existuje vysoký soulad v hodnocení mezi různými skupinami hodnotitelů, a tudíž reprodukovatelnost hodnocení celkového omaku při využití různých skupin hodnotitelů (obrázek 4).



Obrázek 4. Reprodukovatelnost - porovnání prvních hodnocení x_R s vizuálním kontaktem – mezi skupinami 1 a 3

2.3 Vliv vizuálního stimulu na hodnocení omaku

Realizace hodnocení omaku tkanin bez nebo s vizuálním kontaktem patří mezi zásadní podmínky průběhu experimentu při jeho plánování. Ačkoliv jsou hodnotitelé poučeni v souladu s podmínkami senzorického hodnocení, vliv vizuálního podnětu nelze v průběhu hodnocení zcela vyloučit, zvláště v případech, kdy se tkaniny liší výrazně jak v základních parametrech, tak i barevností vzorů. Výsledky uvedené v literatuře vedou k nejednoznačným závěrům. Lauglin [4] poukazuje ve své studii, že konstrukce, lesk a povrch hrají důležitou roli při hodnocení. Na druhou stranu Yenket [5] konstatuje, že vizuální efekt nemá velký význam na hodnocení.

Skupina 1 a 3 hodnotila omak, jednak bez vizuálního stimulu, jednak s vizuálním stimulem. Jelikož se skupina 1 zúčastnila obou typů experimentů dvakrát, bylo pro porovnání výsledků se skupinou 3 bráno pouze první hodnocení.

Hodnoty Spearmanova pořadového korelačního koeficientu jsou v případě obou skupin vysoké (>0,7, tabulka 8), což ukazuje, že se hodnotitelé byli schopni oprostit od vizuálního stimulu během hodnocení. Je však nutno podotknout, že skupina 3 hodnotila omak s vizuálním kontaktem v průměru jako horší než bez vizuálního stimulu, což ukazuje na určitý vliv módnosti vzorů, ke kterému během 8 let od výroby tkanin k jejich hodnocení skupinou 3 mohlo dojít.

Přesto lze konstatovat, že dobře poučení a částečně zkušení hodnotilé jsou schopni se oprostit od vlivu vizuálního stimulu v průběhu hodnocení celkového omaku tkanin.

Tabulka 8. Vliv vizuálního stimulu na hodnocení celkového omaku

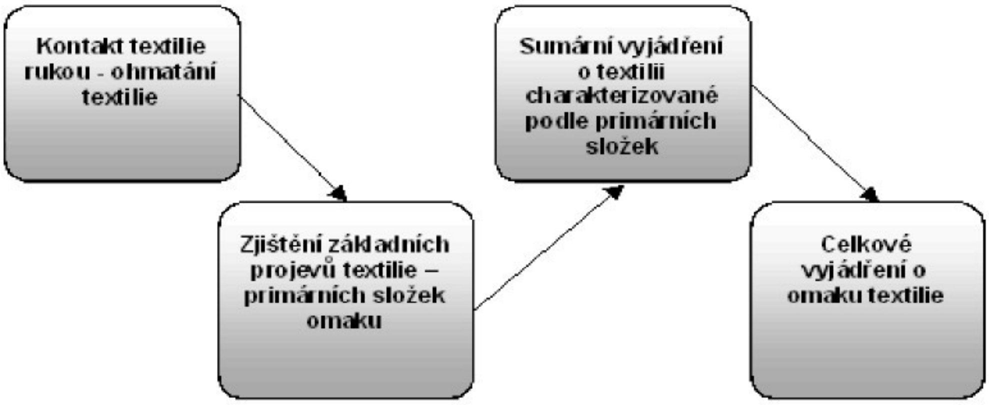
	skupina 1		skupina 3	
odhady regresních koeficientů	b_0	b_1	b_0	b_1
odhad	2,11	0,64	0,40	0,76
směrodatná odchylka	0,62	0,10	1,10	0,18
závěr - významnost	S	S	N	S
hladina významnosti	0,002	0,000	0,728	0,003
95%-ní int. spol. – spodní mez	0,843	0,43	-2,14	0,34
horní mez	3,40	0,85	2,94	1,17
r_S	0,74		0,78	

2.4 Analýza povrchu tkanin

Bylo zjištěno, že hodnotitel nejdříve porovnává základní vlastnosti (primární složky omaku) a teprve na jejich základě stanoví konečný verdikt o omaku textilie (celkový omak – THV). Schematicky je postup subjektivního hodnocení omaku uveden na obrázku 5. Byl zaveden předpoklad, že primární složky souvisejí se 4 senzorickými centry:

- centrum povrchové hladkosti a nerovnosti,
- centrum tuhosti a poddajnosti,
- centrum objemových vlastností (objem, hmotnost),
- centrum tepelných projevů.

Bylo prokázáno, že jednotlivé primární složky nemají stejný význam. Subjektivní vjem omak je pak váženým průměrem velikostí stimulace jednotlivých center. Váhové koeficienty zde představují míru odezvy na jednotlivé stimuly. Pro toto vyjádření se zavedl pojem celkový omak (THV - Total Hand Value) [6]. Ukazuje se, že mezi nejdůležitější vlastnosti patří vlastnosti spojené s centrem povrchové hladkosti (tabulka 9).



Obrázek 5. Postup subjektivního hodnocení omaku

Tabulka 9. Důležitost primárních složek – pánské zimní oblekovky

Vlastnosti	KES	Raheel	Bajzík
centrum povrchové hladkosti	0,3	-	0,3
centrum tuhosti	0,25	0,53	0,26
centrum objemových charakteristik	0,2	0,47	0,23
centrum tepelných projevů	-	-	0,21
Ostatní	0,25	-	-

Východiskem pro predikci omaku je pak soubor vlastností textilií charakterizujících jednotlivá senzorická centra (tabulka 10).

Tabulka 10. Příklady vlastností, které mají vzah k určitému senzorickému centru

Senorické centrum	Objektivně měřitelné vlastnosti
povrchové hladkosti a nerovnosti	koeficient statického tření, koeficient dynamického tření, *MIU*, *MMD*, *SMD*, chlupatost, atd.
tuhosti a poddajnosti	modul pružnosti v tahu, modul pružnosti ve smyku, ohybová tuhost, splývavost, příčný modul, *LT*, *WT*, *RT*, *B*, *2HB*, *G*, *2HG*, *2HG5*, úhel zotavení, tvarová stálost, atd.
objemových vlastností	pórovitost, plošná hmotnost, tloušťka, stlačitelnost, *LC*, *WC*, *RC*, relaxace sráživosti, atd.
tepelných projevů	tepelná jímavost, tepelný odpor, atd.

Drsnost povrchu je jednou z hlavních vlastností, které ovlivňují vnímání omaku. Standardní metody měření drsnosti povrchu jsou založeny na hodnocení profilu povrchu. K měření se používají profilometry, které se pohybují po povrchu a následně je zaznamenávána vertikální změna. Výsledkem je křivka variability výšky povrchu (SHV). Druhou možností je sledovat variabilitu síly, která je zapotřebí k překonání odporu tkaniny, který klade při pohybu kontaktoru po povrchu. Zde je výsledkem záznam profilu průběhu síly po povrchu tkaniny (SFV).

Profil záznamu povrchu má dva základní rysy:

a) náhodný – drsnost kolísá značně náhodně v prostoru a nelze tak pro popis geometrického tvaru profilu použít žádnou funkci,

b) strukturální – rozptyly drsnosti nejsou zcela nezávislé z hlediska uspořádání v prostoru, ale jejich korelace závisí na vzdálenosti. Zvláště povrch tkanin je charakterizován téměř pravidelně se opakujícím vzorováním, a tudíž lze identifikovat často určité periodicity.

Z profilů SHV a SFV lze určit celou řadu parametrů, které charakterizují drsnost. Výpočet parametrů drsnosti je založen na vyhodnocování řady bodů $R(d_j)$, $j=1,2....Q$, které jsou definovány na vzorku délky L. Měřené body d_j mají obvykle ekvidistantní vzdálenosti, a proto $R(d_j)$ může být nahrazena veličinou R_j. Aby mohly být identifikovány pozice v měřítku délky, je vhodné znát vzorkovací vzdálenost $d_s=d_j- d_{j-1} = L/Q$ pro $j>1$. S celkovým omakem byly porovnávány tyto parametry [7]:

I. Průměrná absolutní odchylka (*MAD*) – parametr je roven průměrné absolutní odchylce výšek povrchu od průměrné hodnoty $\bar{R}$.

$$MAD = \frac{1}{Q}\sum_j \left|R_j - \bar{R}\right| \qquad (3).$$

Tento parametr nerozlišuje mezi profily různých tvarů.

II. Směrodatná odchylka (*SD*) – je dána vztahem

$$SD = \sqrt{\frac{1}{Q}\sum_j \left(R_j - \bar{R}\right)^2} \qquad (4).$$

Výhodou *SD* oproti *MAD* je, že pro normálně rozdělená data lze snadno spočítat intervaly spolehlivosti. *SD* je vždy větší než *MAD* a pro data pocházející z normálního rozdělení platí $SD=1,25MAD$. Také tento parametr nerozlišuje mezi profily různých tvarů.

III. Průměrná výška píků (*MP*) – počítá se jako průměr odchylek profilu nad referenční hodnotou R (často $R = \bar{R}$). Je dána jako průměrná hodnota píků P_i, i=1, 2,...$Q1$, kde

$$P_i = R_i - R \quad \text{pro } R_i > 0 \text{ a } P_i = 0 \text{ jinak.} \qquad (5)$$

IV. Průměrná hloubka údolí (*MV*) – počítá se jako průměr odchylek profilu pod referenční hodnotou *R* (často $R = \bar{R}$). Jedná se o průměrnou hodnotu údolí V_i, i=1, 2,...*Q2*, kde

$$V_i = R - R_i \quad \text{pro } R_i < 0 \text{ a } V_i = 0 \text{ jinak.} \tag{6}$$

Parmetry *MP* a *MV* dávají o informaci o složitosti profilu.

V. Směrodatná odchylka sklonu profilu (*PS*) – je dána vztahem

$$PS = \sqrt{\frac{1}{Q}\sum_j \left(\frac{dR(x)}{dx}\right)_j^2} \tag{7}$$

VI. Směrodatná odchylka křivosti profilu (*PC*) – často je nazývána také jako vlnitost. Je dána vztahem

$$PC = \sqrt{\frac{1}{Q}\sum_j \left(\frac{d^2R(x)}{dx^2}\right)_j^2} \tag{8}$$

Sklon a křivost charakterizují tvar profilu. Nižší hodnota odchylky sklonu profilu má za následek nižší tření.

VII. Průměrný sklon profilu (*MS*) – je dán vztahem

$$MS = \frac{1}{Q}\sum_j \left|\frac{dR(x)}{dx}\right|_j \tag{9}$$

Průměrný sklon je důležitý parametr, který má rovněž vztah ke tření.

VIII. Průměr deseti bodů (*TP*) – je definován jako průměrná diference mezi pěti nejvyššími píky a pěti nejhlubšími údolími profilu.

Tyto parametry jsou důležité pro případy funkčních povrchů. Pro charakterizaci omaku je patrně nejdůležitější chrakteristika křivosti *PC*.

IX. Fraktální dimenze (D_F *a* D_{Fp}) – většina umělých objektů je geometricky jednoduchá a může být klasifikována jako složenina pravidelných geometrických tvarů jako jsou čáry, křivky, plochy, kruhy, koule atd. Některé objekty však nemohou být aproximovány přesně pomocí pravidelných geometrických tvarů. Jednou ze tříd těchto objektů jsou fraktály [8]. Mají dvě zajímavé vlastnosti – jsou samopodobné ve vícenásobném měřítku, tj. malý podíl fraktálu vypadá podobně jako celý objekt, a mají fraktální dimenzi – jako protiklad celočíselnému rozměru pravidelných geometrických tvarů. Z měření profilu tkaniny (variabilita tloušťky *R(h)*) je k dispozici řada dat, která znamenají jednorozměrný průběh profilu na délce *L*. Takto získaná data reprezentují křivku v rovině. Fraktální dimenze *D* pak leží v intervalu od 1 (pro hladkou křivku) do 2 (pro „drsnou", hrubou, velmi členitou křivku). Fraktály mohou být odhadnuty např. z mocninné závislosti variogramu na velikosti posunu *h*, tedy

$$\Gamma(h) = c|h|^H \quad (10).$$

Hurstův exponent *H* leží v intervalu od 0 do 1, kde pro *H=0* značí, že křivka je extrémně nepravidelná a pro *H=1* znamená, že křivka je hladká [9]. Exponent *H* a frakální dimenze *D* jsou spojeny vztahem

$$D = 2 - H \quad (11).$$

Označení fraktální dimenze D_F je pro celkovou fraktální dimenzi spočítanou ze všech dat a D_{Fp} je označení pro počáteční fraktální dimenzi spočítanou z prvních 12 bodů (body 4 až 15) variogramu (kromě 3 bodů na počátku), [B6, B7, B9].

Variogram lze určit na základě statistického chování *R(h)*. Základním rysem *R(h)* je autokorelovanost závisející na délce posunu *h* (vzdálenosti mezi hodnocenými místy tloušťky). Hlavní charakteristikou statistického chování *R(h)* je kovariance *C(h)*

$$C(h) = cov[R(d), R(d+h)] = E\{[R(d) - E(R(d))(R(d+h) - E\big(R(d)\big)]\} \quad (12).$$

Autokorelační funkce *ACF(h)* je definována jako normalizovaná verze *C(h)*

$$ACF(h) = \frac{C(h)}{C(0)} \quad (13).$$

V prostorové statistice je variogram definován jako polovina rozptylu rozdílů *(R(d)-R(d+h))*

$$\Gamma(h) = 0{,}5D[R(d) - R(d+h)] = 0{,}5\{E[R(d) - R(d+h]^2 - E^2[R(d) - R(d+h)]\} \quad (14).$$

Pro stacionárně náhodné procesy nezávisí průměrná hodnota na délce posunu *h*, tedy *E[R(h)]=m*. Potom

$$\Gamma(h) = 0{,}5E[R(d) - R(d+h)]^2 \tag{15}$$

a pro náhodné procesy, které mají stacionaritu druhého řádu, platí

$$C(h) = E[R(d)R(d+h)] - m^2 \tag{16}$$.

Rozptyl je pak roven

$$D[R(d)] = C(h=0) = C(0) \tag{17}$$.

Relace mezi variogramem a kovariancí je dána vztahem

$$\Gamma(h) = C(0) - C(h) \tag{18}$$.

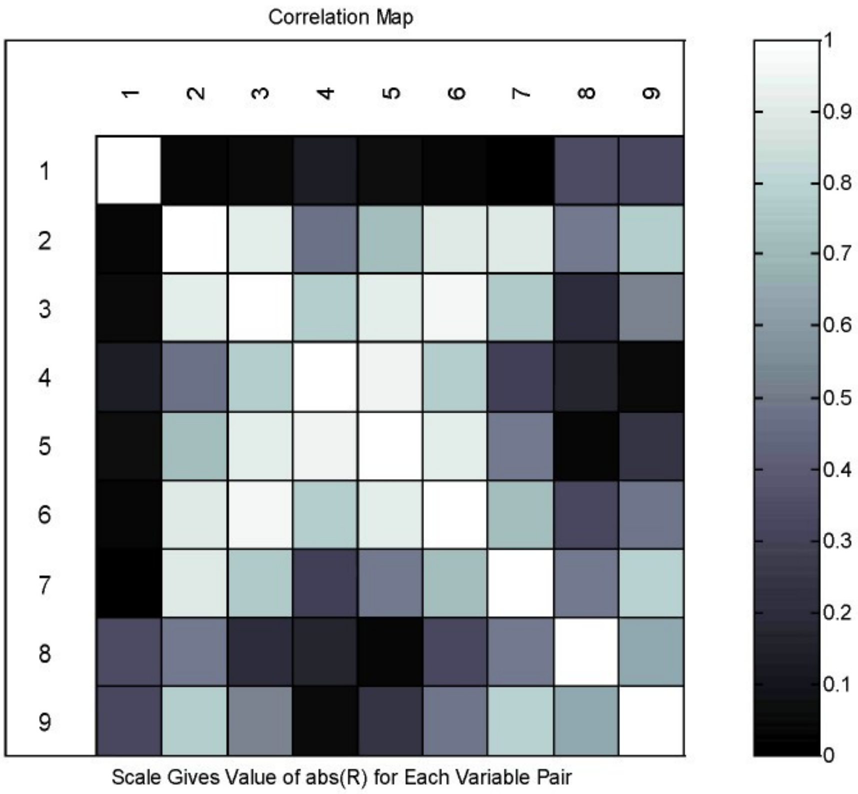
Pro následný výpočet fraktání dimenze D byl variogram odhadnut pomocí vztahu

$$G(h) = \frac{1}{2M(h)} \sum_{j=1}^{M(h)} (R_j - R_{j+h})^2 \tag{19}$$.

2.4.1 Porovnání charakteristik drsnosti povrchu s hodnocením omaku

Vztah mezi charakteristikami, které popisují povrch tkanin, a hodnocením omaku byl zkoumán na 54 nehořlavých tkaninách. Byly použity jak bavlněné tkaniny s nehořlavou úpravou (s plátnovou, keprovou a atlasovou vazbou), tak i tkaniny vyrobené z nehořlavých vláken (Nomex, nehořlavá viskóza a modakrylová vlákna). Povrch byl snímán pomocí přípravku, který je posán v kapitole 3.1.1. Byla získána křivka SFV. Hodnocení omaku bylo realizováno pomocí panelu 30 respondentů, kteří ho hodnotili do jedenáctistupňové ordinální škály. Pro každou tkaninu byl vypočten medián ordinální škály x_{Rm}. Výsledek byl následně vydělen hodnotou 11. Korelační mapa na obrázku 6 zobrazuje korelace mezi následujícími charakteristikami a celkovým omakem:

- celkový omak *THV*,
- průměrná absolutní odchylka *MAD*,
- průměrný sklon profilu *MS*,
- standardní odchylka sklonu profilu *PS*,
- standardní odchylka křivosti profilu *PC*,
- průměr desti bodů *TP*,
- variační koeficient $CV = SD/R_a$,
- průměrná fraktální dimenze D_F,
- výchozí fraktální dimenze D_{Fp}.



Obrázek 6. Korelační mapa

Mezi většinou charakteristik a celkovým omakem je nízká korelace (černá či tmavá barva). Největší korelace je mezi omakem a fraktálními dimenzemi. Je zřejmé, že existuje také korelace mezi charakteristikami drsnosti povrchu navzájem (bílá či světlá barva). Charakteristika *MAD* má vysokou korelaci s ostatními charakteristikami drsnosti. Malá korelace mezi charakteristikami drsnosti a hodnocením omaku ukazuje, že drsnost není důležitá u nehořlavých tkanin.

3. Predikce omaku textilií pomocí techniky BM

Hodnocení omaku s využitím panelu respondentů je časově a organizačně velmi náročné. V průběhu uplynulých několika desítek let byla navržena řada postupů, jejichž cílem je možnost predikovat omak s využitím objektivně měřitelných vlastností s vyloučením hodnotitelů. Systém BM byl navržen z důvodu přiblížení se běžným podmínkám v laboratořích. Jeho výhoda spočívá v tom, že většinu vlastností lze měřit na běžně dostupných přístrojích v laboratořích. Kromě toho zahrnuje takové vlastnosti, které korespondují se všemi 4 centry omaku [10]. Při výběru vlastností byly také brány v úvahu výsledky prací [B6, 11, 12, 13, 14].

Aby mohly být výsledky navrhovaného postupu BM ověřeny, bylo nutno pro porovnání použít některou ze známých metod. Jelikož je systém KES brán jako nepsaný standard, byly výsledky metodiky BM konfrontovány s predikčními schopnostmi modelu, který byl vybudován na vlastnostech KES.

3.1 Použité vlastnosti

Vlastnosti navržené v technice BM jsou:

1) vlastnosti související s centrem povrchové hladkosti a nerovnosti

MAD	průměrná absolutní odchylka [mN]

2) vlastnosti související s centrem tuhosti a poddajnosti

Y	modul pružnosti [MPa]
T	tuhost [mN cm]
Y45	modul pružnosti po diagonále -, soustava nití pootočena o úhel 45° vzhledem ke směru posuvu příčníku [MPa]

3) vlastnosti související s centrem objemových vlastností (objem, hmotnost, tvar)

S	stlačitelnost [-]
t	tloušťka [mm]
M	plošná hmotnost [g/m^2]

4) vlastnost spojená s centrem tepla a chladu

b	tepelná jímavost [W/ (m^2 K^1 s$^{-0,5}$)]

Model konstruovaný z těchto vlastností byl označen BM11.

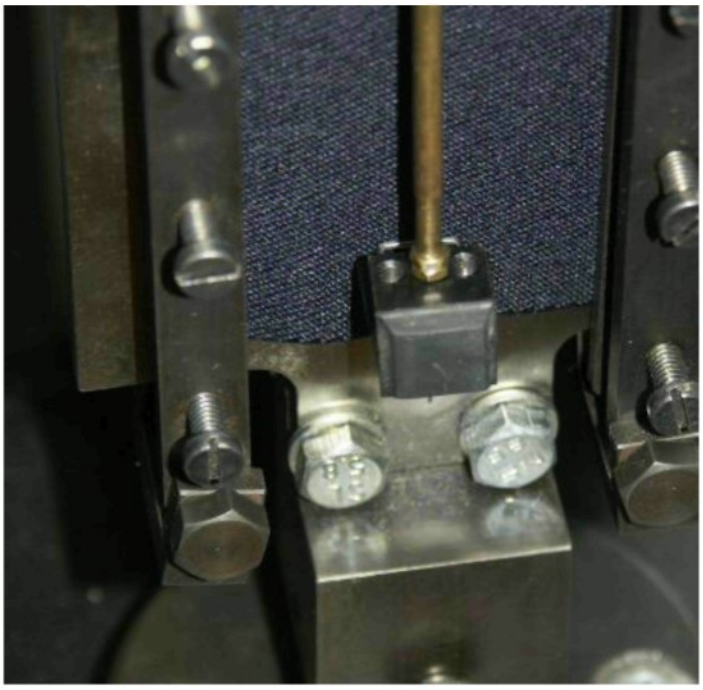
3.1.1 Drsnost povrchu

Pro vyjádření drsnosti byla zvolena průměrná absolutní odchylka *MAD* kolísání výšky povrchu textilie R_j, $j=1,2,\dots Q$. Pro měření výšky povrchu textilie na dynamometru byl navržen přípravek, jehož část (kontaktor) se pohybuje po povrchu textilie (obrázek 7). Výsledný záznam odpovídá síle, která byla zapotřebí k překonání odporu textilie vůči pohybu kontaktoru po jejím povrchu.

$$MAD = \frac{1}{Q}\sum_j \left|R_j - \bar{R}\right| \qquad (3).$$

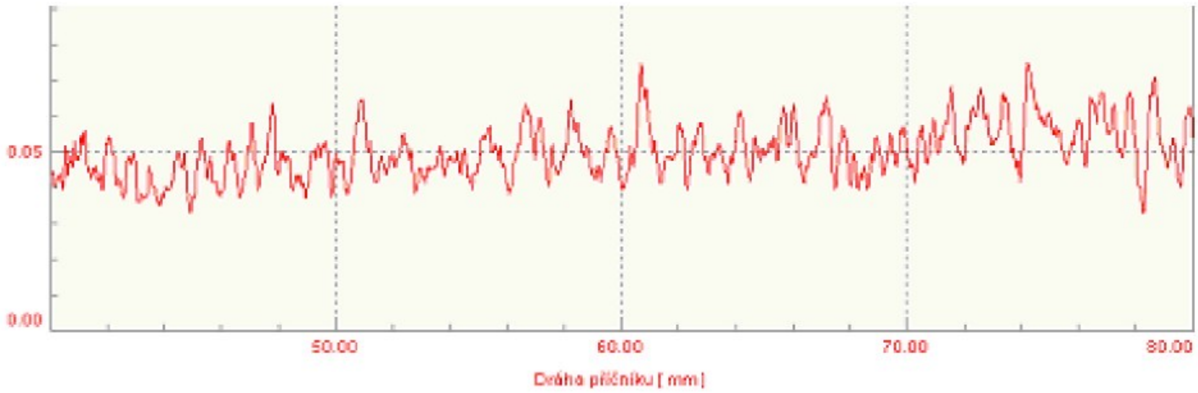
Tvar a rozměr kontaktoru je shodný s tím, který se používá pro měření *SMD* na systému KES. Měřená délka je 100 mm. Pro analýzu pak byla vybrána délka 40 od záznamu 40 do 80 mm (obrázek 8).

a) přípravek



b) detail kontaktoru

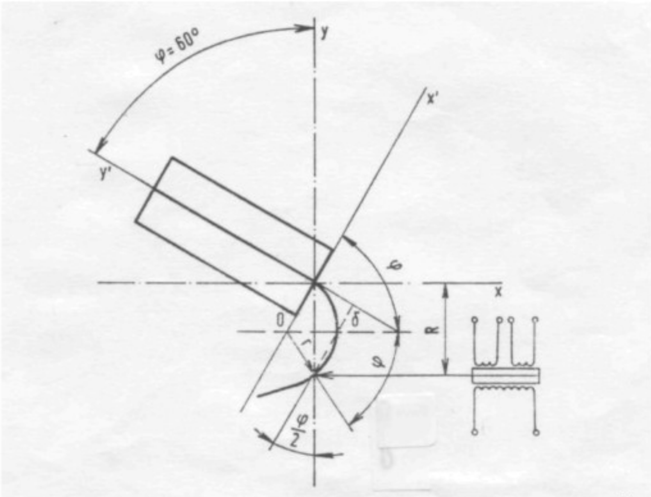
Obrázek 7. Přípravek a detail kontaktoru



Obrázek 8. Ukázka průběhu záznamu síly, která byla zapotřebí k překonání odporu textilie vůči pohybu kontaktoru

3.1.2 Tuhost

Tuhost (princip na obrázku 9) byla měřena na tuhoměru TH5 (ČSN 80 0858). Proměřoval se vzorek o rozměrech 50 x 25 mm, po osnově i po útku.



Obrázek 9. Princip měření tuhosti na tuhoměru TH5, obrázek převzat z ČSN 80 0858

R – vzdálenost čelistí od čidla, r – poloměr křivosti deformovaného vzorku, O – střed křivosti deformovaného vzorku, δ - deformace volného konce vzorku při konečném vychýlení čelisti, φ – výchylka čelisti od osy y

Tuhost se vyjádří jako ohybový moment

$$T = F.K \tag{20}$$

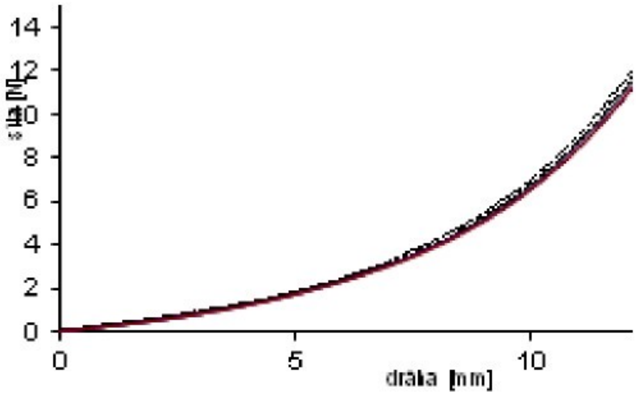
kde $K=l/b$, l je délka měřeného vzorku při výchylce 60° od hrany čelisti k čidlu zkušebního přístroje (l=1,51 cm), b je šířka vzorku (b=2,5 cm), F je síla.

3.1.3 Modul pružnosti *Y*

Modul pružnosti Y byl určován z počáteční části tahové křivky síla – posunutí, kde F_h=10 N a F_s=0. Pro výpočet byl použit vztah

$$Y = \frac{F_h - F_s}{l_h - l_s} \cdot \frac{l_0}{t_0 . b} \tag{21},$$

kde F_h, F_s, – hraniční pevnosti použité pro výpočet, l_h,l_s – protažení odpovídající silám F_h, F_s, l_0 –upínací délka, t_0 – tloušťka vzorku, b – šířka vzorku (obrázek 10).



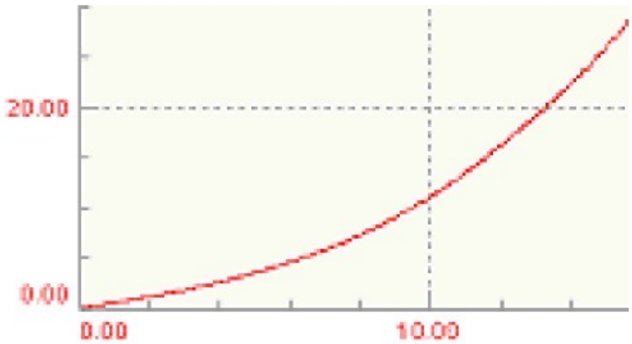
Obrázek 10. Průběh deformační křivky

Upínací délka vzorku byla 0,2 m a šířka 0,05 m.

3.1.4 Modul pružnosti *Y45*

Smykové namáhání při malých deformacích souvisí se schopností posuvu přízí ve tkanině. Bylo simulováno pomocí tahového namáhání tkaniny v diagonálním směru tkaniny na vzorcích o rozměru 100x25 mm na dynamometru. Smyková odolnost *Y45* byla určena z lineární části tahové křivky síla – protažení (obrázek 11).

$$Y45 = \frac{F_h - F_s}{l_h - l_s} \cdot \frac{l_0}{t_0 . b} \quad (22)$$



Obrázek.11. Průběh deformační křivky v okolí počátku

Pro výpočet byly použity hodnoty l_h=5 mm l_s=0 mm a tomu odpovídající hodnoty F_h, F_s.

3.1.5 Stlačitelnost a tloušťka

Stlačitelnost je vyjádřena pomocí poměru tloušťky tkaniny měřené při 2 různých zatíženích.

$$S = \frac{t_0 - t_1}{t_0} \quad (23),$$

kde t_0 je tloušťka měřená při přítlaku 0,5 kPa a t_1 je tloušťka měřená při přítlaku 5 kPa. t_0 je zároveň brána jako tloušťka vzorku. Proměřovaná plocha vzorku byla 1000 mm^2. Tloušťka $t=t_0$.

3.1.6 Tepelná jímavost *b*

Tepelná jímavost [15] charakterizuje tepelný vjem při krátkodobém kontaktu pokožky člověka s materiálem. Lze ji určit podle rovnice

$$b = \sqrt{\lambda . \rho . c} \quad (24),$$

kde ρ je měrná hmotnost, c je měrná tepelná kapacita a λ je koeficient tepelné vodivosti. U měření tepelných vlastností hraje důležitou roli počet kontaktních bodů mezi přístrojem a proměřovanou tkaninou. Proto je důležité provádět měření při konstantním zatížení měřící hlavy (200 Pa). Měření bylo prováděno na přístroji Alambeta [15]. Teplotní spád měřících hlav byl 10°C.

3.2 Analýza použitých vlastností

3.2.1 Porovnání vlastností tkanin s vlastnostmi ze systému KES

Použité tkaniny byly vybrány ze standardní produkce českých výrobců. Jelikož byly vybírány tkaniny pro daný účel použití, pro zabezpečení rozlišitelnosti v hodnoncení a pro vytvoření validní predikční rovnice pomocí techniky BM, byly vybrány tkaniny s co největší variabilitou konstrukce. Byly použity rozsahy vlastností tkanin, které byly použity pro konstrukci predikce omaku pomocí systému KES. V tabulce 11 jsou uvedena výsledná rozpětí naměřených vlastností ze systému KES. Zároveň je zde porovnání rozpětí s hodnotami spočtenými z rovnice KN-101-men's winter suit. Rozmezí hodnot z rovnice KN-101-men's winter suit byly vypočteny podle vztahu

$$rozsah_{vlastnosti} = x_{vlastnosti} \pm 1{,}98 . s_{vlastnosti} \quad (25),$$

tj. pokud by data pocházela z $N(\mu,\sigma^2)$, v uvedeném intervalu by leželo 95% hodnot dané vlastnosti. V případě vlastností *WT*, *B*, *HB*, *G*, *2HG*, *2HG5*, *LC*, *WC*, *MMD*, *SMD*, *T0*, a *W* byly meze spočteny přes odlogaritmování parametrů $\bar{x}$ a s. Vzhledem k naměřeným hodnotám, které byly použity pro konstrukci rovnice pro objektivní hodnocení omaku, lze vlastnosti naměřené na systému KES rozdělit do tří skupin. První skupinu tvoří vlastnosti, které pokrývají nebo překrývají uvedený rozsah: *LT*, *RT*, *B*, *HB*, *T*, *W*. Druhou skupinu tvoří vlastnosti, které nepřekrývají uvedený rozsah, ale jejich celkové rozpětí je větší než uvedený rozsah: *WT*, *MIU*, *MMD*, *SMD*. Třetí skupinu tvoří vlastnosti, jejichž celkový rozsah je nižší než u porovnávaných rozpětí: *G*, *2HG*, *2HG5*, *LC*, *WC*, *RC*.

Výsledná predikční schopnost modelu BM11 byla porovnávána s obdobným modelem vybudovaným z vlastností měřených na systému KES.

Tabulka 11. Porovnání rozsahů vlastností použitých tkanin s rozsahy vlastností KES použitých pro konstrukci rovnice KN-101-men's winter suit.

	rovnice KN-101-men's winter suit		měřené tkaniny		pokrytí rozpětí vzhledem k mezím rovnice KES [%]	upřesnění	poměr rozpětí měřených vlastností a mezí z rovnice KES [%]
	$\bar{x}_v - 2s_v$	$\bar{x}_v + 2s_v$	$x_{v,\,min}$	$x_{v,max}$			
LT	0,486	0,730	0,453	0,771	**>100**	obě meze přes	**130**
*WT**	5,11	16,45	6,31	34,96	**89**	vyšší hodnota přes	**253**
RT	53,31	71,07	53,36	78,52	**99,8**	vyšší hodnota přes	**142**
*B**	0,0547	0,1758	0,052	0,451	**>100**	obě meze přes	**330**
*2HB**	0,0196	0,1029	0,016	0,263	**>100**	obě meze přes	**296**
*G**	0,535	1,750	0,422	1,445	**75**	nižší hodnota přes	**84**
*2HG**	0,565	2,565	0,43	1,795	**61**	nižší hodnota přes	**68**
*2HG5**	1,322	4,984	1,04	3,535	**60**	nižší hodnota přes	**68**
LC	0,221	0,519	0,201	0,434	**71**	nižší hodnota přes	**78**
*WC**	0,102	0,378	0,06	0,253	**55**	nižší hodnota přes	**70**
RC	38,69	73,86	50,57	79,09	**66**	vyšší hodnota přes	**81**
MIU	0,166	0,252	0,124	0,212	**54**	nižší hodnota přes	**102**
*MMD**	0,00877	0,02730	0,01	0,082	**93**	vyšší hodnota přes	**389**
*SMD**	1,553	10,38	2,291	13,24	**92**	vyšší hodnota přes	**124**
*T0**	0,517	1,077	0,31	1,167	**>100**	obě meze přes	**153**
*W**	20,07	34,59	13,78	37,18	**>100**	obě meze přes	**161**

Pozn:
- obě hodnoty přes = hodnota nejmenší resp. největší naměřené hodnoty je nižší resp. vyšší než spočtené meze z rovnice KES
- vyšší hodnota přes= hodnota největší naměřené hodnoty je vyšší než spočtená horní mez z rovnice KES
- nižší hodnota přes= hodnota nejmenší naměřené hodnoty je nižší než spočtená dolní mez z rovnice KES
*- parametry v původní rovnici KN-101- men's winter suit jsou v logaritmech

3.2.2 Vlastnosti techniky BM

V tabulce 12 jsou uvedeny charakteristiky jednotlivých vlastností a v tabulce 13 jsou předloženy párové (nad diagonálou) a parciální (pod diagonálou) korelace mezi jednotlivými vlastnostmi. Opět jsou zde tučně zvýrazněny korelace v absolutní hodnotě větší než 0,6. Porovnání párových korelací s maticovým grafem vlastností (obrázek 12) ukazuje na vazbu mezi geometrickými vlastnostmi tkanin *t* a *M* a ohybovou tuhostí *T*. Korelace je také mezi *t* a *MAD*. Výsledné parciální korelace ukazují na vazbu mezi *M* a *T*. Určitá vazba je ještě mezi *Y* a

Y45. Všechny párové korelace větší než |0,2| a všechny parciální korelace větší než |0,22| jsou statisticky významné na hladině významnosti α=0,05 [B3, B5].

Tabulka 12. Popis základních charakteristik vlastností BM.

	průměr	IS	šikmost	špičatost	normalita	sm.odch.	minim. hodnota	maxim. hodnota
b	237,13	233,65 – 240,62	0,05 N	2,91 N	P	16,64	198,00	277,00
T	4,19	3,82 – 4,55	0,68 V	2,90 N	P	1,76	1,69	9,58
t	0,54	0,51 – 0,58	0,78 V	3,16 N	Z	0,17	0,28	1,05
M	210,72	200,03 – 221,41	0,83 V	3,26 N	Z	51,03	137,80	371,80
S	0,174	0,165 - 0,183	0,82 V	3,75 N	Z	0,04	0,105	0,315
MAD	7,12	6,65 – 7,59	1,42 V	5,74 V	Z	2,26	3,38	16,32
Y45	5,99	5,46 – 6,52	1,10 V	4,94 V	Z	2,54	1,51	15,04
Y	34,93	30,17 – 39,69	1,09 V	3,75 N	Z	22,73	4,52	105,63

K detekci vztahů mezi proměnnými lze použít také metodu hlavních komponent. Cattelův indexový graf úpatí (scree plot, Sutinový graf) na obr. 13a indikuje 3 důležité hlavní komponenty. Grafy komponentních vah (obrázek 13 b-d) pro jednotlivé kombinace prvních tří komponent rovněž ukazují na vazbu mezi tloušťkou *t* a hmotností *M* tkanin. Méně silný vztah lze pozorovat mezi tahovými charakteristikami – modulem pružnosti *Y* a modulem pružnosti po diagonále *Y45*. Proto byly tyto vlastnosti sloučeny:

a) podle jejich charakteru

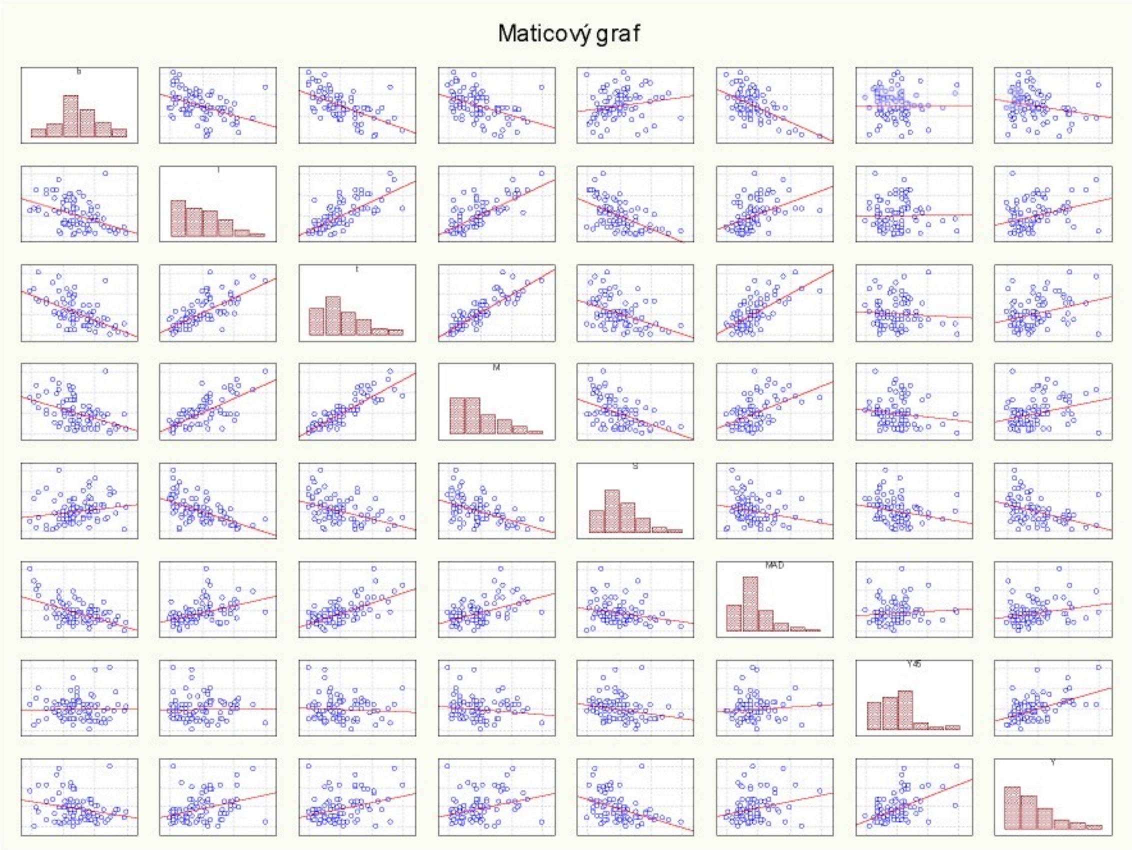
$geom1 = M/t$ a $pružnost1 = \frac{(Y45+Y)}{2}$, model byl nazván BM11upr1,

b) na základě výsledků metody hlavních komponent

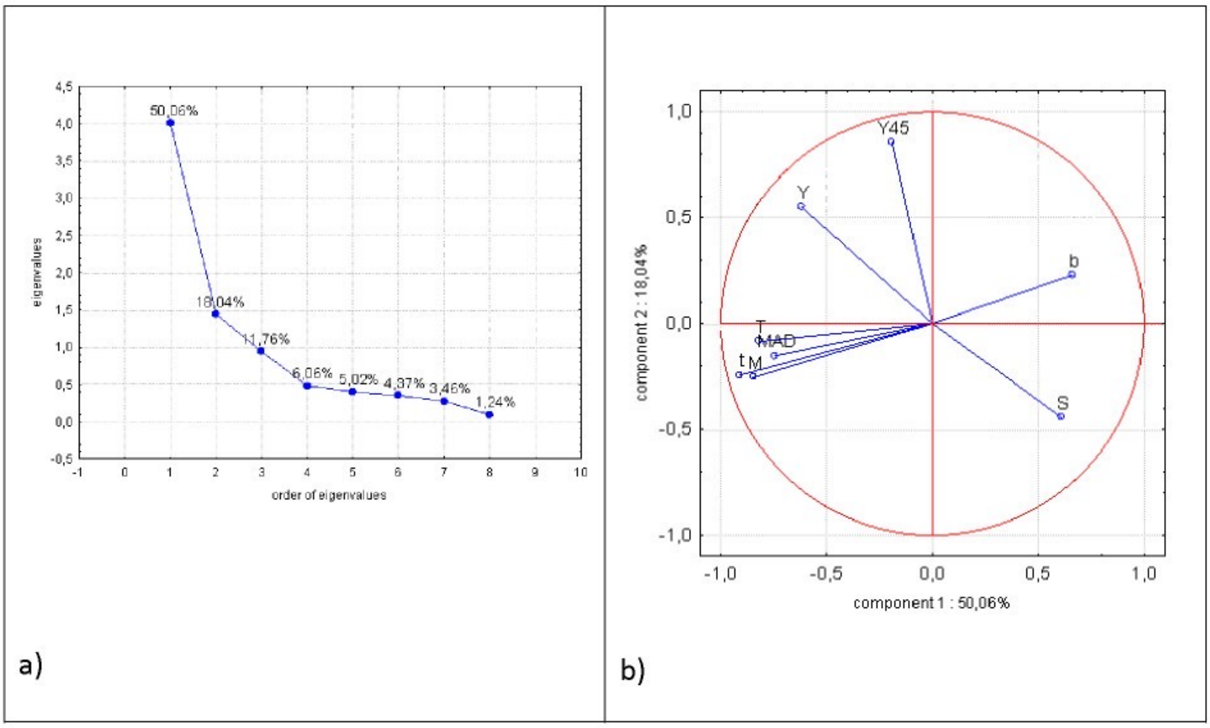
$geom2 = -0.91t - 0.86M$ a $pružnost2 = 0.89Y45$+0.68Y, model byl označen BM11upr2.

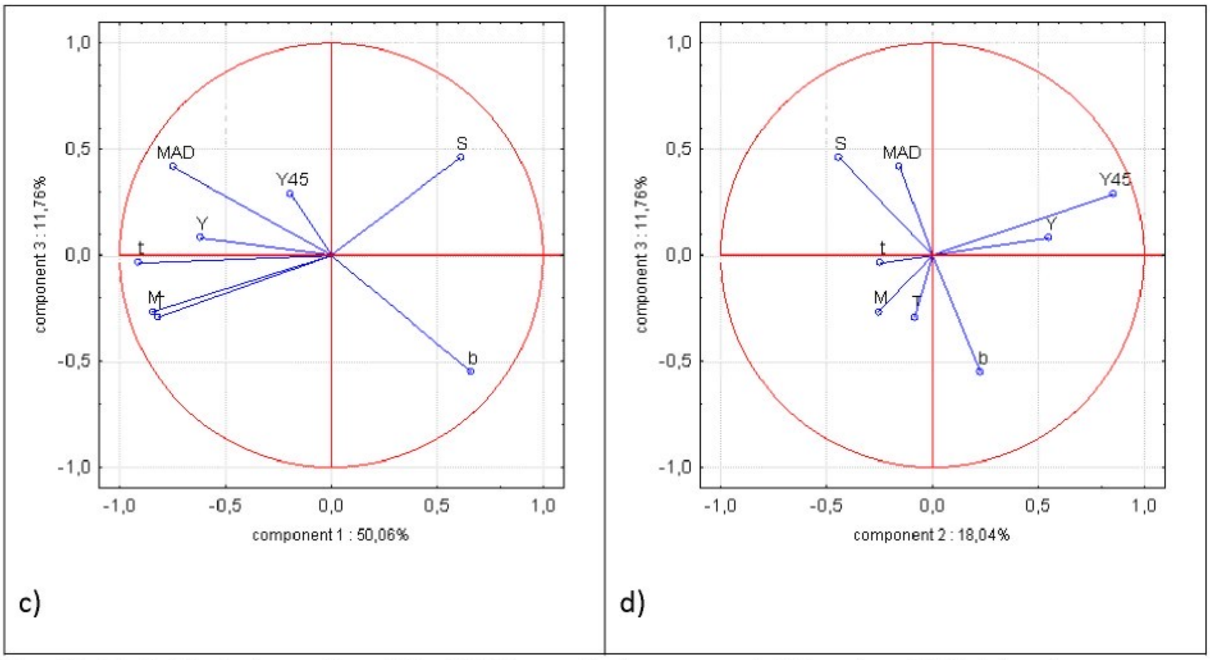
Tabulka 13. Párové a parciální korelace

	b	*T*	*t*	*M*	*S*	*MAD*	*Y45*	*Y*
b	1,00	-0,45	-0,58	-0,45	0,19	-0,55	0,01	-0,24
T	-0,12	1,00	**0,72**	**0,71**	-0,56	0,44	0,02	0,34
t	-0,24	0,22	1,00	**0,86**	-0,43	**0,65**	-0,07	0,33
M	0,11	0,18	**0,67**	1,00	-0,48	0,49	-0,14	0,31
S	-0,10	-0,33	0,02	-0,17	1,00	-0,23	-0,23	-0,42
MAD	-0,26	-0,02	0,38	-0,07	0,06	1,00	0,09	0,25
Y45	0,06	0,01	-0,03	-0,26	-0,20	0,18	1,00	0,51
Y	-0,09	0,02	0,04	0,14	-0,14	-0,05	0,54	1,00



Obrázek 12. Maticový graf párových koeficientů vlastností





Obr. 13. Cattelův indexový graf úpatí (a) a grafy komponentních vah – (b) 1. hlavní komponenta vs. 2. hlavní komponenta, (c) 1. hlavní komponenta vs. 3. hlavní komponenta, (d) 2. hlavní komponenta vs. 3. hlavní komponenta.

3.3 Návrh rovnice pro objektivní predikci omaku

3.3.1 Ordinální logistická regese

Logistická regrese byla navržena jako alternativní technika k metodě nejmenších čtverců [16]. Používá se v případech, kdy závisle proměnná je kategorizovaná, a to jak v případech, kdy je závisle proměnná binární (situace nastala nebo nenastala), tak i multinomická nebo ordinální. Jak plyne z předchozího, porovnáním s klasickou lineární regresí předpoklad normality není u závisle proměnné požadován.

Základní rozdíl mezi použitím logistické a lineární regrese spočívá v tom, že lineární regrese používá spojitou závisle proměnnou, kdežto logistická regrese kategorizovanou (v případě omaku ordinální) proměnnou. Použití lineárního regresního modelu u tohoto typu závisle proměnné může vést ke špatné predikci.

Ordinální logistická regrese se používá v případech, kdy závisle proměnná nabývá více než 2 hodnot. Nejčastější model, který se používá v případě ordinální závislé proměnné je model proporcionálních šancí [16, 17].

$$CL_k = ln\left[\frac{P(y \leq k)}{P(y > k)}\right] \quad (26).$$

Řešení modelu proporcionálních šancí vede ke *K-1* regresím rovnicím, které se liší pouze v hodnotě absolutního členu

$$ln\left[\frac{P(y\leq k)}{P(y>k)}\right] = b_{k,0} + \mathbf{b}^{\mathrm{T}}\mathbf{x} \qquad (27).$$

3.3.2 Testování modelu

Tak jako při lineární regresi se provádí testování významnosti regresních parametrů (v následujícím textu značeny souhrnně b_i). Testují se jednak jednotlivé regresní parametry b_i, jednak význam modelu jako celku. Pro testování významnosti regresních koeficientů b_i lze použít Waldovo testační kriterium

$$W_{a,i} = \left[\frac{b_i}{s(b_i)}\right]^2 \qquad (28),$$

které má rozdělení χ^2 s jedním stupněm volnosti.

Při určování významu modelu jako celku se používá deviance G^2, kde se porovnává maximální věrohodnost modelu, který obsahuje pouze absolutní člen L_0 a maximální věrohodnost modelu L_M čili se testuje, zda všechny odhadované regresní parametry β_i jsou rovny nule kromě parametrů $\beta_{k,0}$.

$$G^2 = -2(\ln L_0 - \ln L_M) \qquad (29)$$

Deviance G^2 má χ^2 rozdělení s $P-1$ stupni volnosti. Čím je hodnota nižší, tím je model jako celek významnější a proložení je těsnější. Pokud je pravděpodobnost menší než 0,01, považuje se model jako celek za statisticky významný. Deviance G^2 se používá také pro porovnání dvou modelů. Nevýhodou však je, že G^2 vede vždy ke zlepšení přidáním další vlastnosti. K eliminaci tohoto vlivu lze použít Bayesovo informační kriterium *BIC* nebo Akaikovo informační kriterium *AIC* [17]:

$$BIC = G^2 - (M - P)\ln M \qquad (30),$$

$$AIC = G^2 - 2(M - P) \qquad (31),$$

kde M je počet tkanin P počet regresních parametrů. Pro obě kriteria platí, čím je jejich hodnota nižší, tím je model lepší.

U lineární regrese se používá pro posouzení kvality modelu koeficient determinace R^2_d, s určitou analogií lze R^2_d použít i u logistické regrese, kde je však interpretace složitější. Používají se např. následující koeficienty determinace:

McFadenův koeficient determinace, který má tvar

$$R_{MF}^2 = \frac{\ln L_0 - \ln L_M}{\ln L_0} \qquad (32)$$

A Nagelkerkeova statistika

$$R_N^2 = \frac{S}{max(S)} \qquad (33),$$

kde

$$S = 1 - \left[\frac{L_0}{L_M}\right]^{\frac{2}{M}} \qquad \text{a} \qquad max(S) = 1 - L_0^{2/M}.$$

3.4 Výsledky a diskuze

Ověření navržené techniky BM bylo realizováno na souboru 90 tkanin, které se používají na výrobu pánských oblekových tkanin. Základní parametry tkanin jsou uvedeny v tabulce 1.

Soubor testovaných tkanin byl zařazován pomocí panelu 40 respondentů do 11 tříd (*k*=1 – omak je velmi nepříjemný, *k*=6 omak je průměrný, *k*=11omak je velmi příjemný). Výsledné počty zařazení jednotlivých tkanin do mediánových kategorií jsou uvedeny v tabulce 14.

Tabulka 14. Počty zařazených tkanin podle mediánových tříd.

číslo třídy	počet zařazených tkanin
1	0
2	2
3	11
4	8
5	16
6	17
7	19
8	8
9	5
10	4
11	0

Z tabulky 14 plyne, že do krajních tříd podle hodnoty mediánové třídy nebyla zařazena žádná tkanina. V případě, že by byla predikcí tkanina zařazena do třídy č. 2 nebo 10, je zapotřebí výsledek interpretovat trochu odlišně. Pro případ zařazení do druhé třídy platí, že výrazně přes 50% hodnocení může být i ve třídě 1. Obdobná interpretace platí i pro případné zařazení tkaniny predikcí do třídy č. 10, tj. že výrazně přes 50% hodnocení může být zařazeno i ve třídě 11. Do tříd č. 2, 9 a 10 bylo zařazeno málo tkanin, proto je při tvorbě závěrů při zařazení objektivní predikcí do těchto tříd přistupovat obezřetně.

Pro účely tvorby predikční rovnice byly zjištěné výsledky rozděleny v poměru 8:1, tj., výsledky 80 tkanin (analyzovaný soubor) byly použity pro vytvoření predikčních rovnic KES11 a BM11 a výsledky 10 tkanin (klasifikovaný soubor) byly použity pro ověření jejich predikčních schopností.

Výsledky zařazení analyzovaného souboru jsou uvedeny v tabulce 15 (model BM11).

U modelu BM11 bylo s chybou větší než *Me*±1 zařazeno 6 tkanin a to o 2 třídy. Správně bylo zařazeno 50 tkanin (62%) a spolu s chybou jedné třídy 74 (92%).

Odhady koeficientů pro model BM11 (tabulka 16) ukazují, že lze za významné považovat vlastnosti *b*, *T*, *t*, *M*, *S* a *MAD*. Z regresních koeficientů lze na hladině významnosti 0,05 považovat za významně odchýlené od nuly koeficienty $\beta_1, \beta_2, \beta_3, \beta_4, \beta_5$ a β_6.

Tabulka 15. Výsledky zařazení do tříd pro model BM11.

naměřené hodnoty omaku	Predikované hodnoty omaku									Procento správně zařazen. Objektů
	THV (O)=2	*THV (O)*=3	*THV (O)*=4	*THV (O)*=5	*THV (O)*=6	*THV (O)*=7	*THV (O)*=8	*THV (O)*=9	*THV (O)*=10	
THV=2	**0**	2	0	0	0	0	0	0	0	0,0
THV=3	0	**8**	1	0	0	0	0	0	0	88,9
THV=4	0	1	**3**	3	0	0	0	0	0	42,9
THV=5	0	1	2	**9**	3	0	0	0	0	60,0
THV=6	0	0	0	1	**11**	3	0	0	0	73,3
THV=7	0	0	0	3	0	**13**	1	0	0	76,5
THV=8	0	0	0	0	1	2	**4**	1	0	50,0
THV=9	0	0	0	0	0	0	2	**1**	1	25,0
THV=10	0	0	0	0	0	0	1	1	**1**	33,3

Tabulka 16. Odhady koeficientů pro model BM11 a vliv jednotlivých proměnných.

proměnná	$\chi 2$	spočtená hladina významnosti	regresní koeficient	odhad	Waldova statistika	spočtená hladina významnosti
			$b_{2,0}$	-20,23	8,79	0,003
			$b_{3,0}$	-14,34	4,91	0,027
			$b_{4,0}$	-11,29	3,33	0,068
			$b_{5,0}$	-7,41	1,52	0,217
			$b_{6,0}$	-5,19	0,76	0,385
			$b_{7,0}$	-2,38	0,16	0,689
			$b_{8,0}$	-0,16	0,0007	0,979
			$b_{9,0}$	1,42	0,054	0,816
b	35,68	0,000	b_1	-0,036	3,84	0,050
T	48,18	0,000	b_2	0,43	4,07	0,044
t	42,28	0,000	b_3	7,13	4,32	0,038
M	6,87	0,009	b_4	0,040	11,97	0,001
S	6,34	0,012	b_5	-17,80	5,81	0,016
MAD	17,34	0,000	b_6	0,67	14,67	0,000
Y45	0,198	0,656	b_7	0,018	0,62	0,433
Y	0,672	0,412	b_8	-0,0012	0,72	0,396

Tabulka 17. Ověření predikčních schopností modelů

číslo vzorku	*THV*	predikovaná hodnota BM11	rozdíl	predikovaná hodnota BM11upr1	rozdíl	predikovaná hodnota BM11upr2	Rozdíl	predikovaná hodnota KES11	rozdíl
T117	6	7x	+1	5x	-1	7	+1	6	
T118	4	4		4		4		2	-2
T135	3	3		5x	+2	4	+1	4	+1
T136	9	8x	-1	8x	-1	8	-1	8	-1
T153	5	5		5		5		5	
T154	3	3		5x	+2	3		4	+1
T171	6	6		6		5	-1	5	-1
T172	7	7		7		6	-1	9	+2
T189	10	9x	-1	8x	-2	8	-2	9	-1
T190	7	6x	-1	6x	-1	6	-1	6	-1

Ověření navrženého modelu bylo realizováno na druhé skupině dat - klasifikovaném výběru, tj. na datech, která nebyla použita pro tvorbu modelu. Výsledky predikčních schopností jsou uvedeny v tabulce 17. Vytvořený model BM11 zatřídil správně 6 z 10 tkanin, tj. 60% vzorků tkanin. Model KES11, který byl použit jako srovnávací, správně zatřídil 2 z 10 tkanin tj. 20% tkanin. Vezme-li se v úvahu možnost tolerovat chybné zařazení *Me±1* třída, tak model KES11 správně zařadil 80% tkanin, model BM11 zařadil správně všechny tkaniny. Upravené modely BM11upr1 a BM11upr2 nepřinesly zlepšení.

Spočtené hladiny významnosti *p* pro všechny čtyři modely mají hodnotu menší než 0,01 (tabulka 18) což značí, že modely lze považovat za významné. Deviance G^2 ukazuje, že nejlepším modelem je BM11upr1. Provede-li se však eliminace vlivu počtu vlastností, vyjde závěr opět nejednoznačně. Bayesovo informační kriterium *BIC* je u modelu KES11 nejnižší, avšak Akaikovo informačního kritéria *AIC* je nejnižší u modelu BM11. Pomocí uvedených indikátorů kvality modelu nelze jednoznačně určit, který z modelů je lepší.

Tabulka 18. Výsledky analýzy modelů

Charakteristika	KES11	BM11	BM11upr1	BM11upr2
G^2	147.06	157.55	**114.86**	152.93
p	<0.01	<0.01	<0.01	<0.01
R^2_{MF}	0.47	**0.49**	0.36	0.48
R^2_N	0.92	**0.93**	0.78	0.87
BIC	**81.55**	124.8	88.57	126.67
AIC	-2.35	**-2.44**	2.94	2.46

4. Závěr

Pro konstrukci rovnic pro predikci omaku se využívá vlastností, které mají vztah k hodnocení omaku pomocí respondentů. Navržený model BM11 ukazuje, že lze predikovat hodnocení omaku s pomocí vlastností, které lze měřit s využitím standardních přístrojů. Predikční schopnost navrženého modelu je srovnatelná s výsledky získanými měřením na systému KES.

V navrženém modelu BM11 je snaha využít přístrojů, které jsou běžně dostupné v textilní laboratoři. Pro konstrukci modelu byla použita logistická regrese (návrh metodiky nese označení BM). Vzhledem k tomu, že bylo zapotřebí predikční schopnosti navržených a používaných vlastnosti v BM modelu ověřit, byly pro komparaci použity vlastnosti ze systému KES.

Tvorba predikční rovnice pro objektivní hodnocení omaku má smysl, pokud je hodnocení omaku realizované respondenty v čase stabilní. Pro ověření stability hodnocení subjektivního hodnocení omaku se ověřovala opakovatelnost a reprodukovatelnost měření.

Pro tvorbu modelu byly použity tkaniny, jež se používají na výrobu pánských obleků. Byly vybrány z toho důvodu, že patří do skupiny typů tkanin, pro které má systém KES vypracovaný postup, a tudíž umožňují komparaci s výsledky ze systému KES.

Opakovatelnost – pro test opakovatelnosti byly použity 3 skupiny hodnotitelů, kteří hodnotili vybrané tkaniny v průběhu asi 8 let. Hodnocení omaku bylo realizováno jak bez vizuálního stimulu (hodnotitelé při hodnocení neměli oční kontakt s hodnocenými tkaninami), tak i s vizuálním kontaktem. Výsledky v obou případech ukazují, že hodnotitelé jsou schopni opakovaně hodnotit tkaniny obdobným způsobem.

Reprodukovatenost – pro ověření reprodukovatelnosti byly rovněž porovnávány výsledky hodnocení stejných tří skupin hodnotitelů jako v případě opakovatelnosti. I přes ne zcela jednoznačné výsledky lze konstatovat, že existuje vysoký soulad v hodnocení mezi různými skupinami hodnotitelů, a tudíž reprodukovatelnost hodnocení celkového omaku při využití různých skupin hodnotitelů.

Pro objektivní predikci omaku byl navržen model založený na logistické regresi. Model je označen BM11 a jeho modifikace BM11upr1 a BM11upr2. Tyto modely byly porovnávány s modelem vytvořeným na vlastnostech systému KES, který byl označen KES11.

Při konstrukci regresních modelů založených na logistické regresi se vychází z předpokladu, že jev, který má být následně predikován, je při tvorbě modelu jednoznačně určen. Což bohužel u omaku takto jednoznačně nelze určit. Pro stanovení třídy, do které byla tkanina výsledně zařazena, byla použita mediánová třída. Výsledné zařazení pak neukazuje pouze na to, s jakou pravděpodobností daná textilie přísluší do dané třídy, ale interpretace je daleko volnější. Ukazuje spíše, s jakou pravděpodobností by ji kolem 50% hodnotitelů hodnotilo lépe či hůře.

Všechny modely vyšly statisticky významné na hladině významnosti 0,01. Porovnání výsledků analýz G^2, R^2_{MF}, R^2_N, *BIC* a *AIC* ukazuje, že predikční schopnosti obou typů (KES11 a BM11) jsou prakticky shodné. Modifikace modelu BM nevedla ke zlepšení predikčních schopností.

Uvedené závěry ukazují, že objektivní predikce omaku tkanin založena na metodice BM je použitelná pro praktické účely. Navíc jsou výchozí údaje získány ze standardních měření a není třeba mít k dispozici extrémně drahý systém KES.

Navržený postup hodnocení omaku pomocí panelu respondentů byl využit při vývoji nového typu denimu, u kterého byla bavlna v útkové přízi nahrazena polypropylénovou. Výsledky ukázaly, že hodnotitelé z hlediska omaku nebyli schopni určit rozdíl mezi klasickým denimem a „novým“ denimem. Na „nový“ typ denimu byl podán návrh na užitný vzor.

Souhrn příspěvků na konferencích, které mají vztah k habilitační práci

Část výsledků zatím nebyla publikována v časopisech, ale byla prezentována na konferencích. Jedná se především o práce č. 15, 16 a 18.

A. Příspěvek ve sborníku - mezinárodní konference

a) Konference se záznamem v databázích WOK a SCOPUS

1. Militký, J., Bajzík, V., Militká, J. Surface Roughness of Heat Protective Clothing Textiles. In *International Textile Clothing and Design Conference*. 2002, s. 522 – 527. Dubrovnik, Chorvatsko. ISBN 953-96408-8-1.
2. Bajzík, V. Influence of Damage During Dyeing on Fabric Handle and Mechanical Properties of Wool Type Fabrics. In *TEXTILE SCIENCE 93*. 1993, s. 142-149. Liberec, Česká republika.
3. Bajzík, V., Militký, J. Comparative Study of Objective Hand Evaluation. In *TEXTILE SCIENCE 93*. 1993, s. 259-266. Liberec, Česká republika.
4. Hes, L., Bajzík, V. Water Vapour Permeability of Wool Blended Fabrics. In *TEXTILE SCIENCE 93*. 1993, s. 194-196. Liberec, Česká republika.

b) Ostatní mezinárodní konference

5. Bajzik, V. A New Way to the Objective Hand Prediction using Ordinal Logistic Regression. In *TEXCO 2010*. 2010, s. 10-11. Ružomberok, Slovensko. ISBN 978-80-969610-7-8. plný text na CD, 6 s.
6. Militký, J., Bajzík, V. Characterization of Protective Clothing Surface Roughness. In *International Textile Congress*, 2004, s.251-265, Terrassa, Španělsko.ISBN 84-608-0188-8
7. Militký, J., Bajzík, V. Objectiveve Prediction Of PES/WOOL Fabric Hand. In *Proceedings of Inauguta Wool Conference*, Hamilton, Australia.
8. Bajzík, V. Hand Prediction using Ordinal Logistic Regression, In *Innovations in Clothes and Footwear*. Volume XIII - Monographic series: Leather, clothing and footwear design, materials and technology. Radom:Wydawnictwo Politechniky Radomskiej, 2010, s. 191-198, ISBN 978-83-7351-377-8.
9. Militký, J., Bajzík, V. Comparison of Methods for Hand Evaluation. In *The Second International Scientific Engineering Conference*. 1997, s. 469-477. Mansoura, Egypt.
10. Militký, J., Bajzík, V. Prediction of Subjective Hand of Woolen Fabrics. In *Metrology in the Textile Engineering*. 1996, Lodz, Poland.
11. Bajzík, V. Reproducibility of Subjective Hand Evaluation and Appearance of Woolen Fabrics. In *24rd International Textile Research Symposium at the Foot of Mt. Fuji*. 1995. Japonsko.
12. Bajzík, V. Relationship between Subjective Hand Evaluation and Appearance of Woollen Fabrics. In 29th *symposium on novelties in textile technology and design*. 1995, Ljubljana, Slovinsko. ISBN 961-6045-07-5.
13. Militký, J., Bajzík, V., Štočková, H. Influence of Wool Content on Surface and Utility Properties of Blended Fabrics. In METLAN 91. 1991. Gdyně, Polsko.

B. Příspěvek ve sborníku - tuzemská konference

14. Bajzík, V. Objektivní predikce omaku s využitím ordinální logistické regrese. In *REQUEST09*. 2010, s. 4-11. Liberec, TU Liberec, ISBN 978-80-7372-619-5.
15. Bajzík, V. Analýza mínění hodnotitelů pro predikci omaku. In *3μ – Moderní matematické metody v inženýrství*. 2008, s. 9-13. Dolní Lomná. ISBN 978-80-248-1871-9.
16. Bajzík, V. Porovnání logistické regrese a diskriminační analýzy pro predikce subjektivního hodnocení omaku. In *Zajištění kvality analytických výsledků*. 2007, s. 102- 110, Komorní Lhotka, 2Theta. ISBN 978-80-86380-37-7.
17. Bajzík, V. Využití logistické regrese pro hodnocení omaku. In *Request 06*, 2007, s. 5-11. Praha, ISBN 978-80-01-03709-7.
18. Bajzík, V. Predikce subjektivního hodnocení omaku pomocí vícerozměrných statistických metod. In *Zajištění kvality analytických výsledků*. 2006, s. 94-101. Komorní Lhotka, 2Theta. ISBN 80-86380-32-7.
19. Bajzík, V. Data Comparison from Two KES Instruments. In *STRUTEX*. 2004, s. 9-14. Liberec, TU Liberec. ISBN 80-7083-769-1 .
20. Bajzík, V., Militký, J., Vacková, N. Subjektivní hodnocení omaku tkanin vlnařského typu. In *STRUTEX*. 1994, s. 129-137. Liberec, TU Liberec.

Další časopisecké publikace autora

21. Tunák, M. Bajzík, V., Testik, M.C. Monitoring Chenille Yarn Deffects Using Image Processing with Control Charts. *Textile Research Journal*. 2011, roč. 81, č. 13, s. 1344 – 1353. ISSN 0040-5175.
22. Bajzík, V., Pařilová, H. Hodnocení efektivnosti e-learningové výuky. *Media4u Magazine*. 2009, roč. 6, č. 1, s. 29-31. ISSN 1214-9187.
23. Militký, J., Kovačič, V., Bajzík, V. Mechanical Properties of Basalt Filaments. *Fibres & Textiles in Eastern Europe*. 2007, roč. 15, č. 5/6 s. 49-53. ISSN 1230-3666.
24. Kovačič, V., Rubnerová, J., Militký, J., Bajzík, V. Application of Instrument Aquasem for Investigation of Fibrous Structures. *Fibres & Textiles in Eastern Europe*. 2000, roč. 8, č. 2, s. 79 – 81. ISSN 1230-3666.
25. Militký, J., Křemenáková, D., Kovačič, V., Bajzík, V. Mechanical Characteristics of Cottonized Flax Fibers. *Wlokienictwo*. 2000, roč. 59, s. 203-210. ISSN 0076-0331.
26. Militký, J., Kovačič, V., Bajzík V. Particle Size Analysis of Basalt Dust. *Fibres & Textiles in Eastern Europe*. 1998, roč. 6, č. 2, s. 70 – 72. ISSN 1230-3666.
27. Militký J., Trávníčková M., Bajzík V. Air Permeability and Porosity of Weaves. *Vlákna a textil*. 1998, roč. 5, č. 3, s. 72 – 76. ISSN 1335-0617.
28. Militký, J., Bajzík, V. Influence of Washing/Ironing Cycles on Selected Properties of Cotton Type weaves. *International Journal of Clothing Science and Technology*. 1997, roč. 9, č. 2/3, s. 193-199. ISSN 0955-6222.
29. Militký J., Bajzík V. Přístupy k objektivnímu hodnocení omaku textilií. *Textil*. 1993, roč. 48, č. 7, s. 130-131.
30. Militký, J., Bajzík, V. Hodnocení organoleptických vlastností textilií. *Chemická vlákna*. 1992, roč. LII, mimoř. číslo, s. 196-201. ISBN 80-233-0242-6.

Literatura

[1] Pokorný, J., Valentová H., Panovská, Z. *Senzorická analýza potravin*. 1.vyd. Praha: VŠCHT Praha, 1999. ISBN 80-7080-329-0.

[2] Bishop, D. P. Fabric:Sensory and Mechanical Properties. *The Textile Progress.* 1996, roč. 26, č. 1, s. 1-62.

[3] Řehák, J., Řeháková, B. *Analýza kategorizovaných dat v sociologii*, 1. vyd. Praha: Academia, 1986.

[4] Laughlin, J. Perception of Texture, Visually and Tactually. *Internatinal Journal of Clothing Science and Technology*. 1991, roč. 3, č.1, s. 28 – 36.

[5] Yenket, R., Chambers IV, E., Gatewood, B.M. 2007. Color Has Little Effect on Perception of Fabric Handfeel Tactile Properties in Cotton Fabrics. *Journal of Sensory Studies*. 2007, roč. 22, č. 3, s. 336-352.

[6] Kawabata, S. *The Standardisation and Analysis of Hand Evaluation*. 2. vyd. Osaka: The Textile Machinery Society of Japan, 1980.

[7] Wu, J.J. Characterization of Fractal Surfaces. *Wear*. 2000, sv. 239, č. 1, s. 36-47.

[8] Mandelbrot, B. B., Van Ness, J.W. *Fractional Brownian Motion, Fractional Noices and Applications. SIAM Review*. 1968, roč. 10, č. 4, s. 422-437.

[9] Wu, J.J. Spectral Analysis for the Effect of Stylus Tip Curvature on Measuring Rough Profiles. *Wear*. 1999, sv. 230, č. 2, s. 194-200.

[10] Lundgren, H.P. New Concepts in Evaluating Fabric Hand. *Textile Chemists and Colorists*. 1969, roč. 1, č. 1, s. 35-45.

[11] Raheel, M., Lin, J. An Empirical Model for Fabric Hand. Part I: Objective Assesment of Light Weight Fabrics. *Textile Research Journal*. 1991, roč. 61, č. 1, s. 31-36.

[12] Pan, N., Yen, K. C., Zhao, S.J., Yang S.R. A New Approach to the Objective Evaluation of Fabric Handle from Mechanical Properties. Part I: Objective Measure for Total Handle. *Textile Research Journal*. 1988, roč. 58, č. 8, s. 438-444.

[13] Behery H. M. *Effects of Mechanical and Physical Properties on Fabric Hand*. 1. vyd. Cambridge:Woodhead Publishing Limited. 2005. ISBN 978-85573-918-5.

[14] Meie, L., Xiaoan, S., Li, Z. A Study of Method of Measuring and Evaluting Fabric Handle. In *Textile Science 91: Technická univerzita v Liberci*. 1. vyd., 1992. s. 41-50.

[15] Hes, L., Doležal, I. New Method and Equipment for Measuring Thermal Properties of Textiles. *Journal of Textile Machinery Society of Japan*. 1989, roč. 35, č. 8, s. 124-128.

[16] Hosmer, D., Lemeshow, S. *Applied Logistic Regression*. 1. vyd. New York: John Wiley&Sons, 2000. ISBN 0-471-35632-8.

[17] Powers, D. Xie, Y. *Statistical Methods for Categorical data Analysis*. 1. vyd. San Diego: Academic Press, 2000. ISBN 0-12-563736-5

THE EFFECT OF FINISHING TREATMENT ON THERMAL INSULATION AND THERMAL CONTACT PROPERTIES OF WET FABRICS

BİTİM İŞLEMLERİNİN ISLAK KUMAŞLARIN ISIL İZOLASYON VE ISIL TEMAS ÖZELLİKLERİNE ETKİSİ

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ABSTRACT

Comfort properties of textiles became important part of marketing of clothing with high added value in last decades. The most important parameters characterizing thermo physiological comfort of sport and protective garments are thermal resistance and water vapour permeability. Contrary to common textiles, protective and functional garments and some technical textiles are also used in wet state, which affects their comfort properties. However, these properties can be improved by application of special finishing agents. The objective of this paper is to investigate the effect of moisture on thermal comfort properties of 3 different cotton fabrics which were subject to 5 different finishing treatments. Thermal conductivity, thermal resistance, thermalabsorptivity and water vapour permeability of fabrics in dry and wet state were measured. Wet state of the studied fabrics was achieved by means of the so called "sweating impulse". The achieved results were treated by means of advanced statistics and displayed in diagrams. It was found the presence of moisture affected substantively all thermal-insulation and thermal-contact properties.

Key Words: Wet state, Thermal resistance, Thermal absorptivity, Water vapour permeability, Finishing treatment, Analysis of variance.

ÖZET

Son yıllarda, yüksek katma değerli giysilerin pazarlanmasında tek stillerin konfor özellikleri önemli bir yere sahiptir. Spor ve koruyucu giysilerin ısıl konfor özelliklerini karakterize eden en önemli parametreler ısıl direnç ve su buharı geçirgenliğidir. Klasik tekstillerin aksine, koruyucu ve fonksiyonel giysiler ve bazı teknik tekstiller ıslak durumda da kullanılmakta ve bu durum konfor özelliklerini etkilemektedir. Ancak bu özellikler özel bitim işlemi uygulamaları ile geliştirilebilir. Bu çalışmanın amacı nemin, 5 farklı bitim işlemi uygulanan 3 farklı pamuklu kumaşın ısıl konfor özelliklerine etkilerinin incelenmesidir. Bu kumaşların ısıdil etkenlik, ısıldirenç, ısıl soğurganlık ve subuharı geçirgenliği özellikleri kuru ve ıslak durumda test edilmiştir. Kumaşları ıslatma işlemi "terleme impulsu" adı verilen yöntemle gerçekleştirilmiştir. Elde edilen sonuçlar istatistiksel olarak değerlendirilmiş ve grafiklerle gösterilmiştir. Kumaş tanem bulunmasının, tüm ısıl izolasyon ve ısıl temas özelliklerini önemli derecede etkilediği bulunmuştur.

Anahtar Kelimeler: Islak durum, Isıl direnç, Isıl soğurganlık, Su buharı geçirgenliği, Bitim işlemleri, Varyans analizi.

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1. INTRODUCTION

Comfort of clothing plays important role during many human activities. Clothing should keep humans in the state of psychological, sensorial and thermo physiological comfort, i.e. state of wellbeing when the person is able to work for long time (1).

Contrary to common textiles, protective and functional garments and some technical textiles like textile dressings are, due to sweat sorption, rainy climate or some technological reasons, also used in wet state, which affects their comfort properties.

The effect of fibre type, blend level or fabric structure on water vapour transmission werestudied by several authors (2-4).Özdil at al. (5) found that yarn count and yarn twist exhibit also certain effect on the liquid transport properties of fabrics. Irandoukht S. and Irandoukht A. presented in (5)some nonlinear models for prediction of water vapour resistance of fabrics based on fibre volume, air permeability, weight and thickness of the fabric models, which give very good results. However, all models were proposed for fabrics in dry state only.

Moisture can change many parameters of clothing comfort, but the most important for the wearer of wet clothing are three principal components of thermo physiological and thermal contact comfort of garments: thermal resistance in wet state, thermal absorptivity in wet state and cooling flow resulting from the following mechanisms:

a) moisture evaporation from the skin and passing through the clothing,

b) direct evaporation of sweat from the fabric surface.

Both mentioned parameters could be improved by application of special finishing agents on the individual fabrics creating the clothing. The influence of sweating on thermal comfort properties is discussed in study (7). It is shown that mercerization has significant influence on thermal properties of knits produced from carded or combed yarns. Increasing content of moisture also has the influence on friction coefficient which increases to limit 40% of moisture regain (8).

In the paper the effect of two type hydrophobic finishes, one softening finish, sanforisation and temporary inflammable finish on thermal comfort properties of three cotton fabrics with square mass 0.145, 0.2 and 0.24 ($kg.m^{-2}$) were investigated. For each of these finishes three concentrations were applied.

The mentioned thermal comfort properties involved thermal conductivity, thermal resistance, thermal absorptivity, relative water vapour permeability, evaporative resistance and air permeability. Wet wearing conditions were simulated by means of the so called "sweating impulse, depending in the application of 0.3 ml of water in the middle of the tested sample.

In the first part of the paper, special measuring instrument for the measurement of thermal conductivity of fabrics in wet state and to experimental determination of thermal conductivity of selected woven fabrics in wet state are described. These instruments exhibit one special advantage when measuring the fabrics in wet state: time of measurement is so short, that during the measurement the sample is kept fully wet, which improves the measurement precision. That is why current measuring instruments for the evaluation of thermo physiological comfort of fabrics cannot be used in such research, as they require more than 30 minutes for full reading, which causes humidity decrease during the measurement. That is also the reason why papers characterising thermal comfort properties of fabrics in wet state are almost missing in the literature. The only few papers were published Schneider et al. (9), and by Ren and Ruckman (10). None of these authors investigated the effect of finishing on thermal comfort of wet fabrics.

2. MATERIAL AND METHOD

2.1. Materials

As already stated, protective and functional garments and some technical textiles are also used in wet state, which affects their comfort properties (10, 11). These properties depend not only on the fabrics structure and composition, but also on their finishing treatment, as mentioned in the previous chapter.

In this study, we focused on the effect of 5 different finishing treatments on 100 % cotton fabrics differing in their square mass – see the next Table 1.

In present time properties as waterproof, size stability and pleasant r yor required for many types of functional garments. On the other hand very good thermophysiological comfort has to be maintained. Therefore 2 types of hydrophobic, softening and sanforisation (to prevent shrinking) finishes were tested. The cotton fabrics are often used for production of protective garments exposed to higher temperatures. In addition temporary inflammable finish was applied and changes in thermophysiological comfort were observed, too.

Three concentration levels of all types of finishes were used in the experiments. The water dispersion of r yor (marked as HP1) and silicone (HP2) based hydrophobic finishes were applied. The sanforisation (SA) was achieved by means of product based on dimethyloldihydroxyethyleneurea – DMDHEU, softening using the products based on non-ionic ammonium compound with addition of stabilizing substances (SO) and inflammable finish (IF) was realized using the product based on the etherification of $(NH_4)_2HPO_4$ on cellulose. The applied concentrations of the single finishes are presented in Table 2 and processes of the used finishing treatments are in Table 3. Three measurements were realized for all types of finishes and stages of concentrations.

It should be noted, that the fabrics treated with hydrophobic finishes do not absorb liquid water, but in our case the distilled water simulating the sweat impulse contained 0,1% of r yor wetting agent, and the water drops were during the measurement subject to vertical pressure originated by the falling measuring head. Thus, water entered into the fabric structure and caused some changes of thermal parameters of the fabrics, despite their hydrophobic treatment.

Table 1. Fabric details

Sample	Areal weight (g/m^2)	Sett – warp (threads/1 cm)	Sett – weft (threads/1 cm)	weave
W140	145	26	23	Plain
W200	200	41	20	Atlas
W240	240	32	18	Twill

Table 2. Applied finishes and concentrations

sample	level of concentration	finish ($g.g^{-1}$- grams of product per gram o fabric)				
		HP1	HP2	SA	SO	IF
No.1	Level 1	0,054	0,01	0,026	0,015	0,07
	Level 2	0,066	0,021	0,037	0,024	0,09
	Level 3	0,081	0,03	0,05	0,03	0,111
No.2	Level 1	0,057	0,01	0,029	0,013	0,07
	Level 2	0,076	0,02	0,042	0,025	0,096
	Level 3	0,09	0,03	0,055	0,033	0,126
No.3	Level 1	0,053	0,01	0,028	0,016	0,07
	Level 2	0,069	0,019	0,04	0,023	0,09
	Level 3	0,086	0,03	0,05	0,031	0,12

Table 3. The course of the sample preparation

finish				
HP1	HP2	SA	SO	IF
sample size for all types of finishes: 0.3 x 0.21 cm				
preparation of padding bath with required concentration				
padding				
hot air drying at 130°C, 5 min	hot air drying 155°C, 5 min	hot air drying 100°C	hot air drying 80°C	hot air drying 100°C
		baking 160°C, 4 min		baking 155°C, 15 min
ironing				

The measurements were carriedout on the instruments ALAMBETA (12), PERMETEST (13)and TEXTEST FX 3300. All of them provide reliable non-destructive measurements connected with thermo physiological comfort.

2.2. Measured properties

a) Thermal properties of textiles

Thermal properties of textiles such as thermal resistance, thermal conductivity and thermal absorptivity are influenced by fabric properties such as structure, composition, density, humidity, and properties of fibres, surface treatment, temperature and other factors (10, 11). Thermal properties were measured on the Alambeta device (12).

Thermal conductivity λ of polymers is quite low, ranging from 0.2 to 0.4 W/(m.K), and that of textile structures generally reaches levels from 0.033 to 0.1 W/(m.K). Thermal conductivity of steady air by 20°C is 0,026 W/(m.K), while thermal conductivity of water is 0.6 W/(m.K), which is 25times more. That is why the water presence in textile fabrics is undesirable.

Thermal resistance R (thermal insulation value) depends on fabric thickness h and thermal conductivity λ:

$$R = \frac{h}{\lambda} \quad (m^2K/W) \qquad (1)$$

Thermal absorptivity$b$ of fabrics was in 1987 introduced by Hes (7) to characterise thermal contact feeling during short contact of human skin with the fabric surface. For time of thermal contact τ between the human skin and the fabric shorter then several seconds, the measured fabric can be simplified into semi-infinite homogenous mass with thermal capacity ρc (J/m^3) and initial temperature t_2. Unsteady temperature field between the human skin (with temperature t_1) and fabric with respect to of boundary conditions offers a relationship, which enables to determine the heat flow q (W/m^2) course passing through the fabric:

$$q = \frac{b(t_1 - t_2)}{\sqrt{\pi\tau}}$$

where

$$b = \sqrt{\lambda\rho c} \quad (Ws^{1/2}/(m^2K)) \qquad (2)$$

Whereρc (J/m^3) is thermal capacity of the fabric and the term b presents thermal absorptivity of fabrics. The higher is thermal absorptivity of the fabric the cooler is its feeling. In the textile praxis this parameter ranges from 20 Ws$^{1/2}$/(m^{2}K) for fine nonwoven webs to 600 Ws$^{1/2}$/(m^{2}K) for heavy wet fabrics.

b) Water vapour permeability

The used PERMETEST instrument enables the determination of relative water vapour permeability P_{WV} (%) and evaporation resistance R_{et} (m^{2}Pa/W) of dry and wet fabrics within 3 -5 minutes. Cooling flow caused by water evaporation from the thin porous layer is immediately recorded by a special sensing system and evaluated by the computer (10).

Results of measurement can be expressed in terms of the water vapour resistance R_{et} defined in the ISO 11092 Standard, according to the following relationship:

$$R_{et} = (p_{wsat} - p_{wo})\left(\frac{1}{q_o} - \frac{1}{q_s}\right) = C(100 - \varphi)\left(\frac{1}{q_o} - \frac{1}{q_s}\right) \qquad (3)$$

Here, $q_s$andq_o mean heat loses of moist measuring head in the free state and covered by a sample. The values of water vapour partial pressures p_{wsat} and p_{wo}(Pa) in this equation represent the water vapour saturate partial pressure valid r yor temperature of the air in the measuring laboratory t_o (22-25°C), and the partial water vapour pressure in the laboratory air. The constant C can be determined by the calibration procedure.

Besides the water vapour resistance, also the relative water vapour permeability of the textile sample P_{WV} can be determined by the instrument, where P_{wv} = 100% presents the permeability of free surface. This practical parameter is given by the relation

$$P_{WV} = 100\frac{q_s}{q_o} \quad [\%] \qquad (4)$$

c) Air permeability

This parameter was measured by means of the non- destructive instrument TEXTEST FX 3300 instrument at the pressure drop 200Pa. The measurement procedure is fully described at the ISO 811 Standard. The relative water vapour permeability, evaporative resistance and air permeability has been measured in dry state only.

3. RESULTS AND DISCUSSION

For data analysis the one-way analysis of variance was used. Generally, hypothesis H_0 means that effects of factor X are the same and the factor X has no influence on the observed property. All F-tests were realized for level of significance α=0.05. The hypothesis H_0 is accepted for $\alpha \geq 0.05$. For α<0,05 the hypothesis H_0 is omitted and alternative hypothesis H_1 is accepted, where H_1 means, that at least one of effects is differed from the other for the factor X.Calculations werecarried out by means of the statistical software STATISTICA 9.

It was found that the concentration increase does not play statistically significant role in changes of all measured properties. Therefore, only comparisons between samples without any finishes and with finishes are discussed in the following two chapters.

As regards thermal resistance, the concentration level of all kinds of finishes exhibits no statistically significant effect on this parameter.

a) *Thermal properties*

The reached results show that only sanforisation led to the statistically significant changes in all measured thermal properties in wet state and except thermal absorptivity also in dry state (see Table 3). The explanation depends in reduced porosity and increased thickness of the treated fabrics, due to thermally induced shrinking. Softening did not cause any significant changes in thermal properties, as it did not result inbigger structural changes. Other three finishes affected properties only in the single cases.

Application of both hydrophobic finishes led to the approx. 15 – 25% increase of thermal conductivity for textiles in dry state. Here, the mentioned increment has probably an origin in the increased mass of thermally more conductive polymer on fabric/fiber surface. Only for finish HP2 the increase was not statistically significant (Table 4 and Figure 1). For textiles in wet state the increase was not statistically significant or no changes were found, as the amount of water entering the studied samples during the sweating impulse simulation is quite low and moisture in the treated fabrics is mostly well conducted along the fabric surface. Therefore, local concentration of moisture under the measuring sensor can be quite low, thus avoiding bigger changes in thermal properties of the studied fabrics. Similar results were also achieved forsanforisedtextiles in dry state, where the increase of $\lambda$was about 10% only. Increasing level of concentration has no statistical significance for other changes of thermal conductivity for all type of finishes.

Higher thermal resistance was found for both hydrophobic finish for textiles in dry state (probably due to reduced amount of moisture in fabrics), but for HP2the change was not significant. The statistically significant changes were observed also for sanforisation and inflammable finish (growth) for textiles in dry state. For textiles in wet state following results were found: for hydrophobic finishes and softening no changes were recorded and for inflammable finish no significant growth was determined, probably due to good conduction of moisture along the fabrics surface out of the measuring zone of the instrument. Only one difference of influence of finishes was found for sanforisation where application of this finish led to high increase of thermal resistance.

No changes or statistically not significant differences in thermal absorptivitywere found for the most finishes for textiles both in dry and in wet state. The reasons of this behavior will be similar to the above mentioned reasons,onlysanforisation led to the significant decrease of thermal absorptivity for textiles in wet state, due to lower porosity, which caused lower local concentration of moisture.

b) *Relative water vapour permeability P_{WV}, evaporative resistance R_{et} and air permeability AP*

No trends or only statistically not significant differences were found for all these properties. Due to optimized, relatively low amount of the used finishing, small reduction of porosity only can be expected, which results in small changes of the above mentioned parameters.

All the effects of finishing treatment on relative water vapor permeability, evaporative resistance and air permeability are summarized in Table 5.

When evaluating the results in the Table 4, it is necessary to emphasize, that these results present just the relative changes in relation to the initial level of these results, either in r yor wet state. Thus, wet thermal conductivity of the tested fabrics is higher than thermal conductivity of these fabrics in dry state (see Fig. 1). Similarly, thermal absorptivity of the studied fabrics in wet state is higher (cooler) then this property measured on dry fabrics, and that inversely, thermal resistance of fabrics in wet state is lower than this in dry state. The results are in compliance with findings of Oğlakcioğlu and Marmarali (7).

Table 4. Generalized results of the effect of the finishing agents on thermal properties.

Finishing treatment	thermal conductivity λ		thermal resistance r		thermal absorbtivity b	
	dry / wet conditions		Dry / wet conditions		dry / wet conditions	
	Dry	Wet	Dry	Wet	dry	wet
IF	increasing (n)	decreasing(n)	increasing (s)	increasing (n)	increasing (n)	decreasing(n)
SA	increasing (s)	decreasing(s)	increasing (s)	increasing (s)	decreasing (n)	decreasing(s)
HP1	increasing (s)	no trend	increasing (s)	no trend	no trend	decreasing(n)
HP2	increasing (s)	no trend	increasing (n)	no trend	no trend	decreasing(n)
SO	increasing (n)	increasing (n)	no trend	no trend	no trend	no trend

s – statistically significant change, n – statistically not significant change, α=0.05.

Table 5. Generalized results of the effect of the finishing agents on water vapor and air permeability.

finishing treatment	relative water vapour permeability P_{WV}	evap. resistance R_{et}	air permeability *AP*
IF	decreasing (n)	increasing (n)	decreasing (n)
SA	no trend	no trend	no trend
HP1	no trend	no trend	decreasing (n)
HP2	no trend	no trend	no trend
SO	no trend	no trend	decreasing (n)

s – statistically significant change, n – statistically not significant change, α=0.05.

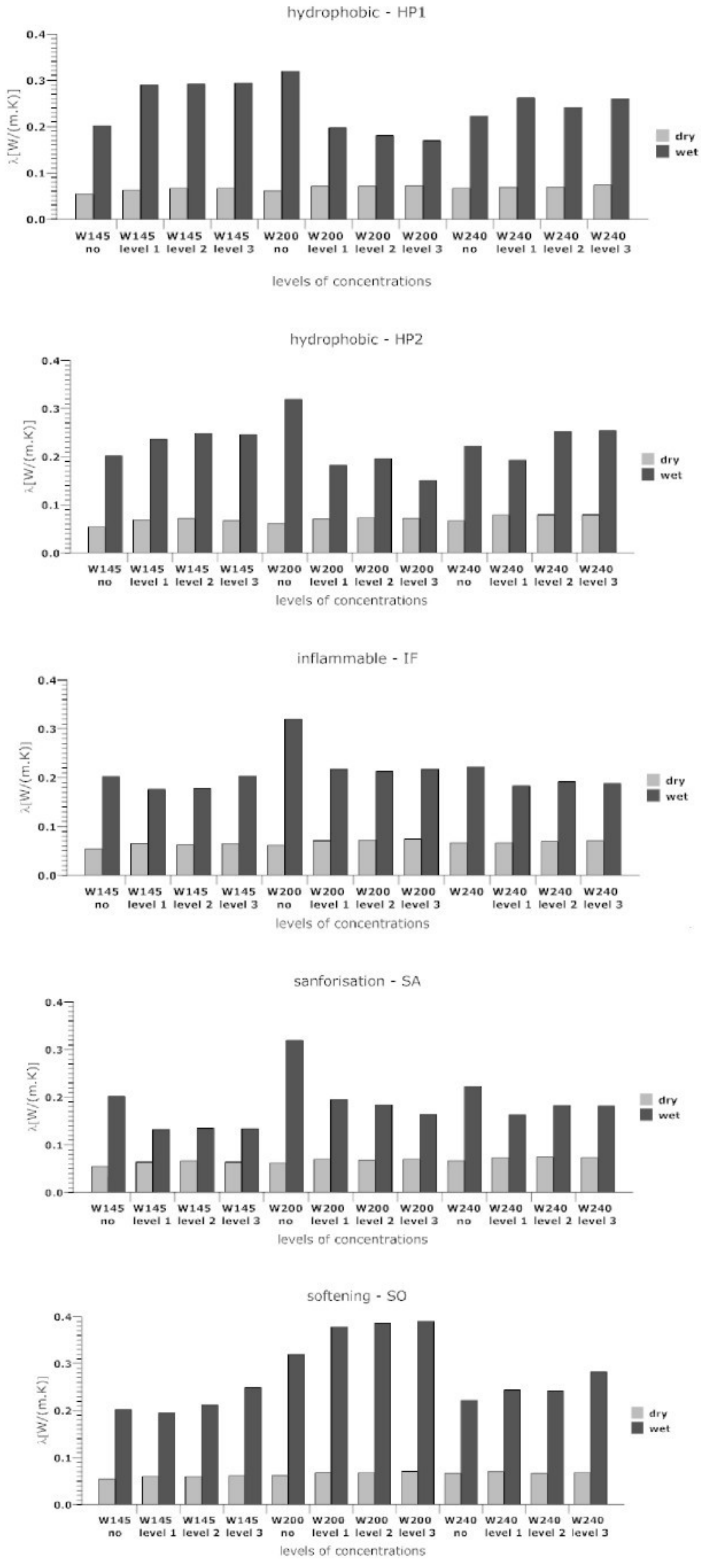

Figure 1. Comparison of thermal conductivity λ of textiles in dry and wet state under different concentrations of finishing agens.

4. CONCLUSION

The effect of two type hydrophobic finishes, softening finish, sanforisation and temporary inflammable finish on thermal comfort properties, such as thermal conductivity, thermal resistance, thermalabsorptivity were studied. Measurements on dry fabrics were carried out under standard laboratory conditions. Wet state of the studied textiles was achieved by means of the so called "sweating impulse", based on the injection of 0.3 ml water in the middle of the tested sample. It was found that this simulation of sweating affected thermal properties of the studied fabrics quite substantively.

The highest influence was found for sanforisation, which causedsubstantial (up to one third) decrease of thermal conductivity of the studied fabrics in wet state.The wet thermal conductivity of the tested fabrics was higher than thermal conductivity of these fabrics in dry state. Similarly, thermal absorptivity of the studied fabrics in wet state was higher (cooler) then this property measured on dry fabrics, and that inversely, thermal resistance of fabrics in wet state was lower than this in dry state.

As regards the effect of various finishing treatmentson relative water vapor permeability, evaporative resistance and air permeability, only textilefabrics in dry statewere studied. However, practically no changes of the mentioned fabric properties were found.

The effect of concentration of the used finishing agents on all the studied properties of fabrics both in dry and wet state was not observed.

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REFERENCES

1. Fanger P.O., 1974, "Thermal Comfort", McGraw-Hill. New York, USA.
2. Long H., 1999, "Water Transfer properties of Tow Layer Weft Knitted fabrics",*International Journal of Clothing Science and Technology*, 11(4), pp:198-205.
3. Yoo S.H., Barker R.L.,2004, "Moisture Management Properties of Heat Resistant Work Wear Fabrics Effects of Hydrophilic Finishes and Hygroscopic Fiber Blends",*Textile Research Journal*, 74(11), pp:995-1000.
4. Borhari S., Seirafianpour S., Ravandi S.A.H., Sheikhzadeh M., Mokhtari, R., 2010, "Computational and Experimental Investigation of Moisture Transport of Spacer Fabrics", *Journal of Engineered Fibers and Fabrics*, 5(3), pp:42-48.
5. Özdil N., Özcelik G., Süpüren G., Průchová J., 2009, "A Study on the Moisture Transportation properties of the Cotton Knitted Fabrics in Single Jersey Structure", *TekstilveKonfeksiyon*, 19 (3), pp: 218-223.
6. Irandoukht S, Irandoukht A., 2011, "Development of the predictive Models for the Fabric Water Vapour Resistance", *Journal of Engineered Fibers and Fabrics*, 6(2), pp: 40- 48.
7. Oğlakcıoğlu N., Marmarali A., 2010, "Thermal Comfort Properties of Cotton Knitted Fabrics in Dry and Wet State", *TekstilveKonfeksiyon*, 20(3), pp: 213-217.
8. Hes L.,Marmarali A., Oğlakcioğlu N., Özdil N., Lima N., 2008, "The Effect of Moisture on Friction Coefficient of Elastic Knitted Fabrics", *TekstilveKonfeksiyon*, 18(3), pp: 206-210.
9. Schneider A.M. et al., 1987,"Heat Transfer Through Moist Fabrics", PhD Thesis, University of New South Wales, Australia.
10. Ren Y., Ruckman J.E., 2003,"Water vapour transfer in wet waterproof breathable fabrics", *Journal of Industrial Textiles*, 32(3), pp: 165-175.
11. Hes L., 2007, "Thermal comfort properties of textile fabrics in wet state", In: *Proc. Izmir International Textile and Apparel Symposium*, Çeşme, Turkey.
12. Hes L., Dolezal I., 1989, "New Method and Equipment for Measuring Thermal Properties of Textiles", *Journal of Textile Machinery Society of Japan*, 35(8), pp: 124-128.
13. Dolezal I., Hes L., 2003, "P-TEST – Computerized Instrument Testing of the Water Vapour and Thermal Resistance of Fabrics", In: *Proc. of 2003 IEEE Internat. Symp. on Industrial Electronics*, Rio de Janeiro, pp: 5.

Impact of Different Weft Materials and Washing Treatments on Moisture Management Characteristics of Denim

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ABSTRACT
The aim of this study was to investigate the effects of different types of weft yarn materials and washing treatments on the moisture management properties of denim fabrics. Fabrics were developed with five different types of weft yarns made of cotton, polyester, spun polypropylene, air-textured polypropylene and stuffer-box crimped polypropylene. In all cases 100% cotton yarn was used as warp. Samples from each fabric were subjected to 10 diverse types of washing/finishing treatments and the treated samples were tested for dissimilar moisture management indices on an SDL Atlas moisture management tester. The statistical analyses of the test data show that the effect of different types of weft yarns and washing treatments is significant. Based on the results of this study, denim fabrics can be developed with enhanced moisture management properties.

Keywords: moisture management, denim, weft variation, garment washing

INTRODUCTION

When water is dropped on the surface of any textile material it moves in multi directions. Its movement depends upon the chemical and physical nature of the textile material. The ability to control the movement of moisture is called moisture management of textile material [Hu 2005].

Clothing comfort is one of the basic needs of the wearer. It depends upon the thermo- physiological characteristics of the textile material. In addition to tactile feeling, heat and moisture transfer are key factors, which contribute to clothing comfort perception. Moreover, air and water-vapor permeability properties of clothing also have a significant influence on comfort characteristics. There is a significant difference in thermal properties of water and textiles. One of the most important factors is thermal conductivity. Water has 0.6 ($Wm^{-1}K^{-1}$), which is quite higher than textile materials. Textile materials may be hydrophobic or hydrophilic in nature. Many complexities are attached with the adsorption and absorption processes. Overall, adsorption and absorption of water in textiles create a big change in their thermal characteristics. This change leads to change in their thermal and moisture sensation and overall comfort properties. There is a strong correlation between moisture management properties of a fabric and its final comfort perception (Amrit, 2007; Barker, 2006; Hes & Martins, 1993; Satsumoto, Murayama, & Takeuchi, 2009; Kandjov, 1999; She & Kong, 2000; Suleiman, 2006).

This study investigated the moisture management properties of denim woven with a constant warp and five different weft yarns and subjecting the samples to 10 different types of washing processes. The specific objectives of this study were as follows: (a) to investigate the effect of different weft yarn materials on the moisture management properties of denim fabrics and (b) to investigate the effect of different washing treatments on the moisture management properties of denim fabrics.

WATER VAPOR TRANSPORT MECHNAISM THROUGH NOVEL AND TRADITIONAL DENIM

Traditional denim is composed of 100 % cotton and has the ability to absorb moisture from the human skin and can transport it to the outer side following Fick's law. In the case when the surface which touches the human skin is partially composed of polypropylene or polyester, which is hydrophobic in nature, moisture transfer from inner side to outside becomes quicker. In the case of denim made of 100% cotton, there are more chances that moisture will accumulate between the human skin and the inner side of the denim, and the difference in moisture percentage between human body and the microclimate will decrease, which is the driving force for the transfer of moisture from inner climate to outer climate. Nevertheless, in the case of the inner side partially covered by manufactured fibers, the amount of moisture absorbed will be less. In addition, manufactured fibers will provide a channel for the transfer of the moisture. Moreover, the presence of 100% material on the surface (outer side) will absorb moisture from the inner side. Exposure of the outer side to the external environment will boost transfer of moisture. The most common sweat shirts are made by using a polyester-cotton blend as the inner side yarn and an outer yarn of 100% cotton. Gunesoglu, et al (2005) tested knitted fabrics having different composition of cotton and polyester for loop and finally concluded that fleece made by using polyester-cotton (87:13) for loop has the lowest thermal absorptivity, an indicator of warm and cool effect, under wet processing conditions, which shows that touching of hydrophobic and hydroscopic material with human skin helps in keeping the skin dry and provides support in transport of moisture from inner side to the outer side.

MATERIALS AND METHOD

Specifications of five varied denim fabrics used in this study are given in *Table I*. Samples from all five fabrics were subjected to 10 distinctive washing treatments. A description of specialty chemicals used in washing treatments is given in *Table II*. Hydrogen Peroxide and Acetic Acid used were of commercial grade. A short description of all washing treatments is given in *Table III*.

All the treated fabric samples were tested on an SDL Atlas Moisture Management Tester according to AATCC Test Method 195-2009. The Moisture Management Tester (MMT) was developed by Yi Li, Qing Wen Song and Jun Yan Hu to measure the flow of water when drops of water touch the surface of fabric (Hu, Li, Yeung, Wong, & Xu, 2005). The instrument gives different indices, which quantify the movement of water in different directions in a textile material. The fabric side that was used as 'top' during testing in this study refers to that side of the denim fabric on which the weft or filling yarns are predominant. This is the side of denim fabric, which would come into contact with skin when the denim garment is worn. The 'bottom' fabric side had predominantly the cotton warp yarns exposed, which were held constant in the study while the weft yarns were varied from cotton to polyester, spun polypropylene, air-textured polypropylene and stuffer-box crimped polypropylene.

TABLE I. Specifications of denim fabrics used in this study.

No.	Warp Yarn Material	Weft Yarn Material	Warp linear density (tex)	Weft Linear Density (tex)	Fabric Weave	Fabric weight (gmm^{-2})
D1	Cotton	Spun polypropylene (SPP)	49.25	54.00	3/1 Z	239
D2	Cotton	Stuffer-box crimped polypropylene (SBC PP)	49.25	38.00	3/1 Z	224
D3	Cotton	Air-textured polypropylene (AT PP)	49.25	44.0	3/1 Z	229
D4	Cotton	Cotton (CO)	49.25	49.0	3/1 Z	230
D5	Cotton	Polyester (PES)	49.25	37.0	3/1 Z	231

TABLE II. Specialty chemicals used in denim washing.

No.	Name	Description	Manufacturer/Supplier
1	Lenitol EHDS	Amylase enzyme	CHT, GMBH
2	Sltafon D	Wetting agent	Mukashi Pakistan
3	Forelase SWGR	Cellulase enzyme	CHT, GMBH
4	Fortress ECO2	Anti back-staining agent	Mukashi Pakistan
5	Belfasin OET	Cationic softener	Cognis
6	Rucofin GWE	Silicon softener	Rudolf Chemical
7	RucoStar EEE	Water repellent chemical	Rudolf chemical
8	RUCO PUR SEC	Quick Dry chemical	Rudolf chemical

TABLE III. Description of different denim washing treatments.

No.	Type	Description
W1	Desizing + Rinsing (D)	Desizing was done using Lenitol EHDS (0.75ml/l), Sltafon D (0.375 ml/l) and ECO2 (0.5 ml/l) at 60°C for 15 min. Desizing was followed by rinsing with water at ambient temperature.
W2	Desizing + Cellulase Treatment (D+C)	Desizing was done as in W1 followed by treatment with Forelase SWGR (0.75 g/l) and ECO2 (0.5 ml/l) at 60°C for 15 min. and then rinsing with water at ambient temperature.
W3	Desizing + Cellulase Treatment + H_2O_2Treatment (D+C+B)	Desizing and Cellulase treatment was done as in W2 followed by treatment with H_2O_2 (4 g/l) at 60°C for 5 min. and then rinsing with water at ambient temperature.
W4	Desizing + H_2O_2Treatment + silicone softener (D+B+SS)	Desizing was done as in W1 followed by treatment with H_2O_2 (4 g/l) at 60°C for 5 min. and then treatment with Rucofin GWE (3.75 g/l).
W5	Desizing + H_2O_2Treatment (D+B)	Desizing was done as in W1 followed by treatment with H_2O_2 (4 g/l) at 60°C for 5 min. and then rinsing with water at ambient temperature.
W6	Desizing + H_2O_2Treatment + Quick-dry finish (D+B+QD)	Desizing and H_2O_2 treatment was done as in W5 followed by treatment with RUCO PUR SEC (3.75 g/l).
W7	Desizing + H_2O_2Treatment + Cationic Softener (D+B+CS)	Desizing and H_2O_2 treatment was done as in W5 followed by treatment with Belfasin OET (4 g/l).
W8	Desizing + Cellulase Treatment + Pumice Stones (D+C+St)	Desizing and Cellulose treatment was done as in W2 in the presence of pumice stones.
W9	Desizing + H_2O_2Treatment + Water-repellent finish (D+B+WR)	Desizing and H_2O_2 treatment was done as in W5 followed by treatment with RucoStar EEE (4 g/l).
W10	Desizing + Peach Finish[1] (D+P)	Desizing and rinsing was carried out as W1 followed by peaching on brushed peaching machine.

[1] Peaching is process in which fabric is rubbed against some brushes or in some case against some sand papers to have a protruding (outstanding) fibers of very small height to get a soft look like skin of Peach fruit. It is also called sueding.

RESULTS AND DISCUSSION

Effect of Different Types of Washing Treatments and Weft Yarns on Fabric Wetting Time

Table IV gives two-way analysis of variance (ANOVA) results for the effect of type of washing treatments and weft yarns on fabric wetting time. It can be observed from *Table IV* that the effect of type of washing treatment is significant on wetting time of the fabrics' top and bottom sides ($P = 0.004$ & 0.000). The 'top' in this study refers to that side of the denim fabrics where weft yarns are pre-dominant while 'bottom' refers to that side where warp yarns are predominantly exposed. During moisture management testing, the water drop was allowed to fall first on the 'top' surface wherefrom it spread outwards as well as penetrated towards the bottom side of the fabric. The effect of type of weft yarn was not found to be significant on fabric wetting time.

TABLE IV. Two-way ANOVA for effect of type of washing treatments and weft yarns on fabric wetting time.

	Source	DF	SS	MS	F	P
Top Wetting Time (WTt)	Type of Washing Treatment	9	707.14	78.5714	3.47	0.004
	Type of Weft Yarn	4	127.44	31.8604	1.41	0.251
	Error	36	815.11	22.6419		
	Total	49	1649.69			
	R-sq = 50.59%					
Bottom Wetting Time (WTb)	Type of Washing Treatment	9	67671.3	7519.04	14.82	0.000
	Type of Weft Yarn	4	1336.0	333.99	0.66	0.625
	Error	36	18262.1	507.28		
	Total	49	87269.3			
	R-sq = 79.06%					

Effect of different types of washing treatments on fabric wetting time on the top and bottom sides is shown in *Figure 1 and 2* respectively. It is obvious that the top wetting time is shorter as compared to the bottom wetting time. All fabric tops wet fairly quickly except that was subjected to peaching (D+P) finish. Peaching was done on the top fabric side only where the hydrophobic polypropylene and polyester fibers are predominant in all the fabrics except one that had cotton weft yarns. The short protruding fibers, resulted by peaching, may have caused interference in the wetting of the fabric top. *Figure 2* shows that bottom wetting time is longest in the fabric that was treated with water repellent finish (WR), which is obviously due to hydrophobic nature of the finish.

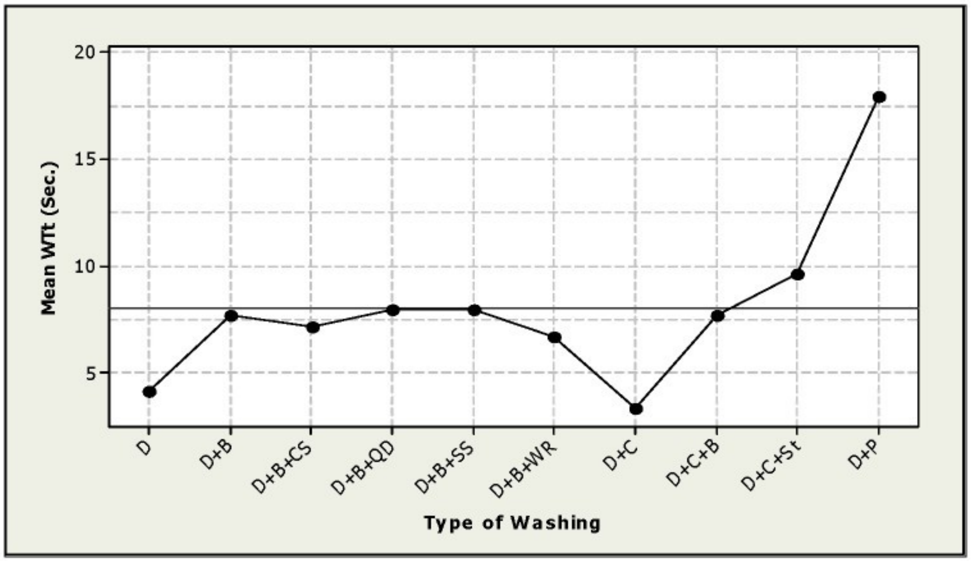

FIGURE 1. Effect of different types of washing treatments on top wetting time.

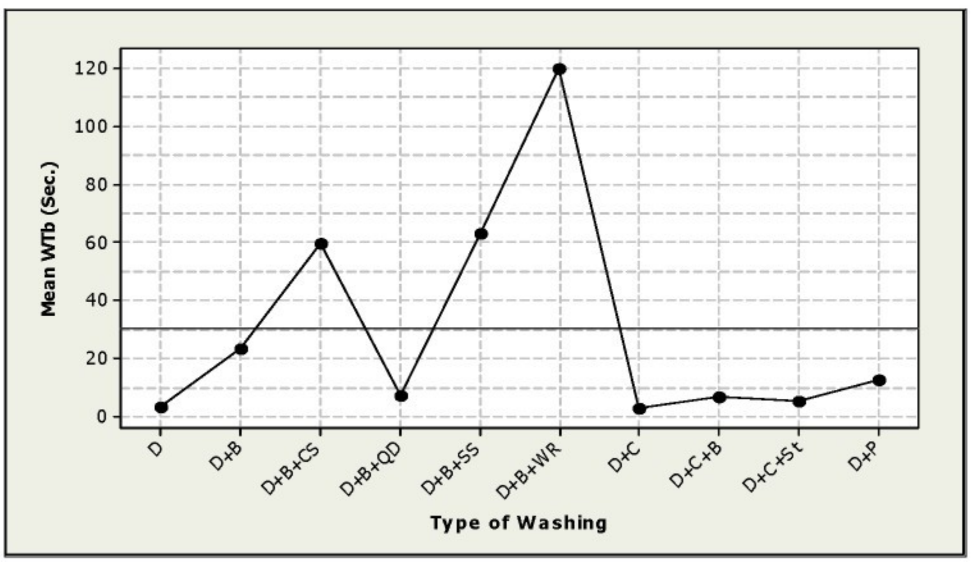

FIGURE 2. Effect of different types of washing treatments on bottom wetting time.

Effect of Different Types of Washing Treatments and Weft Yarns on Maximum Wetted Radius of the Fabric

The effect of different type of washing treatments and weft yarns on the top and bottom maximum wetted radii of the fabric is given as a two-way ANOVA in *Table V*. It can be observed that the effect of type of washing is significant on both the top and bottom maximum wetted radii (P = 0.000). However the effect of different types of weft yarns is only significant on the bottom wetted radius (P = 0.016) and not on the top maximum wetted radius (P = 0.151).

TABLE V. Two-way ANOVA for effect of type of washing treatments and weft yarns on maximum wetted radii of the fabric.

	Source	DF	SS	MS	F	P
Top Maximum Wetted Radius (MWRt)	Type of Washing Treatment	9	3150.5	350.056	18.89	0.000
	Type of Weft Yarn	4	133.0	33.250	1.79	0.151
	Error	36	667.0	18.528		
	Total	49	3950.5			
	R-sq = 83.12%					
Bottom Maximum Wetted Radius (MWRb)	Type of Washing Treatment	9	5348	594.222	40.21	0.000
	Type of Weft Yarn	4	208	52.000	3.52	0.016
	Error	36	538	14.778		
	Total	49	6088			
	R-sq = 91.26%					

Figure 3 and 4 illustrate the effect of different washing treatments on top and bottom maximum wetted radii, respectively. It is clear that treatments containing hydrophobic finishes such as cationic softener (CS), silicon softener (SS) and water-repellent (WR) resulted in poor water spreading along with peached fabric where the tiny protruding fibers may also have hindered the spreading phenomenon.

The effect of different types of weft yarns on a bottom maximum wetted radius is depicted in *Figure 5*. It can be observed that the spreading is higher in case of hydrophobic weft polypropylene and polyester yarns as compared to hydrophilic cotton weft. It follows from the results that having hydrophobic yarns on the inner garment side and hydrophilic yarns on the outer garment side will result in higher perspiration spreading on the outer side which will also help in its quicker evaporation because of larger wetted radius.

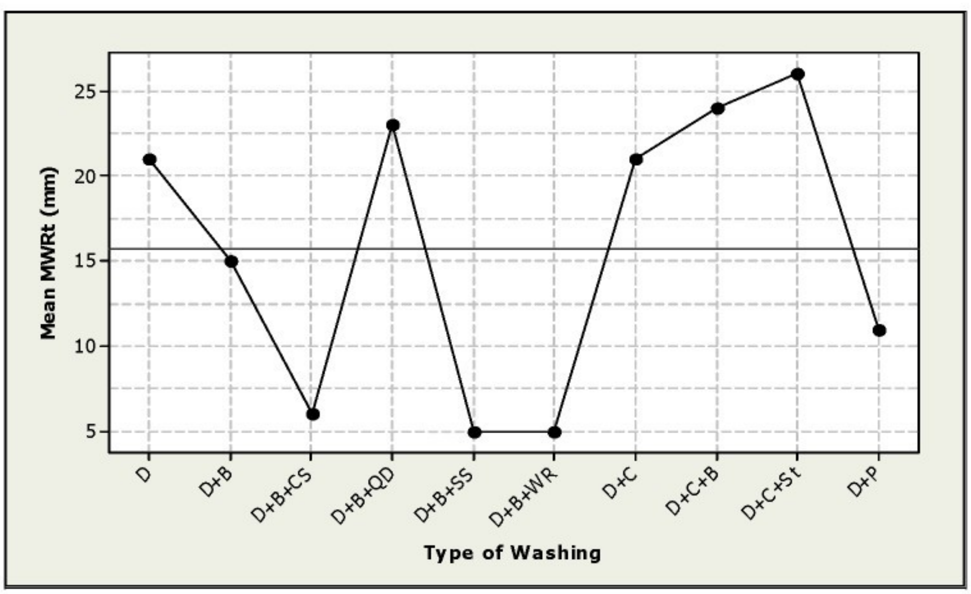

FIGURE 3. Effect of different types of washing treatments on top max. Wetted radius..

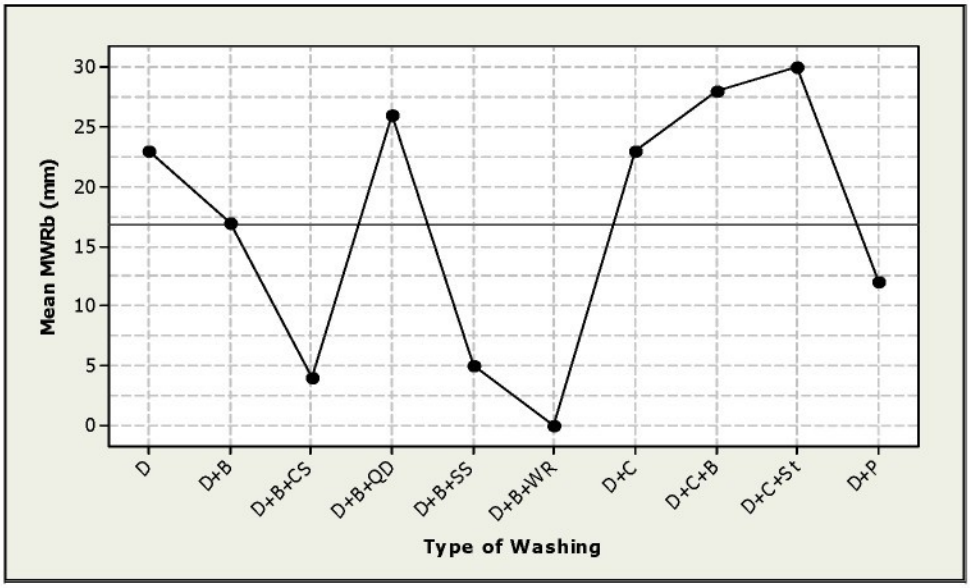

FIGURE 4. Effect of different types washing treatments on bottom max. Wetted radius.

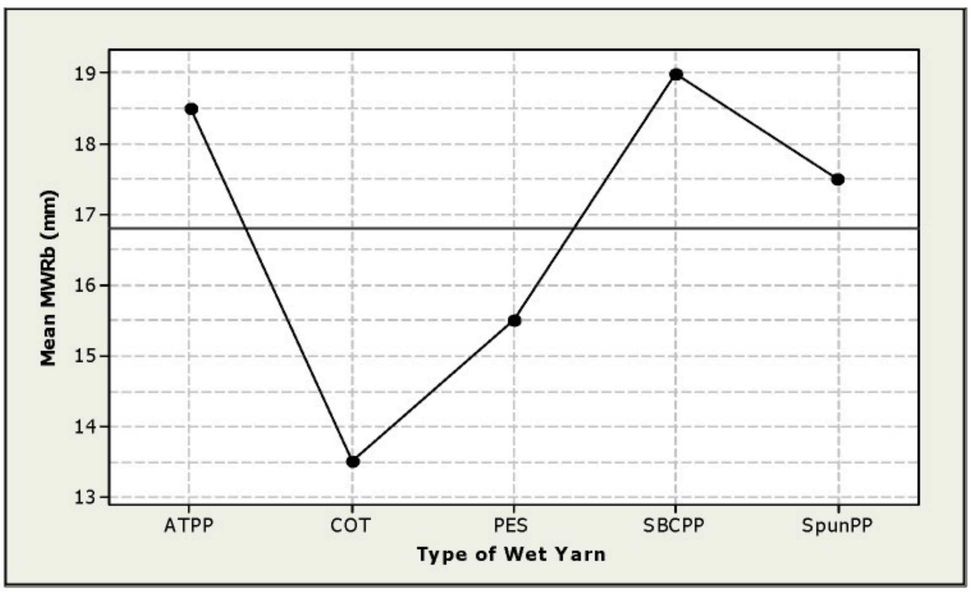

FIGURE 5. Effect of different types of weft yarns on bottom max. Wetted radius.

Effect of Different Types of Washing Treatments and Weft Yarns on Water Spreading Speed

Two-way ANOVA results for the effect of different washing treatments and weft yarns on water spreading speed on the top and bottom fabric sides is given in *Table VI*. Although the effect of type of washing treatment was found to be significant on both top and bottom spreading speed (P = 0.000), the effect of type of weft yarn was only found significant on the bottom fabric side (P = 0.009). The effect of type of washing treatment on top and bottom spreading speeds depicted in *Figure 6 and 7* shows similar trends as that of top and bottom maximum wetted radii. The same is true for the effect of different weft yarns on water spreading speed at the bottom fabric side (*Figure 8*), where the spreading speed is higher in case of hydrophobic weft yarns at the top fabric side and hydrophilic cotton yarn at the bottom fabric side.

TABLE VI. Two-way ANOVA for effect of type of washing treatments and weft yarns on water spreading speed.

	Source	DF	SS	MS	F	P
Top Spreading Speed (SSt)	Type of Washing Treatment	9	110.705	12.3006	27.37	0.000
	Type of Weft Yarn	4	3.005	0.7514	1.67	0.178
	Error	36	16.178	0.4494		
	Total	49	129.888			
	R-sq = 87.55%					
Bottom Spreading Speed (SSb)	Type of Washing Treatment	9	204.795	22.7550	45.84	0.000
	Type of Weft Yarn	4	7.906	1.9764	3.98	0.009
	Error	36	17.872	0.4964		
	Total	49	230.573			
	R-sq = 92.25%					

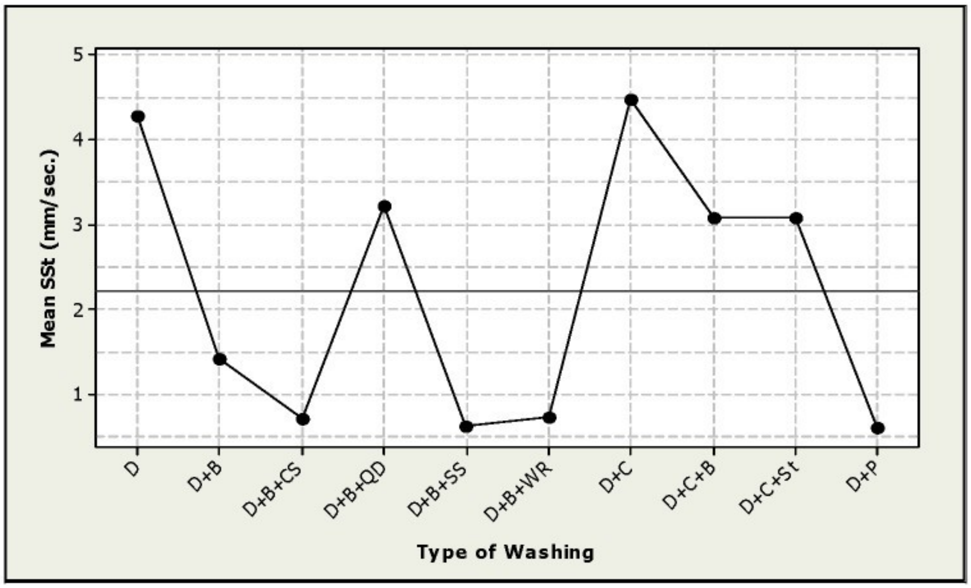

FIGURE 6. Effect of different types of washing treatments on top spreading speed.

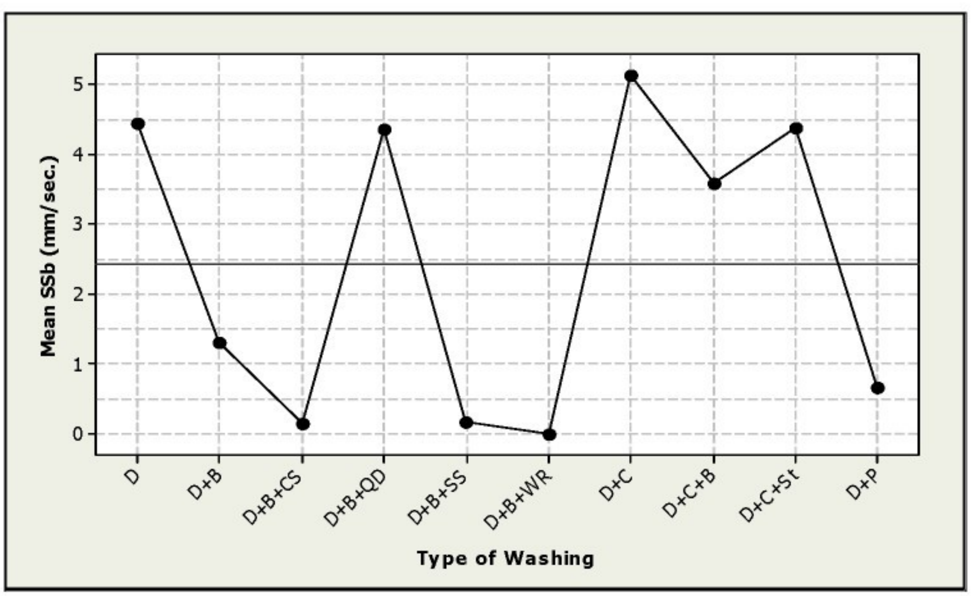

FIGURE 7. Effect of different types of washing treatments on bottom spreading speed.

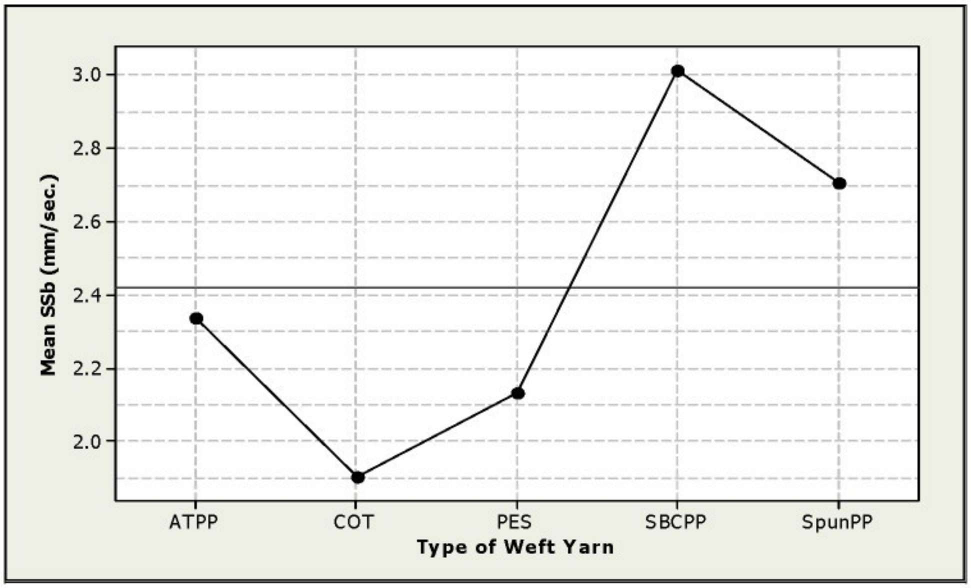

FIGURE 8. Effect of different types of weft yarns on bottom spreading speed.

Effect of Different Types of Washing Treatments and Weft Yarns on Accumulative One-Way Transport (AOWT)

Accumulative one-way transport is a measure of the difference between the areas of the liquid moisture content curves of the top and bottom surfaces of a specimen with respect to time. *Table VII* gives the two-way analysis of variance (ANOVA) results of accumulative one-way transport (AOWT) of fabric samples versus different types of washing treatments and weft yarns. It can be observed that the effect of type of wash (P = 0.000) and the type of weft (P = 0.013) is statistically significant. This means that different types of washing treatments and weft yarns result in significantly different values of overall moisture management capacity of fabrics. For the AOWT data, R-sq equals 78.10%, which gives the percentage variation in AOWT that can be explained by the type of washing and the weft changes.

TABLE VII. Two-way ANOVA for effect of type of washing treatments and weft yarns on accumulative one-way transport.

Source	DF	SS	MS	F	P
Type of Washing Treatment	9	7797893	866433	12.62	0.000
Type of Weft Yarn	4	1011407	252852	3.68	0.013
Error	36	2470908	68636		
Total	49	11280208			

A main effect plot for effect of type of washing on AOWT is given in *Figure 9*. It is evident that accumulative one-way transport of moisture is maximum in case Spun Polypropylene weft yarn, followed by Air-textured Polypropylene (ATPP), Stuffer-box Crimped Polypropylene (SBCPP), Polyester (PES) and Cotton (COT) weft yarn. It follows from the results that denim fabrics with weft yarns made from polypropylene will keep the skin of the wearer dry by transporting the perspiration towards the outer side of the fabric which is away from the skin. This is because in denim, the fabric side which comes in contact with the skin has predominantly exposed weft yarns and the side which is away from the wearer has predominantly exposed warp yarns. Hence a fabric with good accumulative one-way transport from the inner fabric side to the outer side will offer good sweat management to the wearer.

The effect of different types of washing on AOWT is given in *Figure 10*. It is clear that desizing (D), desizing + cellulose treatment (D+C), desizing + cellulose treatment + bleaching (D+C+B), desizing + celllulase treatment + stone washing (D+C+St), desizing + quick-dry finish (D+QD) and desizing + peaching (D+P) resulted in good accumulative one-way transport of moisture from the treated fabric, whereas washing treatments containing water repellent finish (WR), silicon softener (SS) and cationic softener (CS) resulted in poor AOWT, which can be explained by the hydrophobic nature of these finishes. *Figure 10* further elaborates that desized, bleached and having water repellant finish has the lowest value of AOWT. It may be due to the influence of water repellent chemicals on the surface of the fabric.

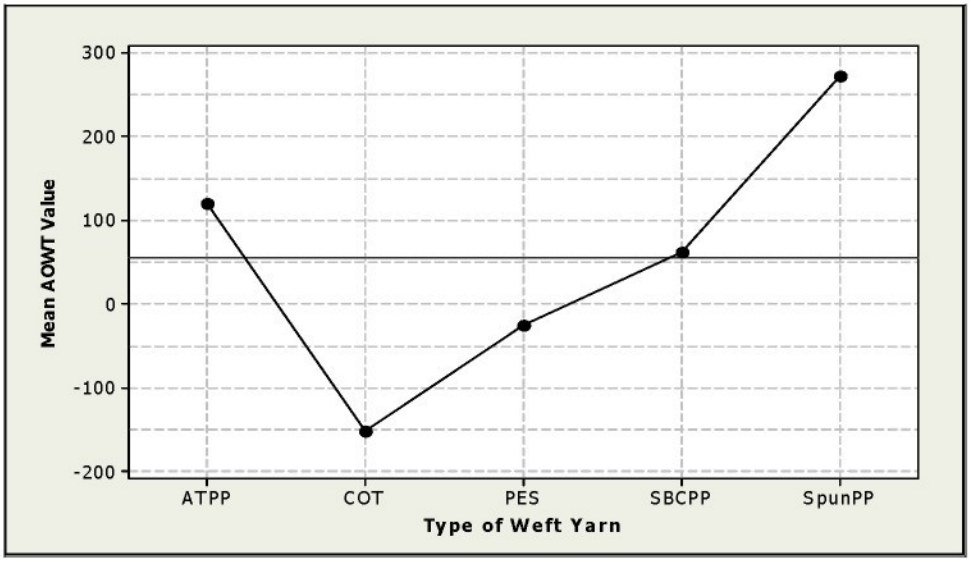

FIGURE 9. Effect of different types of weft yarn on AOWT.

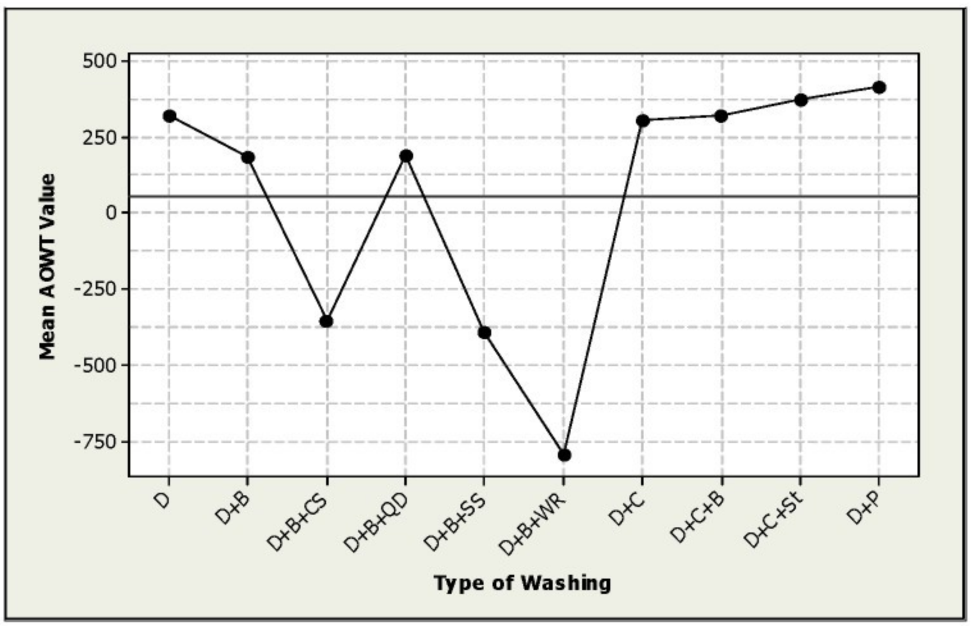

FIGURE 10. Effect of different types of washing treatment on AOWT.

Effect of Different Types of Washing Treatments and Weft Yarns on Overall Moisture Management Capacity

Table VIII gives the two-way analysis of variance (ANOVA) results of overall moisture management capacity (OMMC) of fabric samples versus different types of washing treatments and weft yarns. It is clear from the table that the effect of type of wash (P = 0.000) and the type of weft (P = 0.014) is statistically significant. This indicates that different types of washing treatments and weft yarns result in significantly different values of overall moisture management capacity of fabrics. For the OMMC data, R-sq equals 82.50%, which gives the percentage variation in OMMC that can be explained by the type of washing and the weft changes.

TABLE VIII. Two-way ANOVA for effect of type of washing treatments and weft yarns on OMMC.

Source	DF	SS	MS	F	P
Type of Washing Treatment	9	3.78827	0.420919	17.25	0.000
Type of Weft Yarn	4	0.35303	0.088258	3.62	0.014
Error	36	0.87834	0.024398		
Total	49	5.0164			

A main effect plot for the effect of type of washing on OMMC is given in *Figure 11*. Clearly overall moisture management capacity is maximum in case Spun Polypropylene weft yarn, followed by Air-textured Polypropylene (ATPP), Stuffer-box Crimped Polypropylene (SBCPP), Polyester (PES) and Cotton (COT) weft yarn.

The effect of different types of washing on OMCC is given in *Figure 12*. It is clear that desizing (D), desizing + cellulose treatment (D+C), desizing + cellulose treatment + bleaching (D+C+B) and desizing + celllulase treatment + stone washing (D+C+St) resulted in good overall moisture management capacity of the treated fabric, whereas washing treatments containing water repellent finish (WR), silicon softener (SS) and cationic softener (CS) resulted in poor OMMC, which can be explained by the hydrophobic nature of these finishes. The OMMC of fabrics treated with the quick dry finish (QD) was also found to be above average followed by that of the desized + peached (D+P) fabrics.

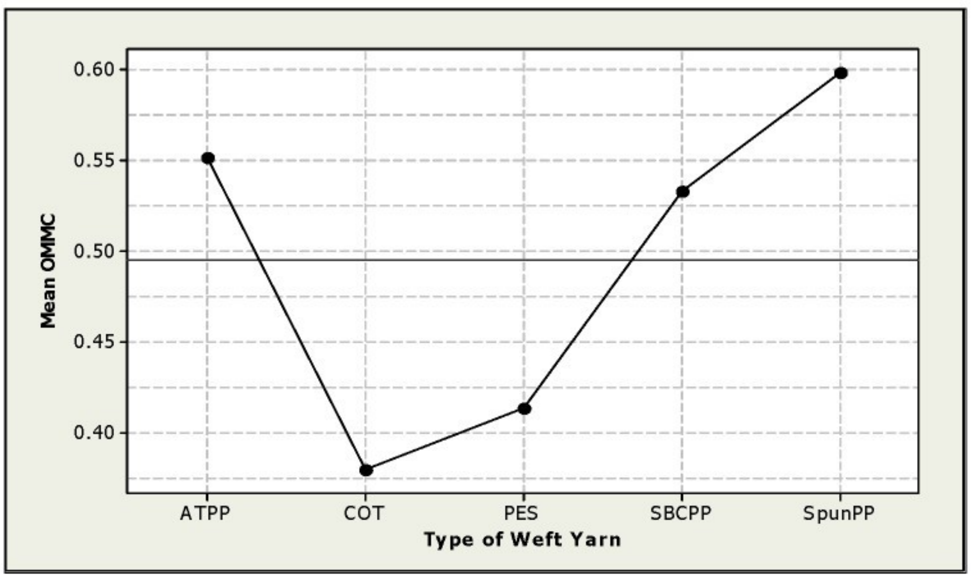

FIGURE 11. Effect of different types of weft yarns on OMMC.

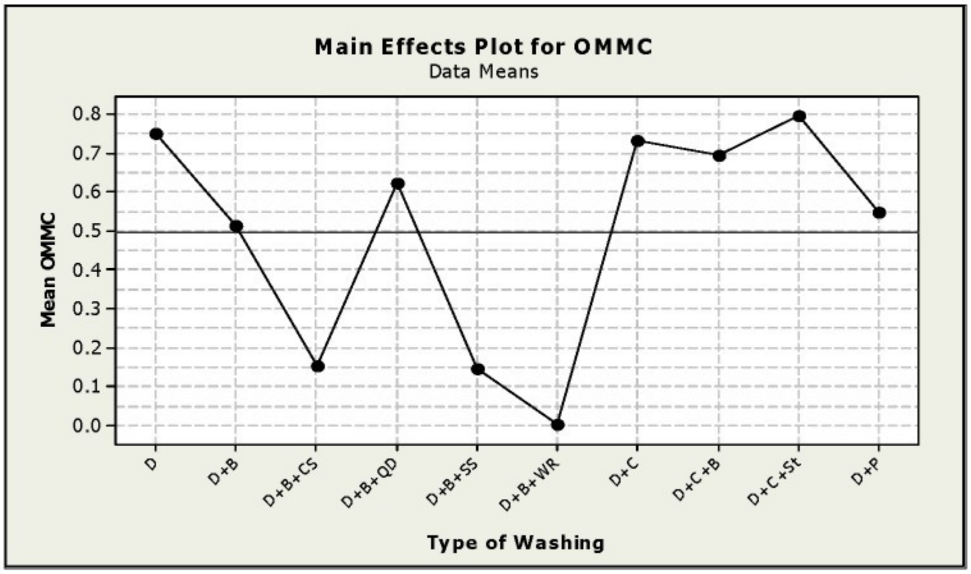

FIGURE 12. Effect of different types of washing treatment on OMMC.

CONCLUSIONS

On the whole moisture management capacity of denim fabrics is significantly affected by unlike types of weft yarns and washing treatments. Fabrics with pleasurable moisture management capacity can be developed by using a blend of hydrophilic and hydrophobic yarns in the fabric in such a way that the hydrophobic yarns are predominantly present on one fabric side, which would come directly in contact with the skin and the hydrophilic yarns are predominantly present on the other fabric side. Use of hydrophilic and quick-dry finishes can further enhance the overall moisture management capacity of denim fabrics.

REFERENCES

[1] Amrit, U. R. (2007). Bedding textiles and their influence on thermal comfort and sleep. AUTEX Research Journal, 8 (7).

[2] Barker, R. L. (2006). Effects of Moisture on the Thermal Protective Performance of Firefighter Protective Clothing in Low-level Radiant Heat Exposures. Textile Research Journal, 76 (1), 27-31.

[3] Gunesoglu, S., Meric, B., & Gunesoglu,C. (2005). Thermal Contact Propertiesof 2-Yarn Fleece Knitted Fabrics Fleece Knitted Fabrics. FIBRES & TEXTILES in Eastern Europe 13(2 (50), 46-50.

[4] Hes, Lubos & Martins, Jorge. (1993). Experimental Heat Transfer, Fluid Mechanics, and Thermodynamics Third World Conference held 31 October - 5 November, 1993 in Honolulu, HI. Edited by M.D. Kelleher, R.K. Shah, K.R. Sreenivasan, and Y. Joshi. Amsterdam: Elsevier Sci. Third World Conference. Honolulu.

[5] Hu, J., Li, Y., Yeung, K.-W., Wong, A. S., & Xu, W. (2005). Moisture Management Tester: A Method to Characterize Fabric Liquid Moisture Management Properties. Textile Res. J., 75 (1), 57-62.

[6] Kandjov, I. M. (1999). Heat and mass exchange processes between the surface of the human body and ambient air at various altitudes. International Journal Biometeorol (43), 38-44.

[7] Satsumoto, Y., Murayama, C., & Takeuchi, M. (2009). Effect of Moisture Sorption of Underwear Material on Clothing Microclimate in a Hot Environment. Heat Transfer—Asian Research, 38 (1).

[8] She, F., & Kong, L. (2000) Theoretical Investigation of Heat and Moisture Transfer through Porous Textile Materials. Research Journal of Textile and Clothing, 4 (1), 37-41.

[9] Suleiman, B. M. (2006). Moisture effect on thermal conductivity of some major elements of a typical Libyan house envelope. Journal of Physics D: Applied Physics, 39, 547.

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A NEW WAY TO THE OBJECTIVE HAND EVALUATION

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Abstract: *In present paper a new method named BM technique leading to the objective hand evaluation is presented. The method is based on the evaluation of 8 measurable properties using instruments occurring commonly in textile laboratories. The properties were selected from four basic groups of properties corresponding to the hand sensory centre. As prediction equation the ordinal logistic regression was applied. At first the total hand value (THV) of 90 men suits was evaluated subjectively using the panel of 40 respondents and median category M of eleven degree ordinal scale was calculated for each fabric. From 90 fabrics the set of 80 ones was applied for creation of the prediction formulae. The rest 10 fabrics served for verification of prediction ability. Prediction ability of BM techniques was compared with the same approach but on the properties obtained from KES system. Also 2 types of prediction equation derived on the basis of analysis from BM properties were compared. Results flowing from both sets of properties and 4 equations show the comparable results. The most of 10 fabrics was objectively classified to the category M±1 in comparison with subjective evaluation.*
Key Words: *objective hand evaluation, subjective hand evaluation, THV, ordinal logistic regression*

1 INTRODUCTION

The hand of textiles belongs among the basic tactile properties of textiles and is understood as the complex psychophysical property. It means that the subjective precept hand is weighted mean of single primary hand stimulus and personal knowledge of evaluator. Its definition still is not given clearly. Generally, hand can be understood as sensation evoked by contact between the skin and textile. Some definitions are presented in [1-4]. Before and during subjective hand evaluation it is necessary to solve several key problems which realization can affect the results:

- choice of respondents,
- choice of scale,
- choice of properties and its definition,
- the course and conditions of experiment,
- analysis of results.

Bishop [5] in his summary review presents the similar key elements:

- the judges,
- the criteria of judgement,
- the assessment conditions,
- the assessment technique,
- the method of ranking or scaling the assessment,
- analysis of results.

It is evident to prepare and realize experiment for subjective hand evaluation needs a lot of time.

During approximately last 40-50 years the big effort to objective hand evaluation was dedicated. As the main reason the prediction of subjective hand evaluation is. The research realized by Binns [6] and Peirce work [7] belongs among the first works in the field of subjective hand evaluation and its objective prediction. The introduced principles of objective hand evaluation according to applied methods and instruments can be divided to three groups:

- set of special instruments – e.g., here the most spread system KES [8] can be placed. It is consisted from 4 instruments where 15 characteristics is measured,
- special instrument, where the principle is based on pulling sample through round or conic hole [9, 10],

- standard instruments, which are mostly to disposal in a textile laboratory [11, 12].

Kawabata in his work [8] proved that primary hand hands are evaluated at first and then a total hand is expressed. In the present paper the technique (BM technique) at which the choice of properties was realized on the basis of idea of Lundgren [1] that evaluation of hand is connected with four centres:

- centre of surface smoothness and unevenness,
- centre of stiffness and compliance,
- centre of volume properties,
- centre of thermal phenomena.

Ordinal logistic regression (OLR) was applied for design of formula for objective hand evaluation. The application of OLR is presented in [13] and results indicated its application as suitable. Therefore, the results flowing from BM technique were compared with results built on the properties from KES.

2 ORDINAL LOGISTIC REGRESSION

Ordinal logistic regression can be applied in the case when depended variable y is ordinal. This is typical for subjective hand evaluation when fabrics are classified to K ordered categories – in this case K is mostly 11, k=1, 2,...K, from evaluation – hand is very bad (k=1, y=0) to the excellent one (k=K, y=K-1). The most suitable model is called proportional odds model [14]

$$CL_k = \ln\left[\frac{P(y \leq k)}{P(y > k)}\right] \quad (1)$$

The solution of the proportional odds model leads to $K-1$ regression equations which differ only in the value of absolute member $b_{k,0}$ whose value grows

$$\ln\left[\frac{P(y \leq k)}{P(y > k)}\right] = b_{k,0} + \mathbf{b}^{\mathrm{T}}\mathbf{x} \quad (2)$$

The phenomenon is placed to category for which $P(y=k)$ is maximum. Advantage of the model is that the effects of the vector of independent properties $\boldsymbol{x}$ are invariant in respect to the dependent variable [13].

Significance of the model was tested using the deviance G^2 and single regression parameters by means of Wald test.

3 EXPERIMENTAL PART

The prediction of the hand was made from eight objectively measurable characteristics selected from four basic groups of properties corresponding to the hand sensoric centre [1].

1. For characterisation of the fabric <u>surface roughness</u>
   - mean absolute deviance *MAD* [mN] has been selected.
2. The deformability has been characterised by the
   - tensile modulus in diagonal direction *Y45* [MPa],
   - initial tensile modulus *Y* [MPa],
   - stiffness *T* [mN cm].
3. Bulk behaviour has been expressed by the
   - area weight *M* [g m^{-2}]
   - compressibility *S* [-]
   - thickness *t* [mm].
4. Thermal part of hand has been characterised by the
   - thermal absorbtivity *b* [W m^{-2}s$^{1/2}$K^{-1}].

Experimental data were collected for 90 men suit fabrics. The basic parameters are shown in Table 1. In the next step data were divided to two groups. The first group (data representing 80 fabrics) called training group was used for the calculation of estimation of regression parameters *b* and the second group of the rest 10 fabrics helped for verification of prediction ability of the model. The estimated regression coefficients are in Table 3. The significant coefficients and properties are in bold format.

Table 1 The basic characteristics of fabrics

areal weight	g/m^2	140 - 370
sett - warp - weft	threads/10 cm	170 - 560 150 - 370
fibre composition	100% wool, 45/55 wool/polyester, wool/polyester/polyamide	
basic types of weaves	mostly different types of twills, plain weave	

To obtain the formula for objective hand evaluation the subjective evaluation of fabrics also had to be realized. The panel of 40 judgers classified samples to 11 degree ordinal scale in accordance with scale used in [8]. As result 40 evaluations of total hand value (THV) for 90 fabrics had been obtained. For prediction the estimation of the median category of ordinal scale *M* was chosen which is defined

$$F_{M-1} < 0{,}5 \qquad F_M \geq 0{,}5 \qquad (3)$$

where *Fz* cumulative relative frequency is (*z=M-1* or *M*). Number of median categories is presented in Table 2.

Table 2 Number of fabrics classified into the median categories *M*

median category	number of classified fabrics
1	0
2	2
3	11
4	8
5	16
6	17
7	19
8	8
9	5
10	4
11	0

It is evident from Table 2 that no fabrics has median category 1 or 11 and to the median categories 2, 9 and 10 was classified only a few fabrics. The final interpretation of results is affected by this situation.

The model created on the basis of BM technique is marked BM11 and compared model flowing from KES characteristics as KES11.

Relations among the single properties used in BM technique were investigated. The paired (above the main diagonal) and partial (below the main diagonal) coefficients of correlation are presented in Table 3. The bold is used for correlations in absolute value higher than 0.6. All correlations with value higher than $|\mathbf{0.2}|$ are statistically significant on the level of significance α=0.05.

The principal component analysis (PCA) was also applied for detection of relations among the properties. Scree plot (Figure 1a) indicates 3 important principal components. Components weight graphs (Figure 1b-d) show for the individual combinations of 3 principal components dependencies and relations of the single properties. As results in Table 3 as graphs in Figure 1 leads to conclusions that among area weight *M* and thickness *t* dependence exist. Less strong relation between properties tensile modulus in diagonal direction *Y45* and initial tensile modulus *Y* can be observed. Therefore properties were collected according to their character

$$\mathrm{geom1} = \frac{M}{t} \text{ and } \mathrm{tenacity1} = \frac{(Y45 + Y)}{2}$$

model is called BM11v1.

in accordance with results PCA

$$\mathrm{geom2} = -0.91t - 0.86M \text{ and}$$

$$\mathrm{tenacity2} = 0.8945Y45 + 0.68Y$$

model is called BM11v2.

Table 3 Paired and partial coefficients of correlation

	b	T	t	M	S	MAD	Y45	Y
b	1.00	-0.45	-0.58	-0.45	0.19	-0.55	0.01	-0.24
T	-0.12	1.00	**0.72**	**0.71**	-0.56	0.44	0.02	0.34
t	-0.24	0.22	1.00	**0.86**	-0.43	**0.65**	-0.07	0.33
M	0.11	0.18	**0.67**	1.00	-0.48	0.49	-0.14	0.31
S	-0.10	-0.33	0.02	-0.17	1.00	-0.23	-0.23	-0.42
MAD	-0.26	-0.02	0.38	-0.07	0.06	1.00	0.09	0.25
Y45	0.06	0.01	-0.03	-0.26	-0.20	0.18	1.00	0.51
Y	-0.09	0.02	0.04	0.14	-0.14	-0.05	0.54	1.00

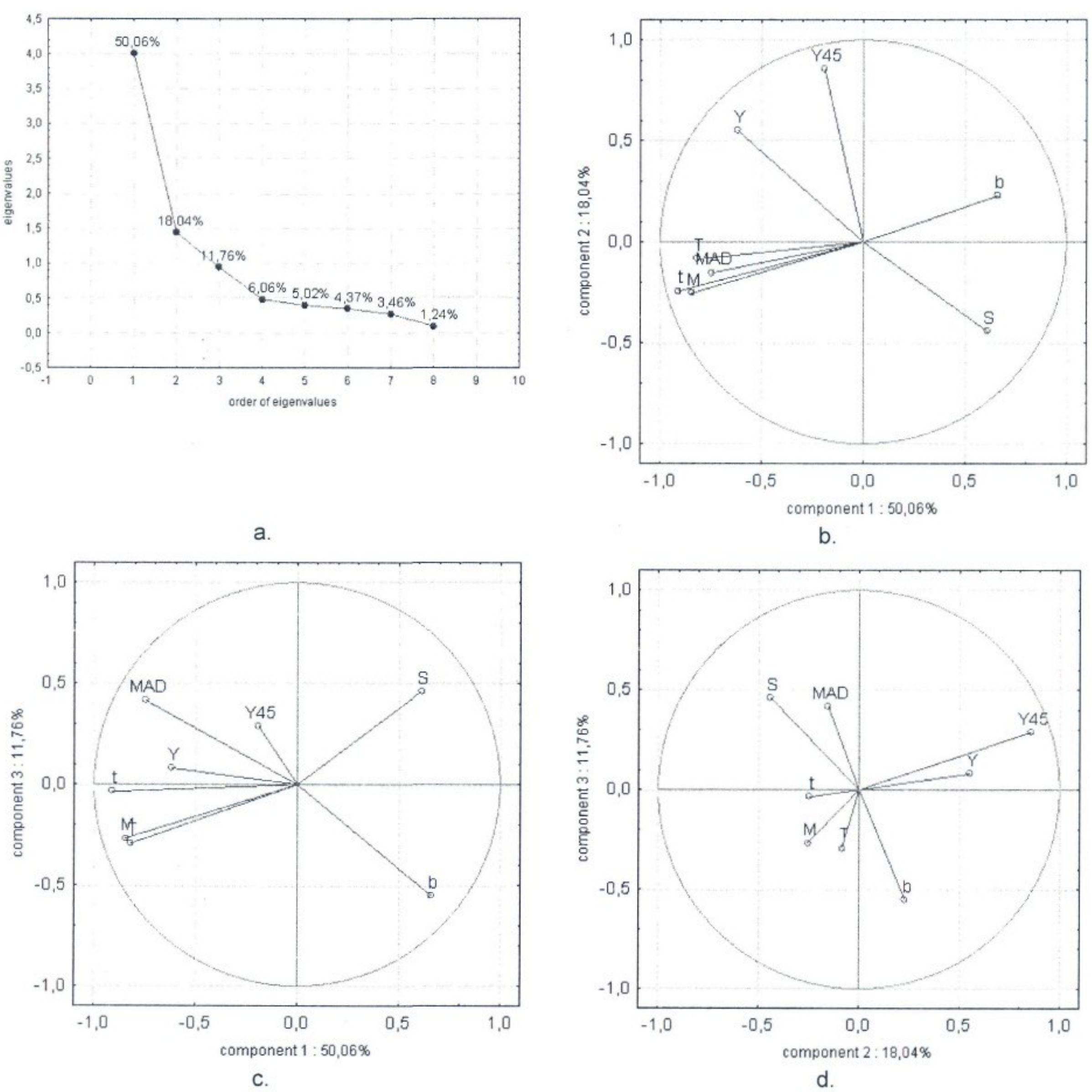

Figure 1 Scree plot (a) and components weight graphs – (b) the 1st principal component vs the 2nd principal component; (c) the 1st principal component vs the 3rd principal component; (d) the 2nd principal component vs the 3rd principal component

Table 4 Comparison of models

characteric	KES11	BM11	BM11v1	BM11v2
G^2	147.06	157.55	**114.86**	152.93
p	<0.01	<0.01	<0.01	<0.01
R^2_{MF}	0.47	**0.49**	0.36	0.48
R^2_N	0.92	**0.93**	0.78	0.87
BIC	**81.55**	124.8	88.57	126.67
AIC	-2.35	**-2.44**	2.94	2.46

Table 5 Comparison of predicted and measured values of median categories of THV

Sample No.	THV	Predicted value by BM11	Diff.	Predicted value by BM11v1	Diff.	Predicted value by BM11v2	Diff.	Predicted value by KES11	Diff.
T117	6	7x	+1	5x	-1	7	+1	6	
T118	4	4		4		4		2	-2
T135	3	3		5x	+2	4	+1	4	+1
T136	9	8x	-1	8x	-1	8	-1	8	-1
T153	5	5		5		5		5	
T154	3	3		5x	+2	3		4	+1
T171	6	6		6		5	-1	5	-1
T172	7	7		7		6	-1	9	+2
T189	10	9x	-1	8x	-2	8	-2	9	-1
T190	7	6x	-1	6x	-1	6	-1	6	-1

The models were compared using Bayesian (*BIC*) and Akaike (*AIC*) information criterions, McFaden coefficient of determination (R^2_{MF}) and Nagelkerke statistic (R^2_N). It is valid for both criterions that lower value means better model. Advantage of these criterions is that adding new independent variable does not mean automatically better model in comparison with deviance G^2. McFaden coefficient of determination and Nagelkerke statistic indicate better model when its value is higher.

Proposed models based on BM technique are compared with the similar model in which the KES properties were used [8].

Results in Table 4 indicate that no model is significantly better. Parameter p shows that all models are significant and can be used for prediction.

The verification of prediction ability of the proposed models was realized on the second group of 10 textiles. Results presented in Table 5 show that model BM11 predicted 6 samples in accordance with the results of sensory analysis and the rest of samples with the mistake 1 category. All other models classified at least one sample with the difference 2 categories. On other hand, as variability in subjective hand evaluation of THV exists, difference 1 category is acceptable. From this point of view all of samples were classified well by model BM11, and 90% by model BM11v2, 80% by model KES11 and 70% by model BM11v1. No fatal classification (e.g., the excellent classification instead of very bad) was predicted.

4 CONCLUSION

Presented paper show objective hand evaluation using properties which are possible to measure in the textile laboratory by means of standard instruments. The ordinal logistic regression for the prediction of total hand – THV was introduced. For prediction the median category of THV was applied. The median category indicates that about 50% judgers will evaluate THV to median category and better (or worse). However, it is necessary take to consideration that to the terminal categories No. 1, 2, 9, 10 and 11 was sorted less textiles than it is necessary.

Results show that application of the ordinal logistic regression is possible. Proposed model called BM designed from 8 properties provided very similar prediction ability as model based on KES characteristics. Applied properties mean absolute deviance *MAD*, initial tensile modulus in diagonal direction *Y45*, initial tensile modulus *Y*, stiffness *T*, area weight *M*, compressibility *S*, thickness *t* and thermal absorbtivity *b* are suitable for building of formula for objective hand evaluation.

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5 REFERENCES

1. Lundgren H.P: New Concepts in Evaluating Fabric Hand. Textile Chemists and Colorists Vol.1, No. 1, 1969, 35-45
2. Matsuo T., Nasu N., Saito M.: Study on the Hand. Journal of the Textile Machinery Society of Japan Vol.17, No.3, 1971, 92-104
3. McIntyre J.E.: Textile Terms and Definitions, The textile Institute, Manchester, England, 10th edition, 1995
4. Fabric Hand: Guidelines to Subjective Evaluation of. AATCC evaluation procedure 5, 2001
5. Bishop D.P. Fabric: Sensors and Mechanical Properties, The Textile Progress Vol. 26, No. 1, 1996, 1-62
6. Binns H.: The Discrimination of Wool Fabrics by the Sense of Touch, British Journal of Psychiatry Vol.16, 1926, 237-247
7. Peirce F.T.: The 'Handle' Of Cloth As a Measurable Quantity, The Journal of The Textile Institute Vol. 21, 1930, 377-416
8. Kawabata S.: The Standardisation and Analysis of Hand Evaluation, The Textile Machinery Society of Japan, Osaka, 1980
9. Meie L., Xiaoan S., Li Z.A.: Study of Method of Measuring and Evaluating Fabric Handle, Proceedings of Textile Science 91, Technical university in Liberec, 1991, 41-50
10. Pan N.: Quantification and Evaluation of Human Tactile Sense Towards Fabrics, Int. Journal of Design & Nature Vol.1, No.1, 2006, 1-13
11. Raheel M., Lin J.: An Empirical Model for Fabric Hand. Part I: Objective Assessment of Light Weight Fabrics, Textile Research Journal Vol. 61, No., 1991, 1, 31-36
12. Pan N., Yen K.C., Zhao S.J., Yang S.R.: A New Approach to the Objective Evaluation of Fabric Handle from Mechanical Properties. Part I: Objective Measure for Total Handle, Textile Research Journal Vol. 58, No. 8, 1998, 438-444
13. Bajzík V. Hand Prediction using Ordinal logistic Regression, Proceeding of Innovation in Clothes and Footwear, Radom, 2010, 191-198
14. Powers D. Xie Y.: Statistical Methods for Categorical data Analysis, San Diego: Academic Press, 2000

NOVÝ PŘÍSTUP K OBJEKTIVNÍMU HODNOCENÍ OMAKU

Translation of the article
A new way to the objective hand evaluation

V příspěvku je představena nová metoda (BM technika) pro objektivní hodnocení omaku. Je použito 8 vlastností. Pro konstrukci predikční rovnice byla použita ordinální logistická regrese. Výsledné predikce byly porovnány s výsledky z obdobné predikční rovnice, kde však byly pro konstrukci použity vlastnosti ze systému KES.

Výsledky ukazují na dobrou predikční schopnost navrženého modelu.

EFFECT OF TWO TYPES OF SOFTENERS AND WEFT COMPOSITION ON THERMAL COMFORT CHARACTERISTICS OF DENIM FABRICS

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Abstract: *Denim manufacturers apply certain textile auxiliaries on denim clothing in industrial clothing washing process to impart assured properties. Such treatment modifies the thermal and sensorial characteristics of denim clothing. For this study two sets of denim; traditional denim by using cotton yarn as warp and weft and novel denim by using cotton yarn as warp and spun PP yarn as weft. These sets were desized, rinsed, bleached and treated with cationic and silicone softeners. Impact of weft variation and application of two distinct softeners was studied. This investigation was carried out by using the Alambeta thermal comfort tester and by conducting a survey. The study reveals that in both cases people prefer hand feeling of denim treated with silicone softener as compared to cationic softener but this conclusion is not statistically significant. Moreover, people state that traditional denim treated with silicone is less cool, which is also verified by the Alambeta. However, in the case of novel denim, there is a contradiction in the views of evaluators and the Alambeta results.*
Keywords: *thermal conductivity, thermal resistance, thermal absorbtivity, subjective evaluation, cationic and silicone softness*

1 INTRODUCTION

Denim is one of the most popular fabrics used for the manufacturing of assorted types of clothing. Significance of subjective evaluation remains one the most critical factors for the marketing of the textile material [1]. Majority of the denim is treated with different textile auxiliaries to have a definite look and hand feeling. Silicone and cationic softeners are most frequently used to have a better hand feeling and to advance the smoothness of the denim surface [2, 3]. At the same time, there is an implicit change in thermal parameters. Any variation in thermal parameters can alter the comprehensive clothing comfort recognition. However, prime objective of softener application is to have a greater degree of hand feeling.

Thermal properties of textiles are main part of total hand value (THV). These ones are touched immediately during the first contact between textiles and skin [4]. Thermal parameters hinge on the chemical and physical structure of any material. It is also logical for textile material. Fabric is made by using various fibers. Moreover, there are many ways to make a yarn and its application to make a fabric. Other than chemical properties of fiber, density of fibers, surface treatment, filling coefficient, compressibility of fabric, etc. play a consequential role in thermal parameters of fabric [5, 6].

Softeners stick on the surface of fabric, and this leads to the modification of the surface. This modification is the rationale of change in thermal and sensorial parameters. It may be a blockage of pores, change in the rigidity, alteration in thermal conductivity and thermal resistance.

People are doing their best to develop instruments able to project the comfort of the textile material having a high correlation with the subjective evaluation. In spite of all efforts, significance of subjective evaluation cannot be underestimated [7, 8].

This study is restricted to measure impact of softeners on denim and comparison of cationic and silicone softeners. Selection of these two softeners is based on the common routine of the industry. During industry survey, it was observed that in most of the cases these two softeners are applied. Nevertheless, in some cases special softeners are also applied. Subjective evaluation of hand (THV) is major part of hand – warm/cool feeling. The results of subjective hand were compared with three objective measured thermal parameters [9]:

A) thermal conductivity λ [$W\,m^{-1}K^{-1}$]

Thermal conductivity (λ) describes the ability of material to allow transfer of heat from one meter square area trough a distance of one meter. Polymers have the lowest thermal conductivity, whereas, metals have the highest thermal conductivity. Thermal conductivity of softeners is different from the cotton since both have different chemical structure. Thermal conductivity of textile ranges from 0.033 to 0.1 [$W\,m^{-1}K^{-1}$].

B) thermal resistance R [m^2KW^{-1}]

Thermal resistance is calculated by using thermal conductivity (λ) and height (h) of the material.

$$R = h / \lambda \quad (1)$$

Above equation demonstrates that resistance depends upon the thermal conductivity and thickness of material. There is an inconsequential different in the thickness of fabric due to application of softeners. However, there is an undeniable difference in thermal conductivity, which will change the thermal resistance.

C) thermal absorbtivity b [$Ws^{1/2}m^{-2}K^{-1}$]

Thermal absorbtivity is an indicator of the warm and cool feeling of the material. It was introduced by Hes [9].

$$b = \sqrt{\lambda\rho c} \quad (2)$$

where b is the thermal absorbtivity, ρ is the fabric density and c is the specific heat capacity. Higher values of thermal absorbtivity indicate the cool feeling of the material in initial contact. The values of the thermal absorbtivity of textile materials lie is in the range from 20 to 600 [10].

Alambeta is an instrument which is commonly used to measure above mentioned thermal parameters was used for objective evaluation.

2 EXPERIMENTAL PART

2.1 Material

Two set of denim samples; traditional and novel denims were prepared (Table 1). These samples were passed through industrial washing and finally applied cationic and silicone softeners (Table 2) by using different textile auxiliaries (Table 3).

Table 1 Sample description

description	traditional denim	novel denim
warp Yarn	cotton	cotton
warp Textile	49.25	49.25
warp set [$yarns.cm^{-1}$]	27.17	27.95
weft Yarn	spun polypropylene	cotton
weft Textile	54.00	49.00
weft set [$yarns.cm^{-1}$]	18.90	18.90
weave	twill 3/1 Z	twill 3/1 Z
weight [$g.m^{-2}$]	236	230

Table 2 Industrial washing description

washing type	
desizing + H_2O_2 treatment + silicone softener	desizing was done using Lenitol EHDS (0.75ml/l), Sltafon D (0.375 ml/l) and Fortress ECO2 (0.5 ml/l) at 60°C for 15 min followed by rinsing with water at ambient temperature. Finally samples were treated with H_2O_2 (4 g/l) at 60°C for 5 min. After that applied silicone softener Rucofin GWE (3.75 g/l).
desizing + H_2O_2 treatment + cationic softener	desizing was done using Lenitol EHDS (0.75ml/l), Sltafon D (0.375 ml/l) and Fortress ECO2 (0.5 ml/l) at 60°C for 15 min followed by rinsing with water at ambient temperature. Finally samples were treated with H_2O_2 (4 g/l) at 60°C for 5 min. After that applied cationic softener Belfasin OET (4 g/l).

Table 3 Textile auxiliaries details

No.	name	description	manufacturer/supplier
1	Lenitol EHDS	amylase enzyme used for desizing	CHT, GMBH
2	Sltafon D	wetting agent	Mukashi Pakistan
3	Fortress ECO2	anti back-staining agent	Mukashi Pakistan
4	Belfasin OET	cationic softener	Cognis
5	Rucofin GWE	silicon softener	Rudolf Chemical

2.2 Subjective Evaluation

For the subjective evaluation following procedures has been adopted:

1. Subjective hand evaluation (THV) were realized using 7 degree ordinal scale (1 – hand is very bed, 4 – hand is average, 7 – hand is excellent)
2. Warm/cool feeling after 2 second contact between hand and textile was tested using 7 degree ordinal scale (1 – feeling is cool, 4 – feeling is average, 7 – feeling is warm)
3. A group of 30 people (18 males and 12 females) were formed. Majority of the group members were linked with textile industry and user of denim.
4. All evaluators were briefed about the process. The evaluation was realized without looking at the sample and so they were not affected by appearance of the samples. For this purpose a box with two small holes for hands was provided so that the judgers could evaluate the samples comfortable.
5. All investigations were made in the room under laboratory conditions.
6. The objective of the study is to find any diversity between the two sets of denim samples treated in two different ways (Table 2) with cationic and silicone softeners. Keeping it in view following questions were formed:
   a) What is your opinion about the overall hand of this sample?
   b) In initial two seconds, do you feel that the fabric is cool?

3 RESULTS AND DISCUSSION

3.1 Kendall's Coefficient of Concordance

Kendall's coefficient is a measure to assess the common ranks among the observers. It ranges from 0-1. If the coefficient is 1, it means that there is a complete agreement among the observers and if it is zero, it means that there is a no agreement among the group and people have diverse view about the product. Following procedure has been adopted to calculate Kendall's coefficient of concordance *W* [8]

$$W = \frac{12SSR}{K^2 n(n^2 - 1)} \tag{3}$$

where

$$SSR = \sum R^2 - \frac{(R)^2}{n}$$

where *R* is total of row (sum of values given by evaluator to two different sets of denims), *n* is number of items, *K* is number of sets of ranks.

Table 4 indicates that in all cases significance *K(n-1)w* is greater than the χ^2 values, which means that it can be rejected the null hypothesis, which claims that there is no common ranking. Values given in Table 4 provide enough information to conclude that there is a substantial agreement among the observers. It is an indicator that judgment is valid and since the degree of association among the observers is significant [8].

Table 4 Kendall's coefficient of concordance *W*

questions	SSR	W	K(n-1)W	$\chi^2_{0.05}(n-1)$
What is your opinion about the overall comfort of the sample? (traditional denim)	139.20	0.0041	1.796	0.0034
In initial two seconds, do you feel that fabric is cool? (traditional denim)	113.47	0.0034	1.464	0.0034
What is your opinion about the overall comfort of the sample? (novel denim)	161.87	0.0048	2.089	0.0034
In initial two seconds, do you feel that fabric is cool? (novel denim)	208.30	0.0062	2.688	0.0034

3.2 Median Comparison

Following procedure has been adopted for calculation of the estimation of the population median *Med* and its (1-α)% confidence interval [11]. At first the estimation of the median of ordinal scale *XM* is determined by formula

$$XM = Me + 0.5 - \frac{F_{Me} - 0.5}{f_{Me}} \quad (4)$$

where *Me* is median category which is defined by inequalities

$$F_{Me-1} < 0.5 \text{ and } F_{Me} \geq 0.5 \quad (5)$$

where: F_{Me} is cumulative relative frequency in median category and f_{Me} is relative frequency in median category. In following step values $F_D{}^*$ and $F_H{}^*$ are calculated

$$\left(F_D^*, F_H^*\right) = 0.5 \pm \frac{0.5u_{1-\frac{\alpha}{2}}}{\sqrt{n}} \quad (6)$$

where $u_{1-\alpha/2}$ is the quantile of standardized normal distribution. On the basis of these values correction *d* and *h* are determined

$$d = \frac{F_D^* - F_{D-1}}{f_D} \text{ and } h = \frac{F_H^* - F_{H-1}}{f_H} \quad (7)$$

Cumulative relative frequencies F_D and F_H are defined by inequalities

for F_D: $F_{D-1} < F_D^*$ and $F_D \geq F_D^*$

and for F_H: $F_{H-1} < F_H^*$ and $F_H \geq F_H^*$

100(1-α) confidence interval of *Med* is then given by

$$D - 0.5 + d \leq Med \leq H - 0.5 + h \quad (8)$$

Results of subjective hand evaluation using 11-degree ordinal scale are presented in Table 5. All calculations were carried out for α=0.05. From presented results can be derived following conclusions:

1. People prefer silicone treated denim as compared to cationic softener treated denim, but results are not statistically significant.
2. In the case of traditional denim, cationic treated denim gives a cooler feeling as compared to silicone treated denim. In case of novel denim, cationic treated denim gives the same cool feeling for both types of softeners.
3. Considering the above discussion, it can be concluded that people will prefer silicone treated denim if they are provided a chance to do the selection from the two different types of denim which are under testing.

3.3 Comparison based on gender

Evaluator group was consisting of male and female members. Mean comparison was conducted to identify any significant variation between male and female. Table 6 explains that in response of two asked questions, there is no significant different in the mean values of the two distinct groups.

3.4 Objective evaluation of thermal parameters

Denim samples were tested by using the Alambeta to measure thermal conductivity, thermal absorbtivity and thermal resistance.

Each sample was measured 5 times. Table 7 provides the mean value of the measured values. The variation coefficient for all tested samples does not exceeded 10%. Following conclusion can be derived from the Table 7:

1. In both cases, thermal conductivity of silicone treated denim is higher than that of the cationic treated denim, but the differences are not statistically significant at α=0.05.
2. In both cases thermal absorbtivity of the silicone treated denim is lower than at the cationic treated denim. It indicates that the silicone treated denim will provide less cool feeling as compared to the cationic treated one.
3. Thermal resistance of the silicone treated traditional denim is comparable with that of the traditional denim treated with cationic softener. Thermal resistance of novel denim treated with silicone softener is higher than thermal resistance of the novel denim treated with cationic softener.

Table 5 Median and 100(1-α) confidence interval

question	median *XM* (cationic softener)	confidence interval		median *XM* (silicone softener)	confidence interval	
		low	high		low	high
What is your opinion about the overall comfort of the sample? (traditional denim)	4.75	3.83	5.42	6.17	5.27	6.76
In initial two seconds, do you feel that fabric is cool? (traditional denim)	4.05	3.56	4.55	3.90	3.30	4.44
What is your opinion about the overall comfort of the sample? (novel denim)	5.17	4.76	6.06	5.50	4.90	6.17
In initial two seconds, do you feel that fabric is cool? (novel denim)	3.94	3.35	4.55	4.50	3.61	5.39

Table 6 Comparison among males and females by using ANOVA (traditional and novel denim)

	sum of squares	df	mean square	F	sig.
In initial two seconds, do you feel that fabric is cool?	2.812	1	2.812	1.611	0.207
What is your opinion about the overall comfort of the sample?	0.006	1	0.006	0.003	0.959

Table 7 Comparison of thermal conductivity, thermal absorbtivity and thermal resistance of traditional and novel denim

washing description	thermal conductivity [$Wm^{-1}K^{-1}$]	thermal absorbtivity [$Wm^{-2}s^{1/2}K^{-1}$]	thermal resistance [Km^2W^{-1}]
desized, bleach and applied silicon softener (traditional denim)	0.054	135.5	0.0206
desized, bleach and applied cationic softener (traditional denim)	0.051	139.5	0.0214
desized, bleach and applied silicon softener (novel denim)	0.050	135.5	0.0234
desized, bleach and applied cationic softener (novel denim)	0.049	155.5	0.0210

4 CONCLUSION

Subjective evaluation of overall comfort indicates that traditional and novel denim treated with silicone softener as compared to the denim treated with the cationic softener has a better hand feeling but differences are not statistically significant. Moreover, people feel that traditional denim treated with silicone softener is warmer as it was verified and it is verified by the results from the Alambeta, which gives lower values of thermal absorbtivity thus confirming warmer contact. Nevertheless, in case of novel denim we found a difference in the observation of people and values by the Alambeta, which indicates that people feel difficult to assess the warm-cool feeling in case of novel denim. In addition to the Alambeta values indicate that thermal conductivity of silicone treated of traditional and novel denim is higher than thermal conductivity achieved by the cationic softener.

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5 REFERENCES

1. Sülar V., Okur A.: Fibres & Textiles in EE 16, 2008, 61-68
2. Tzanov T., Betcheva R., Hardalov I. Hes L.: Text Res J 68, 1998, 749-755
3. Tzanov T., Betcheva R., Hardalov I.: Int J of Cloth Sci and Tech 11, 1999, 189-197
4. Hes L.: Ind J of Fib and Text R 38, 2008, 239-245
5. Oglakcioglu N., Marmaralali A.: Fibres & Textiles in EE 15, 2007, 64-65
6. Das A., Kothari V.K., Sadachar A.: Fibers and Polymers 8, 2007, 116-122
7. Ozcelik G., Supuren G., Tulay G., Tarakcioglu I.: Fibres & Textiles in EE 16, 2008, 52-62
8. Dobilaitė V., Petrauskas A.: Fibres & Textiles in EE 10, 2002, 53-55
9. Hes L.: Thermal properties of nonwovens, In Proceedings of Congress Index 87, Gent. 1987
10. Hes L.: Thermal Comfort Properties of Textile Fabrics in Wet State, In Proceedings of The 11th International Izmir Textile & Apparel Symposiom, Izmir, 2007
11. Řehák J., Řeháková B.: The Categorical Data Analysis in Social Sciences (in Czech) (Academia, Prague), 1986, 86-95

VLIV DVOU TYPŮ ZMĚKČOVADEL A SLOŽENÍ ÚTKU NA TEPELNÉ CHARAKTERISTIKY KOMFORTU DENIMŮ

Translation of the article

Effect of two types of softeners and weft composition on thermal comfort characteristics of denim fabrics

Výrobci denimů používají pro zlepšení vlastností textilní pomocné přípravky. Toto zpracování ovlivňuje senzorické a tudíž i tepelné složky komfortu. V článku je popsán vliv dvou typů změkčovadel na hodnocení omaku a na tepelné charakteristiky komfortu (tepelnou vodivost, tepelnou jímavost a tepelný odpor) u denimových tkanin, kde jedna tkanina má v útku bavlněnou a druhá polypropylénovou přízí. Výsledky ukazují, že u materiálů, kde bylo použito silikonové změkčovadlo, jsou tkaniny hodnoceny lépe než u tkanin, které byly změkčeny kationtovým změkčovadlem. Avšak rozdíly v hodnocení jsou statisticky nevýznamné.

AN ALTERNATIVE APPROACH TO HAND PREDICTION USING ORDINAL LOGISTIC REGRESSION

ALTERNATIVNÍ PŘÍSTUP K PREDIKCI OMAKU S VYUŽITÍM ORDINÁLNÍ LOGISTICKÉ REGRESE

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Abstract: *The new model for objective hand evaluation is presented. The model is based on 8 properties. The most of them are possible to measure on standard instruments which are in textile laboratories. The prediction equation was created by means of ordinal logistic regression. The proposed model BM11 was compared wih model KES11 in which the properties from KES were applied. The results show that both models have simile ability of prediction.*
Keywords: *hand evaluation, ordinal logistic regression, KES*

Abstrakt: *V předloženém příspěvku je navržen model pro predikci hodnocení omaku. Pro konstrukci modelu bylo použito 8 vlastností, jichž většinu lze měřit na přístrojích, které se nacházejí standardně v textilní laboratoři. Predikční rovnice byla vytvořena s použitím ordinální logistické regrese. Navržený model BM11 byl porovnán s modelem KES11, který využívá 16 vlastností měřených na systému KES. Výsledky ukazují, že oba modely mají obdobnou predikční schopnost.*
Klíčová slova: *hodnocení omaku, ordinální logistická regrese, KES*
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1. Úvod

Jedním ze základních kontaktních projevů textilií je "omak". V pracech [1,2] atd. bylo prokázáno, že se jedná o komplexní vlastnost, k jejímuž vyhodnocení dochází na základě ohodnocení tzv. primárních složek (např. tuhost, drsnost atd.) spolu s porovnáním vlastních zkušeností. Jedná se o psychofyzikální vlastnost, kdy o výsledku hodnocení rozhodují nejen materiálové složení, konstrukce textilie, úpravy, vzhled atd., ale také zkušenost, původ, citlivost kontaktního místa hodnotitele (při hodnocení nejčastěji prstů a dlaní) a v neposlední řadě i jeho momentální duševní rozpoložení. Z uvedeného plyne, že definování omaku jednoznačným způsobem je obtížné. Termín "omak" není jednoznačně definován. Jedná se v podstatě o pocit, který je vyvolán textilií při jejím kontaktu s pokožkou. Něktré z definic lze nalézt v [3].

2. Objektivní predikce omaku

Subjektivní hodnocení omaku je časově a organizačně velmi náročné. Pro zajištění reprudukovatenosti a opakovatelnosti je zapotřebí řešit řadu základních problémů spojených s experimentem, jež jsou zmíněny např v [3,4]. Proto byla navržena řada postupů, které mají usnadnit a zrychlit hodnocní omaku. Jsou postaveny na měření fyzikálěmechanických vlastností, které mají vztah k subjektivnímu hodnocení omaku, a následném vytvoření predikční rovnice [1, 5, 6, 7, 8]. Metody tak umožňují objektivní predikci omaku.

2.1. **Systém KES**

V současné době nejrozšířenějším systémem je systém KES. Byl vytvořen pro objektivní predikci omaku textilií, zejména tkanin. Sestává se ze sady 4 přístrojů, které měří 15 vlastností rozdělených do 6 skupin (tahové, smykové, ohybové, objemové, povrchové, geometrické) v rozsazích simulující běžné namáhání oděvních textilií při nošení, šestnáctou vlastností, která se používá při predikci omaku je plošná hmotnost [mg/cm^2] a je začleněna mezi geometrické vlastnosti (tabulka I) [1].

Tabulka I. Přehled vlastností měřených na systému KES

tahové:		objemové:	
LT:	linearita [-]	*LC*:	linearita [-]
WT:	deformační energie [N.cm/cm^2]	*WC*:	energie potřebná ke stlačení [N.cm/cm^2]
RT:	pružnost v tahu [%]	*RC*:	pružnost [%]
ohybové:		povrchové:	
B:	tuhost v ohybu na jednotku délky [N.cm^2/cm]	*MIU*:	koeficient tření [-]
2HB:	moment hystereze na jednotku délky [N.cm/cm]	*MMD*:	průměrná odchylka MIU[-]
		SMD:	geometrická drsnost [μm]
smykové:		geometrické:	
G:	tuhost ve smyku [N/cm.stupeň]	*W*:	plošná hmotnost [mg/cm^2]
2HG:	hystereze při úhlu smyku ϕ =0,5° [N.cm]	*T0*:	tloušťka [mm]
2HG5:	hystereze při úhlu smyku ϕ =5° [N.cm]		

Naměřené hodnoty jsou zpracovány následujícím způsobem:

1. Standardizace naměřených hodnot a výpočet objektivní predikce primárních složek omaku

$$y_j = C_{0j} + \sum_{i=1}^{16} C_{ij} \frac{x_i - \bar{x}_i}{\sigma_i}, \qquad (1)$$

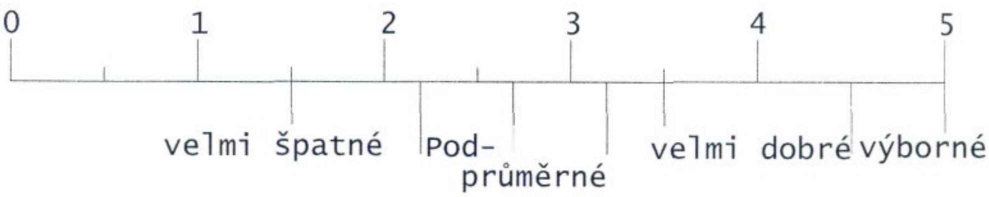
kde y_j je predikce primární složky omaku, x_i je i-tá vlastnost nebo její desítkový logaritmus, $\bar{x}_i$ a σ_i je průměr a směrodatná odchylka i-té vlastnosti, C_{0i} a C_{ij} regresní koeficienty i-té charakteristiky a j-té primární složky omaku.

2. Výpočet celkového omaku *THV(O)* podle vztahu

$$THV(O) = C'_0 + \sum_{j=1}^{3} \left[C'_{j1} \left(\frac{y_j - M_{j1}}{\sigma'_{j1}} \right) + C'_{j2} \left(\frac{y_j^2 - M_{j2}}{\sigma'_{j2}} \right) \right], \qquad (2)$$

kde C'_0, C'_{j1}, C'_{j2} jsou regresní koeficienty, M_{j1}, M_{j2}, σ_{j1}, σ_{j2} jsou průměry a směrodatné odchylky y_j a y^2_j.

3. Výslednou hodnotu objektvní predikce lze následně slovně interpretovat (obrázek 1).



Obr. 1 Slovní popis objektivní predikce omaku podle výsledků měření na KES.

Hodnoty $\bar{x}_i$ a σ_i jsou tabelovány pro jednotlivé typy tkanin podle účelu použití [1]. Pro vlastní výpočet byly použity konstanty KN-101-WINTER pro pánské oblekovky. Navrhovaný model je označen KES11.

2.2. Objektivní predikce omaku technikou BM

Systém BM byl navržen z důvodu přiblížení se běžným podmínkám v laboratořích. Jeho výhoda spočívá v tom, že většinu vlastností lze měřit na běžně dostupných přístrojích v laboratořích. Kromě toho zahrnuje takové vlastnosti, které korespondují se všemi 4 centry omaku [2]. Při výběru vlastností byly také brány v úvahu výsledky prací [5, 6, 9, 10].

Tabulka II. Vlastnosti techniky BM

vlastnosti související s centrem povrchové hladkosti a *nerovnosti:* *MAD:* průměrná absolutní odchylka [mN]	vlastnosti související s centrem objemových vlastností (*objem, hmotnost, tvar*) *b:* tepelná jímavost [W/ (m^2 K^1 s$^{-0,5}$)]
vlastnosti související s centrem tuhosti a poddajnosti *Y:* modul pružnosti [MPa] *T:* tuhost [mN cm] *Y45:* modul pružnosti po diagonále - soustava nití pootočena o úhel 45° vzhledem ke směru posuvu příčníku [MPa]	vlastnosti související s centrem objemových vlastností (objem, hmotnost, tvar) *S:* stlačitelnost [-] *t:* tloušťka [mm] *M:* plošná hmotnost [g/m^2]

V případech, kdy závisle proměnná pochází z ordinální škály a může-li, nabývat více 2 hodnot, lze pro konstrukci regresního modelu použít ordinální logistickou regresi [11]. Nejčastěji se používá model proporcionálních šancí, který má tvar [11, 12]

$$CL_k = \ln\left[\frac{P(y \le k)}{P(y > k)}\right] \tag{3}$$

kde k=1,2,.....K je pořadové číslo třídy. Řešení modelu proporcionálních šancí vede ke K-1 regresím rovnicím, které se liší pouze v hodnotě absolutního členu

$$\ln\left[\frac{P(y \le k)}{P(y > k)}\right] = b_{k,0} + \mathbf{b}^{\mathrm{T}}\mathbf{x} \tag{4}$$

Výsledná soustava regresních rovnic má tvar

$$P(y = k) = \frac{1}{1+\exp(b_{k,0}+\sum_{p=1}^{P} b_p x_p)} \tag{5}$$

kde P je počet nezávisle proměnných. Závisle proměnná je zařazena do té třídy, pro kterou vyjde pravděpodobnost přiřazení jako maximální.

Při subjektivním hodnocení omaku se nejčastěji používá právě 5-ti až 11-ti stupňová ordinální škála, takže z tohoto hlediska může být ordinální logistická regrese použita. Obecně logistická regrese vyžaduje jednoznačné přiřazení závisle proměnné do příslušné třídy. Z podstaty subjektivního hodnocení omaku, který patří mezi senzorické metody, je textilie hodnocena více hodnotiteli, kteří jsou při svém hodnocení ovlivněny různými faktory. Textilie je zařazena do několika kategorií s různou četností. Tak dochází k nejednoznačné klasifikaci hodnocené textilie. Z tohoto důvodu pro tvorbu modelu je použit odhad parametru polohy - mediánová kategorie M, která je definována

$$F_{M-1} < 0{,}5 \qquad \text{a} \qquad F_M \geq 0{,}5 \tag{6}$$

kde F_S představuje kumulativní relativní četnost (*S*=*M* resp. *M-1*). Výsledek objektivní predikce omaku *THV(O)=k* ukazuje, že přibližně 50% hodnotitelů bude hodnotit omak do mediánové třídy a lépe a druhých přibližně 50% hodnotitelů bude hodnotit omak do této třídy a hůře.
Pro testování významnosti regresních koeficientů b_p lze použít Waldovu testovou statistiku

$$W_{a,p} = \left(\frac{b_p}{s(b_p)} \right)^2 \tag{7}$$

která má rozdělení χ^2 s jedním stupněm volnosti.
Při určování významnosti modelu jako celku se používá odchylka G^2, kde se porovnává maximální věrohodnost modelu, který obsahuje pouze absolutní člen L_0 a maximální věrohodnost modelu L_M, čili testuje se, zda všechny odhadované regresní parametry β_p jsou rovny nule kromě koeficientů $\beta_{k,0}$.

$$G^2 = -2(\ln L_0 - \ln L_M) \tag{8}$$

Odchylka G^2 má χ^2 rozdělení s *P-1* stupni volnosti. Čím je hodnota nižší, tím je model jako celek významnější a proložení je těsnější. Pokud je pravděpodobnost menší než 0,01, považuje se model jako celek za statisticky významný. Nevýhodou je, že G^2 vede vždy ke zlepšení přidáním další vlastnosti. K eliminaci tohoto vlivu lze použít Bayesovo informační kriterium *BIC* nebo Akaikovo informační kriterium *AIC* [11, 12]

$$BIC = G^2 - df \ln N \tag{9}$$

$$AIC = \frac{-2\ln L_M + 2P}{N} \tag{10}$$

Navrhovaný model byl označen BM11.

3. Výsledky a diskuze

Ověření navržené techniky BM bylo realizováno na souboru 90 tkanin, kreré se pužívají na výrobu pánských oblekovek. Základní parametry tkanin jsou uvedeny v Tabulce III.

Tabulka III. Rozsah základních parametrů hodnocených tkanin.

hmotnost	g/m^2	140 - 370
dostava - osnovy - útku	nití/10 cm	170 - 560 150 - 370
základní typy složení	100% vlna, 45/55 vlna/PL, vlna/PL/PA	
základní typy vazeb	převážně různé typy keprů, plátno,	

Soubor testovaných tkanin byl zařazován pomocí panelu 40 respondentů do 11 tříd (*k*=1 – omak je velmi nepříjemný, *k*=6 omak je průměrný, *k*=11omak je velmi příjemný). Při volbě 11-ti stupňové škály se vycházelo z postupu tvorby predikčních rovnic, které jsou použity pro

objektivní predikci omaku u systému KES, kde tvůrci systému KES pro tvorbu predikčních modelů použili při subjektivním hodnocení omaku jedenácti stupňovou ordinální škálu. Proto byl vytvořen také model na základě této stupnice.
Výsledné počty zařazení jednotlivých tkanin do mediánových kategorií jsou uvedeny v tabulce IV.

Tabulka IV. Počty zařazených tkanin podle mediánových tříd.

číslo třídy	počet zařazených tkanin
1	0
2	2
3	11
4	8
5	16
6	17
7	19
8	8
9	5
10	4
11	0

Z tabulky IV plyne, že do krajních tříd podle hodnoty mediánové třídy nebyla zařazena žádná tkanina. V případě, že by byla predikcí tkanina zařazena do třídy č. 2 nebo 10 je zapotřebí výsledek interpretovat trochu odlišně. Pro případ zařazení do druhé třídy platí, že výrazně přes 50% hodnocení může být i ve třídě 1. Obdobná interpretace platí i pro případné zařazení tkaniny predikcí do třídy č. 10, tj. že výrazně přes 50% hodnocení může být zařazeno i ve třídě 11. Do tříd č. 2, 9 a 10 bylo zařazeno málo tkanin, proto je při tvorbě závěrů při zařazení objektivní predikcí do těchto tříd přistupovat obezřetně.
Pro účely tvorby predikční rovnice byly zjištěné výsledky rozděleny v poměru 8:1, tj., výsledky 80 tkanin (analyzovaný soubor) byly použity pro vytvoření predikčních rovnic KES11 a BM11 a výsledky 10 tkanin (klasifikovaný soubor) byly použity pro ověření jejich predikčních schopností.
Výsledky zařazení analyzovaného souboru jsou uvedeny v tabulce IVa (model KES11) a v tabulce V (model BM11).

Tabulka IVa. Výsledky zařazení do tříd pro model KES11.

naměřené hodnoty omaku	predikované hodnoty omaku									procento správně zařazen. objektů
	THV (O)=2	*THV (O)*=3	*THV (O)*=4	*THV (O)*=5	*THV (O)*=6	*THV (O)*=7	*THV (O)*=8	*THV (O)*=9	*THV (O)*=10	
THV=2	**1**	0	1	0	0	0	0	0	0	50,0
THV=3	0	**9**	0	0	0	0	0	0	0	100
THV=4	0	1	**5**	1	0	0	0	0	0	71,4
THV=5	0	0	2	**9**	4	0	0	0	0	60,0
THV=6	0	0	0	3	**8**	4	0	0	0	53,3
THV=7	0	0	0	3	2	**9**	3	0	0	52,9
THV=8	0	0	0	1	0	2	**5**	0	0	62,5
THV=9	0	0	0	0	0	0	3	**1**	0	25,0
THV=10	0	0	0	0	0	0	0	1	**2**	66,7

V modelu KES11 bylo správně zařazeno 49 tkanin (61%). Výsledky subjektivního hodnocení omaku ukazují u většiny tkanin intervalový odhad mediánu přesahující hodnotu 1, a tudíž by mediánovou třídou mohly být i třídy sousedící s ní. Vezme-li se toto v úvahu, tak do tříd $M\pm 1$

bylo zařazeno modelem KES11 75 tkanin (94%). Vytvářený model o více než jednu třídu zařadil 5 tkanin. O 2 třídy byly chybně zařazeny 4 tkaniny a o 3 třídy došlo ke špatnému zařazení u jedné tkaniny.

Tabulka V. Výsledky zařazení do tříd pro model BM11.

naměřené hodnoty omaku	Predikované hodnoty omaku									procento správně zařazen. objektů
	THV (O)=2	*THV (O)*=3	*THV (O)*=4	*THV (O)*=5	*THV (O)*=6	*THV (O)*=7	*THV (O)*=8	*THV (O)*=9	*THV (O)*=10	
THV=2	**0**	2	0	0	0	0	0	0	0	0,0
THV=3	0	**8**	1	0	0	0	0	0	0	88,9
THV=4	0	1	**3**	3	0	0	0	0	0	42,9
THV=5	0	1	2	**9**	3	0	0	0	0	60,0
THV=6	0	0	0	1	**11**	3	0	0	0	73,3
THV=7	0	0	0	3	0	**13**	1	0	0	76,5
THV=8	0	0	0	0	1	2	**4**	1	0	50,0
THV=9	0	0	0	0	0	0	2	**1**	1	25,0
THV=10	0	0	0	0	0	0	1	1	**1**	33,3

U modelu BM11 bylo s chybou větší než $M\pm1$ zařazeno 6 tkanin a to o 2 třídy. Správně bylo zařazeno 50 tkanin (62%) a spolu s chybou jedné třídy 74 (92%).

Odhady koeficientů pro model KES11 (tabulka VI.) ukazují, že vlastnosti *LT*, *RT*, *G*, *2HG*, *B*, *2HB*, *WC*, *RC*, *T0*, *MIU* a *MMD* jsou významné na hladině významnosti 0,05. Z koeficientů lze na hladině významnosti 0,05 považovat za nenulové koeficienty b_3, b_4, b_6, b_7, b_9 a b_{10}.

U modelu BM11 (tabulka VII) výsledky ukazují, že lze za významné považovat vlastnosti *b*, *T*, *t*, *M*, *S* a *MAD* a z regresních koeficientů koeficienty b_2, b_3, b_4, b_5 *a* b_6.

Tabulka VI. Odhady koeficientů pro model KES11 a vliv jednotlivých proměnných.

proměnná	χ^2	spočtená hladina významnosti	regresní koeficient	odhad	Waldova statistika	spočtená hladina významnosti
			$b_{2,0}$	-22,615	2,43	0,12
			$b_{3,0}$	-18,603	1,44	0,23
			$b_{4,0}$	-15,521	0,99	0,32
			$b_{5,0}$	-11,660	0,50	0,48
			$b_{6,0}$	-9,644	0,26	0,61
			$b_{7,0}$	-6,879	0,12	0,73
			$b_{8,0}$	-4,949	0,79	0,37
			$b_{9,0}$	-3,382	0,37	0,54
LT	**7,17**	**<0,01**	b_1	6,853	0,25	0,62
WT	<0,01	0,92	b_2	-0,058	0,90	0,34
RT	**30,86**	**<0,01**	b_3	**-0,049**	**5,43**	**0,02**
G	**6,43**	**0,01**	b_4	**2,607**	**7,46**	<0,01
2HG	**16,17**	**<0,01**	b_5	-7,601	3,56	0,06
2HG5	1,01	0,31	b_6	**3,952**	**4,47**	**0,03**
B	**6,80**	<0,01	b_7	**66,631**	**16,44**	<0,01
2HB	**7,98**	<0,01	b_8	-117,318	0,92	0,34
LC	0,01	0,91	b_9	**33,852**	**6,32**	**0,01**
WC	**24,29**	<0,01	b_{10}	**-21,236**	**12,73**	**<0,01**
RC	**12,04**	<0,01	b_{11}	-0,175	0,40	0,53
T0	**19,73**	<0,01	b_{12}	36,083	3,51	0,06
MIU	**6,50**	**0,01**	b_{13}	-18,009	0,79	0,37
MMD	**6,08**	**0,01**	b_{14}	-69,409	1,65	0,20
SMD	0,30	0,58	b_{15}	-0,130	2,43	0,12
W	1,67	0,20	b_{16}	-0,324	1,44	0,23

Tabulka VII. Odhady koeficientů pro model BM11 a vliv jednotlivých proměnných.

proměnná	$\chi 2$	spočtená hladina významnosti	regresní koef.	odhad	Waldova statistika	spočtená hladina významnosti
			$b_{2,0}$	-20,2257	8,78872	0,003031
			$b_{3,0}$	-14,3397	4,91378	0,026643
			$b_{4,0}$	-11,2911	3,32509	0,068230
			$b_{5,0}$	-7,4124	1,52366	0,217067
			$b_{6,0}$	-5,1923	0,75531	0,384801
			$b_{7,0}$	-2,3763	0,16000	0,689153
			$b_{8,0}$	-0,1557	0,00067	0,979393
			$b_{9,0}$	1,4162	0,05407	0,816132
b	35,68051	0,000000	b_1	-0,0360	3,83749	0,050118
T	48,18058	0,000000	b_2	0,4304	4,07187	0,043603
t	42,27711	0,000000	b_3	7,1264	4,31738	0,037725
M	6,86684	0,008781	b_4	0,0401	11,96527	0,000542
S	6,33712	0,011824	b_5	-17,7979	5,80684	0,015964
MAD	17,33830	0,000031	b_6	0,6674	14,66913	0,000128
Y45	0,19828	0,656114	b_7	0,0182	0,61513	0,432862
Y	0,67213	0,412309	b_8	-0,0012	0,72063	0,395936

Ověření navrženého modelu bylo realizováno na druhé skupině dat - klasifikovaném výběru, tj. na datech, která nebyla použita pro tvorbu modelu. Výsledky predikčních schopností jsou uvedeny v tabulce VIII. Vytvořený model KES11 správně zatřídil 2 z 10 tkanin tj. 20% tkanin. Vytvořený model BM11 správně zatřídil 6 z 10 tkanin tj.60% tkanin. Vezme-li se v úvahu možnost tolerovat chybné zařazení *M±1* třída, tak model KES11 správně zařadil 80% tkanin. Model BM11 zařadil správně všechny tkaniny.

Tabulka VIII. Ověření predikčních schopností modelů.

vzorek	*THV_11*	výsledek KES11	odchylka	vzorek	*THV_11*	výsledek BM11	odchylka
T117	6	6		T117	6	7x	+1
T118	4	2	-2	T118	4	4	
T135	3	4	1	T135	3	3	
T136	9	8	-1	T136	9	8x	-1
T153	5	5		T153	5	5	
T154	3	4	-1	T154	3	3	
T171	6	5	1	T171	6	6	
T172	7	9	+2	T172	7	7	
T189	10	9	-1	T189	10	9x	-1
T190	7	6	-1	T190	7	6x	-1

Spočtené hladiny významnosti *p* pro oba modely mají hodnotu menší než 0,01 (tabulka IX), což indikuje, že modely lze považovat za významné. Deviance G^2 ukazuje, že model KES11 je lepší než BM11. Provede-li se však eliminace vlivu počtu vlastností, vyjde závěr opět nejednoznačně. Bayesovo informační kriterium *BIC* je u modelu KES11 nižší než u modelu BM11, avšak u Akaikova informačního kritéria *AIC* je tomu naopak. Pomocí uvedených indikátorů kvality modelu nelze jednoznačně určit, který z modelů je lepší.

Tabulka IX. Výsledky analýzy modelů

charakteristika	KES11	BM11
G^2	147,06	157,55
p	0,00	0,00
BIC	81,55	124,80
AIC	-2,35	-2,44

4. Závěr

Existuje celá řada přístupů k predikci omaku. Pro konstrukci všech typů predikčních rovnic se využívá vlastností, které mají vztah k subjektivnímu hodnocení omaku. Navržený model BM11 ukazuje, že lze predikovat hodnocení omaku s pomocí vlastností, které lze měřit s využitím standardních přístrojů. Predikční schopnost navrženého modelu je srovnatelná s výsledky získanými měřením na systému KES.

Literatura

[1] Kawabata, S. *The Standardisation and Analysis of Hand Evaluation*, The Textile Machinery Society of Japan, Osaka, (1980)

[2] Lundgren, H.P. New Concepts I Evaluating Fabric Handle. Textile *Chemistry Colorimetry*. 1969, roč.1, s. 35-45

[3] Bishop, D.P. Fabric: Sensory and Mechanical Properties, *The Textile Progress*, **26** (1996), No. 1, pp. 1-62

[4] Bajzík, V. Objektivní predikce omaku s využitím ordinální logistické regrese. In: *REQUEST 09*, Technická univerzita v Liberci, 2010, s. 4-11

[5] Raheel, M., Lin, J.: An Empirical Model for Fabric Hand. Part I: Objective Assesment of Light Weight Fabrics,*Textile Research Journal*, **61** (1991), No. 1, pp. 31-36

[6] Pan, N., Yen, K.C., Zhao, S.J., Yang S.R.: A New Approach to the Objective Evaluation of Fabric Handle from Mechanical Properties. Part I: Objective Measure for Total Handle, *Textile Research Journal*, **58** (1988), No. 8, pp. 438-444

[7] Strazdiene, E., Gutauskas, M.: New Method for the Objective Evaluation of Textile hand, *Fibres & Textiles in Eastern Europe*, **13** (2005), No. 2, pp. 35-38

[8] Meie, L.V Xiaoan, S., Li, Z. A Study of Method of Measuring and Evaluting Fabric Handle. In: *Textile Science 91*, Technická univerzita v Liberci , 1992. s. 41-50

[9] Behery H.M. *Effects of Mechanical and Physical Properties on Fabric Hand*. Cambridge:Woodhead Publishing Limited. 1. vyd. 2005. ISBN 978-85573-918-5

[10] Militký, J., Bajzík, V. Surface Roughness of Heat Protective Clothing Textiles. *International Journal of Clothing Science and Technology*. 2003. roč. 13. č. 3/4, s. 258-267

[11] Powers, D. Xie, Y. *Statistical Methods for Categorical data Analysis*. San Diego: Academic Press. 1. vyd. 2000. ISBN 0-12-563736-5

[12] Hebák, P. a kol.*Vícerozměrnmé statistické metody – 3. díl*. Praha: Informatorium. 1. vyd. 2005. ISBN 80-7333-039-3

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Surface roughness of heat protective clothing textiles
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Surface roughness of heat protective clothing textiles

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Keywords *Surface roughness, Measurement, Fractals*

Abstract *The surface roughness is one of the main parts of hand prediction. Classical method of surface roughness measurements is based on the surface profile measurement. Characteristic of roughness is then variation coefficient of surface profile (surface height variation). The main aim of this work is to estimate the surface profile complexity by using variogram (structure function). The surface profile variation is classified to the group according to short- and long-range dependence. The concept of fractal dimension is proposed especially for long-term correlation cases. The applicability of the proposed approach is demonstrated on the typical heat protective clothing fabrics and compared with the results of surface roughness evaluated by the KES system.*

1. Introduction

Roughness of engineering surfaces has been traditionally measured by the stylus profiling method creation of surface profile called surface height variation (SHV) trace (Vandenberg and Osborne, 1992). This profile characterizes thickness (height) variation in selected direction. Modern methods are based on the image processing of surface images (Zhang and Gopalakrishnan, 1996). Surface irregularity of plain textiles has been identified by friction (Ajayi, 1992), contact blade (Ajayi, 1994; Kawabata, 1980), lateral air flow (Ajayi, 1988), step thickness meter (Militký and Bajzík, 2000) or subjective assessment (Stockbridge *et al.*, 1957).

Standard methods of surface profile evaluation are based on the relative variability characterized by the variation coefficient (analogy with evaluation of yarn's mass unevenness) (Meloun *et al.*, 1992) or simply by the standard deviation. This approach is used in Shirley software for evaluation of results for step thickness meter (Operation Manual, 1999). Characterization of roughness based on the mean absolute deviation (MAD) is the classical descriptive statistical approach. This statistical characteristic is useful for random SHV traces, where elements of SHV trace are statistically independent of each other. The SHV profile of a lot of fabrics has been identified as irregular and more structured. The descriptive statistical approach based on the assumptions of independence and normality leads to biased estimators if the SHV has short- or long-range correlations (Meloun *et al.*, 1992). Therefore, it is necessary to distinguish between standard *white Gauss noise* and more complex models. For description of short range correlations, the models based on the *autoregressive*

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moving average are useful (Quinn and Hannan, 2001). The long-range correlations are characterized by the *fractal models* (Constantine and Hall, 1994; Mandelbrot and Van Ness, 1968). The *deterministic chaos* type models are useful for revealing chaotic dynamic in deterministic processes, where variation appears to be random, but in fact they are predictable (Ott *et al.*, 1994).

For the selection among the above-mentioned models, the power spectral density (PSD) curve evaluated from experimental SHV can be applied (Eke *et al.*, 2000). Especially, the fractal models are widely used for rough surface description (Whitehouse, 2001). For these models the dependence of log (PSD) on the log (frequency) should be linear. Slope of this plot is proportional to *fractal dimension* and intercept to the so-called *topothesy*. For, white noise has dependence of log(PSD) on the log(frequency) nearly horizontal plateau for all frequencies (the ordinates of PSD are independent and exponentially distributed with common variance (Ott *et al.*, 1994)). More complicated rough surfaces as a result of grinding can be modelled by the Markov type processes (Sacerdotti *et al.*, 2000). For these models the dependence of log(PSD) on the log(frequency) has plateau at small frequencies than bent down and are nearly linear at high frequencies.

The fractal type models were criticized by Whitehouse (2001), who concluded that the benefits are more virtual than real. On the other hand, the deeper analysis of rough surface should use a more complex model than the classical descriptive statistics. Greenwood (1984) proposed a technique based on the definition of local maxims (peaks) and derivation of peaks height distribution. A lot of recent works is based on the assumption that the stochastic process (Brownian motion) can describe thickness variation (Nayak, 1971). This work is devoted to the analysis of load required to move the blade on fabric surface $R(d)$ obtained from new accessory to tensile testing machine.

2. Surface profile evaluation

Kawabata (1980) constructed a measuring device for registering the SHV trace. The main part of this device is the contactor in the form of wire (diameter 0.5 mm). This contactor is moved at a constant rate 0.1 cm/s and SHV is registered on the paper sheet. The sample length, $L = 2$ cm is used. Characterization of roughness is based on the MAD (the classical descriptive statistical approach).

Similar approach is based on the measurement of $R(d)$ by Shirley step meter with replacement of measuring head by blade (Militký and Bajzík, 2001). We have constructed the simple accessory to the tensile testing machine. The principle is registration of the force $F(d)$ needed for tracking the blade on the textile surface. Roughly speaking, the $F(d)$ should be inversely proportional to the $R(d)$. In reality, the $F(d)$ profile is different due to small surface; deformation caused by the tracked blade. Output from measurements is sequence of loads $F(d_i)$. Variation of thickness $R(d_i)$ or loads $F(d_i)$ can be generally assumed as combination of random fluctuations (uneven threads, spacing between yarns, non-uniformity of production etc.) and periodic fluctuations caused by the repeated patterns (twill, cord, rib etc.) created by weft and warp yarns. For the description of roughness the characteristics computed from $R(d)$ or $F(d)$ in places $0 < d < T$ (T is maximum investigated sample length and M is number of places) are used. Especially, for weaves it is necessary to identify periodic component in $R(d)$ or $F(d)$ as well. For this purpose, the spectral analysis can be useful.

3. Surface roughness description

From the SHV or SFV trace it is possible to evaluate a lot of roughness parameters. Let us define roughness characteristics for SHV (the same equations are also valid for SFV). Classical roughness parameters are based on the set of points $R(d_j), j = 1 \ldots M$ defined in the sample length interval L. The measurement points d_j are obviously selected as equidistant and then $R(d_j)$ can be replaced by the variable R_j. For the identification of positions in length scale, it is sufficient to know sampling distance $d_s = d_j - d_{j-1} = L/M$ for $j > 1$. The standard roughness parameters used frequently in practice are (Wu, 2000):

MAD. This parameter is equal to the mean absolute difference of surface heights from average value (R_a). For a surface profile, this is given by:

$$\mathrm{MAD} = \frac{1}{M} \sum_j |R_j - R_\mathrm{a}| \tag{1}$$

This parameter is often useful for quality control. However, it does not distinguish between profiles of different shapes. Its properties are known for the case when R_j's are independent identically distributed (iid) random variables.

Standard deviation (root mean square) value (SD). This is given by:

$$\mathrm{SD} = \sqrt{\frac{1}{M} \sum_j (R_j - R_\mathrm{a})^2} \tag{2}$$

Its properties are known for the case when R_j's are iid random variables. One advantage of SD over MAD is that for normally distributed data is simplicity of computation of confidence interval and realization of statistical tests. SD is always higher than MAD and for normal data $\mathrm{SD} = 1.25\,\mathrm{MAD}$. It does not distinguish between profiles of different shapes as well. The parameter SD is less suitable than MAD for monitoring certain surfaces having large deviations (corresponding distribution has heavy tail).

Mean height of peaks (MP). This is calculated as the average of the profile deviations above the reference value R (often $R = R_\mathrm{a}$). It is given as mean value of peaks P_i, $i = N_p$ where:

$$P_i = R_i - R \text{ for } R_i - R > 0 \text{ and } P_i = 0 \text{ elsewhere}$$

Mean height of valleys (MV). This is calculated as the average of the profile deviations below the reference value R (often $R = R_a$). It is given as mean value of valleys V_i, $i = N_v$ where:

$$V_i = R - R_i \text{ for } R_i - R < 0 \text{ and } V_i = 0 \text{ elsewhere}$$

The parameters MP and MV give information on the profile complexity. Exceptional peaks or valleys are not considered, but are useful in tribological applications.

The SD of profile slope (PS). This is given by:

$$PS = \sqrt{\frac{1}{M}\sum_j \left(\frac{dR(x)}{dx}\right)_j^2} \tag{3}$$

The SD of profile curvature (PC). This quantity often called as waviness is defined by the similar way:

$$PC = \sqrt{\frac{1}{M}\sum_j \left(\frac{d^2R(x)}{dx^2}\right)_j^2} \tag{4}$$

The slope and curvature are characteristics of a profile shape. The PS parameter is useful in tribological applications. The lower the slope the smaller the friction and wear. Also, the reflectance property of a surface increases in the case of small PS or PD.

Mean slope of the profile (MS). This is given by:

$$MS = \frac{1}{M}\sum_j \left|\frac{dR(x)}{dx}\right|_j \tag{5}$$

Mean slope is an important parameter in several applications such as in the estimation of sliding friction and in the study of the reflectance of light from surfaces.

Ten point average (TP). This characteristic is defined as the average difference between the five highest peaks and five deepest valleys within a surface profile. The parameter TP is sensitive to the presence of high peaks or deep scratches in the surface and is preferred for quality control purposes.

These parameters are useful in the case of functional surfaces or for characterizing surface bearing and fluid retention and other relevant properties. For, the characterization of hand will probably be the best to use waviness PC. The characteristics of slope and curvature can be computed for the case of fractal surfaces from power spectral density, autocorrelation function or variogram. A set of parameters for profile and surface characterization are collected in (Nayak, 1971).

There exist a vast number of empirical profile or surface roughness characteristics suitable often in very special situations. Some of them are closely connected with characteristics computed from fractal models (fractal dimension and topothesy). Greenwood (1984) proposed a general theory for description of surface roughness based on the distribution of heights. The most common way to separate roughness and waviness is spectral analysis. This analysis is based on the Fourier transformation from space domain d to the frequency domain $\omega = 2\pi/d$.

For computation of the above-mentioned characteristics, the program DRSNOST in MATLAB has been created. The following characteristics are computed:

(1) Mean absolute deviation MAD;
(2) Mean profile slope MS;
(3) Standard deviation of profile slope PS;
(4) Standard deviation of profile curvature PC;
(5) Ten point average TP;
(6) Variation coefficient $CV = SD/R_a$;
(7) Mean fractal dimension D_F;
(8) Initial fractal dimension D_{F_p}.

The computation of fractal dimensions is described in chapter 7.

4. Statistical analysis

A basic statistical feature of $R(d)$ is autocorrelation between distances. Autocorrelation depends on the lag h (i.e. selected distances between places of thickness evaluation). The main characteristics of autocorrelation is covariance function $C(h)$

$$C(h) = \text{cov}(R(d), R(d+h)) = E((R(d) - E(R(d)))(R(d+h) - E(R(d)))) \quad (6)$$

and autocorrelation function ACF(h) defined as normalized version of $C(h)$:

$$\text{ACF}(h) = \frac{C(h)}{C(0)} \quad (7)$$

The $E(x)$ denotes expected value of x. ACF is one of the main characteristics for the detection of short- and long-range dependencies in dynamic (time) series. It could be used for the preliminary inspection of data. The computation of sample autocorrelation directly from definition for large data is tedious. The technique of ACF creation based on the FFT is contained in the signal processing toolbox of MATLAB (procedure xcorr.m) [18] (Bloomfield, 2000). In spatial statistics, more frequent variogram (called often as structure function) is defined as one half variance of differences $(R(d) - R(d+h))$

$$\Gamma(h) = 0.5D[R(d) - R(d+h)] \tag{8}$$

Symbol $D(x)$ denotes variance of x. For stationary random process mean value is independent on lag h i.e. $E(R(h)) = m$ and then

$$\Gamma(h) = 0.5E(R(d) - R(d+h))^2 \tag{9}$$

The variogram is relatively simpler to calculate and assumes a weaker model of statistical stationarity, than the power spectrum. Several estimators have been suggested for the variogram. The traditional estimator is

$$G(h) = \frac{1}{2M(h)}\sum_{j=1}^{M(h)}(R(d_j) - R(d_{j+h})^2 \tag{10}$$

where $M(h)$ is the number of pairs of observations separated by lag h. Problems of bias in this estimate when the stationarity hypothesis becomes locally invalid have led to the proposal of more robust estimators.

5. Fractal dimension

Benoit Mandelbrot has coined the term fractal in the 1970s (Mandelbrot and Van Ness, 1968). Fractals have two interesting characteristics. First of all, fractals are self-similar on multiple scales, in that a small portion of a fractal will often look similar to the whole object. Second, fractals have a fractional dimension, as opposite to integer dimension of regular geometrical objects.

The fractional (fractal) dimension D can be evaluated by the following way: The number $N(\delta)$ of line segments of length δ needed to cover the whole curve in plane is measured. The length of curve is estimated as $L(\delta) = N(\delta)\delta$. In the limit $\delta \to 0$ the estimator $L(\delta)$ becomes asymptotically equal to the length of the curve, L, independently on δ. The Hausdorf-Besicovitch dimension D (fractal dimension) of this curve is the critical dimension for which the measure $M_d(\delta)$ defined as:

$$M_d(\delta) = N(\delta)\delta^d \tag{11}$$

changes from zero to infinity (Feder, 1988). The value of $M_d(\delta)$ for $d = D$ is often finite and therefore for sufficiently small δ:

$$N(\delta) \approx \delta^D \text{ or } L(\delta) \approx \delta^{1-D} \tag{12}$$

The fractal dimension is then computed as:

$$D = 1 - \frac{\log L(\delta)}{\log \delta} \tag{13}$$

For, random fractal is simpler to use power spectral density or related functions. Some techniques for fractal dimension computations are summarized, e.g. in Mannelqvist and Groth (2001). The methods for computation or Hurst coefficient is described in Wu (1999). In measurement of the surface profile (thickness variation $R(h)$), the data are available through one-dimensional line transect surface. Such data represent curve in plane. The fractal dimension D_F is then number between 1 (for smooth curve) and 2 (for rough curve).

Fractals are characterized by power type dependence of variogram and power spectral density. For a power law variogram:

$$\Gamma(h) \approx c|h|^H \tag{14}$$

where c is a constant. The Hurst exponent H, lies in the interval (0, 1). Where $H = 0$ this denotes a curve of extreme irregularity and $H = 1$ denotes a smooth curve. Exponents H and fractal dimension D are in fact related:

$$D_F = 2 - H \tag{15}$$

Fractal dimension is conventionally obtained through estimating the parameter from a LSE linear regression of the log-log transformation of equation (14). In practice, its behavior is expressed by equation (14) valid near origin. In general, D_F computed from this relation is denoted as an effective fractal dimension.

Based on these equations the program DRSNOST in MATLAB for estimation of fractal dimension from variogram has been constructed. From the first 12 points (excluding three points near origin) the initial fractal dimension D_{F_p} and from all points the mean fractal dimension D_F are computed.

6. Experimental part

The 54 flame retardant barrier textiles have been selected for investigation. They covered flame retardant finished cotton fabrics (satin, linen and twill patterns), fabrics created from heat resistant fibers (Nomex, FR Viscose and modacrylic fibers) and combinations of heat resistant fibers with flame retardant finished cotton. The $F(d)$ traces have been obtained by means of the above described accessory. The $R(d)$ traces have been obtained from KES device, and Kawabata mean roughness (MAD) was computed. The subjective hand SH was evaluated from judgment of 30 persons. They rated the fabrics to the 11-point scale. The subjective hand SH was computed as median of ratings divided by 11.

7. Results and discussion

For the investigation of mutual relations among subjective hand, classical characteristics of roughness (outputs 1-6 from DRSNOST program) and fractal characteristics of roughness (outputs 7-8 from DRSNOST program) the correlation map has been created. This map is shown in Figure 1(a). In the first

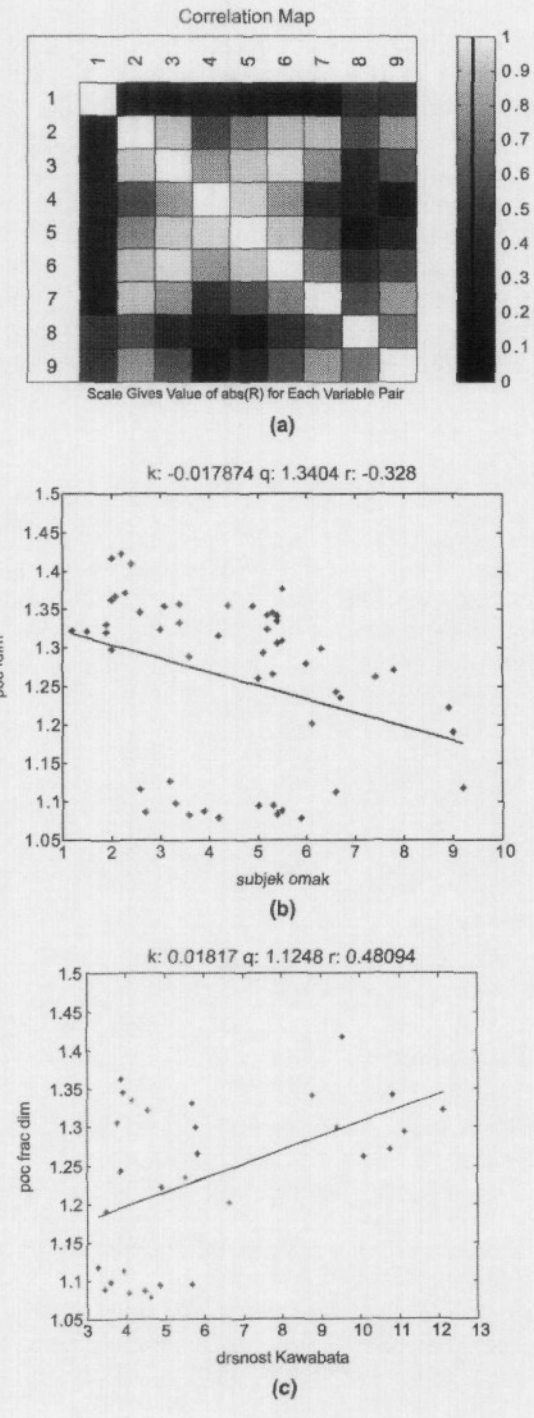

Figure 1.
(a) Correlation map of characteristics (first variable is SH); (b) relation between initial fractal dimension and subjective hand SH; (c) dependence between roughness from SFV (D_{F_p}) and Kawabata SHV (*MAD*)

column of this map are correlations of subjective hand with roughness characteristics. It is clear, that the correlations are not so high (black denotes no correlation and white denotes perfect linear relation). Maximum correlation is between subjective hand and fractal dimensions. There are correlations between some roughness characteristics as well. The dependence between subjective hand and initial fractal dimension D_{F_p} is shown in the Figure 1(b). It can be said that for these materials the roughness has a little influence on hand. The deeper analysis of the correlation map and partial relations between roughness characteristics lead to the following conclusions: MAD highly correlates with other roughness characteristics; MAD correlates with fractal dimensions as well, but some no linearity appears. Comparison of D_{F_p} calculated from SFV and Kawabata *MAD* from SHV is shown in Figure 1(c). Moderate correlation in Figure 1(c) indicates the differences between these two methods. One reason is the filtration of some frequencies realized automatically by the KES device.

8. Conclusion

The initial fractal dimension is probably most suitable for the complexity of roughness characterization. The analysis of SFV based on the DRSNOST program is more complex in reality. The more classical roughness characteristics and topothesy are computed as well and many other techniques of fractal dimension calculation are included.

References

Ajayi, J.O. (1988), "Some studies of frictional properties of fabrics", Doctoral thesis, University of Strathclyde, Glasgow.

Ajayi, J.O. (1992), "Fabric smoothness, friction and handle", *Textile Research Journal*, Vol. 62, pp. 87-93.

Ajayi, J.O. (1994), "An attachment to the constant rate of elongation tester for estimating surface irregularity of fabric", *Text. Res. J.*, Vol. 64, pp. 475-6.

Bloomfield, P. (2000), *Fourier Analysis of Time Series*, Wiley, NY.

Constantine, A.G. and Hall, P. (1994), *J. Roy. Stat. Soc.*, Vol. B56, p. 97.

Eke, A. *et al.*, (2000), *Eur. J. Physiol.*, Vol. 439, p. 403.

Feder, J. (1988), *Fractals*, Plenum Press, NY.

Greenwood, J.A. (1984), "A unified theory of surface roughness", *Proc. Roy. Soc. London*, Vol. A393, p. 133.

Kawabata, S. (1980), "The standardization and analysis of hand evaluation", *Text. Mach. Soc. Japan*.

Mandelbrot, B.B. and Van Ness, J.W. (1968), "Fractional Brownian motion, fractional noises and applications", *SIAM Review*, Vol. 10, p. 442.

Mannelqvist, A. and Groth, M.R. (2001), *Appl. Phys.*, Vol. A73, pp. 347-56.

Meloun, M., Militky, J. and Forina, M. (1992), "Chemometrics for analytic chemistry Vol. I", *Statistical Data Analysis*, Ellis Horwood, Chichester.

Militký, J. and Bajzík, V. (2000), "Description of thickness variation by fractal dimension", *Proc. Conf. STRUTEX 2000*, December Liberec (2000) (in Czech).

Militký, J. and Bajzík, V. (2001), "Characterization of textiles surface roughness", *Proc. 7th Int. Asian Textile Conference*, August 2001, Hong Kong.

Nayak, P.R. (1971), *Trans. ASME: J. Lub. Tech.*, Vol. 93F, p. 398.

Operation Manual (1999), Shirley.

Ott, E., Sauer, T. and Yorke, J.A. (Eds) (1994), *Copying with chaos*, Wiley, NY, USA.

Quinn, B.G. and Hannan, E.J. (2001), *The Estimation and Tracking of Frequency*, Cambridge University Press, Cambridge.

Sacerdotti, F., Griffiths, B.J., Butler, C. and Benati, F. (2000), *Proc. Inst. Mech. Engfs.*, Vol. 214B, p. 811.

Stockbridge, H.C. *et al.*, (1957), "The subjective assessment of the roughness of fabrics", *Journal of the Textile Institute*, Vol. 48, pp. T26-34.

Vandenberg, S. and Osborne, C.F. (1992), *Wear*, Vol. 159, pp. 17-30.

Whitehouse, D.J. (2001), *Wear*, Vol. 249, p. 345.

Wu, J. (1999), *Wear*, Vol. 230, p. 194.

Wu, J. (2000), *Wear*, Vol. 239, p. 36.

Zhang, C. and Gopalakrishnan, S. (1996), "Fractal geometry applied to on line monitoring of surface finish", *Int. J. Mach. Tools Manufact.*, Vol. 36, pp. 1137-50.

SURFACE ROUGHNESS OF PROTECTIVE CLOTHING

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The main goal of protective clothing design is the realization of heat resistance. On the other hand it is necessary to ensure wearing comfort as well. Important parts of mechanical comfort are tactile properties including roughness. Standard methods of surface roughness measurement are based on the surface profile evaluation. Example is Kawabata evaluation system (KES), where the surface height variation (SHV) trace is obtained. In this contribution the simple technique based on the tracking of metal blade on the textile surface and registration of required load is described. The continuous recording of the load is realized on the TIRATEST tensile testing machine. The result of measurements is surface force trace (SFV).

For characterization of roughness the mean absolute deviation MAD (denoted by Kawabata. as SMD) is usually used. The procedure of surface complexity parameters evaluation from SHV traces is based on the fractal dimension computed form power spectral density and variogram (or autocorrelation function). The main aim of this work is quantitative comparison of various roughness characteristics and relation of these characteristics with subjective hand.
KEYWORDS: surface roughness, measuring device, fractal dimension

1. INTRODUCTION

Roughness of engineering surfaces has been traditionally measured by the stylus profiling method creating of surface profile called surface height variation (SHV) trace [7]. This profile characterizes thickness (height) variation in selected direction. Modern methods are based on the image processing of surface images [10]. Surface irregularity of plain textiles has been identified by friction [1], contact blade [2,4], lateral air flow [3], step thickness meter [6] or subjective assessment [5].

Standard methods of surface profile evaluation are based on the relative variability characterized by the variation coefficient (analogy with evaluation of yarns mass unevenness) [8] or simply by the standard deviation. This approach is used in Shirley software for evaluation of results for step thickness meter [9].

Characterization of roughness based on the mean absolute deviation MAD is the classical descriptive statistical approach. This statistical characteristic is useful for random SHV traces where elements of SHV trace are statistically independent each other. The SHV profile of a lot of fabrics has been identified as irregular and more structured.

The descriptive statistical approach based on the assumptions of independence and normality leads to biased estimators if the SHV have short or long-range correlations [8]. There is therefore necessary to distinguish between standard **white Gauss noise** and more complex models. For description of short range correlations the models based on the **autoregressive moving average** are useful [14]. The long-range correlations are characterized by the **fractal models** [15,12]. The **deterministic chaos** type models are useful for revealing chaotic dynamic in deterministic processes where variation appears to be random but in fact there are predictable [13].

For the selection among above mentioned models the power spectral density (PSD) curve evaluated from experimental SHV can be applied [17].

Especially the fractal models are widely used for rough surface description [16]. For these models the dependence of log(PSD) on the log(frequency) should be linear. Slope of this plot is proportional to **fractal dimension** and intercept to the so-called **topothesy**. For white noise has dependence of log(PSD) on the log(frequency) nearly horizontal plateau for all frequencies (the ordinates of PSD are independent and exponentially distributed with common variance [13]). More complicated rough surfaces as result of grinding can be modeled by the Markov type processes [19]. For these models the dependence of log(PSD) on the log(frequency) has plateau at small frequencies then bent down and are nearly linear at high frequencies.

The fractal type models were criticized by Whitehouse, who concluded that the benefits are more virtual than real [16]. On the other hand the deeper analysis of rough surface should use more complex model than classical descriptive statistics.

Greenwood [11] proposed technique based on the definition of local maxims (peaks) and derivation of peaks height distribution. A lot of recent works is based on the assumption that the stochastic process (Brownian motion) can describe thickness variation [20].

This work is devoted to the analysis of load required to move of blade on fabric surface *R(d)* obtained from new accessory to tensile testing machine. The combination of classical roughness characteristics and fractal dimension estimation is used for evaluation of surface roughness of barrier technical textiles having various structures. Roughness characteristics are compared with subjective hand ratings.

2. SURFACE PROFILE EVALUATION

Kawabata [2] constructed measuring device for registration the surface height variation (SHV) trace. The main part of this device is contactor in the form of wire (diameter 0.5 mm). This contactor is moved by constant rate 0,1 cm/sec and SHV is registered on paper sheet. The sample length L = 2 cm is used. The SHV corresponds to the surface profile in selected direction (usually in the weft and warp directions are used for SHV creation). The result of measurements is thickness *R(d)* in various distances *d* from origin. Characterization of roughness is based on the mean absolute deviation MAD (the classical descriptive statistical approach).

Similar approach is based on the measurement of R(d) by Shirley step meter with replacement of measuring head by blade [21].

We have constructed the simple accessory to the tensile testing machine. The principle is registration of the force *F(d)* needed for tracking the blade on the textile surface. Roughly speaking, the *F(d)* should be inversely proportional to the *R(d)*. In reality, the *F(d)* profile is different due to small deformation surface deformation caused by the tracked blade. Based on the preliminary testing the following working conditions have been selected:

Blade contact pressure 0.2 N

Blade movement rate 0.6 mm/s

Sampling frequency 50 1/s (length between samples Δd = 0.013 mm)

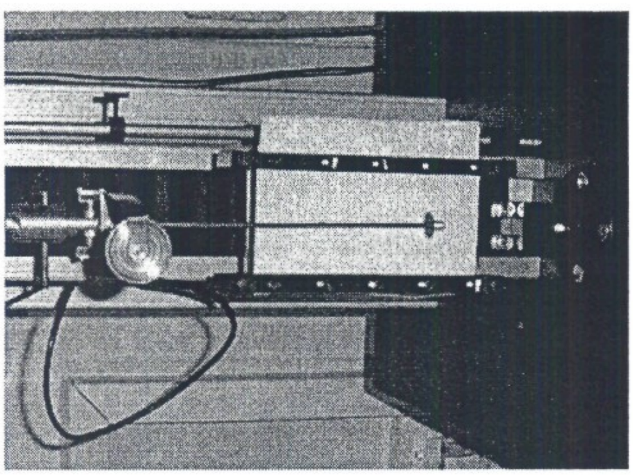

Fig 1 Accessory for roughness evaluation

Investigated length T = 30 mm

The picture of this accessory is on the Fig. 1.

Output from measurements is sequence of loads $F(d_i)$. Variation of thickness $R(d_i)$ or loads $F(d_i)$ can be generally assumed as combination of random fluctuations (uneven threads, spacing between yarns, non uniformity of production etc.) and periodic fluctuations caused by the repeated patterns (twill, cord, rib etc.) created by weft and warp yarns. For description of roughness the characteristics computed from *R(d)* or *F(d)* in places $0<d<T$ (*T* is maximum investigated sample length and *M* is number of places) are used.

Especially for weaves it is necessary to identify periodic component in *R(d)* or *F(d)* as well. For this purpose the spectral analysis can be useful. The position of repeated weave pattern can be estimated from variance spectrum (power spectral density function) $P(w) = PSD$ estimated from periodogram.

3. SURFACE ROUGHNESS DESCRIPTION

There are two reasons for measuring surface roughness. First, is to control manufacture and is to help to ensure that the products perform well. In the textile branch the former is the case of special finishing (e.g. pressing or ironing) but the later is connected with comfort appearance and hand.

From a general point of view, the rough surface display process which have two basic geometrical features:

1. Random aspect: the rough surface can vary considerably in space in a random manner, and subsequently there is no spatial function being able to describe the geometrical form,
2. Structural aspect: the variances of roughness are not completely independent with respect to their spatial positions, but their correlation depends on the distance. Especially surface of weaves is characterized by nearly repeating patterns and therefore some periodicities are often identified.

From the SHV or SFV trace is possible to evaluate a lot of roughness parameters. Let we define roughness characteristics for SHV (the same equations are also valid for SFV). Classical roughness parameters are based on the set of points $R(d_j)$ $j = 1..$ M defined in the sample length interval *L*. The measurement points d_j are obviously selected as equidistant and then $R(d_j)$ can be replaced by the variable R_j. For identification of positions in length scale is sufficient to know sampling distance $d_s = d_j - d_{j-1} = L/M$ for $j>1$. The standard roughness parameters used frequently in practice are [22]:

(i) *Mean Absolute Deviation MAD.* This parameter is equal to the mean absolute difference of surface heights from average value (R_a). For a surface profile this is given by

$$MAD = \frac{1}{M}\sum_j |R_j - R_a| \quad (1)$$

This parameter is often useful for quality control. However, it does not distinguish between profiles of different shapes. Its properties are known for the case when R_j's are independent identically distributed (.i.i.d.) random variables

(ii) *Standard Deviation (Root Mean Square) Value SD.* This is given by

$$SD = \sqrt{\frac{1}{M}\sum_j (R_j - R_a)^2} \quad (2)$$

Its properties are known for the case when R_j's are independent identically distributed (.i.i.d.) random variables. One advantage of SD over MAD is that for normally distributed data can be simple to derive confidence interval and to realize statistical tests. SD is always higher than MAD and for normal data is $SD = 1.25\ MAD$. It does not distinguish between profiles of different shapes as well. The parameter *SD* is less suitable than MAD for monitoring certain surfaces having large deviations (corresponding distribution has heavy tail).

(iii) *Mean Height of Peaks MP.* This is calculated as the average of the profile deviations above the reference value *R* (often is $R = R_a$). It is given as mean value of peaks P_i, $i = Np$ where

$P_i = R_i - R$ for $R_i - R > 0$ and $P_i = 0$ elsewhere

(iv) *Mean Height of Valleys MV.* This is calculated as the average of the profile deviations below the reference value *R* (often is $R = R_a$.). It is given as mean value of valleys V_i, $i = Nv$ where

$V_i = R - R_i$ for $R_i - R < 0$ and $V_i = 0$ elsewhere

The parameters *MP* and *MV* give information on the profile complexity. Exceptional peaks or valleys are not considered but are useful in tribological applications.

(v) *The Standard Deviation of Profile Slope PS.* This is given by

$$PS = \sqrt{\frac{1}{M}\sum_j \left(\frac{dR(x)}{dx}\right)_j^2} \quad (3)$$

(vi) *The Standard Deviation of Profile Curvature PC.* This quantity called often as waviness is defined by the similar way

$$PC = \sqrt{\frac{1}{M}\sum_j \left(\frac{d^2R(x)}{dx^2}\right)_j^2} \quad (4)$$

The slope and curvature are characteristics of a profile shape. The *PS* parameter is useful in tribological applications. The lower the slope the smaller will be the friction and wear. Also, the reflectance property of a surface increases in the case of small *PS* or *PD*.

(vii) *Mean Slope of the Profile MS.* This is given by

$$MS = \frac{1}{M}\sum_j \left|\frac{dR(x)}{dx}\right|_j \quad (5)$$

Mean slope is an important parameter in several applications such as in the estimation of sliding friction and in the study of the reflectance of light from surfaces.

(viii) *Ten Point Average TP.* This characteristic is defined as the average difference between the five highest peaks and five deepest valleys within a surface profile. The parameter *TP* is sensitive to the presence of high peaks or deep scratches in the surface and is preferred for quality control purposes.

These parameters are useful in the case of functional surfaces or for characterizing surface bearing and fluid retention and other relevant properties. For the characterization of hand will be probably best to use waviness *PC*. The characteristics of slope and curvature can be computed for the case of fractal surfaces from power spectral density, autocorrelation function or variogram.

A set of parameters for profile and surface characterization are collected in [20]. These parameters are divided to the following groups:

- Statistical characteristics of height distribution (variance, skewness, kurtosis)
- Spatial characteristics as autocorrelation or variogram (denoted in engineering as structural function)
- Functional characteristics (connected with fluid retention or flow properties)

There exists a vast number of empirical profile or surface roughness characteristics suitable often in very special situations. Some of them are closely connected with characteristics computed from fractal models (fractal dimension and topothesy). Greenwood [11] proposed a general theory for description of surface roughness based on the distribution of heights.

General surface topography is usually broken down to the three components according to wavelength (or frequency). The long wavelength (low frequency) range variation is denoted as ***form***. This form component is removed by using of polynomial models or models based on the form shape. The low wavelength (high frequency) range variation is denoted as ***roughness*** and medium wavelength range variation separates ***waviness***. The most common way to separate roughness and waviness is spectral analysis. This analysis is based on the Fourier transformation from space domain d to the frequency domain $\omega = 2\pi/d$.

For computation of above-mentioned characteristics the program DRSNOST in MATLAB has been created. The following characteristics are computed:

1. Mean absolute deviation *MAD*
2. Mean profile slope *MS*
3. Standard deviation of profile slope *PS*
4. Standard deviation of profile curvature *PC*
5. Ten point average *TP*
6. Variation coefficient $CV = SD/R_a$
7. Mean fractal dimension D_F
8. Initial fractal dimension D_{Fp}

The computation of fractal dimensions is described in chap. 6.

4. SPECTRAL ANALYSIS

The primary tool for evaluation of periodicities is expressing of signal *R(d)* by the Fourier series of sine and cosine wave

$$R(d) = \frac{a_0}{2} + \sum_k (a_k \cos(2\pi kd) + b_k \sin(2\pi kd)) \quad (6)$$

Quantity *d* is often time or distance from origin and *k=1,2,3,4....* The first two terms have period 1, the second two terms have period 1/2, the third two terms have period 1/3 etc. One consequence of this is that the different pairs of terms are orthogonal (integral of their product is zero). This fact facilitates fitting of Fourier series to experimental data. The term $a_0/2$ can be made zero by centralization (i.e. subtracting of mean value). By using of Euler formula *exp(ia)=cos(a)+isin(a),* where *i* is imaginary unit the Fourier series may be written in the compact form

$$R(d) = \sum_k c_k \exp(-2\pi ikd)$$

The complex coefficients c_k have real and imaginary part a_k and ib_k In Fourier series only the terms up to $k = M/2$ contain any useful information. After this bound are real coefficients repeated symmetrically and imaginary coefficients repeated antisymmetrically. The Fourier Transform is conversion of data from series according to *d* to the series of frequencies $\omega = 2\pi k/(ML)$, for k =1, 2, 3...

$$RF(\omega) = \sum R(d) \exp(-i\omega d) \quad (7)$$

Function *RF* is symmetric about frequency $\omega = 2\pi/L$. For discrete data the fast Fourier Transform (FFT) leads to transformed complex vector *DRF*. Vector *DRF* may be used for creation of power spectral density. *P(w)*

$$P(\omega) = DRFconj(DRF)/L^2 = abs(DRF)^2/L^2 \quad (8)$$

where conj(.) denotes conjugate vector. The $P(\omega)$ is estimator of spectral density function and contains values corresponding to contribution of each frequency to the total variance of *R(d).* Frequency of global maxim on $P(\omega)$ is corresponding to the length of repeated pattern and height corresponds to the nonuniformity of this pattern. Spectral density function is therefore generally useful for evaluation of hidden periodicities.

The estimation of the spectral density function $P(\omega)$ is relatively straightforward in theory but in practice situation is more difficult since data are only available in discrete samples of limited extent. For finite sample lengths if is necessary to use windowing (avoiding leakage) de-trending (avoiding non stationarity of mean) and filtration of parasite frequencies [26]. The main spectral estimators are available in Signal Processing toolbox of MATLAB system [28]. The spectral estimators for finite data length corrupted by random errors could be inaccurate. The more sophisticated procedures are very sensitive to the tuning parameters. For estimation of fractal dimension is therefore the best way to use simple FFT based method with proper data pretreatment (detrending, windowing) [27].

5. STATISTICAL ANALYSIS

A basic statistical feature of *R(d)* is autocorrelation between distances. Autocorrelation depends on the lag *h* (i.e. selected distances between places of thickness evaluation). The main characteristics of autocorrelation is covariance function *C(h)*

$$C(h) = \text{cov}(R(d), R(d+h)) =$$
$$= E((R(d) - E(R(d))\ (R(d+h) - E(R(d))))$$

and autocorrelation function ACF(h) defined as normalized version of *C(h)*

$$ACF(h) = \frac{C(h)}{C(0)} \quad (9)$$

The *E(x)* denotes expected value of *x*. ACF is one of main characteristics for detection of short and long-range dependencies in dynamic (time) series. It could be used for preliminary inspection of data. The computation of sample autocorrelation directly from definition is for large data tedious. The technique of *ACF* creation based on the FFT is contained in Signal Processing toolbox of MATLAB (procedure xcorr.m) [28]. The spectral density is the Fourier transform of covariance function *C(h)*

$$P(\omega) = \frac{1}{2\pi} \int_0^\infty C(t) \exp(-i\omega t) dt \quad (10)$$

The ACF is inverse Fourier transform of spectral density

$$C(h) = \int_0^{\infty} P(\omega)\ \exp(i\omega h) d\omega \quad (11)$$

These relations show that characteristics in the space and frequency domain are interchangeable.

In spatial statistics is more frequent variogram, (called often as structure function) which is defined as one half variance of differences *(R(d) – R(d+h))*

$$\Gamma(h) = 0.5\ D[R(d) - R(d+h)] \quad (12)$$

or

$$\Gamma(h) = 0.5\ [E(R(d) - R(d+h))^2 - E^2(R(d) - R(d+h))] \quad (13)$$

Symbol *D(x)* denotes variance of *x*. For stationary random process is mean value independent on lag *h* i.e. *E(R(h)) = m* and then

$$\Gamma(h) = 0.5\ E(R(d) - R(d+h))^2 \quad (14)$$

For random processes having stationarity of second order is valid

$$C(h) = E[R(d)\ R(d+h)] - m^2 \quad (15)$$

Variance is then equal to

$$D(R(d)) = C(h=0) = C(0) \quad (16)$$

and variogram is directly related to covariance

$$\Gamma(h) = C(0) - C(h) \quad (17)$$

The variogram is relatively simpler to calculate and assumes a weaker model of statistical stationarity, than the power spectrum. Several estimators have been suggested for the variogram. The traditional estimator is

$$G(h) = \frac{1}{2M(h)} \sum_{j=1}^{M(h)} (R(d_j) - R(d_{j+h}))^2 \quad (18)$$

where *M(h)* is the number of pairs of observations separated by lag *h*. Problems of bias in this estimate when the stationarity hypothesis becomes locally invalid have led to the proposal of more robust estimators. One such estimator has been created by Cressie and Hawkins [29]. Another estimator has been suggested by Isaaks and Srivastava [30].

It can be summarized that simple statistical characteristics are able to identify the periodicities in data but the reconstruction of "clean" dependence is more complicated. The variogram is often sufficient for characterization of surface profiles.

6. FRACTALS AND FRACTAL DIMENSION

Most of man made objects are geometrically simple and can be classified as composition of regular geometric shapes as lines, curves, planes, circles, spheres etc. Some objects are not be approximated precisely by the regular geometric shapes. One category of these objects is called **fractals**. Benoit Mandelbrot has coined term fractal in the seventies [12]. (From Latin **fractus**, meaning irregular or fragmented). Fractals have two interesting characteristics. First of all, fractals are **self-similar** on multiple scales, in that a small portion of a fractal will often look similar to whole object. Second, fractals have a **fractional dimension**, as opposite to integer dimension of regular geometrical objects.

Because fractals are self similar they are constructed by recursion. For **geometrical fractals** is the recursion explicitly visible. For **stochastic fractals** or **random fractals** the recursion is more little subtle and may be an artifact of an underlying fractal building process that occurs on multiple spatial scales. The main characteristic of both fractals types is fractal dimension. The fractional (fractal) dimension D can be evaluated by the following way. Let the number $N(\delta)$ of line segments of δ length needed to cover the whole curve in plane is measured. The length of curve is estimated as $L(\delta) = N(\delta)\delta$. In the limit $\delta \to 0$ the estimator $L(\delta)$ becomes asymptotically equal to length of curve *L* independently on δ. The Hausdorf-Besicovitch dimension *D* (fractal dimension) of this curve is the critical dimension for which the measure $M_d(\delta)$ defined as

$$M_d(\delta) = N(\delta)\delta^d$$

changes from zero to infinity [23]. The value of $M_d(\delta)$ for $d = D$ is often finite and therefore for sufficiently small δ is valid

$$N(\delta) \approx \delta^D \quad or \quad L(\delta) \approx \delta^{1-D}$$

The fractal dimension is then computed as

$$D = 1 - \frac{\log L(\delta)}{\log \delta}$$

For random fractals is simpler to use power spectral density or related functions. Some techniques for fractal dimension computations are summarized e.g., in [24]. The methods for computation oh Hurst coefficient is described in [25].

In measurement of surface profile (thickness variation *R(h)*) the data are available through one dimensional line transect surface. Such data represents curve in plane. The fractal dimension D_F is then number between 1 (for smooth curve) and 2 (for rough curve).

Fractals are characterized by power type dependence of variogram and power spectral density. For a power law variogram is valid

$$\Gamma(h) \approx c|h|^H \quad (19)$$

where c is a constant. The Hurst exponent H, lies in the interval (0,1). Where $H = 0$ this denotes a curve of extreme irregularity and $H = 1$ denotes a smooth curve. Exponents H and fractal dimension D are in fact related

$$D_F = 2 - H \qquad (20)$$

Similarly, for $P(\omega)$ is valid

$$P(\omega) = c_1 \, |\omega|^{-(1+2H)} \qquad (21)$$

where exponent (1 + 2H) lies in the interval (1,3). Fractal dimension is conventionally obtained through estimating the parameter from a LSE linear regression of the log-log transformation of Equations (19) and (21). *In practice is behavior expressed by* eqn. (19) *valid* near origin and by enq (21) in a neighborhood of infinity. In general, it s D_F computed from this relation denoted as effective fractal dimension.

There are several problems with estimating fractal dimension in this fashion. First, elevation points, points on the variogram and the error term in the LSE regression are likely to be autocorrelated. Second, data points in log-log space are unequally spaced and, third, decisions concerning an acceptable cutoff for goodness of fit (R^2) of the linear function are of an arbitrary a priori nature. Since the aim of the line fitting exercise in estimating fractal dimension is the description of the relationship rather than prediction, the bias introduced by the first problem is not critical. A solution to the second is to re-sample the data using a geometric progression, but at a cost of a dramatic reduction in the number of points used in the line fitting exercise. An alternative to the third is to estimate the standard error SE around the slope of a regression line. Based on these equations the program DRSNOST in MATLAB for estimation of fractal dimension from variogram has been constructed. From the first 12 points (excluding 3 points near origin) the initial fractal dimension D_{Fp} and from all points the mean fractal dimension D_F are computed.

7. EXPERIMENTAL PART

The 54 flame retardant barrier textiles have been selected for investigation. They covered flame retardant finished cotton fabrics (satin, linen and twill patterns), fabrics created from heat resistant fibers (Nomex, FR Viscose anf modacrylic fibers), and combinations of hat resistant fibers with flame retardant finished cotton. The *F(d)* traces have been obtained by means of above described accessory. The *R(d)* traces have been obtained from KES device and Kawabata mean roughness (MAD) was computed. The subjective hand SH was evaluated from judgment of 30 persons. They rated the fabrics to the 11-point scale. The subjective hand SH was computed as median of ratings divided by 11.

8. RESULTS AND DISCUSSION

For investigation of mutual relations among subjective hand, classical characteristics of roughness (outputs 1-6 from DRSNOST program) and fractal characteristics of roughness (outputs 7-8 from DRSNOST program) the correlation map has been created. This map is shown on the fig. 2.

In the first column of this map are correlations of subjective hand with roughness characteristics. It is clear, that the correlations are not so high (black is no correlation and white is perfect linear relation). Maximum correlation is between subjective hand and fractal dimensions. There are correlations between some roughness characteristics as well. The dependence between subjective hand and initial fractal dimension D_{Fp} is shown on the fig. 3

It can be said that for these materials the roughness has a little influence on hand. The deeper analysis of correlation map and partial relations between roughness characteristics leads to the following conclusions:

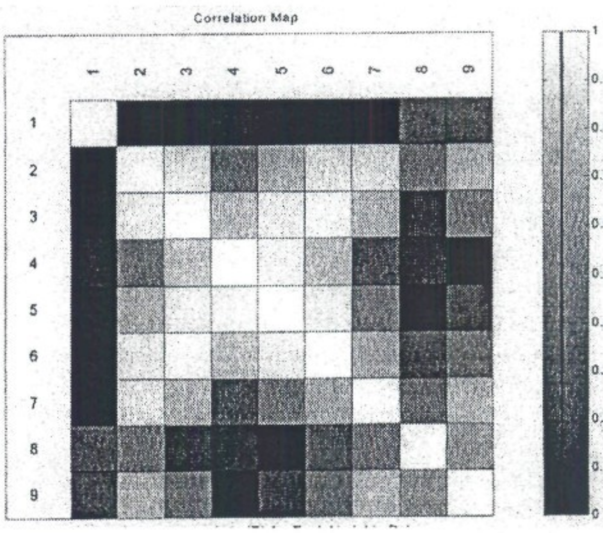

Fig. 2 Correlation map of characteristics (first variable is SH)

- MAD highly correlates with other roughness characteristics
- MAD correlates with fractal dimensions as well but some no linearity appears.

Comparison of D_{Fp} calculated from SFV and Kawabata *MAD* from SHV is shown on the fig. 4.

Moderate correlation on fig.4 indicates the differences between these two methods. One reason is the filtration of some frequencies realized automatically by the KES device. The comparison of KES roughness (*MAD)* and subjective hand *SH* is shown on the fig. 5.

Very low correlation on fig. 5 points at small importance of surface roughness for prediction of hand based on the KES.

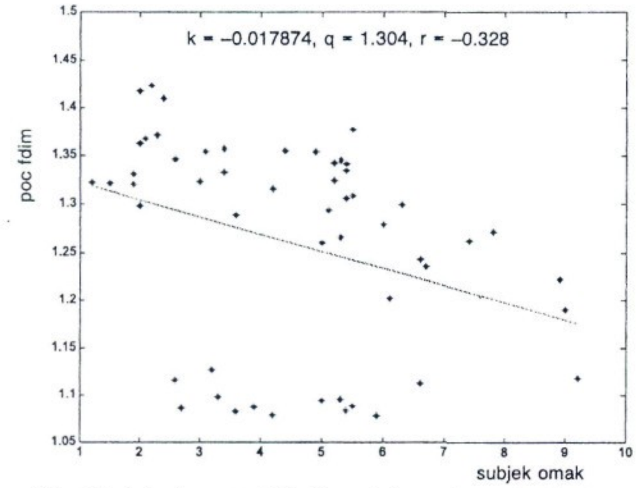

Fig. 3 Relation between initial fractal dimension and subjective hand SH

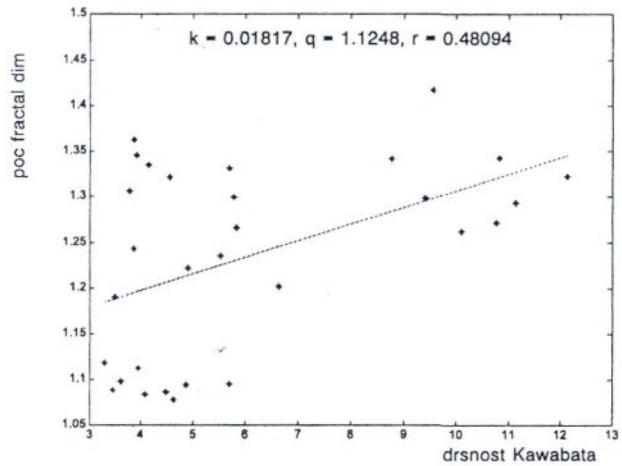

Fig.4 Dependence between roughness from SFV (D_{Fp}) and Kawabata SHV (*MAD*)

9. CONCLUSION

Proposed accessory for measurement of SFV trace is very simple and can be used for practical measurements. The correlation with KES results is week. The initial fractal dimension is probably most suitable for complexity of roughness characterization. The analysis of SFV based on the DRSNOST program is in reality more complex. The more classical roughness characteristics and topothesy are computed as well and many other techniques of fractal dimension calculation are included. In the future the analysis will be extended to the chaotic models and autoregressive models. Small correlation of surface roughness with subjective hand indicates the little importance of this parameter for protective textile fabric mechanical comfort prediction.

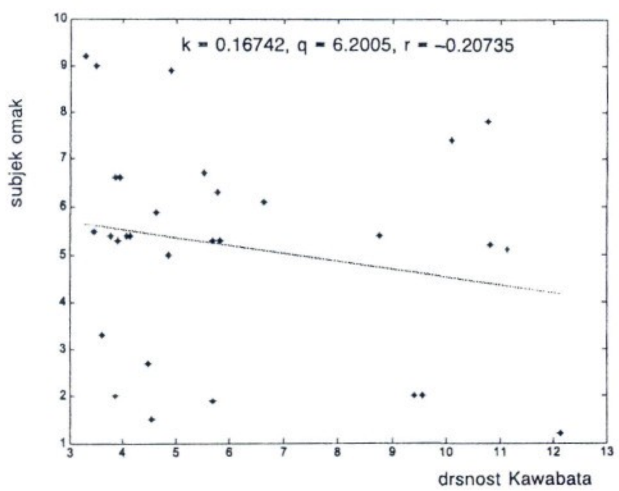

Fig. 5 Comparison of KES roughness (*MAD*) and subjective hand *SH*

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10. REFERENCES

[1] Ajayi J.O.: Fabric smoothness, Friction and handle, Text. Res. J.62, 87–93 (1992)

[2] Kawabata S.: The standardization and analysis of hand evaluation, Text. Mach. Soc. Japan (1980)

[3] Ajayi J.O.: Some Studies of Frictional Properties of Fabrics, Doctoral Thesis, University of Strathclyde, Glasgow (1988)

[4] Ajayi J.O.: An attachment to the constant rate of elongation tester for estimating surface irregularity of fabric, Text. Res. J., 64, 475–476 (1994)

[5] Stockbridge H.C. et. all. : The subjective assessment of the roughness of fabrics, J. Text. Inst. 48, T26–34, (1957)

[6] Militký J, Bajzík.V: Description of thickness variation by fractal dimension, Proc. Conf. STRUTEX 2000, Liberec December (in Czech) (2000)

[7] Vandenberg S., Osborne C.F.: Wear 159, 17–30 (1992)

[8] Meloun M., Militky J., Forina M.: Chemometrics for Analytic Chemistry vol. I, Statistical Data Analysis, Ellis Horwood, Chichester (1992)

[9] Anonym: Operation Manual, Shirley(1999)

[10] Zhang C., Gopalakrishnan S. : Fractal geometry applied to on line monitoring of surface finish Int. J. Mach. Tools Manufact. 36, 1137–1150 (1996)

[11] Greenwood J.A.: A unified theory of surface roughness, Proc. Roy. Soc. London A393, 133 (1984)

[12] Mandelbrot B.B., Van Ness J.W.: (1968) Fractional Brownian motion, fractional noises and applications, SIAM Review 10, 442

[13]Ott E,. Sauer T., Yorke J.A. Eds: Copying with chaos, J. Wiley 1994

[14] Quinn B.G., Hannan E. J.: The estimation and Tracking of Frequency, Cambridge University Press 2001

[15] Constantine A. G,. Hall P.: J. Roy. Stat. Soc. B56, 97, (1994)

[16] Whitehouse D. J.: Wear 249,345 (2001)

[17] Eke A. et all : Eur. J. Physiol. 439, 403 (2000)

[18] Bloomfield P.: Fourier analysis of time series, J. Wiley. New York 2000

[19] Sacerdotti F., Griffiths B. J., Butler C. and Benati F.: Proc. Inst. Mech. Engfs. 214B, 811, (2000)

[20] Nayak P. R.: Trans. ASME : J. Lub. Tech. 93F, 398 (1971)

[21] Militký J., Bajzík V.: Characterization of textiles surface roughness, Proc. 7 th Int. Asian Textile Conference, Hong Kong August 2001

[22] Wu J.: Wear 239, 36 (2000)

[23] Feder J.: Fractals, Plenum Press, New York 1988

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DRSNOSŤ POVRCHU OCHRANNÉHO ODEVU

Translation of abstract:
SURFACE ROUGHNESS OF PROTECTIVE CLOTHING

Hlavným cieľom dizajnu ochranného odevu je zabezpečenie tepelnej odolnosti. Na druhej strane je tiež nutné zabezpečiť komfort pri nosení. Dôležitým aspektom mechanického komfortu sú dotykové vlastnosti včítane drsnosti. Štandardné metódy merania povrchovej drsnosti sú založené na hodnotení povrchu profilu. Príkladom je Kawabatov systém vyhodnotenia (KES, kde sa získa obraz kolísania povrchových nerovností. V tomto príspevku je popísaná jednoduchá technika založená na posúvaní kovového listu po textilnom povrchu a registrácii vyžadovaného zaťaženia. Kontinuálna registrácia zaťaženia je zaznamenaná zariadením na testovanie ťahu – TIRATEST. Výsledkom merania je stopa povrchovej sily (SFV).

Pre charakterizovanie drsnosti povrchu sa obyčajne používa priemerná absolútna odchýľka MAD (označená Kawabatom ako SMD). Spôsob vyhodnotenia súborných povrchových parametrov z SHV stôp je založený na fraktálnom rozmere vypočítanom z hustoty sily a variogramu (alebo autokorelačnej funkcie). Hlavný cieľ tejto práce je kvantitatívne porovnanie rôznych charakteristík drsnosti a vzťah týchto charakteristík so subjektívnym dotykom.

LONG TERM CYCLIC DEFORMATION OF FABRICS WITH IMPROVED ELASTICITY

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The aim of this contribution is description of simple simulation study based on the long-term cyclic tensile deformation of fabric to the selected stress levels combined with one-day recovery. This simulation has been realized on the Tiratest machine for tensile testing. From the experimental results the relative portion of plastic deformation; elastic recovery and change of rigidity were computed. The fabrics with special improved elasticity were evaluated.
KEY WORDS: cyclic tensile deformation, elastic recovery, mixing with Lycra

1. INTRODUCTION

The low stress level cyclic deformation combined with long-term relaxation occurs frequently during the wearing of textile products. The small portion of permanent deformation and small shape instability (good stiffness) due to cyclic deformation are required for clothing purposes.

For improving of there characteristics the small amount of elastomeric fibers are added to fabric. The main aim of this contribution is proposal of methodology for evaluation the textiles response to the cyclic deformation combined with long term relaxation. The parameters characterized recovery; permanent deformation and stiffness change are computed.

2. CYCLIC DEFORMATION OF TEXTILES

Typically, the deformation of textiles is due to cyclic straining to the very small level of stress. The simple deformation cycle consists of phase of straining and strain release (see fig. 1a). The area bounded by the curves from *A* to *B*, from *B* to *C* and from *C* to *A* is proportional to the total deformation energy W_D. Energy of recovered work W_Z is proportional to the surface area bounded by the curves from *D* to *B*, from *B* to *C* and from *C* to *D*. The plastic energy imposed to the textile is then equal

$$W_P = W_D - W_Z \qquad (1)$$

The so called work *r* recovery is defined by the simple relation

$$r = W_Z / W_D \qquad (2)$$

The quantity *(1 – r)* is proportional to the energy dissipated as heat. Plastic deformation energy can by expressed by the form

$$W_P = W_D(1-r) \qquad (3)$$

After *N* deformation cycles is the stored energy ΣW_{Pi} equal to the total work to break *W* and rupture occurs. The work to break is defined by relation

$$W = \int_0^{\varepsilon_P} \sigma(\varepsilon) d\varepsilon \qquad (4)$$

where ε_P is strain to break (tenacity). Number of cycles N_P to the break is then equal

$$\sum_{i=1}^{N_P} (1-r_i) W_{Di} = W \qquad (5)$$

where r_i and W_{Di} are recovery work and total deformation energy for the *i*-th cycle. For the simple case of $r_i = r$, $W_{Di} = W_D$ the following relation can be obtained

$$N_P = \frac{W}{(1-r)W_D} \qquad (6)$$

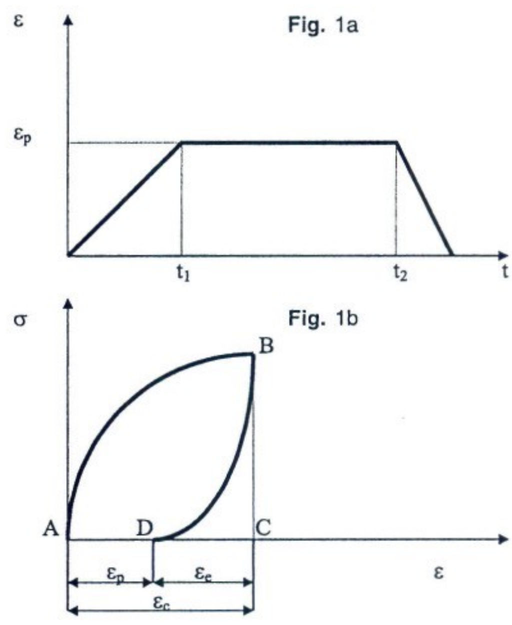

Fig. 1 Typical deformation cycle

Long-term stability after cyclic deformation requires:

I. Fibers with great work to break
II. *Fibers with good recovery*
III. The small energies W_D (low applied stress and stiff fabric)

There exist a lot of various methods of cyclic deformation. For simulation of cyclical action during wearing the variant consists of loading to the required degree ε_C with subsequent relaxation and releasing has been selected. The one cycle of deformation consists of the:

a) Loading up to required level of deformation ε_C at time t_1
b) Stress relaxation in the interval t_2–t_1
c) Recovery (stress releasing).

This cycle for time dependent deformation is shown on the fig. 1b. Plastic deformation after this cycle is equal to

$$\varepsilon_P = \frac{l_{A-B}}{l_0} \tag{7}$$

where l_0 is initial length of sample and l_{A-B} is increment of sample length after finishing the one cycle.

For the long-term deformation and recovery combination the following procedure using this deformation cycle have been applied:

1. 20 times repeating on cycle up to ε_C (one run)
2. One day recovery
3. 20 times repeating of cycle up to ε_C
4. One day recovery
5. 20 times repeating of cycle up to ε_C
6. One day recovery.

For quantifying of this long-term cyclical deformation the following parameters has been selected:

- Maximum load in the first cycle F_{1C}.
- Maximum load in the 20th cycle F_{20C}.
- Plastic deformation after whole procedure ε_P

These parameters can be used for the evaluation of fabric response to this complex procedure

3. EXPERIMENTAL PART

Four types of fabrics containing elastometric fibers have been used for evaluation of portion of plastic deformation and changes of stiffness after above described complex cyclic deformation.

The experiments are realized for the

- Standard fabrics (abbreviation S)
- Washed fabrics (abbreviation W)

Basic information about tested fabrics are summarized in the Table 1.

For characterization of mechanical behavior of individual fabrics the load to break and deformation to break were measured under standard conditions (sample width 5 cm). Results are summarized in the table 3a and 3b.

For characterization of mechanical behavior of individual fabrics the load to break (tenacity) and deformation to break were measured under standard conditions

Table 1 Basic Parameters of Fabrics

Fabric No	*Content*	*Pattern*	Areal weight [g/m^2]	Width [cm]
502	98%cotton, 2% Lycra	Combined	300	130
687	98% cotton, 2% Lycra	Twill (Z)	400	150
700	73% TENCEL, 24% cotton, 3% Lycra	Twill (S)	310	130
549	64% PAD, 32% cotton, 4% Lycra	Twill (Z)	286	140

Table 2 Selected deformations degrees

Fabric No	Deformation degree ε_C
502	5, 7, 10, 12, 15
687	8, 12, 15, 18, 21, 24
700	5, 7, 10, 12, 15
549	15, 19, 23, 27, 31, 35

(sample width 5 cm). Results are summarized in the table 3a and 3b.

Cyclic deformation was realized up to the deformations selected according the deformation to break (see table 2).

Experiments were realized on the tensile testing device TIRATEST under these conditions (see fig. 1b)

- Rate of deformation 0.15 min^{-1}
- Relaxation time 5 min
- Number of cycles in one run 20
- Time between runs 24 hours
- Number of runs 3

For individual ε_C the loads F_{1C} and F_{20C} and plastic deformation after whole procedure ε_P were measured.

In these tables CV denotes coefficient of variation. Confidence intervals are computed after normality proving [2].

4. CYCLIC DEFORMATION CHARACTERISTICS

From the measured parameters of fabrics some characteristics of total recovery, degree of plastic deformation and change of stiffness were computed. For characterization of the fabrics recovery the total recovery Z_C [%] has been computed

$$Z_C = 100\frac{\varepsilon_C - \varepsilon_P}{\varepsilon_C} \tag{8}$$

where ε_C is maximum deformation and ε_P is plastic deformation after finishing of whole deformation procedure (3 days).Portion of plastic deformation has been characterized by the cumulative extension after whole procedure

$$E_P = 100\ln(\varepsilon_P + 1) \tag{9}$$

Higher E_P is indication of the higher plastic deformation during wearing.

Degree of plastic deformation is equal to

Table 3a Tenacity – warp

Fabric No	Before washing Mean [N]	Confidence interval [N]	Standard deviation [N]	CV [%]	After washing Mean [N]	Confidence interval [N]	Standard deviation [N]	CV [%]
502	1100	1070–1129	9,4	0,9	954	879 –1029	20,3	2,1
687	1429	1377–1481	27,6	1,9	1544,5	1383–1706	80,8	5,2
700	1174	931–1417	88,8	7,6	1238,5	1149–1328	39,3	3,2
549	763	679–847	28,5	3,7	703,5	593–814	39,6	5,6

Table 3b Tenacity – weft

Fabric No	Before washing Mean [N]	Confidence interval [N]	Standard deviation [N]	CV [%]	After washing Mean [N]	Confidence interval [N]	Standard deviation [N]	CV [%]
502	565,5	538–593	22,7	4	467	455–479	7,9	1,7
687	647,5	566–729	32,7	5,1	548	530–567	19	3,5
700	529	449–609	21,6	4,1	447	422–472	12,2	2,8
549	870	852–888	26,5	3,1	592	571–613	7	1,2

Table 3c Deformation at break – warp

Fabric No	Before washing Mean [%]	Confidence interval [%]	Standard deviation [%]	CV [%]	After washing Mean [%]	Confidence interval [%]	Standard deviation [%]	CV [%]
502	15,21	14,68–15,73	0,67	4,38	16,93	16,05–17,81	0,29	1,68
687	32,69	31,49–33,89	1,57	4,81	27,42	26,84–28	0,48	1,75
700	12,67	10,98–14,35	0,46	3,76	15,91	15,41–16,42	0,48	3,03
549	61,31	56,21–66,42	1,78	2,91	40,9	38,46–43,33	1,44	3,54

Table 3d Deformacion at break – weft

Fabric No	Before washing Mean [%]	Confidence interval [%]	Standard deviation [%]	CV [%]	After washing Mean [%]	Confidence interval [%]	Standard deviation [%]	CV [%]
502	18,69	17,89–19,5	0,25	1,4	19,48	14,92–24,03	2,93	15,02
687	18,22	17,79–18,7	0,41	2,2	23,81	22,61–25,01	1,01	4,23
700	17,42	16,14–18,7	0,74	4,3	13,72	13,03–14,41	0,2	1,48
549	54,87	51,13–58,6	1,28	2,3	58,44	53,66–63,21	1,65	2,82

$$Z_P = \frac{E_P}{E_C}100 \qquad (10)$$

where $E_C = 100\ln(\varepsilon_C + 1)$ (11)

As the characteristic of stiffness the secant modulus

$$y_C = \frac{F_{1C}}{\varepsilon_C} \qquad (12)$$

has been selected. Stiffness after 20 times repeating of cycle is

$$y_K = \frac{F_{20C}}{\varepsilon_C} \qquad (13)$$

Relative stiffness change Z_T is defined by the relation

$$Z_r = \frac{y_C - y_K}{y_C}100 \qquad (14)$$

Higher Z_T shows higher influence of long-term cyclic deformation to the stiffness change. For the case ε_C = 15 % are above-mentioned characteristics shown on the fig. 2, 3, 4.

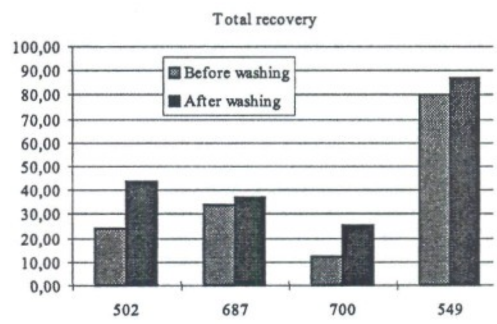

Fig. 1 Total recovery before and after washing

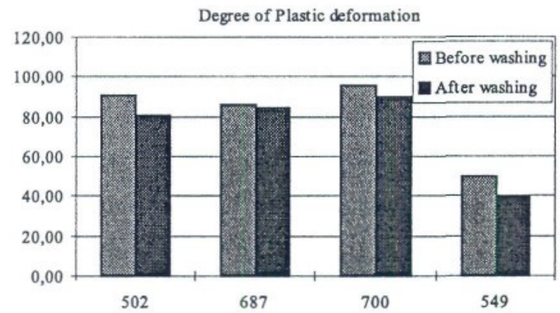

Fig. 2 Plastic deformation before and after washing

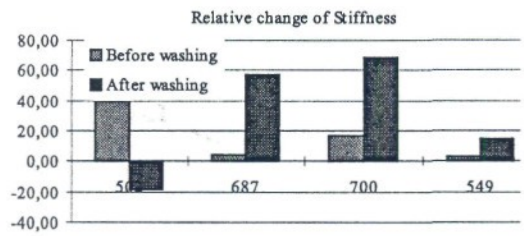

Fig. 3 Stiffness before and after washing

5. RESULTS AND DISCUSSION

The characteristics Z_C, Z_P and Z_T are graphically represented on the figs 2, 3, 4. Based on the previous finding the values Z_C of total deformation recovery at low ε_C are for shape retaining materials above 85–90%. Only the fabric No 549 composed from PAD/cotton/Lycra blend satisfies to this criterion. For other materials is Z_C under 50% and therefore the stability of shape after long-term cyclic deformation will be not on the required level.

Interesting results were obtained by comparison of washed and no washed samples. At low ε_C have fabrics after washing:

a) The better recovery Z_C for all tested samples
b) Lower plastic deformation degree for all samples excluding the No 502
c) Markedly lower degree of stiffness for all samples excluding the No 687.

These results show that the behavior of fabrics under long-term cyclic deformation is very complex and can be significantly changed by the washing. The influence of elastometric fibers could be improved by structure and pattern of fabric.

Acceptable low permanent plastic deformation can be obtained for materials hawing good elastic properties as well (see fabric No 549).

6. CONCLUSION

The proposed procedure for evaluation of the response of fabrics to the cyclic deformation with relaxation a recovery is very simple but can be applied for prediction of shape stability during wear. Influence of washing is important especially for fabric containing cotton

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REFERENCES

[1] Hearle, J.W.S., Morton, W.E.: Physical Properties of Textile Fibers, TI 1993

[2] Meloun M. Militký J. and Forina M. Chemometrics in Analytical Chemistry vol. I, Ellis Horwood, Chichester (1994)

DLOUHODOBÉ CYKLICKÉ NAMÁHÁNÍ TKANIN SE ZLEPŠENOU ELASTICITOU

Translation of Abstract:

Long term cyclic deformation of fabrics with improved elasticity

Cílem této práce je popis simulační studie zaměřené na dlouhodobé cyklické tahové namáhání při vybraných úrovních zatížení kombinované s jednodenním zotavením. Tento speciální experiment byl simulován na trhacím přístroji TIRATEST. Na základě experimentu byl určen podíl plastické deformace, elastické zotavení a změna tuhosti. Experiment byl prováděn na speciálních tkaninách s přídavkem elastomerních vláken.

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Surface Roughness and Fractal Dimension

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Surface Roughness and Fractal Dimension

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Surface roughness is one of the main characteristics of fabric responsible for hand feeling. By using KES, the surface height variation (SHV) trace is obtained. For characterization of roughness the mean absolute deviation (MAD; denoted by Kawabata as SMD) is usually used. The main aim of this work is quantitative description of complexity of roughness based on the SHV. The procedure of surface complexity parameters evaluation from SHV traces is described. The core is inspection of power spectral density and variogram (or autocorrelation function) behavior and classification of SHV signal to some groups. For individual groups, fractal dimension and surface roughness characteristics are computed by suitable methods. Proposed procedure was checked on the simulated SHV profiles and on practical examples.

1. INTRODUCTION

Kawabata (1980) revealed that surface roughness is one of the main characteristics of fabric responsible for hand feeling. By using KES, the surface height variation (SHV) trace can be obtained. The main part of Kawabata's measuring device is contactor in the form of wire (diameter 0.5 mm). This contactor is moved by constant rate 0.1 cm/s and SHV is registered on a paper sheet. The sample length $L = 2$ cm is used. The SHV corresponds to the surface profile in selected direction (usually the weft and warp directions are used for SHV creation). Characterization of roughness is based on the mean absolute deviation (MAD)—the classical descriptive statistical approach. This statistical characteristic is useful for random SHV traces where elements of SHV trace are statistically independent of each other. The SHV profile of a lot of fabrics has been identified as irregular and more structured.

The descriptive statistical approach based on the assumptions of independence and normality leads to biased estimators if the SHV has short- or long-range correlations (Meloun *et al.*, 1992). It is therefore necessary to distinguish between standard *white Gauss noise* and more complex models. For description of short-range correlations the models based on the *autoregressive moving average* are useful (Quinn and Hannan, 2001). The long-range correlations are characterized by the *fractal models* (Constantine and Hall, 1994; Mandelbrot and Van Ness, 1968). The *deterministic chaos* type models are useful in revealing chaotic dynamic in deterministic processes where variation appears to be random but in fact they are predictable (Ott *et al.*, 1994).

For selection among the above-mentioned models, the power spectral density (PSD) curve evaluated from experimental SHV can be applied (Eke *et al.*, 2000).

Especially, the fractal models are widely used for rough surface description (Whitehouse, 2001). For these models the dependence of log (PSD) on the log (frequency) should be linear. Slope of this plot is proportional to *fractal dimension* and intercept to the so-called *topothesy*. For, white noise has dependence of log(PSD) on the log(frequency) at nearly horizontal plateau for all frequencies (the ordinates of PSD are independent and exponentially distributed with common variance (Bloomfield, 2000). More complicated rough surfaces as a result of grinding can be modeled by the Markov type processes (Sacerdotti *et al.*, 2000). For these models the dependence of log(PSD) on the log(frequency) has plateau at small frequencies, then bent down and are nearly linear at high frequencies. The fractal type models were criticized by Whitehouse, who concluded that the benefits are more virtual than real (Sacerdotti *et al.*, 2000). On the other hand, the deeper analysis of rough surface should use more complex model than classical descriptive statistics.

The main aim of this work is quantitative description of roughness complexity based on the SHV. The procedure of roughness parameters evaluation from SHV traces is described. The core is inspection of power spectral density and variogram (or autocorrelation function) behavior and classification of SHV signal to some groups. For individual groups, the fractal dimension and surface roughness characteristics are computed by using suitable methods. Proposed procedure is demonstrated on the simulated SHV profiles and on the practical example.

2. FRACTALS

Most of the man-made objects are geometrically simple and can be classified as composition of regular geometric shapes such as lines, curves, planes, circles, spheres, etc. Some objects are not approximated precisely by the regular geometric shapes. One category of these objects is called *fractals*. Benoit Mandelbrot has coined the term fractal in the 1970s (Mandelbrot and Van Ness, 1968) from Latin *fractus*, meaning irregular or fragmented). Fractals have two interesting characteristics. First of all, fractals are *self-similar* on multiple scales, in that a small portion of a fractal will often look similar to the whole object. Second, fractals have a *fractional dimension*, as opposite to integer dimension of regular geometrical objects.

The fractional (fractal) dimension D can be evaluated by the following way. Let the number $N(\delta)$ of line segments of length δ needed to cover the whole curve in plane is measured. The length of the curve is estimated as $L(\delta) = N(\delta)$. In the limit $\delta \rightarrow 0$, the estimator $L(\delta)$ becomes asymptotically equal to the length of curve L independently on δ.

The Hausdorf–Besicovitch dimension D (fractal dimension) of this curve is the critical dimension for which the measure $M_d(\delta)$ defined as

$$M_d(\delta) = N(\delta)\delta^d$$

changes from zero to infinity (Feder, 1988). The value of $M_d(\delta)$ for $\delta = D$ is often finite and, therefore, for sufficiently small δ is valid

$$N(\delta) \approx \delta^D \quad \text{or} \quad L(\delta) \approx \delta^{1-D}$$

The fractal dimension is then computed as:

$$D = 1 - \frac{\log L(\delta)}{\log \delta}$$

Because fractals are self-similar they are constructed by recursion. For *geometrical fractals* the recursion is explicitly visible. A typical example is the so-called Koch curve shown in Fig. 1.

The interesting facet of the Koch curve is its fractal dimension D. In the nth step, the length of the segment is equal to $\delta = 1/3^n$ in. and the curve consists of 4^n segments.

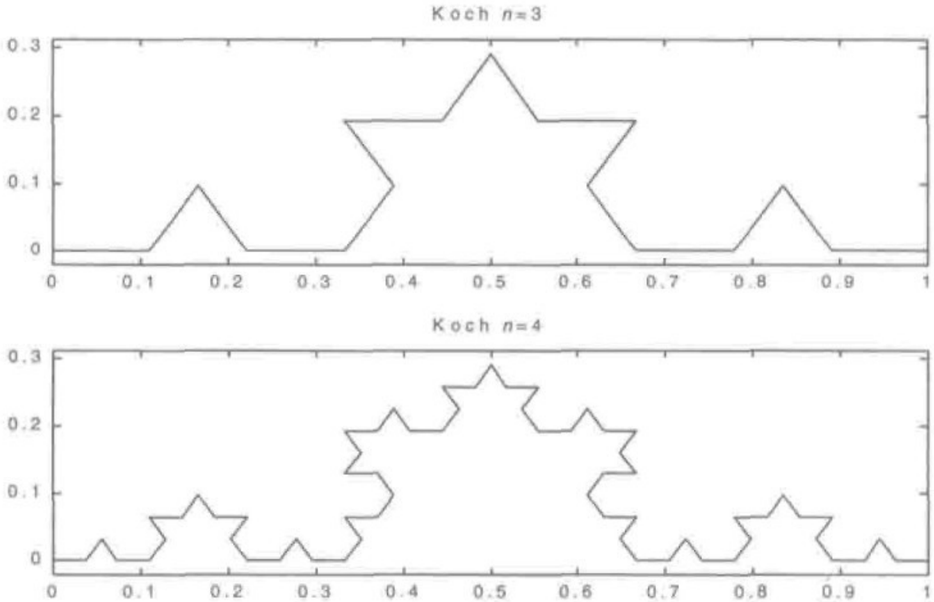

Fig. 1 Koch curve (in each step of construction the middle portion of each segment is removed and replaced by two new line segments. First step is line, having length *l*)

Therefore, the length is $L(\delta) = (4/3)^n$ in. and fractal dimension is $D = 1 - \{[n \log(4/3)]/[-n \log 3]\} = 1.26$. The fractal dimension of Koch curve is therefore slightly complex in comparison with line.

For *stochastic fractals* or *random fractals* the recursion is more little subtle and may be an artifact of an underlying fractal building process that occurs on multiple spatial scales. The typical generating function is Weistrass–Mandelbrot equation, which satisfies the self-affinity requirement (replaces the self-similarity in the case of functions). The height *R(d)* of surface in the point *d* or SHV trace is equal to

$$R(d) = G^{D-1} \sum_{i=n_1}^{\infty} \frac{\cos(2\pi g^i d)}{g^{i(2-D)}} \qquad (1)$$

where $1 < D < 2$ = fractal dimension related to the Hurst coefficient $H = 2 - D$;
G = characteristic length scale of surface; and
g = frequency spectrum of surface roughness.

The suitable value of parameter $g = 1.5$. The simulated stochastic fractal generated by Equation (1) for $H = 0.25$ is shown in Fig. 2.

This curve corresponds to the non-stationary random process and describes the fractional Brownian motion fB. The lowest frequency is then related to the sample length L according to the relation $g^{n_1} = 1/L$.

The evaluation of D and G from random fractals is based on the power spectral density $P(\omega)$ function, which has for Equation (1) the power law form

$$P(\omega) = C\omega^{-B} \quad \text{for } 1/L \leq \omega \leq \infty \qquad (2)$$

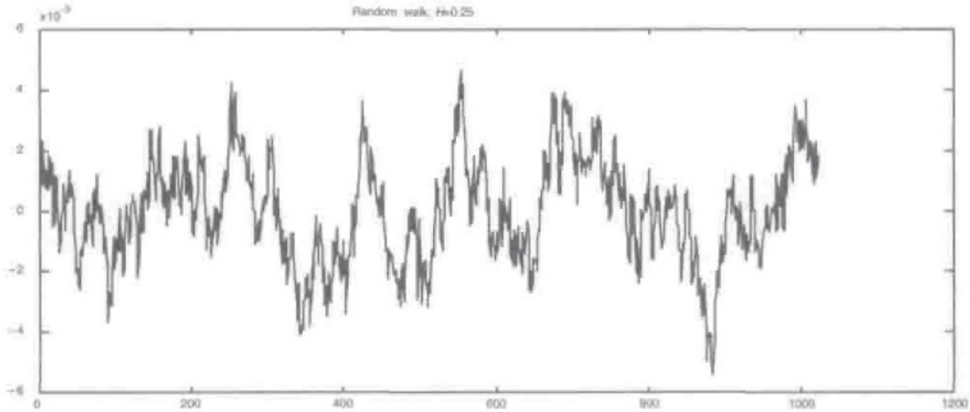

Fig. 2 Stochastic fractal generated by Equation (1) for $D = 1.75(H = 0.25)$

where $$C = \left[G^{2(D-1)}/2\ \ln(g)\right];\ \text{and}$$

$$B = 5 - 2D$$

The power law form is a typical feature of fractals. It is typical for wider class of so-called processes having long memory characteristics (Kendziorski, *et al.*, 1999). Long memory processes can be defined in terms of power scaling in the length domain, i.e. the power type function is valid for autocorrelation function and variogram as well.

In some cases fractals are stationary random processes like fractional Gaussian noise fG. The stationary fG process can be simply obtained as successive differences of fB process. Stationary fG process corresponding to fB from Fig. 2 is shown in Fig. 3.

Fractals in the form of fG are fully characterized by the mean and autocorrelation function $C(x)$ in the form:

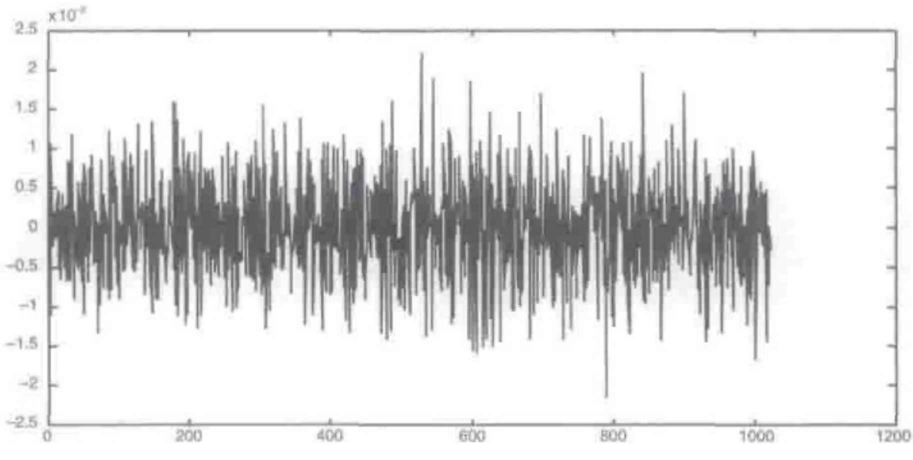

Fig. 3 Fractional Gaussian noise created from fractional Brownian motion (see Fig. 2)

$$C(x) = \frac{1}{2}\left[(x+1)^{2H} - 2x^{2H} + (x-1)^{2H}\right]$$

where H = Hurst coefficient.

For $0.5 < H < 1$, fG process is long memory type. Hurst coefficient is directly connected with the so-called fractal dimension D.

The main characteristic of both fractal types is fractal dimension. The problem with dimension is well known in measurement, e.g. coastal length. English meteorologist, Richardson found that the apparent length of a coastline seemed to increase whenever the length of the measuring stick was reduced. When the log of measuring stick was plotted against the logarithm of the total length of coastline, the points tended to lie on the straight line. The slope of this line is the measure of roughness or meandering of coastline. Mandelbrot has introduced the same approach for the characterization of fractals by fractal dimension. Let us have measuring device for evaluation of some characteristics (for the one-dimensional measure it is *length*, for two dimension it is *area* and for three-dimensional case it is *volume*) having measure Q. The characteristic of the whole object is defined as $N(Q)*Q$, where $N(Q)$ is the number of Q units for measurement of the whole object (e.g. number of stick placements to the measure of coastal length). For fractals, D is not an integer but can be estimated as limit

$$D = -\lim_{Q \to 0}\left(\frac{\log[N(Q)]}{\log(1/Q)}\right) \quad (3)$$

This definition is practically the same as the definition based on the Hausdorf–Besicovitch dimension.

For random fractals, it is simpler to use power spectral density or related functions. Some techniques for fractal dimension computations are summarized by Mannelqvist and Groth (2001). The method for computation of the Hurst coefficient is described by Wu (1999).

3. SURFACE ROUGHNESS DESCRIPTION

There are two reasons for measuring surface roughness. The first is to control manufacture and to help to ensure that the products perform well (Quinn and Hannan, 2001). In the textile branch the former is the case of special finishing (e.g. pressing or ironing) but the latter is connected with comfort appearance in hand.

From a general point of view, the rough surface display process has two basic geometrical features:

(i) Random aspect: the rough surface can vary considerably in space in a random manner, and subsequently there is no spatial function being able to describe the geometrical form.

(ii) Structural aspect: the variances of roughness are not completely independent with respect to their spatial positions, but their correlation depends on the distance. Especially, surface of weaves is characterized by nearly repeating patterns and, therefore, some periodicities are often identified.

From the SHV trace, it is possible to evaluate a lot of roughness parameters. Classical roughness parameters are based on the set of points $R(d_j)$ $j = 1$. M *is* defined in the sample length interval L. The measurement points d_j are obviously selected as equidistant and then $R(d_j)$ can be replaced by the variable R_j. For identification of positions in length scale it is sufficient to know sampling distance $d_s = d_j - d_{j-1} = L/M$ for $j > 1$. The standard roughness parameters used frequently in practice are (Wu, 2000):

(i) *Mean absolute deviation(MAD)*. This parameter is equal to the mean absolute difference of surface heights from average value (R_a). For a surface profile this is given by:

$$\mathrm{MAD} = \frac{1}{M}\sum_j |R_j - R_a| \tag{4}$$

This parameter is often useful for quality control. However, it does not distinguish between profiles of different shapes. Its properties are known for the case when R_js are independent identically distributed (i.i.d.) random variables.

(ii) *Standard deviation (root mean square) Value(SD)*. This is given by:

$$\mathrm{SD} = \sqrt{\frac{1}{M}\sum_j (R_j - R_a)^2} \tag{5}$$

Its properties are known for the case when R_js are independent identically distributed (i.i.d.) random variables. One advantage of SD over MAD is that, for, normally distributed data can be simple to derive confidence interval and to realize statistical tests. SD is always higher than MAD and for normal data is SD = *1.25*MAD. It does not distinguish between profiles of different shapes as well. The parameter SD is less suitable than MAD for monitoring certain surfaces having large deviations (corresponding distribution has heavy tail).

(iii)*Mean height of peaks(MP)*. This is calculated as the average of the profile deviations above the reference value R (often is $R = R_a$). It is given as the mean value of peaks P_i, $i = Np$

where $$P_i = R_i - R \quad \text{for } R_i - R > 0$$

and

$$P_i = 0 \quad \text{elsewhere}$$

(i) *Mean height of valleys(MV)*. This is calculated as the average of the profile deviations below the reference value R (often is $R = R_a$). It is given as the mean value of valleys V_i, $i = Nv$

where $$V_i = R - R_i \quad \text{for } R_i - R < 0$$

and

$$V_i = 0 \quad \text{elsewhere}$$

The parameters MP and MV give information on the profile complexity. Exceptional peaks or valleys are not considered but are useful in tribological applications.

(i) *The standard deviation of profile slope(PS)*. This is given by

$$PS = \sqrt{\frac{1}{M}\sum_j \left(\frac{dR(x)}{dx}\right)_j^2} \tag{6}$$

(ii) *The standard deviation of profile curvature (CP)*. This quantity often called waviness is defined in a similar way

$$PC = \sqrt{\frac{1}{M}\sum_j \left(\frac{d^2R(x)}{dx^2}\right)_j^2} \tag{7}$$

The slope and curvature are characteristics of a profile shape. The PS parameter is useful in tribological applications. The lower the slope the smaller will be the friction and wear. Also, the reflectance property of a surface increases in the case of small PS or PD.

(iii)*Mean slope of the profile (MS)*. This is given by

$$MS = \frac{1}{M}\sum_j \left|\frac{dR(x)}{dx}\right|_j \tag{8}$$

Mean slope is an important parameter in several applications such as in the estimation of sliding friction and in the study of the reflectance of light from surfaces.

(iv) *Ten point average(TP)*. This characteristic is defined as the average difference between the five highest peaks and five deepest valleys within a surface profile. The parameter TP is sensitive to the presence of high peaks or deep scratches in the surface and is preferred for quality control purposes.

These parameters are useful in the case of functional surfaces or for characterizing surface bearing and fluid retention and other relevant properties. For the characterization of hand it will be probably best to use waviness PC. The characteristics of slope and curvature can be computed in the case of fractal surfaces from power spectral density, autocorrelation function or variogram.

A set of parameters for profile and surface characterization are collected (Sacerdotti *et al*., 2000). These parameters are divided into the following groups:

- Statistical characteristics of height distribution (variance, skewness, and kurtosis).
- Spatial characteristics as autocorrelation or variogram (denoted in engineering as structural function).
- Functional characteristics (connected with fluid retention or flow properties).

There exist a vast number of empirical profile or surface roughness characteristics often suitable in very special situations. Some of them are closely connected with characteristics computed from fractal models (fractal dimension and topothesy). Greenwood (1984) proposed a general theory for the description of surface roughness based on the distribution of heights.

General surface topography is usually broken down to three components according to wavelength (or frequency) (Sacerdotti *et al*., 2000). The long wavelength (low frequency) range variation is denoted as *form*. This form component is removed by using polynomial models or models based on the form shape. The short wavelength (high frequency) range variation is denoted as *roughness* and medium wavelength range variation separates *waviness*. The most common way to separate roughness and waviness is spectral analysis. This analysis is based on the Fourier transformation from space domain d to the frequency domain $\omega = 2\pi/d$.

4. SPECTRAL ANALYSIS

The primary tool for evaluation of periodicities is expressing signal $R(d)$ by the Fourier series of sine and cosine wave:

$$R(d) = \frac{a_0}{2} + \sum_k [a_k \cos(2\pi kd) + b_k \sin(2\pi kd)] \tag{9}$$

Quantity d is often time or distance from origin and $k = 1, 2, 3, 4, \ldots$ The first two terms have period 1, the second two terms have period 1/2, the third two terms have period 1/3, etc. One consequence of this is that the different pairs of terms are orthogonal (integral of their product is zero). This fact facilitates fitting of the Fourier series to experimental data. The term $a_0/2$ can be made zero by centralization (i.e. subtracting of mean value). By using the Euler formula $\exp(ia) = \cos(a) + \mathrm{i}\sin(a)$, where i is the imaginary unit, the Fourier series may be written in the compact form

$$R(d) = \sum_k c_k \exp(-2\pi ikd)$$

The complex coefficients c_k have real and imaginary parts a_K and $\mathrm{i}b_k$. In Fourier series only the terms up to $k = M/2$ contain any useful information. After this bound real coefficients are repeated symmetrically and imaginary coefficients are repeated antisymmetrically. The Fourier transform is conversion of data from series according to d to the series of frequencies $\omega = 2\pi k/(ML)$, for $k = 1, 2, 3, \ldots$

$$\mathrm{RF}(\omega) = \sum R(d)\exp(-\mathrm{i}\omega d) \tag{10}$$

Function RF is symmetric about frequency $\omega = \pi/L$. For discrete data the fast Fourier transform (FFT) leads to transformed complex vector DRF. Vector DRF may be used for creation of power spectral density $[P(\omega)]$

$$P(\omega) = \mathrm{DRF}\,\mathrm{conj.}(\mathrm{DRF})/L^2 = \mathrm{abs}(\mathrm{DRF})^2/L^2 \tag{11}$$

where conj$(\cdot)$ denotes conjugate vector. $P(\omega)$ is the estimator of spectral density function and contains values corresponding to contribution of each frequency to the total variance of $R(d)$. Frequency of global maxim on $P(\omega)$ corresponding to the length of repeated pattern and height corresponds to the non-uniformity of this pattern. Spectral density function is therefore generally useful for evaluation of hidden periodicities. For the continuous case the Fourier spectrum has the form

$$P(\omega) = \frac{1}{L}\int_{-\infty}^{\infty} R(x) \exp(-2\pi i\omega x)\mathrm{d}x \tag{12}$$

where $R(x)$ = height amplitude function estimated as SVH trace $R(d)$;
L = sample length; and
i = imaginary unit.

The estimation of the spectral density function $P(\omega)$ is relatively straightforward in theory, but in practical, situations it is more difficult since data are only available in discrete samples of limited extent. For finite sample lengths it is necessary to use windowing (avoiding leakage) detrending (avoiding non-stationarity of mean) and filtration of parasite frequencies (Muthuswamy and Thakor, 1998). Several methods of estimating the spectral density function are available. More precise estimates can be obtained by using sophisticated procedures as averaged periodogram of overlapped windowed signals (Welch method) or multiple signal classification (MUSIC). The maximum entropy spectral analysis (MEM) provides smoother and higher resolution spectra for red-noise processes, which therefore would appear to be more suitable for good estimation. The method of MEM spectral estimation uses the Fourier transform between $P(\omega)$ and the autocorrelation function (Kendziorski *et al.*, 1999). It is necessary to specify before computation the order of AR model. $P(\omega)$ is then selected to maximize entropy such that the inverse Fourier transform of $P(\omega)$ yields the autocorrelation function. These spectral estimators are available in Signal Processing toolbox of MATLAB system (Anon., 2000). For the white noise (independent standard normal random numbers) the estimators of spectral density are as shown in Fig. 4.

It is clear that the rough FFT based estimator shows the random fluctuations. Both, more sophisticated, estimators show at first sight the false one or more periodicities. By using statistical testing these local peaks were found to be insignificant.

For simulation of these estimators, behavior for periodic structure with added random noise $N(0,1)$ the function

$$R(d) = 3\sin(2\pi 10\ t) + 4\sin(2\pi 4\ t) + N(0,1)$$

was generated.

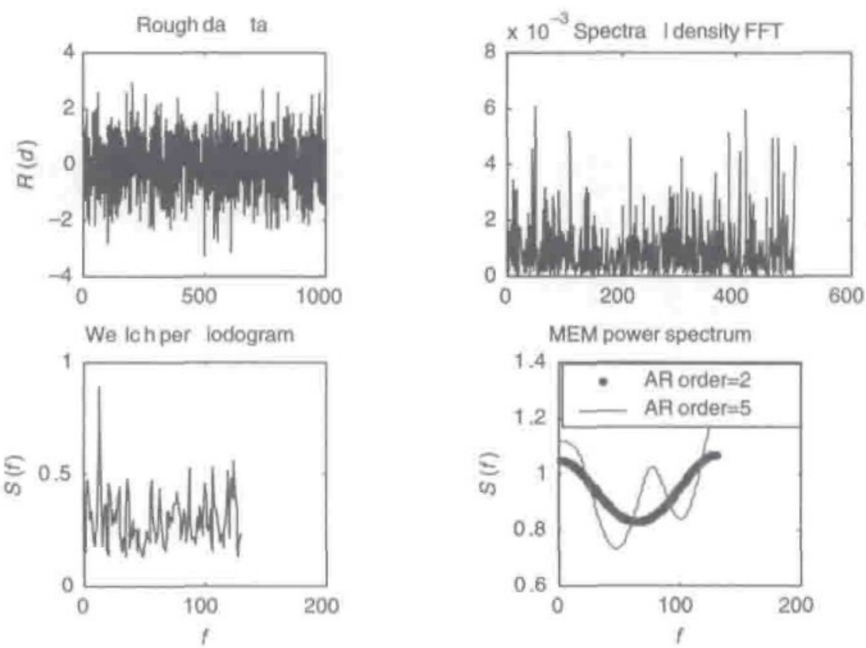

Fig. 4 Raw data (white noise) and estimators of power spectral density

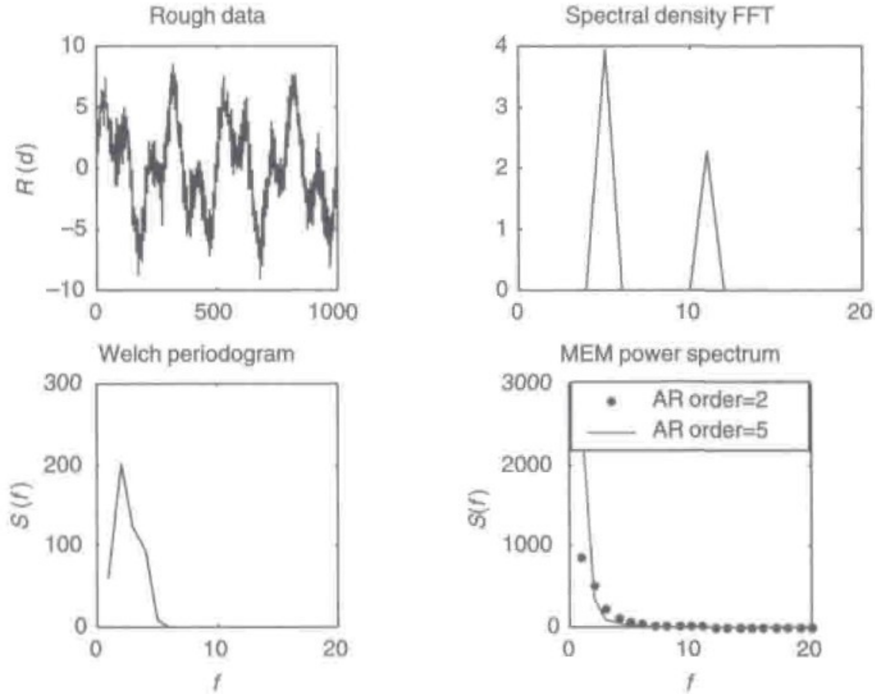

Fig. 5 *Spectral densities for periodic function with added white noise*

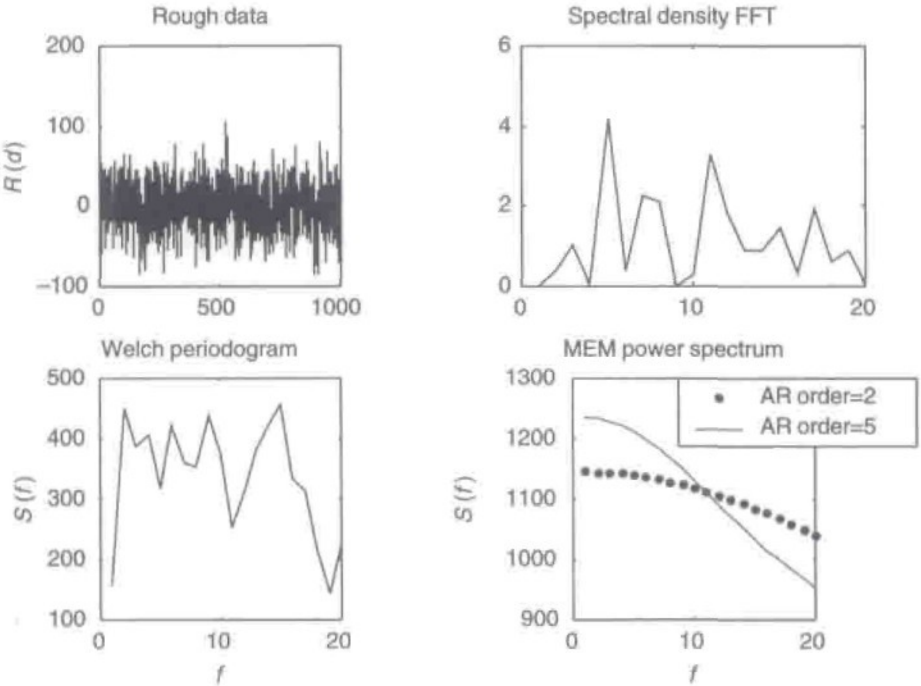

Fig. 6 Spectral estimators for data from Fig. 2 with high level of noise $N(0,400)$

The estimators of spectral density and raw data are shown in Fig. 5.

For very high level of noise $N(0{,}400)$, these estimators are non-effective (see Fig. 6).

The spectral estimators for finite data length corrupted by random errors could be inaccurate. The more sophisticated procedures are very sensitive to the tuning parameters. So, the estimation of fractal dimension is therefore the best way to use simple FFT based method with proper data pre-treatment (detrending, windowing) (Wu, 1999).

5. STATISTICAL ANALYSIS

A basic statistical feature of $R(d)$ is autocorrelation between distances. Autocorrelation depends on the lag h (i.e. selected distances between places of thickness evaluation). The main characteristics of autocorrelation are the covariance function $C(h)$

$$C(h) = \operatorname{cov}\left[R(d), R(d+h)\right] = E\left(\left\{R(d) - E\left[R(d)\right]\right\}\left\{R(d+h) - E\left[R(d)\right]\right\}\right)$$

and the autocorrelation function ACF(h), defined as the normalized version of $C(h)$

$$\mathrm{ACF}(h) = \frac{C(h)}{C(0)} \tag{13}$$

$E(x)$ denotes the expected value of x. ACF is one of the main characteristics for detection of short- and long-range dependencies in dynamic (time) series. It could be used for preliminary inspection of data. The computation of sample autocorrelation directly from definition for large data is tedious. The technique of ACF creation based on the FFT is contained in Signal Processing toolbox of MATLAB (procedure xcorr.m) (Anon. 2000). The spectral density is the Fourier transform of the covariance function $C(h)$

$$P(\omega) = \frac{1}{2\pi}\int_0^\infty C(t)\exp(-i\omega t)\mathrm{d}t \tag{14}$$

ACF is the inverse Fourier transform of spectral density

$$C(h) = \int_0^\infty P(\omega)\exp(i\omega h)\mathrm{d}\omega \tag{15}$$

These relations show that the characteristics in the space and frequency domain are interchangeable.

In spatial statistics, more frequent variogram (called often as structure function) is defined as one-half variance of differences $[R(d) - R(d+h)]$

$$\Gamma(h) = 0.5D\left[R(d) - R(d+h)\right] \tag{16}$$

or

$$\Gamma(h) = 0.5\left\{E\left[R(d) - R(d+h)\right]^2 - E^2\left[R(d) - R(d+h)\right]\right\} \tag{17}$$

Symbol $D(x)$ denotes variance of x. For stationary random process, mean value is independent on lag h, i.e. $E(R(h)) = m$, then

$$\Gamma(h) = 0.5E\Big(R(d) - R(d+h)\Big)^2 \tag{18}$$

For random processes having stationarity of second order is valid

$$C(h) = E[R(d)R(d+h)] - m^2 \tag{19}$$

Variance is then equal to

$$D[R(d)] = C(h=0) = C(0) \tag{20}$$

and variogram is directly related to covariance

$$\Gamma(h) = C(0) - C(h) \tag{21}$$

The variogram is relatively simpler to calculate and assumes a weaker model of statistical stationarity than the power spectrum. Several estimators have been suggested for the variogram. The traditional estimator is

$$G(h) = \frac{1}{2M(h)}\sum_{j=1}^{M(h)}[R(d_j) - R(d_{j+h})]^2 \tag{22}$$

where $M(h)$ = number of pairs of observations separated by lag h.

Problems of bias in this estimate when the stationarity hypothesis becomes locally invalid have led to the proposal of more robust estimators. One such estimator has been created by Cressie and Hawkins (Muthuswamy and Thakor, 1998). Another estimator has been suggested by Isaaks and Srivastava (Middleton, 2000).

The sample co-variance function (ACF is normalized by variance) is defined as

$$C_k = \frac{1}{M-k}\sum_{i=1}^{M-k}[R(d_i) - Ra][R(d_{i+k}) - Ra] \tag{23}$$

where Ra = sample mean.

Corresponding sample spectral density is

$$P_k = \frac{1}{M}\sum_{z=0}^{M-1} C_z \exp\left(-\frac{2\pi izk}{M}\right) \tag{24}$$

and for variogram is valid

$$G_k = \frac{2}{M}\sum_{z=0}^{M-1} P_z * \left[1 - \exp\left(\frac{2\pi izk}{M}\right)\right] \tag{25}$$

For the white noise (independent standard normal random numbers), the estimators of ACF, variogram and covariance function are shown in Fig. 7.

The same estimators are given for the case of periodic function with added white noise (see Fig. 5) in Fig. 8.

For very high level of noise $N(0, 400)$ periodicities are hidden and not detected by these estimators (see Fig. 9). This level of noise is, in practice, not the result of measurement errors but a result of random fluctuations of surface profile.

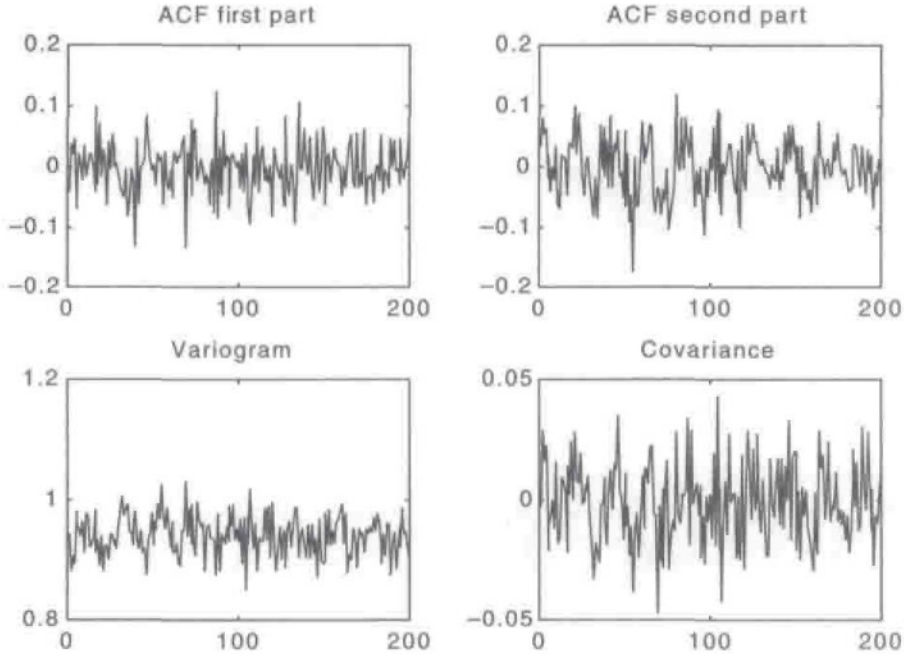

Fig. 7 Estimators of ACF, variogram and covariance function for white noise

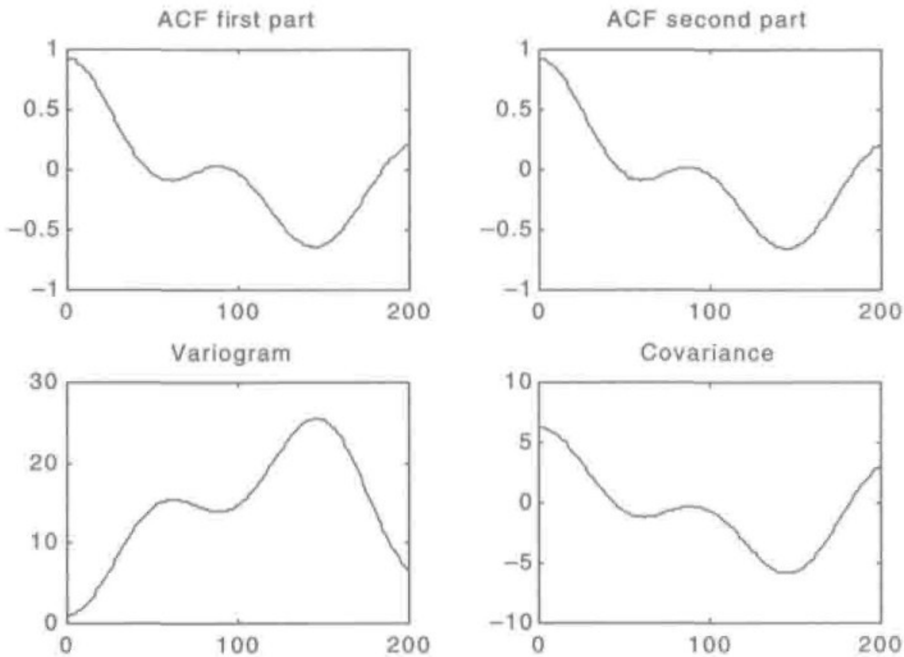

Fig. 8 The ACF, variogram, and covariance function for periodic function with added white noise

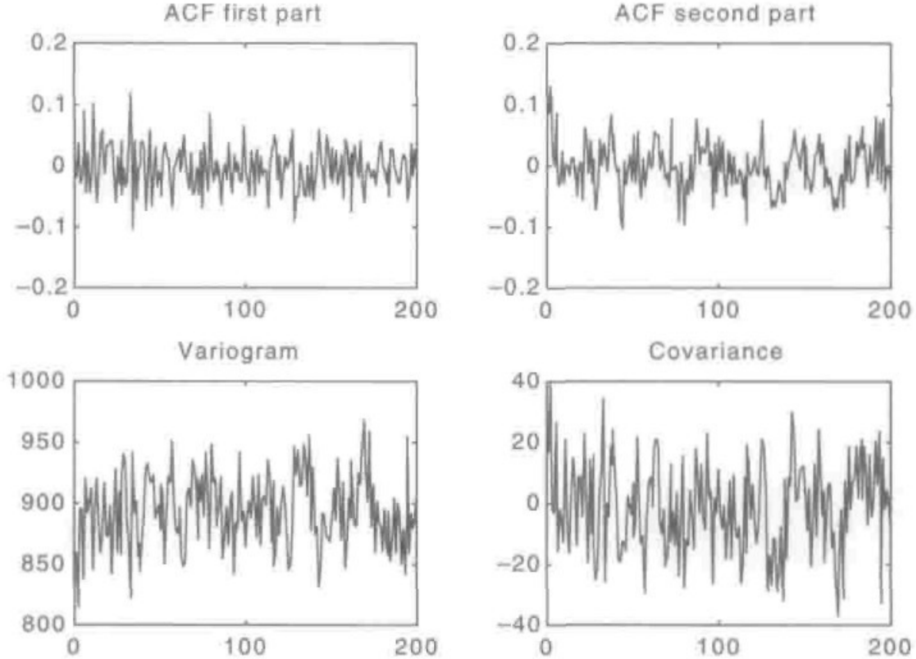

Fig. 9 ACF, variogram and covariance for periodic data embedded in high level noise $N(0,400)$

It can be summarized that simple statistical characteristics are able to identify the periodicities in data but the reconstruction of 'clean' dependence is more complicated. The variogram is often sufficient for characterization of surface profiles.

6. NATURE OF SURFACE PROFILES

There exists a lot of surface profile models. For illustration of individual characteristics describing their complexity, the main types of these models were generated.

6.1 Fractal Surface fB

The simulated stochastic fractal generated by Equation (1) for $D = 1.75$ is shown in Fig. 10 and for $D = 1.25$ in Fig. 11. Power spectral densities in log–log scale, variograms in log–log scale and amplitude histogram are represented in the same figure. The practically perfect linearity of log variograms and scattered linearity of log power spectral densities are typical for self-affine curves. Histograms of amplitudes R_i indicate multimodality or skewed distribution.

These curves correspond to the non-stationary random process and describe fractional Brownian motion fB.

6.2 Fractional Gaussian Noise fG

The simulated stationary fG process corresponding to fB from Fig. 11 is shown in Fig. 12.

It is clear that in this case it is not simple to identify the self-affine behavior from log of variogram or log of power spectral density.

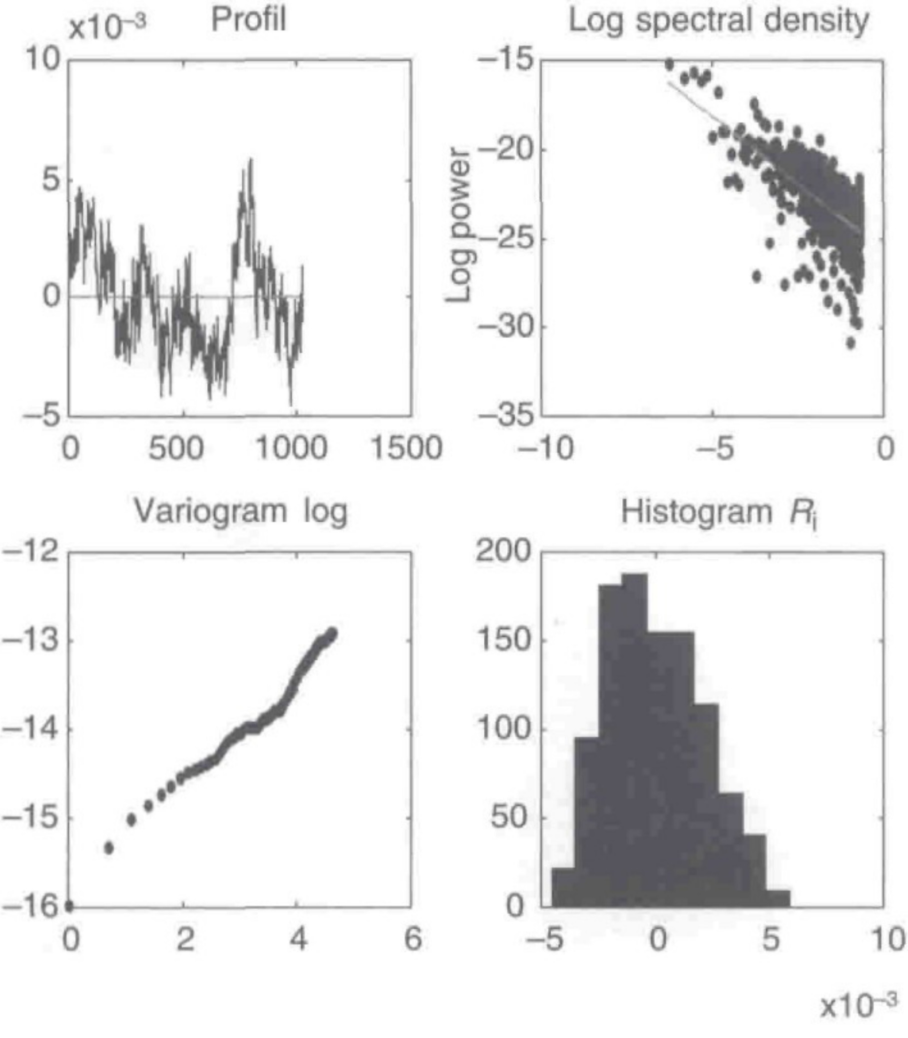

Fig. 10 Stochastic fractal generated by Equation (1) for $D = 1.75$

6.3 Markov Model

A lot of engineering surfaces obey fractal like behavior for high frequencies. For low frequencies the log–log power spectral density exhibits a nearly constant line. The Markov type models can express this behavior. Simplest one has the form

$$R_{i+1} = rR_i + (1 - r)\sigma_m N(0, 1) \tag{26}$$

where r = autocorrelation coefficient.

For this process, the variance $C(0)$ is equal to

$$C(0) = \frac{1 + r}{1 - r}\sigma_m^2$$

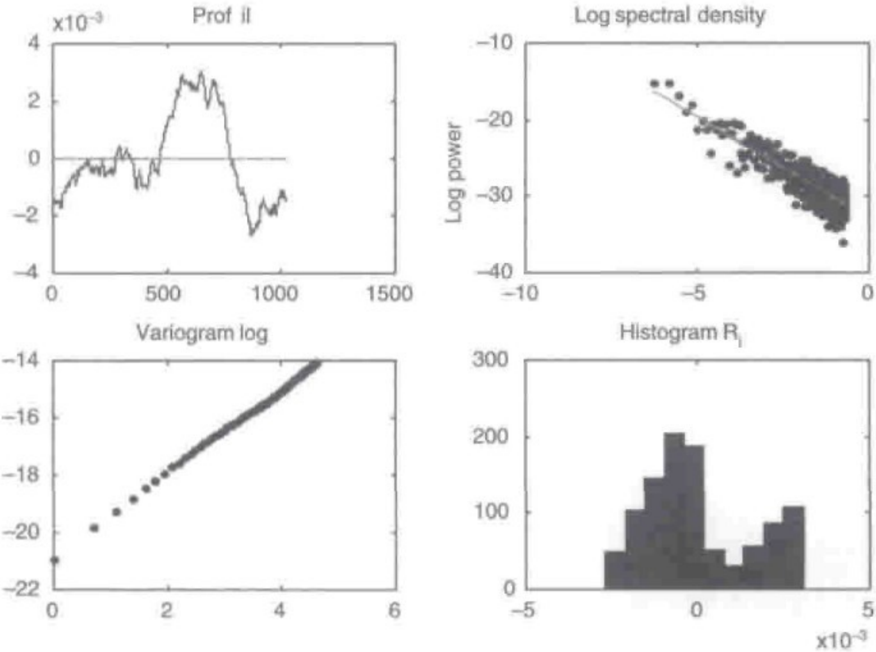

Fig. 11 Stochastic fractal generated by Equation (1) for $D = 1.25$

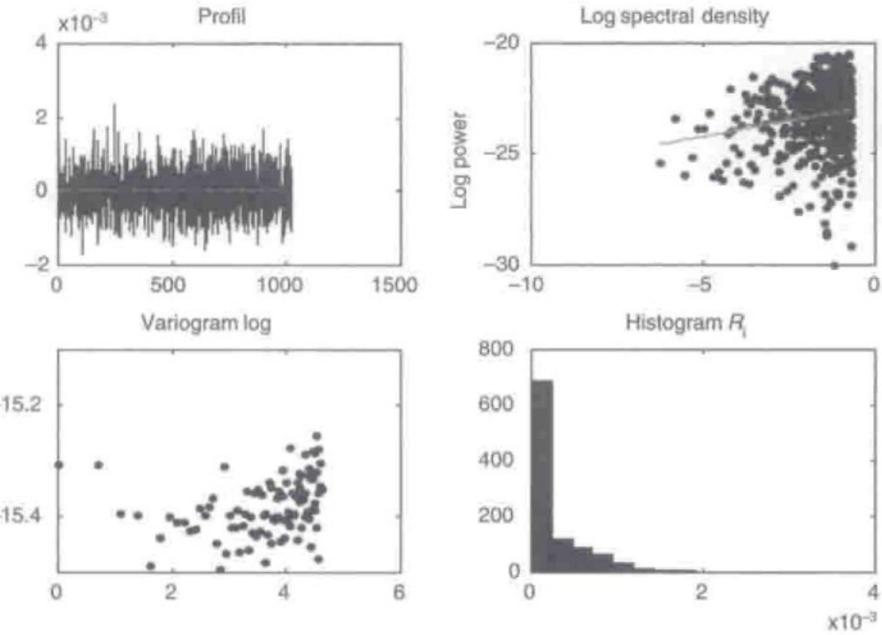

Fig. 12 Fractional noise corresponding to first difference of the fractional Brownian motion from Fig. 11

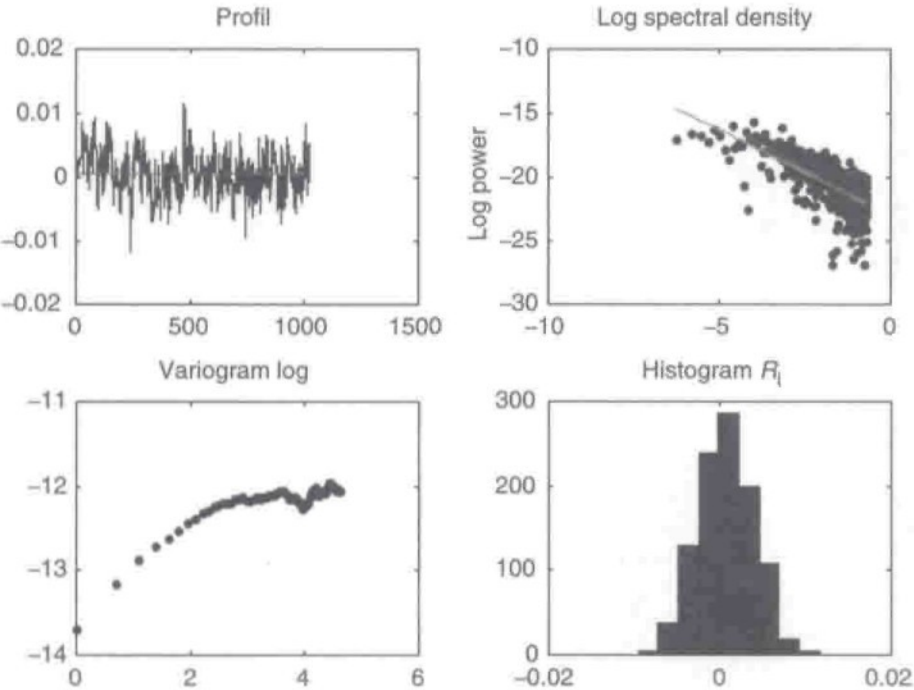

Fig. 13 Markov type surface profile generated by Equation (26)

The ACF has a very simple form

$$\mathrm{ACF}(h) = \sigma_m^2 r^h \tag{27}$$

and for power spectral density is valid

$$P(\omega) = \frac{b\sigma_m^2}{\pi(1 + b^2\omega_m^2)} \tag{28}$$

where b = a constant connected with r.

Markov type profile for $r = 0.8$ is shown in Fig. 13

It is evident that the degree of linearity for small lengths (corresponds to the high frequencies) is still very high for log–log variogram.

Based on these and other extended simulations we can conclude that:

- Power spectral density of Gauss noise has a lot of local extremes. Variogram has random fluctuations in small scale.
- Power spectral density of composite sine waves embedded in high-level noise exhibits no right pattern. The same is valid for variogram.
- Power spectral density of fractal type (fBm) surface profiles exhibits scattered linear trend according to the theory. The variogram exhibits more strict linearity with relative small scatter. Variogram here is a typical power function of h.
- Fractional Gaussian surface profiles are typical by random fluctuations of variogram.

- Markov like surface profiles have linear portion on variogram at smaller lags h. For higher lags the plateau is visible.

The simply calculated variogram can replace the spectral power density. For periodic surface profiles, having small noise level enables power spectral density for the identification of periodicities.

7. ESTIMATION OF THE FRACTAL DIMENSION

A convenient way of characterizing the smoothness of an isotropic surface is Hausdorf or fractal dimension. If the surface is very smooth fractal dimension is equal to two ($D_p = 2$). For extremely rough surface, fractal dimension approaches the limit value ($D_p = 3$). General definition of fractal dimension is based on the capacity principle (Nayak, 1971). In the measurement of surface profile [thickness variation $R(h)$], data are available through one-dimensional line transect surface. Such data represent curve in plane. Two-dimensional fractal dimension D is then a number between 1 (for smooth curve) and 2 (for rough curve). If a surface is modeled by a stationary, isotropic Gaussian field, then the relation

$$D_p = D + 1 \tag{29}$$

is valid. The expected variance of the increment of Brownian motion can be expressed using a value of the Hurst exponent H, where $H = 0.5$ (Wu, 1999)

$$E[R(d) - R(d+h)]^2 \approx |h|^{2H} \tag{30}$$

For fractional Brownian motion fB, H is in the interval (0,1). Where $H = 0$ denotes a surface of extreme irregularity and $H = 1$ denotes a smooth surface. Exponents H and fractal dimension D are in fact related by:

$$D = D_T + 1 - H \tag{31}$$

where D_T = the topological dimension such that D is in the interval (2,3) for a surface and (1, 2) for a cut across a surface.

Note that fractional Brownian motion can be expressed in terms of a power law variogram

$$\Gamma(h) \approx c|h|^H \tag{32}$$

where c = a constant.

Similarly, for $P(\omega)$ is valid

$$P(\omega) = c_1|\omega|^{-(1+2H)} \tag{33}$$

where exponent ($1+2H$) lies in the interval (1,3). Fractal dimension is conventionally obtained through estimating the parameter from a LSE linear regression of the log–log transformation of Equations (32) and (33). The same results can be obtained assuming that the thickness variation $R(d)$ is a stationary Gaussian process and the covariance function $C(h)$is sufficiently smooth (Bloomfield, 2000; Nayak, 1971). The behavior of this function near the origin can be described by power type model

$$C(0) - C(h) \approx c|h|^\alpha \tag{34}$$

These formulae may also be verified for other processes related to Gaussian one. In practice, behavior expressed by Equation (32) is valid near origin and by Equation (33) in a neighborhood of infinity. In general, D computed from this relation is denoted as effective fractal dimension.

There are several problems in estimating fractal dimension in this fashion. First, elevation points, points on the variogram, and the error term in the LSE regression are likely to be autocorrelated. Second, data points in log–log space are unequally spaced and, third, decisions concerning an acceptable cut-off for goodness of fit (R^2) of the linear function are of an arbitrary *a priori* nature. Since the aim of the line-fitting exercise in estimating fractal dimension is the description of the relationship rather than prediction, the bias introduced by the first problem is not critical. A solution to the second is to re-sample the data using a geometric progression, but at the cost of a dramatic reduction in the number of points used in the line-fitting exercise. An alternative to the third is to estimate the standard error (SE) around the slope of a regression line. Based on these equations the program TLOU in MATLAB for estimation of fractal dimension from variogram and power spectral density has been constructed. Based on the preliminary testing the results of computation from variogram were more stable and reliable. From power spectral density the d corresponding to the global maximum of $P(\omega)$ can be evaluated as well.

8. ROUGHNESS AND FRACTAL DIMENSION

It can be shown that most of the classical roughness characteristics such as RMS roughness, the density of summits, and the mean absolute surface slope are functions of fractal dimension and cut-off frequencies only. These roughness parameters are not intrinsic properties of a surface, and vary with the conditions of measurement. Self-similar fractal curves and surfaces are described completely by a single parameter, the fractal dimension D, which is an intrinsic property of the surface and does not change with the scale of measurement.

Nayak (1971) showed that the statistical geometry of an isotropic random Gaussian surface could be expressed in terms of the moment of power spectral function

$$m_k = \int_{\omega_H}^{\omega_L} \omega^k P(\omega) d\omega \tag{35}$$

The frequencies ω_H and ω_L are high and low frequency bounds of integration of the spectrogram. These bounds can be converted to the wavelength limits. The long wavelength limit is $l_H = 2\pi/\omega_H$ and the short wavelength limit is $l_L = 2\pi/\omega_L$. The roughness Rq (standard deviation) is simply $\mathrm{Rq} = \sqrt{m_0}$ and the density of summits is

$$\mathrm{DS} = \frac{m_4}{m_2 6\pi\sqrt{3}} \tag{36}$$

After substituting Equation (33) to Equation (35) and when integration for the case is $\omega_L >> \omega_H$, the following approximations are valid

$$m_0 = \frac{-c_1}{\alpha+2}\omega_H^{\alpha+2} \quad m_2 = \frac{c_1}{\alpha+4}\omega_L^{\alpha+4} \quad m_4 = \frac{c_1}{\alpha+6}\omega_L^{\alpha+6} \tag{37}$$

Parameter $\alpha = -(1+2H)$. None of the roughness parameters defined by the moment equations is an intrinsic property of the surface (Thomas and Rosen, 2000). The roughness Rq is independent of the sampling interval but depends on the high/pass cut-off, while summit densities are independent of the high/pass cut-off but depend on the sampling interval. Furthermore, Equation (37) requires that $-3 < \alpha + 1 < -1$, i.e. to say those amplitudes of surface wavelengths must fall off quite sharply, but not too sharply, as the wavelengths get smaller. Fortunately, this condition is usually satisfied for real surfaces.

More simple equations can be derived by using the variogram *G(h)*. The standard deviation of profile slope is given by (Wu, 1999 and Feder, 1988)

$$\mathrm{PS} = \sqrt{\frac{G(d_s)}{d_s^2}} = \sqrt{c d_s^{2-2D}}$$

and the standard deviation of profile curvature is

$$\mathrm{PD} = \sqrt{\frac{4G(d_s) - G(2d_s)}{d_s^4}} = \sqrt{(4 - 2^{4-2D}) c d_s^{-2D}}$$

In these equations D is the fractal dimension estimate obtained from variogram, c is intercept in log–log variogram plot [see Equation (32)] and d_s is sampling distance.

9. SHV TRACE EVALUATION

The processing of SHV traces from Kawabata device can be divided into two phases. In the *first phase* the following tasks are solved.

- Digitalization of trace picture by image analysis system;
- Removing parasite objects (grid, axes, base-line etc);
- Creation of PSD and variogram.

First of all the low ω_L and high ω_H surface frequency bands have to be specified. These cut-off frequencies are related to the wavelength limits l_L and l_H. The low pass cut-off is related to Nyquist criterion i.e. $l_L = 2d_s$ and the high pass cut-off is dependent on the maximum interesting wavelength. For non-regular SHV $l_H = L$ has to be selected. The results of digitalization and parasite object removing is set of 'clean' heights $R(d_i)$ of fabric in places $0 < d_i < L$ (L is the maximum investigated sample length and $i = 1,\dots, M$ number of places). The distance between places $d_s = d_{i+1} - d_i$ is constant. For the case of Kawabata device $L = 2$ cm and $d_s = 2/(M-1)$ cm.

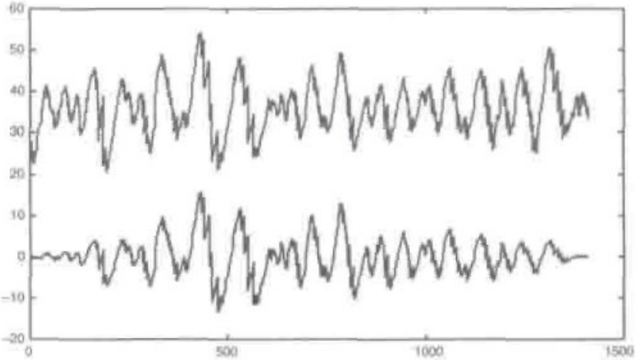

Fig. 14 Clean data (upper curve) and data after removal of trend, centering and windowing

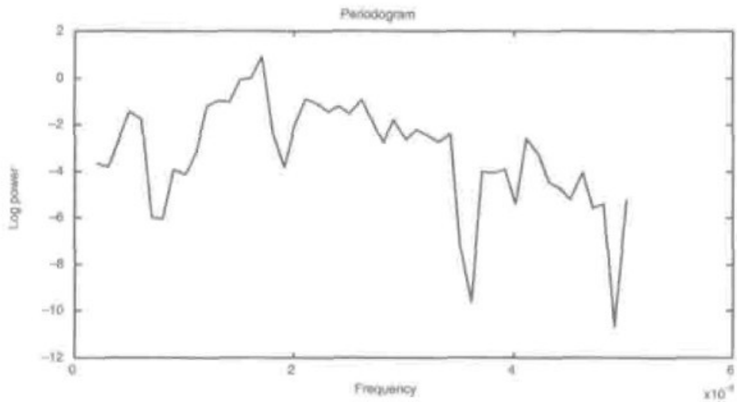

Fig. 15 Power spectral density in semi-log scale

The core of *pre-treatment phase* is creation of PSD. Rough estimator is based on the FFT and it is a vector having elements as the squared spectral amplitudes abs(Pk)^2. The FFT has its own drawbacks and limitations (Muthuswamy and Thakor, 1998). It has problems with leakage and resolution and non-stationary signals. The removal of mean value and linear trends is then necessary. For reduction of leakage effect, the windowing i.e. multiplying by suitable spectral window is useful. In program *TLOU* the simple parabolic window or hamming window is selected. Clean data and data after windowing for weave are used as examples as shown in Fig. 14.

The resultant spectral 'leakage' distorts the actual signal but reduces effect of finite length. The dependence of log[P(ω)] on spatial frequency for pre-treated signal from Fig. 14 is shown in Fig. 15.

In the *second phase* the signal is classified according to the slope $S = (\alpha + 1)$ of log[$P(\omega)$] on the log(frequency) dependence. The following categories have been proposed [see (Eke *et al.*, 2000):

1. *Fractional Gaussian noise* fG for the range $-1 < S < 0.38$. In this case, the fractal dimension from power spectrum can be used but variogram is not suitable.
2. *Fractional Brownian motion* fB for the range $1.04 < S < 3$. In this case, the variogram can be used for estimation of fractal dimension as well.
3. *Transition case* for the range of S between 0.38 and 1.04. In this case, the cumulative sum of SHV should be created (transformation to the case 2).
4. *No fractal behavior* for cases when the power law model is invalid (in two decade range). For this case the *chaotic models* (broad bands) or *ARIMA models* (narrow peaks) have to be used.

Special techniques for estimation of fractal dimension for the above mentioned cases are presented by Eke *et al.*, (2000). For realization of this computation and evaluation of fractal dimension, based on the definition (Equation 3), the MATLAB program *TLOU* has been created. This program uses the cleaned and pre-treated $R(d_j)$ for creation of variogram and $P(\omega)$ function (based on FFT). Fractal dimensions [D_p from $P(\omega)$] and D_v from variogram) are obtained by estimating the parameter from a LSE linear regression of the corresponding models. The fractal dimension D_d based on the definition is computed by using the code Divider2 described by Middleton (2000).

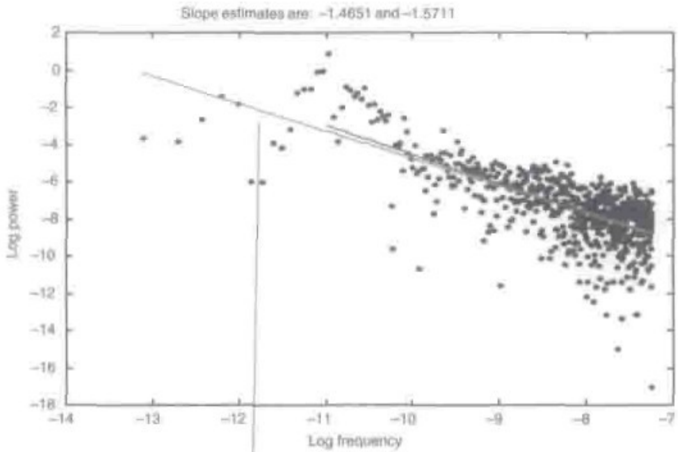

Fig. 16 The test of fractality (log–log PSD trace). The least squares lines correspond to the full data and portion of data having high frequencies

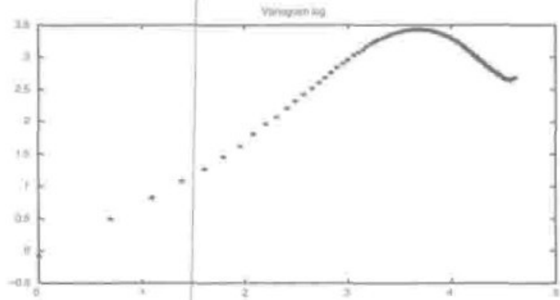

Fig. 17 Variogram in log–log scale

9.1 Example

The computation of surface roughness parameters based on the concept of fractality is critically dependent on the estimation of $P(\omega)$. Our procedures in the program TLOU have been selected based on the simulated fB and fG fractal curves by using code Mwfractal described by Middleton (2000). As an example of practical application of TLOU the surface roughness profile for one weave has been measured on the Kawabata instrument. Weave was three end twill (weft sett 35 and warp sett 16) created from ply polyester yarns 25×2 tex. The clean SHV trace is shown in Fig.14 and $P(\omega)$ curve in Fig. 15. The log–log $P(\omega)$ trace and regression lines are shown in Fig. 16.

The slope S about 1.48 classifies the SHV signal to the second group. The plot of variogram in log–log scale is shown in Fig. 17.

It is visible that the linearity is acceptable up to three and half decades. The computed fractal dimensions are $D_v = 1.629$, $D_p = 1.714$ and $D_d = 1.536$. Characteristic from Kawabata device for this case is $SMD = 4.931$.

10. CONCLUSION

The analysis of SHV based on the TLOU program is in reality more complex. The classical roughness characteristics and topothesy are computed as well and many other techniques of fractal dimension calculations are included. In future the analysis will be extended to the chaotic models and autoregressive models. The roughness parameters PC and PS will be correlated with subjective roughness meaning. With some modifications it will be possible to use this approach for characterization of the surface profiles obtained from other techniques or longitudinal variability of linear (yarns) or plane textile structures (fabric).

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REFERENCES

Anon. Signal Analysis Toolbox, Mathworks Inc., 2000
Bloomfield P., 2000. *Fourier analysis of time series*, Wiley, New York, NY, USA.
Constantine A.G., and Hall P., 1994. *J. Roy. Stat. Soc.*, **B56**, 97.
Eke A. *et al.*, 2000. *Eur. J. Physiol.*, **439**, 403.
Feder J., 1988. *Fractals*, Plenum Press, New York, NY, USA.
Greenwood J.A., 1984. *Proc. Roy. Soc. London*, **A393**, 133.
Kawabata S., 1982. *The Standardization and Analysis of Fabric Hand, The Textile Machinery Society of Japan*, Osaka.
Kendziorski C.M. *et. al.*, 1999. *Physica A*, **273**, 439.
Mandelbrot B.B., and Van Ness J.W., 1968 *SIAM Review* **10**, 42.
Mannelqvist A., Groth M.R., 2001. *Appl. Phys.* **A69**.
Meloun M., Militkú J., and Forina M., 1992. Chemometrics for Analytical Chemistry. In *PC Aided Statistical Data Analysis*, vol.1 Ellis Horwood, Chichester.
Middleton G.V., 2000. *Data analysis in the earth science using MATLAB*, Prentice Hall, Englewood Cliffs, NJ, USA.
Muthuswamy J., Thakor N.V., 1998. *J. Neurosci. Meth.* **83,** 1.
Nayak P.R., 1971. Trans. *ASME:J. Lub. Tech.* **93F**, 398.
Ott E., Sauer T., and Yorke J.A., (Editors), 1994. *Copying with chaos*, Wiley, New York, NY, USA.
Quinn B.G., and Hannan E.J., 2001. *The estimation and tracking of frequency*, Cambridge University Press, Cambridge, UK.
Sacerdotti F., Griffiths B.J., Butler C., and Benati F., 2000. *Proc. Inst. Mech. Engrs.*, **214B**, 811.
Thomas T.P., and Rosen B.G., 2000. *Tribology Int.*, **33**, 601.
Whitehouse D.J., 2001. *Wear* **249**, 345.
Wu J., 1999. *Wear* **230**, 194.
Wu J., 2000. *Wear* **239**, 36.

SOME OPEN PROBLEMS OF HAND EVALUATION

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In proposed contribution the reproducibility of the subjective hand evaluation and prediction of subjective hand are discussed. For reliable subjective evaluation of hand the reproducibility and good representation of results has to be performed. For representation of results the approach based on categorized variables is used. For the case of subjective hand the ordinal median and its 95% confidence interval were applied. The set of properties indirectly connected with hand are specified. The methodology of prediction of subjective hand based on these properties is described. The whole procedure is demonstrated on PET/wool men's winter suit fabrics

1. INTRODUCTION

The basic properties of clothing textiles (strength, shrinkage, drape ability, etc.) can be measured objectively and then applied for estimation of garment behavior. These properties have usually physical sense. The other ones (appearance, comfort, hand) are not directly measurable in laboratory. Evaluation is carried out by consumer on the basis of his feeling evoked by in contact of his preceptors (eye for appearance, eye and fingers for handle). These so-called tactile properties play important role as the first characteristics entering to contact with consumer. Evaluation is carried out by consumer on the basis of his feeling evoked by textile with contact of his preceptors (e.g., eye for appearance, fingers and palms for hand). The second possibility is to use the so-called indirect measurements in combination with calibration equations. With development of new types of technologies and textile products objective characterization hand becomes more important. The use of computer oriented methods for textile design needs of objective hand prediction evaluation as well.

2. SUBJECTIVE HAND AND ITS EVALUATION

Principles of textile production are known more then 6000 years. In this period the optimal condition of their manufacturing was found. However, mechanisms affecting the psychophysical appearances of textiles leading to pleasant sense during wearing are not fully explained up to this time. One of the basic contact properties of textiles is hand. The term "hand" is difficult to define precisely. It belongs to textile quality evaluation as one of the most important utility properties. It is possible to include hand among subjective feelings evoked by measurable textile characteristics. The subjectively evaluated hand is connected especially with surface, mechanical and thermal properties. The first attempts of hand evaluation of textiles were published in 1926 [1].Two basic procedures of subjective hand evaluation were proposed [5]:

a) **direct method** – is based on principle of sorting of individual textiles to defined subjective grade ordinal scale (e.g., 0 – very poor, 1 – sufficient,...., 5 – very good, 6 – excellent)

b) **comparative method** – is based on sorting of textiles according to subjective criterion of evaluation (e.g., ordering from textiles with the most pleasant hand to textiles with the worst hand).

The wide range of word expressions is connected with term hand, e.g., smooth, full, bulky, stiff, warm, cool, sharp, etc. The expressions are used for denotation of primary hand [2, 3, 4, 5, 6]. For prediction of hand using any subjective method it is necessary to solve following problems:

- choice of respondents
- choice of grade scale
- definition of semantic.

2.1. Choice of respondents

The method of choice of respondents has very strong influence on obtained data and therefore also on results of hand evaluation. It is obvious, that subjective evaluation is based on quality of sensorial receptors of the individual respondents. Results of evaluation are also dependent on the psychical state of respondents and the state of environment. Different results are often obtained by experts and by consumers. It is given by different points of view on textile and used terminology.

Above indicated problems show that it is very difficult to maintain reproducibility and choice of respondents has to be strongly defined. The significant differences exist between men and women, too. The men evaluate usually close to scale center in comparison with women. The special problem is size of respondent group. The minimum size for expressing of consumer meaning is 25–30 people and for looking for relationships with objective characteristics more then 200 people.

2.2. Choice of grade scale

If the paired comparison [7] is not applied it is possible to choose grade scale according to the actual criterion and needs. The size of grade scales varies from 5 to 99. The 99 grade scale is more suitable for experts handling with fabrics. For consumers grade scale from 5 to 11 is preferred as they have not so high sensitivity for judgement of very weak differences. Generally is valid, that the area of grade scale centre is frequently used in comparison with the areas near the scale ends.

2.3. Definition of Semantic

Evaluation of total hand is not sufficient when more precise results are required. It is suitable to introduce primary hand values. Primary hand values are connected with surface, thermal and geometric properties. Following polar pairs are very often used for expressing of primary hand values:

rough – smooth
stiff – flexible
open – compact
cold – warm.

Paired comparison of several samples is often carried out and then the ranks are got together. This method is easy for statistical data processing but it is suitable for small sets of textiles only.

3. OBJECTIVE HAND EVALUATION

A lot of methods are used for indirect objective hand evaluation. These techniques can be divided to three groups according to used instruments:

a) **special instruments** – the hand is result of the measurement. Drawing of textile through the nozzle of defined shape and evaluation of dependence "strength-displacement" course is usual principle [9].

b) set of special instruments for measuring of properties corresponding to hand. Kawabata's evaluation system (KES) belongs here. It consists of four instruments for measuring of tensile, shear, bending, surface and compressive properties under special conditions of measuring. By these instruments 16 mechanical characteristics are measured [10].

c) **standard instruments** for evaluation of properties corresponding of hand [11].

Techniques of objective hand evaluation can be divided to two groups according to data processing.

a) result is **one number** characterizing hand – this number is very often obtained from conversion equation (e.g., regression model), where subjective hand is endogenous variable and measured properties are exogenous ones [10, 11].

b) result is the **vector of numbers** characterizing hand. Comparison of hand is then carried out on the basis of multivariate statistical methods (e.g., factor analysis [12], discrimination analysis [10] and cluster analysis [13]).

Applicability of various methods for objective hand evaluation is connected with the choice of measured textiles properties.

4. SUBJECTIVE HAND AND APPEARANCE

During the subjective hand evaluation the visual inspection of samples can have influence on final decision. In this section the comparison of results obtained with and without "visual inspection" are presented. The handle evaluations were compared and influence of appearance on handle evaluation was investigated.

The 28 fabrics for men's suit were chosen for subjective appearance evaluation and subjective handle evaluation with and without visual inspection. For achievement of reproducibility of handle evaluation two groups of respondents were applied. Size of the first was 92 and the second was 160. Ratio of ages of respondents and ratio of men and women was similar. As respondents the consumers were used. Each of them was precisely informed what and how has judge. The second group beside handle evaluation with visual inspection carried out evaluation of handle without visual inspection and appearance evaluation. The second group judged one year after the first. The first group had to disposal five grade scale and the second group eleven-grade scale. For comparison of judgment Spearman's rank correlation coefficient was applied.

The relationship between results of both groups is high (Spearman's rank correlation coefficient is 0.89). It can be said, if respondents are well informed, it is possible to achieve reproducibility. On other hand, five-grade scale is less sensitive to differences in judgment and this less sensitivity leads to higher loss of information.

Relationship between two types of subjective handle evaluations (with and without visual inspection) is high, as well (Spearman's rank correlation coefficient is 0.98). It indicates that well-informed respondent is able to restrain visual perception even if majority of respondents remarked their influence by pattern (color of textile). The relation between handle and appearance is weaker (Spearman's rank correlation coefficient is 0.52 for the case with visual inspection and 0.47 for the case without visual inspection). It is interesting that most of fabrics at whom the handle was evaluated at the borders of scale (it means with very good handle or very poor handle) had the similar appearance evaluation.

The results indicate when the respondents are well prepared it is possible to ensure the reproducibility of data concerning the handle evaluation. The handle can be judged with visual inspection but the condition of well-informed respondents is necessary, as well.

5. PREDICTION OF THE SUBJECTIVE HAND

Subjective hand of the set of 28 men's suit fabrics was carried out by means of group of 92 well-informed respondents. They had 5-order grade scale to disposal (1 – very bad, 2 – poor, 3 – average, 4 – good, 5 – excellent). The estimations of hand grades from subjective evaluation results were treated by means of technique described bellow. The basic characteristics are presented in Table 1.

Table 1 Range of Basic Parameters of Tested Fabrics

weight	[g/m^2]	140–380
sett – warp weft	[yarns/10 cm]	160–500 140–300
blending		100% wool 45/55 wool/PES 70/30 PES/viscose wool/PES/PAD
basic types of weaves	plain, two-and-two twill, satin, prunell	

Statistical analysis of subjective hand results is obviously based on the classical arithmetic mean. The more correct approach based on the categorized variables [15, 16] is proposed in this contribution. Generally, for categorized variable case the population of all events is divided to the categories C_1,.......C_P. Here, P = 5 categories were used. Special case of categorized variable is ordinal variable [10, 14]. For ordinal variable the categories C_1,.......C_P are sorted according to external criterion (here hand). It is assumed that the first category is worst and last category is best. The category C_{i+1} is better that C_i for all i = 1,.....P – 1. Statistical treatment of ordinal variable is based on absolute frequencies n_i, i = 1,.....P corresponding to categories C_1,.......C_P.

Total number of events is

$$n = \sum_{i=1}^{P} n_i \tag{1}$$

Relative frequencies are then

$$f_i = \frac{n_i}{n} \tag{2}$$

and cumulative relative frequencies are

$$F_j = \sum_{i=1}^{j} f_i, \quad j = 1, \ldots\ldots P \tag{3}$$

For characterization of location of ordinal variable the sample rating median can be computed. The median category Me is defined by inequalities

$$F_{Me-1} < 0.5, \; F_{Me} \geq 0.5 \tag{4}$$

The sample-rating median of ordinal variable has the form

$$X_{Me} = Me + 0.5 - \frac{F_{Me} - 0.5}{f_{Me}} \tag{5}$$

Subjective judgment of fabrics handle is widely used within the textile, clothing and by the ultimate consumers.

For estimation of mean handle grade the sample rating median X_{Me} defined by eqn. (5) is suitable. Characteristic X_{Me} is estimator of population rating median *Med*. Median of ordinal variable X_{Me} was used as y_i for prediction of subjective hand.

The prediction of the subjective hand was made from eight objectively measurable characteristics selected from four basic groups of properties corresponding to the hand sensorial centers.

1. For characterization of the fabric **surface roughness**
   - Coefficient of static friction $f_s \equiv x_6$ [-] has been selected.
2. The **deformability** have been characterized by the
   - Shear resistivity $G \equiv x_1$ [N],
   - Initial tensile modulus $Y \equiv x_8$ [MPa],
   - Stiffness $T \equiv x_7 \, 10^{-7}$ [N m^{-2}].
3. **Bulk behavior** has been expressed by the
   - Area weight $M \equiv x_2$ [g m^{-2}]
   - Compressibility $S \equiv x_5$ [-]
   - Thickness $t \equiv x_4$ [mm].
4. **Thermal part** of hand has been characterized by the
   - Warm/cool feeling coefficient $B \equiv x_3$ [W m^{-1}K^{-1}].

The data y_i, x_{1i}, x_{1i}, x_{2i}, x_{3i}, x_{4i}, x_{5i}, x_{6i}, x_{7i}, x_{8i}, i = 1,2,....47 were collected for 47 woolen men suit fabrics. Individual x data are mean values computed from 10 repeated measurements.

Predictive, regression type models were constructed in the following steps:

I. Standardization of data x_{ji}, j = 1,2,....8 i = 1,2,....47 by using of relation

$$u_{ji} = \frac{x_{ji} - x_j^*}{s_j} \tag{6}$$

where x_j^* is sample mean and s_j is corresponding standard deviation for j-th variable, see Table 2.

II. Non-linear transformation to the special psycho-physical scale by using of Harrington type function

$$w_{ji} = \exp(-\exp(-u_{ji})) \tag{7}$$

Table 2 Sample mean values and variances.

Property	Mark	x_j^*	s_j
subjective hand	y	3.126	0.775
shear resistivity	x_1	0.118	0.051
areal weight	x_2	209.74	42.03
warm/cool feeling coeff.	x_3	42.23	5.156
thickness	x_4	0.521	0.072
compressibility	x_5	1.375	0.105
coeff. of static friction	x_6	0.291	0.0274
stiffness	x_7	3.501	2.76
initial tensile modulus	x_8	119.88	55.076

III. Selection of statistically suitable regression sub-model from following three basic ones

LIN: $$y_i = b_0 + \sum_{j=1}^{8} b_j . w_{ji} + \varepsilon_i \quad (8)$$

GEOM: $$\ln y_i = \ln b_0 + \sum_{j=1}^{8} \ln w_{ji} + \varepsilon_i \quad (9)$$

TAYL: $$y_i = b_0 + \sum_{j=1}^{8} b_j . w_{ji} + \sum_{j=1}^{8} \sum_{k=2}^{8} b_{jk} w_{ki} w_{ji} + \varepsilon_i \quad (10)$$

Predicted correlation coefficient R_P, mean quadratic error of prediction $MEP$and mean relative error of approximation E [%] can be used for determination of regression model quality. For calculation of MEP, the following equation is valid

$$MEP = \frac{1}{n} \sum_{(i)} \frac{e_i^2}{(1 - H_{ii})^2} \quad (11)$$

where $e_i = y_i - y_{ipred}$ and H_{ii} are diagonal elements of projection matrix $X(X^T X)^{-1} X^T$.

Predicted correlation coefficient R_P is defined as

$$R_P = \sqrt{\frac{1 - n.MEP}{\sum_{(i)} y_i^2 - n.y^{*2}}} \quad (12)$$

where y^* is median of ordinal variable of hand. Both these characteristics use the special prediction from estimates when single points are left out when the prediction is calculated (prediction in i-th point is calculated without information about this point).

Table 3 Characteristics of regression model quality for various models.

Model	R_P	MEP	E
LIN	0.621	0.308	12.0
GEOM	0.476	–	12.7
TAYL	0 *)	1.9	5
RLIN	0.693	0.261	12.1

*) Close to zero

Table 4 Regression results for LIN model

parameter	estimation	standard deviation of estimation	Test $H_0 : b_j = 0$ t-criterion	a
b_0	2.914	0.302	9.638	0.000
b_1	−1.238	0.376	−3.295	0.002
b_2	0.770	0.493	1.561	0.127
b_3	−0.342	0.342	−0.999	0.324
b_4	0.0634	0.415	0.153	0.879
b_5	0.929	0.414	2.243	0.031
b_6	−0.0449	0.299	−0.150	0.882
b_7	−0.399	0.689	−0.579	0.566
b_8	0.528	0.295	1.79	0.081

For above-mentioned models the characteristics R_P, MEP and E are shown in Table 3.

It is evident, that from the point of view of prediction ability the LIN model is the most suitable. The estimations of b_0,......b_8 parameters together with standard deviations and significance tests ($H_0 : b_j = 0$) are presented in Table 4.

It is clear that, the independent variable x_4 (thickness) and x_6 (coefficient of static friction) are the least significant.

The model without these ones is marked as RLIN. The characteristics of regression quality (Table 3) show that RLIN has better prediction ability then origin LIN model. For this model the estimations of b_0,......b_6 parameters and results of basic tests are shown in the Table 5.

In respect to the fact, that chosen textiles created representative sample of woolen textiles it is possible use parameter estimations of RLIN model for subjective hand prediction of other woolen textiles of the same type.

Methodology of prediction of subjective hand consists from following steps:

a) **determination** of sample means for shear resistance $G = x_1$, area weight $M = x_2$, warm/cool feeling coefficient $b = x_3$, compressibility $S = x_5$, stiffness $T = x_7$, and initial modulus $Y = x_8$ by the above mentioned techniques,

b) **transformation** to standardized variables x_j (eqn. 6) with use the x_j and s_j values (Table 2),

Table 5 Regression results for RLIN model

parameter	estimation	standard deviation of estimation	Test $H_0 : b_j = 0$ t-criterion	a
b_0	2.903	0.262	11.071	0.000
b_1	−1.260	0.336	−3.753	0.001
b_2	0.809	0.426	1.901	0.065
b_3	−0.337	0.315	−1.071	0.291
b_5	0.950	0.392	2.421	0.020
b_7	−0.371	0.614	−0.603	0.550
b_8	0.516	0.283	1.824	0.076

$$y = 2.9 - 1.27w_1 + 0.81w_2 - 0.34w_3 + \\ +0.95w_5 - 0.37w_7 + 0.52w_8 \quad (13)$$

This model has been successfully tested for subjective hand prediction.

6. DISCUSSION

Prediction model defined by the eqn. (13) is simple and suitable for estimation of the median of woolen fabrics subjective hand based on the measurable characteristics.

Described method can be used for other types of fabrics as well. Precision of the prediction is comparable with precision of subjective estimation.

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1979, *32*

[3] Kawabata, S.: J.Text. Mach. Soc. Japan, Osaka, 1980

[4] Howorth, W. S., Oliver, P. H.: J. Text. Inst., 1958, *49*, p. 540

[5] Howorth, W. S.: J. Text. Inst, 1964, *55*, p. 251

[6] Lundgren, H. P.: Text. Chem. Color., 1969, *1*, p. 35

[7] Militký J.: VI. Conference Textile Testing, Hradec Králové 1989 (in Czech)

[8] Kawabata S.: J. Text. Mach. Soc. Japan, 1975

[9] Alley V. L.: Trans. Am. Soc. Mech. Eng. 102, 25 (1980)

[10] Kawabata S.: The Standardization and Analysis of Fabric Hand, 2nd. ed., The Textile Machinery Society of Japan, Osaka 1982

[11] Raheel M., Lin J.: Text. Res. 61, 31 (1991)

[12] Brand R. H.: Text. Res. J. 34, 791 (1964)

[13] Pan N.: Text. Res. J. 58,439 (1988)

[14] Militký J.: Analysis of Subjective Hand Evaluation Results, Textile Science'93 Conference, Liberec, September 1993

[15] Plackett R. L.: The Analysis of Categorical Data, Griffin, London 1974

[16] Rehák J., Reháková B.: The Categorical Data Analysis in Social Sciences, Academia Prague 1986 (in Czech)

Air permeability and light transmission of weaves

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Keywords *Fabric, Light*

Abstract *The main aim of this contribution is characterization of fabric porosity by the light transmission and comparison of this characteristic with air permeability and idealized geometrical structure of selected weaves. For characterization of air permeability the classical apparatus has been used. The transmission of light through fabrics has been measured on the system LUCIA for image analysis. The porosity of textiles has been evaluated from corresponding construction parameters and idealized models of fabric geometry. The dependencies between the above mentioned characteristics were formalized by using regression analysis.*

1. Introduction

It is well known that air permeability and light transmission through fabrics depend on the many factors starting with geometrical structure. Both properties are apparently very closely connected and can be explained as so called porosity.

Porosity has a decisive influence on utilization of fabric for some technical application (filters, sails, parachutes) and clothing application as well. Fabric porosity depends generally on the fabric and yarn construction. Numerous methods have been proposed for porosity measurement. A classical one is based on the investigation of air permeability. Modern systems of image analysis enable the measurement of porosity as transmission of light through fabric.

It has been shown that for tightly woven fabrics there exists good agreement between air permeability and interfiber pore volume (porosity) (Robertson, 1950). For open-woven fabrics the correlation between air permeability and construction parameters of fabrics is not so strong.

The main aim of this contribution is measurement of fabric porosity by light transmission and comparison of this characteristic with air permeability and idealized geometrical structure of simple weaves. For characterization of air permeability the classical apparatus is selected. The transmission of light through fabrics is measured on the system LUCIA for image analysis. The apparent porosity of textiles is evaluated from corresponding construction parameters and idealized fabrics models.

The dependencies between the above mentioned characteristics are formalized by using regression analysis.

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2. Evaluation of fabric porosity

There are a lot of models characterizing the idealized porosity P_I from some construction parameters of weaves. Classical parameters are sett (texture) of weft D_C [1/m], sett of warp D_M [1/m], fineness of weft yarn T_C [tex], fineness of warp yarn T_M[tex], planar weight of weave W_P[kg m^{-2}], density of fibers ρ_F [kg m^{-3}] and thickness of fabric t_W [m]. The idealized arrangement of yarns in fabric is

$$t_I = d_c + d_m \quad (1)$$

where d_C is diameter of weft yarn and d_M is diameter of warp yarn. When $t_W \approx t_I$ the yarns in fabric are roughly circular. This type of arrangement is assumed in sequel.

The idealized circular yarn with the same packing density is simple to compute diameters from relation

$$d_C = \frac{2\sqrt{T_C}}{10^6 \pi \rho_C} \quad (2)$$

$$d_M = \frac{2\sqrt{T_M}}{10^6 \pi \rho_M} \quad (3)$$

Here ρ_C and ρ_M are unknown densities of weft and warp yarns. These densities are combinations of densities of fibers ρ_F and air ρ_A = 1.175 [kg m^{-3}] according to packing of fibers in yarns. For known packing density μ_M is $\rho_M = \mu_M \rho_F$ and the same relation is valid for weft yarn. The values ρ_C and ρ_M are therefore function of twist and method used for yarn creation. For the moderate level of twist it has been empirically found that

$$\rho_C / \rho_F = \mu_C \approx 0.525 \quad (4)$$

and this correction can be imposed to the relations (2) and (3) for computation of d_C or d_M.

For the noncircular yarns we can simply compute the area of yarn cross section

$$S_{YC} = T_C / (\rho_C * 10^6) \quad (5)$$

or

$$S_{YM} = T_M / (\rho_M * 10^6) \quad (6)$$

It is clear that ideal fibrous form (without pores) having the area S_Y has density equal to fiber density ρ_F. The yarn porosity is then defined as

$$P_{YC} = \rho_c / \rho_F \quad (7)$$

or

$$P_{YM} = \rho_M / \rho_F \quad (8)$$

In the same way we can evaluate the "density" porosity of fabrics from relation

$$\rho_W = \rho_W/\rho_F \tag{9}$$

where ρ_W is defined by the relation

$$\rho_W = \frac{m_V}{\upsilon_V} = \frac{W_P}{t_W} \tag{10}$$

where m_υ[kg] is weight of fabrics and υ_V[m^3] is corresponding volume of fabrics having a surface of 1m^2. From the measured planar weight W_P, fabric thickness t_W and known density of fibers it is simple to compute the "density" porosity

$$P_W{}^R = \frac{W_P}{\rho_F * t_W}. \tag{11}$$

Ideal value $P_W{}^I$ can be evaluated from ideal thickness t_I (equation (1)) and ideal planar weight

$$W_P{}^I = 10^{-6}[D_C l_C T_C + D_M l_M T_M] \tag{12}$$

where l_C is length of weft yarn in the 1m portion of fabric and l_M is length of warp in the 1m portion of fabric. In some cases the yarn shortening in weft S_C [%] and warp S_M [%] directions (due to crimping of yarns in fabric) are known. Then $l_c = (1 + S_C/100)$ and $l_m = (1 + S_M/100)$.

For practical computations it is better to use $P_W{}^R$ value which is not based on the simplified model assumptions.

Second possibility of porosity evaluation is based on the definition of hydraulic pore for the filtration purposes (Robertson, 1950). The "volume" porosity is defined as

$$P_{HW} = 1 - \frac{\textit{volume covered by yarns}}{\textit{whole accessible volume}} = 1 - \frac{\upsilon_Y}{\upsilon_V} = 1 - \frac{\upsilon_Y}{t_W}. \tag{13}$$

The υ_Y is equal to the sums of volume of weft yarns SU_C and warp yarns SU_M:

$$\upsilon_Y = SU_C + SU_D \tag{14}$$

where

$$SU_C = D_C \upsilon_{1C} \tag{15}$$

$$SU_D = D_M \upsilon_{1M}. \tag{16}$$

Here the υ_{1C} and υ_{1M} are volumes of weft and warp yarn in the 1m portion of fabrics

$$v_{1C} - l_C \pi {d_C}^2/4 = l_C \frac{T_C}{10^3 \rho_C} \cong \frac{(1 + S_C/100)T_C}{525 * 10^3 * \rho_C}. \quad (17)$$

For v_{1M} the indexes C are replaced by the indexes M. Combination of equations (14), (15), (16) and (17) and rearrangement leads to the equation

$$v_Y = \left[D_C \frac{(1 + S_C/100)T_C}{525^* 10^{3*} \rho_{F_C}} + D_M \frac{(1 + S_M/100)T_M}{525^* 10^{3*} \rho_{F_M}} \right]. \quad (18)$$

For the case of negligible S_C and S_M and $\rho_{FC} = \rho_{FM} = \rho_F$ can be porosity P_{HW} expressed by the relation

$$P_{HW} = 1 - \frac{1.9^* 10^{-6}}{\rho_f{}^* t_w} [D_C T_C + D_M T_M] = 1 - \frac{1}{t_W} [D_C{}^* v_1 + D_M{}^* v_{1M}]. \quad (19)$$

From a pure geometrical point of view surface porosity can be evaluated from cover factor CF of fabric. Classical Pierce definition of CF is based on the idealized projection of fabric (see Figure 1).

CF is defined as the area of yarn in the dotted rectangle

$$A_Y = \frac{d_c}{D_M} + \frac{d_M}{D_c} - d_c d_M$$

divided by the area of dotted lines bounded rectangle $A_C = (D_C D_M)^{-1}$. The CF has then the form

$$CF = D_C d_c + D_M d_M - d_c d_M D_c D_M.$$

The diameters of yarn can approximately be computed from equations (2), (3) with corrections (4). More realistic are elliptical shapes of yarns (Hoffmann, 1952).

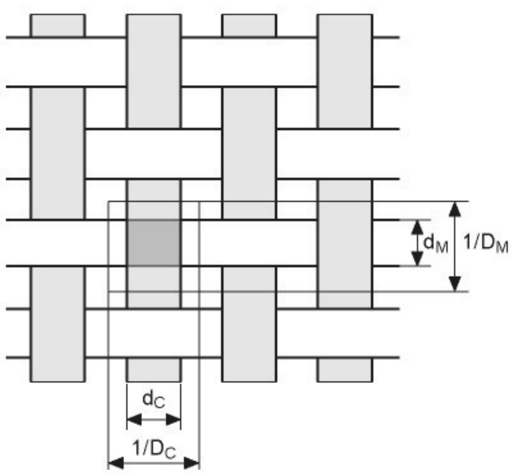

Figure 1.
Idealized fabrics for computation of cover factor CF

Porosity based on CF is then

$$P_{GW} = 1 - CF \tag{20}$$

This surface porosity is nearly the same as porosity P_o used in the evaluation of air porosity (see equation (22)).

3. Air permeability and porosity

Let the fabrics be modeled as the semi-porous sheet of thickness t_W. The overall pressure drop $\Delta p = p_{ahead} - p_{behind}$ of air flow passing through this semi-porous sheet is dependent on its porosity. This loss is suitably indicated by the loss of pressure coefficient LP (Hoerner, 1952).

$$LP = \frac{\Delta p}{0.5^* \rho^* w^2} \tag{21}$$

where ρ is air density (for dry air at standard atmosphere and 25°C is ρ = 1.175kg m^{-3}) and w is air velocity ahead of the material. The pressure loss depends upon the Reynolds number Re (ratio of the dynamic to the viscous forces of the flow).The Re can be expressed as (Hoerner,1952):

$$Re = \frac{w^* d}{P_0{}^* \vartheta} \tag{22}$$

Here d is diameter of mean (cylindrical pore), P_o is the so called surface porosity (open area of fabric divided by the total area of fabrics) and ϑ is kinematic viscosity of air. In the standard tests the mean value Re $\cong$ 200. The pressure loss can be divided into the dynamic losses and friction losses. Combining these losses the LP can be expressed in the semi-empirical form (Hoerner, 1952):

$$LP = \frac{1 - P_o}{P_o^2} * \left(\frac{40}{Re^{0.75}} + (1 - P_o) \right) \tag{23}$$

valid between $Re \cong 1$ (for all porosity ratios) and $Re \cong 10^3$ (for porosity ratio lower than 0.5).

Gorbach (1968) derived the semi-empirical relation

$$LP = k_1 * \frac{k_2{}^*(1 - P_0)}{P_o^{2*}(P_o + \sqrt{P_o})} \tag{24}$$

where coefficients k_1 and k_2 are dependent on the Re and fabric structure.

If the pressure drop Δp is small, the airflow through fabrics of surface area S_W follows Darcy's law

$$\frac{w}{S_W} = \frac{1}{R_o} * \frac{\Delta p}{t_W} \tag{25}$$

where R_o is air flow resistance. In the standard test is S_W = 20cm^2 and Δp (200 Pa) fixed. The air permeability AP is expressed in the form

$$AP = \frac{w}{S_W} = 50 * w[m^3 s^{-1} m^{-2}]. \quad (26)$$

The standard test is the dry air permeability AP connected with coefficient of pressure loss LP through relation

$$LP = \frac{400}{1.175 * w^2} = 8.5 * 10^5 / AP^2. \quad (27)$$

The relation between air permeability and porosity can be obtained by combining the relation (27) and (23) or (22). In the contribution by Dent (1976) the relation between AP and planar weight of fabric W_P has been derived.

4. Experimental part

The 40 various weaves from wool and blends of wool with polyester, polyamide and viscose fibers has been selected. The following construction parameters of fabrics are measured: sett (texture) of weft D_C [1/m], sett of warp D_M [1/m], fineness of weft yarn T_C [tex], fineness of warp yarn T_M [tex], planar weight of weave W_P [kg m^{-2}], density of fibers ρ_F [kg m^{-3}] and thickness of fabric t_W [m]. Three specimens were measured and the means used for calculations. From these parameters the following porosity characteristics $P_W{}^R$, P_{HW} and P_{GW} were computed. The air permeability AP has been measured at standard conditions Δp = 200 Pa and S_w = 200cm^2 in the standard atmosphere. Ten repeats of measurements were realized and mean value is used for calculations.

The light transmission was investigated by the image analysis system. The system consists of microscope, CCD camera and personal computer. The treatment of digital images was made by the software LUCIA-M. This software is designed for analysis of the high color (3×5 bits) images having resolution of 752×524 pixels. The original image of one fabric is shown in Figure 2.

The white objects (corresponding to the areas transmissible for light) were extracted from the original image. The threshold value 62 (all gray patterns are converted to black) has been chosen. The relative porosity for light P_L was defined as the area of white objects divided by the whole area (see Figure 3).

5. Results and discussion

First of all the correlation between various characteristics of porosity ($P_W{}^R$, P_{HW}, P_{GW}) and variables (AP or P_L) has been computed by using ADSTAT package (Meloun *et al.*, 1994).

- Correlation for variable P_L. Paired correlation coefficients:
  P_L, $P_W{}^R$ = –3.1190E-01

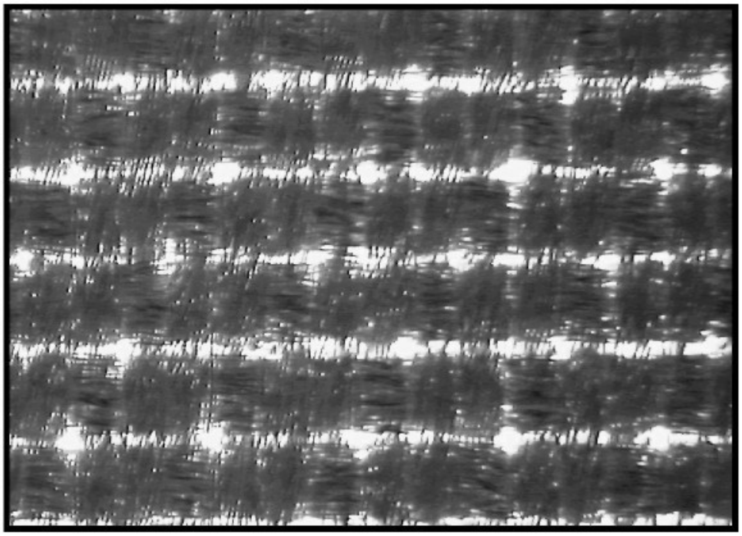

Figure 2.
Original image for one fabric

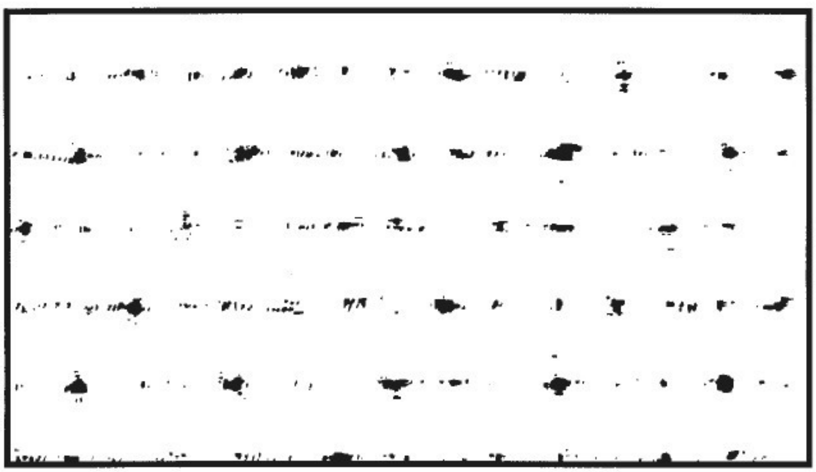

Figure 3.
Inverted image (white objects are black spots) for one fabric

$P_L, P_{HW} = 1.8418\text{E-}01$
$P_L, P_{GW} = 5.3734\text{E-}01$
$P_L, AP = 8.4862\text{E-}01$

- Correlation for variable AP. Paired correlation coefficients:
  $AP, P_W^R = -4.1622\text{E-}01$
  $AP, P_{HW} = 1.75152\text{E-}01$
  $AP, P_{GW} = 4.47988\text{E-}01$
  $AP, P_L = 8.48620\text{E-}01$

It is clear that the highest correlation exists between air permeability AP and light transmission P_L. From the point of view of correlation of fabrics the geometric characteristics of porosity with air permeability and light transmission is the best the surface porosity P_{GW} (Table I).

In the second run the relation between air permeability and porosity P_L evaluated from light transmission has been created. Based on the preliminary analysis the linear regression model has been selected. Parameters have been estimated by the least squares criterion by using of ADSTAT package (Meloun *et al.*, 1994).

Regression line has the form

$$AP = 2.8881\text{E} + 02 + 3.6364\text{E} + 03 * P_L$$

The regression line and experimental data are shown in Figure 4.

From Figure 4 and results of linear regression it is clear that the dependence of air permeability on porosity evaluated from light transmission is without marked nonlinearity.

The nonlinear dependence of AP on the geometrical porosity predicted by equations (24) and (28) has been tested in the work (Militký and Trávníčková, 1998). The porosity computed from the geometrical characteristics of fabrics was probably far from reality.

Parameter	Estimate	Standard deviation	Test of H0: B[j] = 0 vs. HA: B[j]<>0 *t*-criterion	H0 hypothesis is	Sig. level
B[0]	1.8985E+03	2.8881E+02	6.5736E+00	Rejected	0.000
B[1]	3.5960E+04	3.6365E+03	9.8890E+00	Rejected	0.000

Notes: Correlation coefficient, R = 8.4862E-01; Predicted correlation coefficient, Rp^2 = 8.3098E-01

Table I. Results of regression of AP on P_L

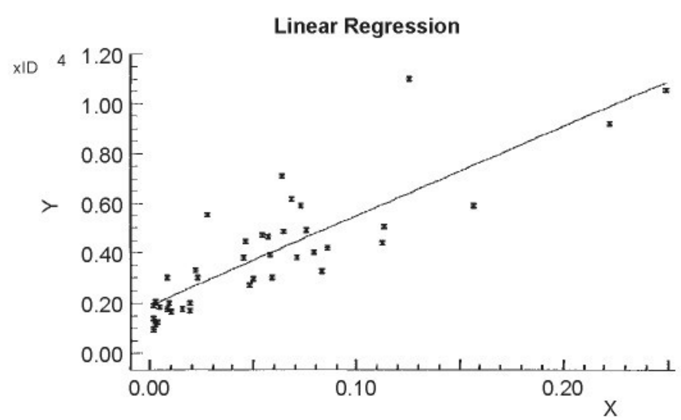

Figure 4. The regression dependence of AP on the P_L and experimental data

6. Conclusion

The image analysis can be simply used for prediction of air permeability. Porosity computed from fabric geometry is too idealized for close correlation with air permeability. The analysis of porosity estimated from air permeability data is presented in the contribution of Militký and Trávníčková (1998).

References

Dent, R.W. (1976), *J. Text. Inst.,* Vol. 67, p. 220.

Gorbach, N.I. (1968), *IVUZ Technol. Text. Prom.*, Vol. 64, p. 8.

Hoerner, S.F. (1952), *Text. Res. J.*, Vol. 21, p. 274.

Hoffmann, R.M. (1952), *Text. Res. J.*, Vol. 21, p. 170.

Meloun, M., Militký, J. and Forina, M. (1994), *Chemometrics for Analytical Chemistry,* Vol. 2, Ellis Horwood.

Militký, J. and Trávníčková, M. (1998), "Novelties in weaving research and technology", *Proc. Int. Conf. Liberec,* September.

Robertson, A.F. (1950), *Text. Res. J.,* Vol. 19, p. 838.

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Influence of Wool Content on Properties of Blended Fabrics

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Introduction

Wool/polyester blended fabrics are widely applicable in the production of materials for clothing purposes. The main problem is to find such combinations of each component so that the resulting fabrics may have suitable utility properties, surface properties and handle. For constructing of optimally blended fabrics it is necessary to predict the influence of wool and polyester components on the above-mentioned properties of the final textiles.

There are a lot of publications which discuss the effect of wool/polyester composition in blended fabrics on selected utility properties[1-3]. The resulting dependencies usually are in the graphic form and are not applicable for designing purposes. Obviously, the examined fabrics are not prepared in comparable conditions, either.

In this article, especially prepared plain weave with similar areal weight $200 gm^{-2}$[4] were used. The standard utility properties, surface properties, total hand value and thermal permeability of fabrics were determined.

An attempt to use a simple generalized mixing rule to describe the properties of blended fabrics was made.

Material

Wool fibres (W) and modified high-shrinkable polyester fibres named Velana S (P), are used for the preparation of woollen type fabrics. Velana S is a modified fibre containing the sodium salt of 5-sulphoisophthalic acid. The fibre properties are presented in Table I.

The combed intimately blended yarns were constructed. The resulting yarn fineness was 25 × 2 tex and twist levels were 520 turns per metre. Blended yarns with 0, 15, 30, 45 and 100 per cent of wool content were prepared.

The plain weaves were fabricated from these yarns. The resulting areal weights, the used setts of warp and weft and the fabric thickness are summarized in Table II. Fabrics were finished by usual woollen type technology. Details about fabric production and finishing are described in [4].

Selected Utility Properties

A lot of properties connected with fabrics applicability were measured. With respect to the aim of this work, only such properties were selected for which the wool content significantly changed the measured quantities (95 per cent confidence intervals of means for various wool levels were not crossed). It means that

Fibre type	Fineness (tex)	Tenacity ($mN.dtex^{-1}$)	Break elongation (%)
Wool (W)	0.63	21.2	49.9
Velana (P)	0.47	36.8	54.1

Table I.
Properties of Used Fibres

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Wool content (%)	Sett ($10\ cm^{-1}$) Warp	Weft	Areal weight (gm^{-2})	Thickness (mm)
0	176	152	195.8	0.41
15	177.6	152	201	0.5
30	188.8	155	208	0.6
45	186	159	202	0.63
100	202	180	201	0.52

Table II.
Geometric Fabrics Characteristics

statistically significant differences which are influenced by wool content exist among mean values of properties.

Tenacity (T)

Textile strength was measured on an Instron tensile tester in accordance with the test standard. Strength is expressed as break force of a 5 cm-wide sample. The resulting mean values are given in Table III.

Break Elongation (B_e)

Break elongation was measured together with strength. Resulting mean values of relative break elongation (per cent) are given in Table III.

Abrasion (A)

Fabrics were abraded according to test standards on the Accelerator device. Abrasion was characterized by relative loss in weight (per cent). Results are summarized in Table III.

Heat Permeability (H_p)

Heat permeability was assessed on a special device ALAMBETA. The mean values of heat permeability H_p [$Wm^{-2}\ K^{-1}$] are summarized in Table III.

Objective Handle Evaluation

For objective handle evaluation the Kawabata KES system was adopted. From the resulting properties the total hand values THV were computed according to Kawabata's methodology[5].

A simple program in spreadsheet software Quattro Pro for THV computation was created. Resulting THV values are given in Table III.

Surface Properties of Textiles

It is well-known that organoleptic properties of fabrics are highly correlated with surface properties. Therefore the method for assessment of the fabric roughness and friction resistance by using a special adaptor to the Instron tensile tester was selected[6]. The principle is to register the force course S [mN] needed to move the metal disk along the fabric surface which is fixed vertically on the metal desk. This force course presents many local minima S_{Li} and local maxima S_{ui}.

The surface roughness can be calculated as a mean difference between maxima and minima

$$R = K_R\,(\Sigma_i\, S_{Ui} - \Sigma_i\, S_{Li}) \quad \text{(mN)}. \qquad (1)$$

Wool content (%)	T (N)	B_e (%)	A (%)	THV	H_p ($Wm^{-2}K^{-1}$)	R (mN)	U (mN)
0	810	33.3	2.9	2.823	31.3	90.58	158.49
15	684	35.1	6.0	2.307	29.5	96.16	176.53
30	600	34.8	7.9	2.695	29.5	99.44	228.4
45	523	29.4	8.7	2.202	26.2	102.36	233.97
100	303	30.3	9.6	3.168	31.1	86.7	220.2

Table III.
Experimentally Determined Average Values of the Selected Fabric Properties

Here K_R is proportionality coefficient (recount to the force unit). The second surface characteristic is average friction resistance defined as

$$U = K_F\,(\Sigma_i\, S_{Ui} + \Sigma_i\, S_{Li}) \quad \text{(mN)} \qquad (2)$$

where K_F has the same meaning as constant K_R in the equation (1).

If variance of measurement of local extremes (S_U, S_L) is equal to σ^2, then variances of a surface characteristic σ_s^2 lie in the interval $2\sigma^2 < \sigma_s^2 < 4\sigma^2$[6]. It was determined on the basis of previous experiments that $\sigma_s^2/\sigma^2 \approx 2$.

The average values of R and U for individual fabrics are presented in Table III.

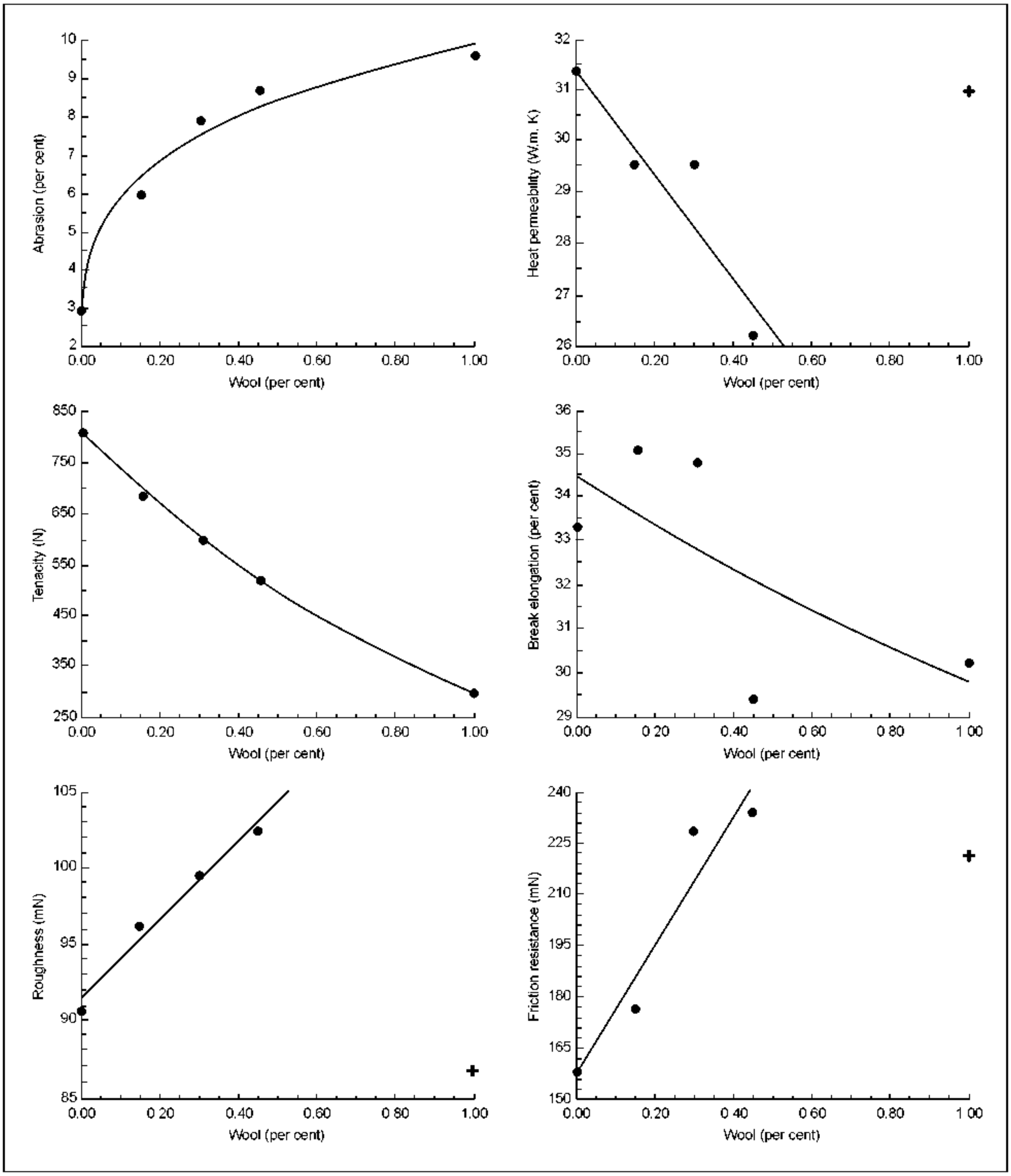

Figure 1.
Dependence of Some Properties of Wool/Polyester Blended Fabric on Wool Content

Property Prediction of Blended Fabrics

It is evident that fabric properties will depend on the content of single components for constant parameters of fabric construction, in some way. The simplest model of linear mixing is based on the hypothesis that the influence of a given fibre type on blended fabric property is directly proportional to its content.

If the value of blended fabric property is denoted as P_B, the same property of pure wool fabric as P_W and property of pure polyester fabric P_P, the linear mixing rule has the form

$$P_B = WP_W + (1-W)P_P \qquad (3)$$

where W is the relative content of wool fibres ($0 < W < 1$). This equation is not applicable in cases when dependence P_B on W is either concave or convex. The simple model of the general mixing rule can be used in these cases:

$$P_B{}^m = WP_W{}^m + (1-W)P_P{}^m \qquad (4)$$

where m is the constant of mixing. This equation describes convex (for $m < 1$) and concave (for $m > 1$) type dependencies.

A special case for $m = 0$ is the so-called logarithmic mixing rule, which has the form

$$P_B = p_W{}^W P_P{}^{(1-W)}. \qquad (5)$$

Generally, the problem of estimation of parameters m, P_W and P_P leads to the problem of non-linear regression. Program ADSTAT for IBM personal computers was used for parameters estimation.

Results and Discussion

Testing of the convenience of mixing models for particular properties was realized on the basis of experimental dependence from Figure 1. It is perceptible that results of friction resistance, roughness, handle and heat permeability in pure wool fabrics are markedly different from the tendency of other points.

This tendency may be connected with the fact that used fabrics have various cover factors. The cover factor calculated for pure wool fabric is 80.8 per cent and for pure polyester fabric is only 73 per cent. Therefore values for 100 per cent wool roughness, friction resistance and heat permeability were omitted in the calculations. The THV values are not dependent on wool content in a systematic way and therefore are not analysed here.

Tenacity

Tenacity dependence on relative wool content was described as means of the general mixing rule (equation (4)), as by means of the logarithmic mixing rule (equation (5)). It was calculated on the basis of statistical tests that the logarithmic mixing rule is more convenient. Corresponding residual variance is $s = 56.4$. The model of logarithmic mixing has the form

$$P_B = 303.04^W \times 803.97^{(1-W)}.$$

As 95 per cent confidence intervals of both parameters P_W and P_P cover experimentally determined values $P_{We} = 303$ (for $W = 1$) and $P_{Pe} = 810$ (for $W = 0$), we may use experimentally determined boundary strength-for-strength prediction of blended fabrics based on the logarithmical mixing rule.

□

Abrasion dependence on relative wool content is concave

□

It is interesting that this rule was proven for two-and-two twill weave, too. On the other hand, for other types of polyester fibres, the logarithmic mixing rule is only a rough approximation.

Break Elongation

Break elongation dependence on relative wool content was modelled by a relation (4). On the basis of non-linear least squares the following model was determined:

$$P_B{}^{-2.2} = W29.9^{-2.2} + (1-W)34.4^{-2.2}.$$

Corresponding residual variance is equal to 7.47. We may notice that experimental values P_{We} and P_{Pe} lie in the 95 per cent confidence interval of the model parameters.

Abrasion

It is evident that abrasion dependence on relative wool content is concave; this means that parameter m in equation (4) will be positive. By the means of least squares this model was found:

$$P_B{}^{4.5} = W9.89^{4.5} + (1-W)2.89^{4.5}.$$

Corresponding residual variance is equal to 0.31. Similarly, as in the last cases, experimental

Parameters	P_W	P_P	r
Roughness	117	91.3	0.98
Friction resistance	342	157.7	0.99
Heat permeability	21.2	31.42	0.93

Table IV.
Parameters of Linear Mixing

values P_{We} and $P_{P_{pe}}$ lie in the range of confidence intervals of model parameters for $W = 1$ and $W = 0$.

The Other Performance Characteristics

The linear mixing rule for the description of dependence of roughness, friction resistance and heat permeability on relative wool content was used. Model parameters P_W and P_P estimated by means of least squares are shown in Table IV. Correlation coefficients are presented here too.

Tests of the significance of correlation coefficients show that a linear mixing model on level $\alpha = 0.05$ is significant for roughness and friction resistance only. Critical significance level $\alpha = 0.071$ resulted for heat permeability. Therefore heat permeability appears to be statistically independent of wool content.

Conclusion

It was verified that a simple general mixing rule is possible for modelling the dependence of selected blended fabric properties on relative wool content.

Even though the rule is formal, we may use it easily for prediction purposes and for the designing of optimum blends.

□

References

1. Sayere, J.F., *Modern Textiles Magazine,* No. 4, 1956, p. 38; No. 5, 1956, p. 58.
2. Hargreaves, H.A. and Brooke, B.I., *Journal of Textile Institute*, No. 2, 1963, p. 112.
3. Čirlič, J., Doctoral Thesis, MTI Moskva, 1965.
4. Čirlič, B., Thesis, TU Liberec, 1983.
5. Kawabata, S., *The Standardization and Analysis of Hand Evaluation*, 2nd ed., HESC, the Textile Machinery Society of Japan, 1980.
6. Militký, J., Bajzík, V. and Stočková, H., *Proceedings of the Conference on Textile Testing 90*, Hradec Králové, 1990.