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Towards self-optimizing and self-adaptive milling processes

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Abstract

This paper presents a novel control architecture system which is composed of a multi-objective cost function which Pareto optimises the programming of cutting parameters while adapting the milling process to new cutting conditions if new constraints appear.

The paper combines a self-optimised module which looks for and finds Pareto optimal cutting parameters according to multi-objective purposes and, a multi-estimation adaptive control module which keeps the cutting forces under prescribed upper safety limits independently of programmed cutting conditions and material properties while maintaining the performance of the process. A supervised controller acts as decision support-software to automatically switch to best performance tracking adaptive controller among those available at each required time.

1. Introduction

The dynamical complexity of milling processes combined with the more exigent performance requirements requires more sophisticated and complex control systems. The selection of adequate cutting parameters for multi-objective optimization in milling processes has occupied an extensive research study in manufacturing literature [1-5], using Computer Aided Programming Planning, decision support systems and bio-inspired systems to cope with the problem of multi-objective optimization.

Moreover, the adaptive control of milling forces has been applied successfully in a broad range of milling applications [6-9].

In this paper, intelligent control architecture is proposed which is composed of self-optimizing and self-adaptive levels which inter-actuate in order to Pareto optimise cutting parameters while controlling milling forces in the selected working points. The self-optimisation kit for cutting parameters is based on a cost function.

This cost function is composed of three parameters but some others can be added or subtracted depending on the objectives of the process. Then, as a representative illustration example, in this paper three parameters namely: tool-life, surface roughness, and material remove rate represents objective purposes. A weighting factor measures the importance of each term in the cost function. Initial weighting factors have to be programmed by operators but the system incorporates algorithms for automatic modification and renormalization of the weighting factors based on a novel mathematical approach. Then, Pareto optimal cutting parameters are obtained from the cost function depending on the process requirements and constraints.

Furthermore, a multi-parallel scheme is presented for adaptively controlling milling forces. The multi-parallel scheme allows taking into account different possible behaviours of the system at different working points through different adaptive control structures or to take into account possible changes in the parameters of the system. Finally, a supervised controller based on a rule-based expert system switches the set of parallel available controllers to the one with better performance at each required time. An example illustrates the behaviour of the system.

2. System description

Milling processes are well characterized as mechanical systems which are particularly sensitive to acquiring vibrations. In this section, the milling process is modelled as a second order differential equation, which is excited by forces whose inherent terms excite the modal parameters of the system. This fact results in the conversion of resultant energy into vibrations of the system. Those vibrations are generated under certain cutting conditions depending on the process being carried out, clamping of the workpiece, tool and workpiece materials, etc.

In this frame of mind, the standard milling system responds to a second order differential equation excited by the cutting forces,

$$M \cdot \ddot{r}(t) + B \cdot \dot{r}(t) + C \cdot r(t) = F(t) \qquad (1)$$

where $r(t) = \{x(t), y(t)\}^T$ are the relative displacements between the tool and the workpiece in the $X-Y$ plane, $F(t) = \{F_x(t), F_y(t)\}^T$, and M, B and C are the modal mass, damping and stiffness matrices, all of them represented in two dimensions. The milling cutting force is represented by a tangential force proportional with the instantaneous chip thickness, and a radial force which is expressed in terms of the tangential force [6],

$$F_t(t) = K_t \cdot a_{dc} \cdot t_c(t) \text{ and } F_r(t) = K_r \cdot F_t(t) \qquad (2)$$

where K_t and K_r, the tangential and radial specific cutting constants which are dependent on the tool material for any geometry, a_{dc}, the axial depth of cut and, $t_c(t)$, the chip thickness, obtaining the cutting forces in Cartesian coordinates. The most critical variable in the equation of motion, the chip thickness, $t_c(t)$, consists of a static part and a dynamic one. The static part is proportional to the feed rate and it is attributed to the rigid body motion of the cutter. The dynamic part models two subsequent passes of the tool through the same part of the work-piece. The phase shift between two consecutive passes of one tooth on the work-piece is widely modelled and represented [6] by,

$$t_c(t) = f_r \cdot \sin\phi_j + \left[x(t-\tau) - x(t)\right] \cdot \sin\phi_j + \left[y(t-\tau) - y(t)\right] \cdot \cos\phi_j \quad (3)$$

where f_r is the feed rate, ϕ_j the immersion angle and τ is a delayed term defined as $\tau = \frac{60}{N_t S_s}$, N_t is the number of teeth and S_s the spindle speed in rpm. Figure 1 pictures this mathematical representation in a drawing.

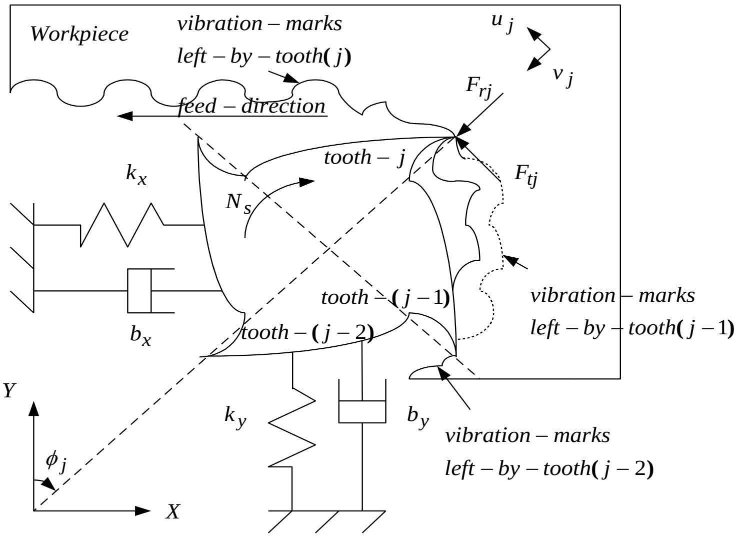

Figure 1: Cross-sectional view of a milling tool [6].

Furthermore, the transfer function of the system, in chatter and resonant free zones, can be separated as a series decomposition of the transfer function which relates the resultant force and the actual feed delivered by the drive motor, which models the deflection of the tool, and the transfer function which represents the Computerized Numerical Control (CNC). Then, a continuous transfer function which relates both signals, measured resultant force and the actual feed delivered by the drive motor can be showed as a first order dynamic [6],

$$G_p(s) = \frac{F_p(s)}{f_a(s)} = \frac{K_c a_{dc} r(\emptyset_{st}, \emptyset_{ex}, N_t)}{N_t S_s} \frac{1}{\tau_c s + 1} \quad (4)$$

Where $K_c\left(N/mm^2\right)$ is the resultant cutting pressure constant, $a_{dc}(mm)$ is the axial depth of cut, $r(\phi_{st}, \phi_{ex}, N_t)$ is a non-dimensional immersion function, which is dependent on the immersion angle and the number of teeth in cut, N_t is the number of teeth in the milling cutter, $S_s(rev/s)$ the spindle speed and $\tau_c = {}^{1}/_{N_t S_s}$. At the same time, the relationship between the machine tool control, the CNC and, the motor drive system can be approximated as a first order system within the range of working frequencies [6]. This transfer function relates the actual, f_a, and the command, f_c, feed velocities,

$$G_s(s) = \frac{f_a(s)}{f_c(s)} = \frac{1}{\tau_s s + 1} \tag{5}$$

where τ_s represents an average time constant.

The combined transfer function of the system is given by,

$$G_c(s) = \frac{F_p(s)}{f_c(s)} = \frac{K_p}{(\tau_c s+1)(\tau_s+1)} \quad (6) \text{ with } K_p\left(kN \cdot s/mm\right) = K_c a_{dc} r_{dc} / N_t S_s$$

3. Self-optimized tool-box

A novel cost function has been conceived to allow an inference engine to carry out the selection of suitable cutting parameters. The tool cost model for a single milling process can be calculated using the following equation, (7):

$$J\left(TOL, MRR, SURF; R, c_{i(i=1,..,3)}\right) =$$

$$= c_1 \cdot NF_1 \cdot TOL + c_2 \cdot NF_2 \cdot MRR + c_3 \cdot NF_3 / SURF$$

The cost function has three terms. Each term is composed of a weighting factor (c_i), a normalisation factor (NF_i) and the function which delimits the process efficiency. These functions are: the life of the tool, TOL; the material remove rate, MRR; and the surface finish, $SURF$. The tool cost function is designed to be directly proportional to the life of the tool and material remove rate and inversely proportional to surface roughness. So, optimal solutions will maximise TOL and MRR while minimising $SURF$. These parameters play an important role when selecting cutting parameters since they are usually used as benchmark indices in industries to measure the performance of the system. They are defined as following:

3.1 Life of the tool (*TOL*)

TOL is a measure of the length of time a cutting tool will cut effectively. According to previous studies [3], an increase in the cutting speed, feed rate and axial depth of cut will decrease the tool life. In this paper, the Taylor Equation for Tool Life Expectancy, a model typically used in literature, is used to evaluate TOL in the expert system. This model is represented by the equation [3]:

$$TOL = K_{tol} \cdot V^{-\alpha_1} \cdot a_{dc}^{-\alpha_2} \cdot f_t^{-\alpha_3} \tag{8}$$

where K_{tol} is a model constant, α_1, α_2 and α_3, are model parameters and V, a_{dc} and f_t, the cutting speed $(m/\min)$, axial depth of cut (mm) and feed per tooth $(mm/tooth)$.

3.2 Material or metal remove rate (*MRR*)

The MRR measures the amount of material removed from the workpiece. Its definition is,

$$MRR = a_{dc} \cdot r_{dc} \cdot f_c \ , \tag{9}$$

where a_{dc} is the axial depth of cut (mm), r_{dc} the radial depth of cut (mm) and f_c the feed velocity (mm/s).

3.3 Surface roughness (*SURF*)

The variations of the surface roughness are widely used criteria for the assessment of the surface quality. Some research works use the empirical relationship of the equation (10), [3]. This approach is adopted in this paper:

$$SURF = K_{surf} \cdot V^{\beta_1} \cdot f_c^{\beta_2} \cdot a_{dc}^{\beta_3} \tag{10}$$

where V, f_c and a_{dc} are the cutting velocity (m/min), the feed velocity (mm/s) and axial depth of cut (mm), and K_{surf} is a model constant and, β_1, β_2 and β_3 surface roughness model parameters.

Finally, the weighting factors, $c_i, i = 1,2,3$ have the restriction that the sum of the parameters is the unity, i.e. $\sum_{i=1}^{3} c_i = 1$. Their declaration depends on process constraints. Normalization factors, $NF_i, i = 1,..,3$, equalize the magnitude order of each term in the cost function. They are defined as:

$$NF_i = \frac{J_i - J_{\max}}{J_{\max} - J_{\min}} \tag{12}$$

where J_i, represents each term of the cost function of the equation (9), which eventually, can be represented as

$$J = \sum_{i=1}^{3} c_i \cdot NF_i \cdot J_i \tag{13}$$

The selected cutting parameters will be the values of S_s, a_{dc} and f_c corresponding to the minimum value of the cost function according to selected values of the c_i parameters. It can be expressed mathematically as follows,

$$q^* = \left(S_s^*, a_{dc}^*, f_c^*\right) = \arg\max_{q_j \in Q} \left\{ J\left(TOL\left(q_j\right), MRR\left(q_j\right), SURF\left(q_j\right); NF_i, c_i\right) \right\}$$

, (14) obtaining the 3-tuple of candidate input cutting parameters, $\left(S_s^*, a_{dc}^*, f_c^*\right)$.

In order to achieve certain process or machine tool requirements in the cost function variables, the c_i parameters are automatically redefined (self-modified) as in the following equation, (15): $J = \sum_{i=1}^{3} c_i \cdot NF_i \cdot J_i$, which represents the proposed cost function of the equation (7). Then, for a given operation, **if** $k = \dot{k}_o = l \cdot k_o, l \in N$ and $\underline{J_i} \le J_i \le \sigma_i \cdot J_i = \overline{J_i}, \sigma_i > 1$ **then if**

$\sum_{k_o(i-1)}^{k_o i} J_i > \sum_{k_o(i-1)}^{k_o i} \overline{J_i}$, $c_i \leftarrow \left(1+\rho_i \frac{\overline{J_i}-J_i}{\overline{J_i}}\right) c_i$ **else** **if** $\sum_{k_o(i-1)}^{k_o i} J_i < \sum_{k_o(i-1)}^{k_o i} \overline{J_i}, c_i \leftarrow \left(1-\rho_i \frac{\overline{J_i}-J_i}{\overline{J_i}}\right) c_i$, **end**.

Weighting factors need to be normalized again to fulfil the constraint $\sum_{i=1}^{3} c_i = 1$. Then, $0 < \bar{c} \leftarrow \sum_{i=1}^{3} c_i, c_i \leftarrow c_i / \bar{c} \Rightarrow \sum_i c_i = 1$.

4. Self- adaptive control toolbox

The self-adaptive controller is broken up into two parts. First, a parallel process control scheme is proposed, which aims to maintain milling forces constant at each Pareto optimal working point. This control scheme incorporates least squares parameter estimators in order to adapt the system to changes in process requirements. For each working point, the multi-scheme controller proposes using different adaptive control structures to face the challenging milling non-linear force control problem. The used of different control structures is supported by the idea that, as the milling system is a highly non-linear problem, the system will face different potential models at different working points. Also, it can deal with the possible changes of parameters in the milling system. The second part is a *supervised controller*, which incorporates actuation logic hinged on taken measurements over the allowable cutting parameter space to know how the system works at each required point and switch to the adequate force controller at each time. It is based on a rule-based expert system. Then, the actuation logic is switched depending on the structure of the controller or depending on the value of system parameters.

In the current paper and, as practical work each candidate adaptive control is supposed to address possible changes of parameters, while the structure of the control remains the same at each parallel controller. Moreover, the supervised controller is based on a series of expert rules which switch the controller to the most adequate one depending on the cutting conditions and tool and workpiece material properties. As a result, the multi-parallel adaptive control scheme managed by the supervised controller allows dealing with the milling force control problem automatically and, independently of changes in cutting parameters and taken into account possible uncertainties in modelled parameters.

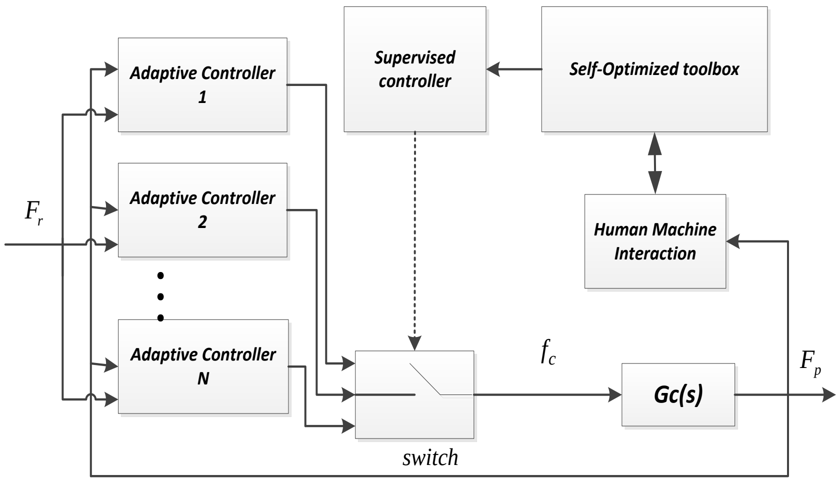

Figure 2: Architecture of the self-optimized and self-adaptive system

Finally, figure 2 pictures the proposed control architecture for the interaction between the self-adaptive and the self-optimized toolboxes. It works as follows, the operator or engineer inputs constraints to the self-optimized toolbox according to the interaction interface with the cost function presented in equation 7, i.e. the weighting factors. Then, the self-optimized toolbox outputs the programming Pareto optimal cutting parameters. At the same time, a multi-parallel adaptive control scheme, which is composed of N work in parallel controller, processes different control signals according to possible different structures of the controllers or parameters in different sets of knowing Pareto optimal cutting parameters. The supervised controller, which is composed of a rule-based expert system, is able to switch to adequate force controller in order to keep the forces of the system under the prescribed upper bound in a wide range of cutting conditions for a given pairs of tool and workpieces materials.

5. Example

For implementing the above explained control scheme a practical end mill has been chosen with the modal characteristics in the X and Y directions corresponding to table 1, with three tooth and 30 millimetre diameter. The work-piece is a rigid aluminium block whose specific cutting energy is $k_t = 600kN \cdot mm^{-1}$ and the proportionally factor is taken to be $k_r = 0.07$.

Table 1 Tool modal parameters.

	$\omega_n \left(rad \cdot s^{-1}\right)$	$\xi(\%)$	k$(kNmm^{-1})$
X	603	3.9	5.59
Y	666	3.5	5.715

Regarding to the model reference adaptive control, the transfer function of the equation (6); the cutting pressure of the transfer function has been selected to be constant and equal to $1200N \cdot mm^{-2}$ in all range of cutting parameters, the CNC time constant, $\tau_m = 0.1ms$ and, $\tau_c = 1/N_t S_s$. The continuous model reference system of the adaptive control is chosen to be a typical continuous second order plant with $\xi = 0.75$ and $\omega_n = 2.5/(4 \cdot T)$, where T is the sampling period., which is usually selected as inversely proportional to the spindle speed, $T = 1/S_s$. Also, it is desirable for the reference force to be maintained at $1200N$.
The input space parameter where the system looks for Pareto optimal cutting parameters is given by the stability border line (first graph of figure 2). This figure says that if programming cutting parameters are over the border line chatter vibrations will appear and the system will be unstable [6]. However, if programmed cutting parameters are below this border line the system will work correctly against chatter vibrations. Other mechanical and electrical restrictions when searching for programming adequate cutting parameters are referred to spindle power consumption and feed drive limitations. Other safety constraints can be added in order to avoid uncertainty in searching regions.
For example purposes, it is supposed that the following cutting parameters represent three Pareto optimal fronts. Those are represented in the table 2. A more in-depth explanation of how to obtain Pareto optimal cutting parameters is provided by Rubio et al. [10].

Table 2: Cutting parameters and cost function values.

	$S_s(rpm)$	$a_{dc}(mm)$	$f_c(^{mm}/_s)$	$MRR\left(^{cm^3}/_s\right)$	$TOL(min)$	$SURF(\mu m)$
1.	2325	0.3326	5.22	0.0441	37.05	1.4048
2.	2985	0.7890	13.94	0.2793	5.1921	9.8730
3.	3510	0.5124	11.04	0.1436	20.8051	5.6167

Figure 3 depicts, from top to bottom, the stability lobes with the situation of the programmed cutting parameters, the adaptive controller with changes in the cutting parameters and the frequency response of the programmed cutting parameters, which incorporates different adaptive controllers to face the problem of changing parameters of the system and changing cutting parameters combined with expert rule-based supervised controller.
Then, to test the system it is supposed that the first production requirements give to program the cutting parameters associated to the point 1 in table 2 and point 1 in lobes of figure 2. Then, new constraints are given. They are represented by point 2 in table 2 and figure 2. And, finally, the last requirements are given by cutting parameters represented in point 3.
It can be observed that the proposed cutting parameters given by the Self-optimized toolbox are below the stability border-line in the stable zone and their frequency responses do not excite the chatter frequency (close to one natural frequency of the system). Moreover, the adaptive controller developed in parallel allows the system to move around the cutting space parameter

keeping the forces below a prescribed upper limit bound while programming feasible command feed rates.

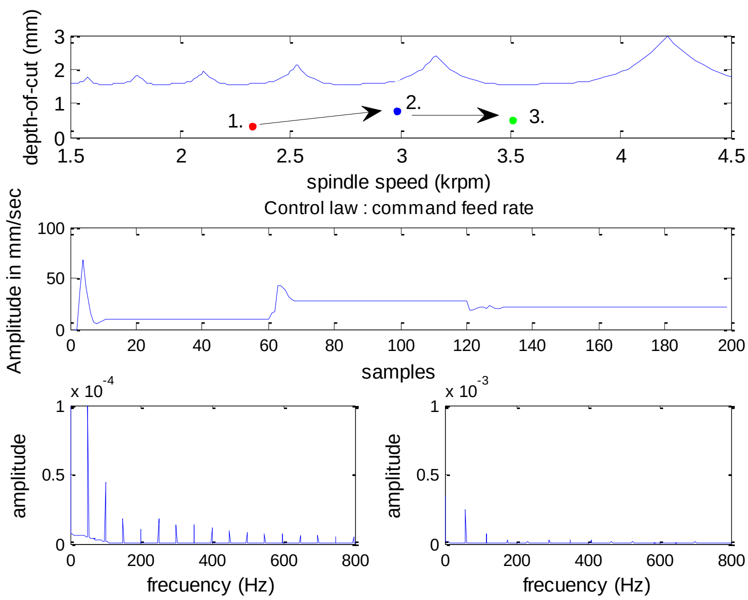

Figure 3: Situation of the programmed cutting parameters in stability lobes, control signal and frequency responses (points 1 and 3).

6. Conclusion

A novel control scheme is proposed. It is composed of two levels. The first one, the self-optimised cutting parameters layer compromises life of the tool, material remove rate, surface roughness and the robustness of the system. While the second one, the multi-parallel adaptive controller, provides an environment to adaptively control the milling process under changes in cutting parameters. A rule-based supervised controller is able to choose automatically the most suitable controller among the set of designed for each Pareto optimal cutting parameters. As a result, the control architecture leads to automatically work out the complex milling system using an easy interface with the operator. Simulation results support the performance of the system.

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References

[1] CUS, F. & BALIC, J., (2003). OPTIMIZATION OF CUTTING PROCESS BY GENETIC ALGORITHM APPROACH. ROBOTICS AND COMPUTER-INTEGRATED MANUFACTURING, 19 (1-2), 113-121.

[2] AVELLAN, J.V., ROMEROS, F., SILLER, H.R., ESTRUD, A. & VILA, C.,(2008). ADAPTIVE CONTROL OPTIMIZATION OF CUTTING PARAMETERS FOR HIGH QUALITY MACHINING OPERATIONS BASED ON NEURAL NETWORKS AND SEARCH ALGORITHMS. ADVANCE IN ROBOTICS, AUTOMATION AND CONTROL, I-TECH VIENNA AUSTRIA.

[3] SURECH, R., BASAVARAJAPPA, S., GAITONDE, V. N. & SAMUEL, G.L., (2012). MACHINABILITY INVESTIGATIONS ON HARDENED AISI 4340 STEEL USING COATED CARBIDE INSERTS. INTERNATIONAL JOURNAL OF REFRACTORY METALS AND HARD MATERIALS, IN PRESS.

[4] WONG, S.V. AND HAMOUDA, A.M.S. ,(2003). MACHINABILITY DATA REPRESENTATION WITH ARTIFICIAL NEURAL NETWORK, JOURNAL OF MATERIALS PROCESSING TECHNOLOGY, 16, 538-544.

[5] ZUPERL, U. & CUS, F. ,(2003). OPTIMIZATION OF CUTTING CONDITIONS DURING CUTTING USING NEURAL NETWORKS. ROBOTICS AND COMPUTER-INTEGRATED MANUFACTURING, 19 (1-2), 189-199.

[6]ALTINTAS, Y. (2012). MANUFACTURING AUTOMATION. CAMBRIDGE UNIVERSITY PRESS.

[7] ZUPERL, U., CUS, F. & MILFELNER, M. ,(2005). FUZZY CONTROL STRATEGY FOR AN ADAPTIVE FORCE CONTROL IN END-MILLING. JOURNAL OF MATERIAL PROCESSING TECHNOLOGY, 1472-1478.

[8] RUBIO, L., DE LA SEN M. & BILBAO-GUILLERMA, A., (2007). INTELLIGENT ADAPTIVE CONTROL OF FORCES IN MILLING PROCESSES. PROCEEDINGS OF THE 2007 IEEE MEDITERRANEAN CONFERENCE ON CONTROL AND AUTOMATION, ATHENS, GREECE, 1-6.

[9] LIANG, S.Y., HECKER, R.L. & LANDERS, R.G., (2004). MACHINING PROCESS MONITORING AND CONTROL: THE STATE OF THE ART. ASME J. OF MANUFACTURING SCIENCE AND ENGINEERING, 126 (2), 297-310.

[10] RUBIO, L., DE LA SEN, M., LONGSTAFF, A.P. AND FLETCHER, S. (2012). MODEL-BASED EXPERT SYSTEM TO AUTOMATICALLY ADAPT MILLING FORCES IN PARETO OPTIMAL MULTI-OBJECTIVE WORKING POINTS. EXPERT SYSTEMS WITH APPLICATIONS, DOI:10.1016/JESWA.2012.10.034.