Optimum design with intelligent control of a log manipulator
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Abstract
The goal is to study the product development of the structure and control logic of a log manipulator using virtual prototype models. The design goals are to satisfy the economical and technical performance needs of the end user using fuzzy goal formulations. The manufacturing development goal is to reduce optimally the complexity or cost. Also the utility of intelligent control to maximize the efficiency of handling are considered. The following methods are used. A virtual 3D full dynamics simulation prototype of the machine and its operation space are modeled using Working Model program. The model is run through a representative work cycle as required by the end user to get simulated loads at members. Using these loads some parts are modeled with FEM to get stress strain and deflection data at critical locations. One critical machine element is optimised using the optimising algorithm with a mix of discrete and continuous variables of component geometries, materials and manufacturing and strength constraints in a fuzzy way. The result is a machine model which satisfies the manufacturability criteria of the producer and also the end user by performing all the kinematic functions within the work space. The next step is the reconstruction of a new model which has more intelligence both built into the structure and also to the controlling algorithms and then the verification of its performance and comparison with the predictions of the virtual prototype.
1 Introduction

The aim of this study is to present some results in a project for developing the mechanical structure [1] and also control logic of a log manipulator. The first goal in the project was to formulate a 3D virtual prototype [2] for dynamic analyses using Working Model [3] which would output the dynamic loads for the next stages. The second goal was study how to construct a control algorithm for making a virtual prototype more intelligent. The third goal was to optimise a critical part. First optimum design goals are specified to satisfy the economical and technical performance needs of the end user and of the manufacturer. Then this goal was reached using an analytical nonlinear optimization algorithm based on fuzzy goal formulations used by Diaz [4] and Martikka [5]. The aim was maximise the cost-effectiveness of the log loading. Further goal is to implement more optimal control methods as considered by Lewis and Vassilis and [6].

2 Methods and experimental work

The following methods are used. The input data was obtained from one manipulator type of a product group. It was used to construct a virtual model which was then optimised.

2.1 Multibody dynamics simulation using a virtual prototype

A virtual 3D full dynamics simulation prototype of the machine and its operation space is modeled using Working Model [3]. The stress resultants at one critical section were obtained using free bodies, Fig. 1.

\[ F_x = -(F_{C18x} + F_{C29x} + F_{C21x}), \quad F_y = 0, \quad F_z = F_{C21z} = 8600 \]

\[ T_x = 193, \quad T_y = F_{C29x} \cdot h + F_{C21z} \cdot h, \quad T_z = 174 \text{Nm} \]  \hspace{1cm} (1)

A typical force output at constraint C18 is shown in Fig.2.
Figure 1: The beam under consideration. a) The work cycle, force and torque loads and effective stress schematically. b) Approximate stress history with effective stress means and amplitudes. c) The beam and its loads at time \( t = 12 \text{ s} \). Load magnitudes are: \( F_{czv} = 138000 \text{N} \), \( F_{c18} = -141000 \text{N} \), \( F_{czlx} = 10000 \text{N} \), \( F_{c2,r} = -8600 \text{N} \), \( T_{nc18} = 193 \text{Nm} \), \( T_{zc,8} = 174 \text{Nm} \).

Figure 2: Force components at constraint C18
Some results of the WM simulations are shown in Fig. 3.

Figure 3: Results of simulations of the log manipulator from initial position to gripping position at \( t = 12 \) s and to unloading position.
2.2 Control of the manipulator

2.2.1 Practical control methods
In the simpler manipulator machines manual control is frequently used as an adequate method. In these applications human intelligence is essential. But as the requirements on the quantity and quality of the work output increase due to general needs then implementation and utilisation of artificial intelligence is becoming more necessary even in simpler machines.

The typical work cycle and work load were given by the manufacturer and modified to get a realistic work cycle. The operations and durations are:

1. The boom is moved from the carrier, 4s.
2. The gripper is moved to maximum extension and then opened, 6s
3. The log is gripped, 1s
4. The boom extension is withdrawn, 2s
5. The log is lifted and then rotated to a position above the carrier, 4s.
6. The boom is lowered and the gripper is opened to drop the log, 2s

The machine has 5 cylinders whose extensions have to be controlled. Now the cylinders were controlled as follows.

Table 1. Data for control algorithm. The velocities $v$ (m/s) of cylinders are controlled using the volume flows $q$ (m$^3$/s). The final time is 25 sec.(2).

<table>
<thead>
<tr>
<th>start</th>
<th>end</th>
<th>v(m/s)</th>
<th>q</th>
<th>v</th>
<th>q</th>
<th>v</th>
<th>q</th>
<th>q</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>1</td>
<td>0.12</td>
<td>36.2</td>
<td>0.16</td>
<td>48.3</td>
<td>-</td>
<td>13.3</td>
<td>97.7</td>
</tr>
<tr>
<td>1</td>
<td>2</td>
<td>0.12</td>
<td>36.2</td>
<td>0.16</td>
<td>48.3</td>
<td>0.45</td>
<td>13.3</td>
<td>97.7</td>
</tr>
<tr>
<td>2</td>
<td>3</td>
<td>0</td>
<td>30.0</td>
<td>0.16</td>
<td>48.3</td>
<td>0.45</td>
<td>0</td>
<td>48.3</td>
</tr>
<tr>
<td>3</td>
<td>4</td>
<td>-0.255</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>30.0</td>
</tr>
<tr>
<td>etc</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Now the aim was to study first the present work cycles and then to devise methods of implementing artificial intelligence type controls based on fuzzy and neural algorithm methods for controlling optimally the manipulator. The aim is to make log handling more cost-effective also by optimising the work paths so that the unnecessary load maxima are minimised. This ensures higher probability of reliable life for all components. A control model can be based on the kinematics of the work cycle is shown in Fig. 4.
2.2.2 Use of artificial intelligence methods in control and design

2.2.2.1 Kinematics model

Now a kinematics model of the mechanism was made for studying various methods of controlling and designing it optimally, Fig. 4.

Figure 4: The skeleton of the vector loops of the mechanism.

The three independent loop equations are

\[ \begin{align*}
Z_4 + f_1 Z_2 + f_2 Z_2 - Z_3 - f_3 Z_1 &= 0 \\
Z_1 e^{iT_1} + f_1 Z_2 e^{iT_2} + f_2 Z_2 e^{i(T_2 - \pi/2)} - Z_3 e^{iT_3} - f_3 Z_1 e^{i(T_2 - \pi/2)} &= 0 \\
(1 - f_4) Z_2 + Z_4 - Z_9 - f_2 Z_2 &= 0 \\
(1 - f_4) Z_2 e^{iT_1} + Z_9 e^{iT_4} - Z_2 e^{i(T_2 + \pi/2)} &= 0 \\
\end{align*} \]

\[ \begin{align*}
f_6 Z_2 + Z_7 - Z_5 - Z_4 &= 0 \\
f_6 Z_2 e^{i(T_2 - \alpha)} + Z_7 e^{iT_4} - Z_2 e^{iT_3} - Z_4 e^{iT_4} &= 0
\end{align*} \]
Table 2. Variables and parameters. The $V$ variables are independent and $U$ variables are dependent variables.

<table>
<thead>
<tr>
<th>Length $Z_1$ of vector $Z_k$</th>
<th>Angle $T_1$ of vector $Z_k$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$Z_1 = Z_{1c}$ = const</td>
<td>$T_1 = \pi/2$</td>
</tr>
<tr>
<td>$Z_2 = Z_{2c}$ = const</td>
<td>$T_2 = U_1$</td>
</tr>
<tr>
<td>$Z_3 = V_1$ = variable</td>
<td>$T_3 = U_2$</td>
</tr>
<tr>
<td>$Z_4 = Z_{4c}$ = const</td>
<td>$T_4 = U_3$</td>
</tr>
<tr>
<td>$Z_5 = Z_{5c}$ = const</td>
<td>$T_5 = U_4$</td>
</tr>
<tr>
<td>$Z_6 = V_2$ = variable</td>
<td>$T_6 = T_2 - \alpha$</td>
</tr>
<tr>
<td>$Z_7 = Z_{7c}$ = const</td>
<td>$T_7 = U_5$</td>
</tr>
<tr>
<td>$Z_8 = V_3$ = variable</td>
<td>$T_8 = T_7 - \beta = U_6 \cdot \beta$</td>
</tr>
<tr>
<td>$Z_9 = V_4$ = variable</td>
<td>$T_9 = U_6$</td>
</tr>
</tbody>
</table>

2.2.2.2 Definition of operational goals using fuzzy operations It is desired that the log is moved from an initial terrain area to the target area at the wood forwarder. In the simulations these areas are now defined using fuzzy models.

The goal of achieving the target area is defined as a conjunction or now as product intersection of satisfaction function on log $x$-location $P_{gx}$ and on log $y$-location $P_{gy}$, or

$$I(P_{gx}, P_{gy}) = P_{gx} \cdot P_{gy}$$  \hspace{1cm} (3)

The constraint space is now defined disjunctively as probabilistic sum of satisfaction functions

$$P_G = U(1 - P_1) + U(1 - P_2) = P_1 + P_2 - P_1P_2$$  \hspace{1cm} (4)

where $P_1$ and $P_2$ are fuzzy membership function goals or satisfactions of constraint violations in $x$ and $y$ directions respectively.

The total goal is now defined as intersection of two desired events

$$P_G = P_{G_g} \cdot P_{G_c} = P_{gx} \cdot P_{gy} \cdot (P_1 + P_2 - P_1P_2)$$  \hspace{1cm} (5)

In the program code formulation these are conveniently expressed in terms of the $U$ and $V$ variables. The number of constraints due to loops is $m = 6$ and the number of $U$ variables $n = 6$ and the number of $V$ variables is $v = 3$. So the number of degrees of freedom is $f = 3$.

Fig.5 shows the satisfaction function $P_G$. 


Figure 5: The satisfaction functions for intelligent positioning.

One simple algorithm is illustrated in a pseudocode way. It has some of the basic ingredients of an AI system but not yet the third one.

\[
\text{FOR } t = \text{Time1} \text{ TO Time2 with suitable timestep} \\
\text{New actuator length variables } V(i) \text{ are generated} \\
V(t) = V_{\text{best}}(t) + (V_{\text{max}} - V_{\text{min}}) \cdot (0.5 - \text{RND}) \cdot \text{Learn} \quad (6)
\]

This has an initial search range which can be diminished by a learning function \text{Learn} around the latest best value. \text{RND} is a random number between 0..1.

Next assemble the mechanism with new actuator length variables

\text{A Knowledge acquisition both from outside and by own inference}

The AI system has now knowledge about the positions of its parts and the goals. The goal is to reach the midpoint \(x_m, y_m\) of the max satisfaction area

\[
\text{minimize } Q = 1/(P_x + 0.01) + r^2 \\
P_x = P_{x12} \cdot P_{x34} \text{ is satisfaction in } x\text{-location} \\
r^2 = (x_9 - x_m)^2 + (y_9 - y_m)^2 \text{ is squared distance from goal point}
\]

\text{B Goal directed behaviour}

\[
\text{IF } Q_{\text{best}} < Q \text{ THEN success is achieved with the newest } Q(V) \\
\text{store the best values as new reference points} \\
Q_{\text{best}} = Q : V_{\text{best}}(i) = V(i) \\
\text{gosub DODRAW print and draw the situation} \\
\text{ELSE go on searching. END IF:}
\]

\text{NEXT } t : \text{ END}

\text{C Skill acquisition.} An advanced AI system has ability to learn and improve its performance. Now this system would need some neural network addition in order to learn while repeating the routine work cycles.
Some results with this algorithm are shown in Fig. 6

Figure 6: Kinematic simulation with position goal searching
a) The initial configuration and
b) the search steps until the goal is close enough.

\[
\begin{align*}
 x_1 & \quad x_2 & \quad x_3 & \quad P_x & \quad x_4 & \quad P_x \quad \text{new \ Qbest} = \frac{1}{P_x + r l} \\
-1.40 & \quad -0.60 & \quad -0.80 & \quad 0.88 & \quad 1.00 & \quad 1.00 & \quad 1.00 & \quad 0.50 \\
13.744 & \\
\end{align*}
\]

\[
U(i) = \text{length of hydraulic cylinder} \ i
\]

CLOCK for showing time in seconds \( t = 10 \)

CLOCK for showing time in seconds \( t = 358 \)
2.2.2.3 Additional possibilities of enhancing the intelligence of optimisation Using the kinematics model many features can be optimised in addition to control. One is optimum dimensioning during the work cycle. The balance of moments of the FB at the critical section gives

\[ \Sigma M = M + R \times P = 0 \]
\[ M_z = R_z P_y - R_y P_z = R_z mg = \]
\[ = ((1 - f_d)Z_2 \cos T_2 + Z_6 \cos T_6 + Z_7 \cos T_7 + Z_8 \cos T_8) mg \] (7)

Using this information of the applied torque the following optimising actions can be taken. If the goal is minimum weight with adequate fatigue life then the method is

a) Simulate the load cycle to get moment and stress history
\[ \Delta \sigma = \frac{M_z}{W} \] (8)

b) Calculate the optimum bending resistance \( W \)
\[ R(1) = N - N_{\text{min}} \geq 0, \quad \rightarrow \quad \frac{C}{\Delta \sigma^3} - N_{\text{min}} \geq 0, \quad \rightarrow \quad W \geq W_{\text{min}} \] (9)

2.3 FEM modelling

Some parts are modeled with FEM to get stress-strain and deflection data at critical locations. The geometry was created with AutoCAD and then it was transferred to Working Model and then to Cosmos FEM program.[7]. The available components and interconnectivity rules are modelled. The model is activated to run through the representative work cycle as required by the end user. The results of FEM and analytical analyses are compared in Table 3.

<table>
<thead>
<tr>
<th>Method</th>
<th>width ( B )</th>
<th>height ( H )</th>
<th>wall ( t )</th>
<th>steel choice</th>
<th>max stress</th>
</tr>
</thead>
<tbody>
<tr>
<td>FEM</td>
<td>0.115</td>
<td>0.115</td>
<td>0.01</td>
<td>Hst ( R=640 )</td>
<td>( \sigma_{\text{max}} = 299 )</td>
</tr>
<tr>
<td>Anal.</td>
<td>0.1</td>
<td>0.124</td>
<td>0.008</td>
<td>Hst ( R=640 )</td>
<td>( \sigma_{\text{max}} = 306 )</td>
</tr>
</tbody>
</table>
The Mises stresses are shown in Fig. 7

![Image of beam stresses]

Figure 7: Mises stresses of the beam at time $t = 12s$. The maximum stress is 212MPa.

2.4 Analytic optimization

The reliability of the total structure is determined largely by the most stressed critical beam section. For this reason the optimization method was applied first to it.

2.4.1 Optimization search method

This method was based on analytical models and learning random search optimization developed by Martikka. A mix of continuous, integer and discrete variables are used. The continuous variables were the height $H$ and width $B$. These were generated by

$$x(j) = x_{\text{best}}(j) + \left[ x_{\text{max}}(j) - x_{\text{min}}(j) \right] \left[ 0.5 - \text{RND} \right]$$

where $x(j)$ is a continuous variable. Its momentary search range is diminished by a learning function $\text{Learn}$ around the latest best value. $\text{RND}$ is a random number between 0...1. Discontinuous variables were activated, e.g. the set of standard plate thicknesses $t(IT)$, $IT = 1,2,...$ and standard steel classes with $R_m(IM)$ and cost per mass $C(IM)$, $IM = 1, 2,$...
These were generated by

$$x(i) = \text{INT}[\text{max}(i) - \text{min}(i) + 1] \cdot \text{RND} + \text{min}(i)$$  \hspace{1cm} (11)

2.4.2 Satisfaction functions of the goals

The satisfaction functions were satisfaction on the cost and on the fatigue life as measured by the magnitude of the fatigue life exponent $V$ in the SN model $N = 10^6$. This gives the crack initiation life. A good design event is thus

$$G = G_{\text{cost}} \text{ AND } GV$$  \hspace{1cm} (12)

This is measured in a scale from 0 to 1 by a functions $P()$ giving

$$P(G) = PG = P(G_{\text{cost}} \text{ AND } GV) = PG_{\text{cost}} \cdot PGV$$  \hspace{1cm} (13)

Volume $V$ and cost $K$ of the part are

$$K = c\rho V \quad V = AL$$  \hspace{1cm} (14)

where $c$ is the cost per mass [FIM/kg], $K$ is cost [FIM] and $\rho$ is density [kg/m$^3$]. $A$ is cross sectional area and $L$ is the length of the part of the beam under consideration.

![Satisfaction functions](image)

Figure 8: Satisfaction functions, a) for the cost, b) for fatigue life exponent $V(1)$, $PGV(1)$ at section $i = 1$ and c) the most satisfactory design area is shown on a fatigue life exponent vs. cost plot.

2.4.3 Fatigue life estimations

These were estimated at critical cross sections with two assumptions.

2.4.3.1 Fatigue life of a structure with no initial flaw assumption

Here $V(i)$ is the exponent in the fatigue life formula at section $i = 1, 2, ..., \ldots$ and $V_0$ is the reference value. It was set to $V_0 = 6$ to obtain a life of $10^6$ cycles.
\[ N(i) = 10^{V(i)} \quad V(i) = \log \left[ \frac{V_a V_e}{(1 - V_m) x^2} \right] \left[ \frac{3}{\log(V_e / c)} \right] \]  

(15)

where \( c = 0.9 \) and the three stress ratios are:

\[ V_a = \frac{\sigma_{va}}{R_m} \] is relative effective stress amplitude

\[ V_m = \frac{\sigma_{vm}}{R_m} \] is relative effective mean stress

\[ V_e = \frac{S_c}{R_m} \] is relative effective fully corrected fatigue strength

\[ \sigma_{vm} = \left( \sigma_m^2 + 3\tau_m^2 \right)^{1/2} \]

\[ \sigma_{va} = \left( \sigma_a^2 + 3\tau_a^2 \right)^{1/2} \]  

(16)

This method of calculating fatigue lives combines the Haigh diagram of modified Goodman type and the S-N diagram.

\[ \log(R_m) \]

\[ \log(cR_m) \]

\[ \log(\sigma_m) \]

\[ 10^N = N = 10^N \]

\[ R_m \]

\[ S_c \]

\[ (\sigma_e, \sigma_m) \]

\[ R_e \]

\[ \log(\sigma_m) \]

\[ \log(cR_m) \]

\[ \log(R_m) \]

\[ \sigma_m \]

\[ R_m \]

\[ \sigma_m \]

\[ N = 10^N \]

\[ N = 10^N \]

Figure 9: The method of calculating fatigue lives of crack initiation time.

The ideal fatigue strength or the mean endurance limit of the rotating-bending specimens of steels can be calculated from static strength \( R_m = UT S \) by \( \sigma_w = 0.5 R_m \). The fully corrected fatigue strength is \( S_c \):

\[ S_c = \frac{1}{K_f} \sigma_c = C_f C_1 \sigma_w = S_c = C_f C_p C_2 C_3 C_4 C_m \sigma_w \]  

(18)

Here \( C_1 \) and \( C_2 = 1/K_f \) are fatigue strength reduction factors and \( K_f \) is the notch effect factor. Several notch factors in bending can be used.

2.4.3.2 Petersons model. The notch factor \( q \) depend on the radius of curvature of the notch \( r = \rho(mm) \).
The notch effect factor in bending is

\[ K_f = 1 + q(K_t - 1) \]  

(20)

2.4.3.3 Doege’s model. According to Doege [8] the conventional notch effect models overestimate the fatigue strength lowering effect of the notch form number \( K_t \). An approximate model can be fitted to the data [8].

\[ K_f = 1 + \left[ \frac{R_m \text{ (MPa)}}{1000 \text{ (MPa)}} \right] (K_t - 1)^{0.3} \]  

(21)

The factors affecting the fatigue strength are

- \( C_p = 1 \) is factor of shotpeening. Now it was not applied.
- \( C_t = 1 \) is temperature factor. This goes zero above 450°C.
- \( C_m = 1 \) is environmental factor. Now no corrosion is assumed.
- \( C_r = 1 \) is reliability factor.
- \( C_s = 0.8 \) is surface quality factor.
- \( C_z \) is size effect factor. Now the simple model by Hundal is applicable \( C_z = 0.608 d(\text{m})^{-0.007} \), where \( d \) is the equivalent shaft diameter. The shot peening factor \( C_p \) depends on the surface quality factor \( C_s \) and UTS \( C_p = 1 + Y(C_s, R_m) \).

The reliability factor is based on the observation that the ideal fatigue strength is a stochastic variable which is normally distributed with a mean and standard deviation

\[ \sigma_w = (\bar{\sigma}_w, \sigma_w) = (\bar{\sigma}_w, \bar{\sigma}_w) \]  

\[ C_r = \frac{(\bar{\sigma}_w - z^2 \sigma_w)}{\sigma_w} = 1 - C_v z \]  

(22)

here \( C_v = 0.08 \) is the coefficient of variation and \( z \) is the normed variable of normal distribution. The reliability that fatigue fracture of an ideal specimen does not occur at an amplitude \( \sigma_a \) is

\[ RL(z) = \Pr \left\{ \sigma_a \leq C_r \bar{\sigma}_w \right\} \]  

\[ RL(z) = 0.5 + \int_0^z \frac{1}{(2\pi)} e^{-u^2} \, du \]  

(23)
2.4.3.4 The load. Now the load force varied harmonically as \( F = 0...F_{\text{max}} \) giving the stress amplitude as \( \sigma_a = 0.5 \sigma_{\text{max}} = \sigma_{\text{va}} \) and the mean stress as \( \sigma_m = 0.5 \sigma_{\text{max}} = \sigma_{\text{vm}} \).

2.4.3.5 Fatigue life estimation with fracture mechanics. When the structure contains initial flaws the fatigue life is about the same as time spent in crack growth since initiation time not needed. The Paris-Erdogan law is

\[
\frac{da}{dN} = C (\Delta K)^m \quad \Delta K = Y \Delta \sigma \sqrt{\pi a}
\]

where \( a \) is crack length, \( \Delta K \) is stress intensity factor range, \( \Delta \sigma \) is stress, factor \( Y \) is due to geometry close to crack is now set to \( Y = 1.2 \). The crack grows from initial crack length to final crack length. Now for steel with \( R_m > 700 \), \( a_0 = 0.015 \text{ mm} \) and with \( R_m < 700 \), \( a_0 = 0.05 \text{ mm} \). Now \( a_0 = 0.1 \text{ mm} \). The final crack length and the factor \( C [9,] \) and exponent \( m \) depend on the strength approximately as by eqn. (25)

\[
a_f = \frac{1}{\pi} \left( \frac{K_c}{R_c} \right)^2 \quad m = 600 \left( \frac{R_c [\text{Pa}]}{\sigma_{\text{m}}} \right)^{-0.264} \quad C' = \frac{A}{B^m} \quad C = C_{\text{corr}} C'
\]

where \( A = 131.5 \times 10^4 \), \( B = 895.4 \) at the stress ratio \( R = \sigma_{\text{m}}/\sigma_{\text{max}} = 0 \), \( C_{\text{corr}} \) is corrosion enhancement factor, with no corrosion it is 1 and with wet corrosion it may be 10 times higher at medium \( \Delta K \). \( C_{\text{corr}} \) increases when the surface moisture is increased from dry to 80%. At very low \( \Delta K \) values \( C_{\text{corr}} \) is 20 and at high \( \Delta K \) values it is about 3. The fatigue life in number of cycles is
\[ N_p = \frac{1}{C \left( \frac{1}{2} m - 1 \right) \left( \Delta \sigma Y \sqrt{n} \right)^m} \left[ \frac{1}{a_0^{\frac{1}{m} - 1}} - \frac{1}{a_1^{\frac{1}{m} - 1}} \right] \] (26)

The units are \( \Delta \sigma \) (MPa) and crack lengths \( a_0 \) and \( a_1 \) are in (mm) units. Now \( \Delta \sigma = \sigma_{\text{max}} - \sigma_{\text{min}} = \sigma_{\text{max}} - 0 \).

2.4.4 Results of analytic optimization

Some results are shown in Tables 4 and 5. Generally, a machine element is created in an intersection of materials, geometry and function or life time task. Material thickness classes were IT = 8-10.

Three main material choices were a) the low strength steel Fe37 (IM=1, \( R_e = 200, R_m = 330 \)), b) medium strength steel Fe 52 (IM=2, \( R_e = 315, R_m = 520 \)) and c) a high strength weldable RAEX steel, code Hst (IM=3, \( R_e = 640, R_m = 760 \)). Generally high strength steels are more sensitive to corrosion assisted crack growth than soft steels. Paris law is used to estimate crack propagation life with \( Y = 1.2 \) and crack length range \( a_0 =.1 \) to \( a_1 =10 \) mm. Using it the effect of corrosion on material selection was studied by varying the enhancement factor \( C_{\text{corr}} = 1, 5, 10 \). The tables show that by requiring the crack propagation life to exceed of 0.1 \( \cdot 10^6 \) this trend is confirmed. The total satisfaction function is \( PG \), satisfaction function on cost is \( PG_{\text{cost}} \) and on fatigue life exponent \( V(1) \) it is \( PGV(1) \).

Table 4: Available variable ranges and optima.

No corrosion risk at the critical section, \( C_{\text{corr}} = 1, \sigma_{\text{max}} = 306 \) MPa. giving.

The best choice was Hst with values: \( PG = 0.16, PGV = 0.7, Pgcost =.23 \). Fatigue life with no initial cracks was estimated as \( N = 1.2 \cdot 10^6 \), \( K_i = 1.47, C_k =0.81 \). Fatigue life by Paris’ law was \( N = 0.1 \cdot 10^6 \).

<table>
<thead>
<tr>
<th>Material class IM</th>
<th>1. Fe37</th>
<th>2. Fe 52</th>
<th>3. Hst</th>
</tr>
</thead>
<tbody>
<tr>
<td>Thickness ( t ) (IT)</td>
<td>( t(8) = .08 )</td>
<td>( t(9) = .010 )</td>
<td>( t(10) = .012 )</td>
</tr>
<tr>
<td>( B ) width (m), continuous</td>
<td>( .05 &lt; B )</td>
<td>( B = .1 )</td>
<td>( B &lt; .2 )</td>
</tr>
<tr>
<td>( H ) height (m), continuous</td>
<td>( .05 &lt; H )</td>
<td>( H = .124 )</td>
<td>( H &lt; .15 )</td>
</tr>
</tbody>
</table>
Table 5: Severe corrosion risk at the critical section, $C_{corr} = 10$.
The best choice was medium strength steel Fe 52 with values: $PG = 0.156$, $PGV = 1$, $PG_{cor} = .156$. Fatigue life estimate, with no initial cracks, $Kf = 1.32$, $Ck = 0.81$, $N = 1.2 \cdot 10^6$ and fatigue life by Paris’ law was obtained as $N_p = 0.1 \cdot 10^6$.

<table>
<thead>
<tr>
<th>Material class IM</th>
<th>1, Fe37</th>
<th>2, Fe 52</th>
<th>3, HSt</th>
</tr>
</thead>
<tbody>
<tr>
<td>Thickness $t(IT)$</td>
<td>$t(8) = .08$</td>
<td>$t(9) = .010$</td>
<td>$t(10) = .012$</td>
</tr>
<tr>
<td>$B$ width (m), continuous</td>
<td>$0.05 &lt; B$</td>
<td>$B = .142$</td>
<td>$B &lt; .2$</td>
</tr>
<tr>
<td>$H$ height (m), continuous</td>
<td>$0.05 &lt; H$</td>
<td>$H = .150$</td>
<td>$H &lt; .15$</td>
</tr>
</tbody>
</table>

3 Discussion

Artificial intelligence is a tool whose importance for engineers is growing. Design work is highly interdisciplinary and the designer needs tools for defining the really desired goals and methods to reach them cost-efficiently and creatively. In this project the case in study was a log manipulator and the need was to develop also integration of design and manufacturing.

The result is a machine model which satisfies the manufacturability criteria of the producer and also satisfies the end user customer by performing all the kinematic functions within the work space.

The next goal is to construct a new model which has more intelligence both built in and also externally directed. New types of controlling algorithms are being considered. This study showed that it would be profitable to implement AI methods into mechanism design programs. The simple kinematic control simulation system had most of the ingredients of an AI system: knowledge acquisition, goal directed behaviour and skill acquisition. This latter property is being devised using the method of neural networks and heuristic knowledge capturing.

These virtual simulation models can be made to output large amounts of virtual data. But also very intelligent algorithm is needed to find out what is relevant and reliable information in this flow which can be used to optimise the mechanism topology and individual members and kinematics.

One result of the project highlights the importance on focusing on the actual satisfaction of the end user instead of intermediate stages and going on with the designing with the available information using concurrent engineering and accumulating relevant information while striving to the goals.
4 Summary and conclusions

The following conclusions may be drawn:

• The first goal in the project goal was to formulate a 3D dynamic virtual prototype model which would output the dynamic loads for the next FEM analysis and optimum design. This was reached satisfactorily although interface applications are still somewhat clumsy in the data transfer from AutoCAD to WM and to Cosmos FEM.

• The second goal was study how to make the control algorithm of the virtual prototype more intelligent. Even a simple kinematics control search method can be made to act in an AI way.

• The third goal was to specify optimum design goals to satisfy the economical and technical performance needs. Next this goal was reached using analytical nonlinear optimisation algorithm based on fuzzy and penalty goal formulations.

References

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7. COSMOS FEM program.