1 Introduction

Solving constrained non linear optimization problems begins with identification of the Karush-Kuhn-Tucker conditions. This is due to the fact that for a differentiable convex system where constraint qualification holds, the solution of NLP is the solution to the KKT system and vise versa. The KKT conditions enables solving the NLP model as an MCP model by representing the KKT conditions as complimentarily equations. Thus, it is often advantageous to explicitly model the KKT conditions and solve them as a Mixed Complementarity Problem (MCP), as described in the PATH Solver Manual (/link) using the example of a Linear Transportation model. The traditional model of fixed demand and price is made more realistic by making the variables endogenous, i.e. the price of commodity is market affects the demand of the commodity, and the model is solved as a complimentarily problem. At times the complexity of the model causes errors in formulation of KKT conditions, leading to incorrect or infeasible solutions. Finding the source of the error can be a particularly tedious task. Thus, in this article, we propose a systematic method for identification of errors in the explicit KKT conditions for solving an NLP.

We begin by understanding the definition of complementarity. If a function $F(z): \mathbb{R}^n \to \mathbb{R}^n$, lower bounds $l \in \mathbb{R} \cup -\infty^n$ and upper bounds $u \in \mathbb{R} \cup \infty^n$ has a solution vector $z \in \mathbb{R}$ such that for each $i \in 1, ..., n$, one of the following three conditions hold:

$$F_i(z) = 0$$
 and $l_i \le z_i \le u_i$ or $F_i(z) > 0$ and $z_i = l_i$ or $F_i(z) < 0$ and $z_i = u_i$

then function F is complementary to the variable z and its bounds. This is written in compact form as $F(z) \perp L \leq z \leq U$

Where the symbol \perp means "perpendicular to". From point of view of optimization, if F(z) is non zero (non-binding constraint), changes in z may further optimize the objective function until the constraint becomes binding. If F(z) is binding, no changes in z would further enhance the objective function, causing the marginal to be zero.

Consider the generalized NLP formulation below.

min
$$f(x)$$

s.t. $g_{i}(x) \leq 0$ $i = 1, 2...m$
 $h_{k}(x) = 0$ $k = 1, 2...p$
 $d_{l}(x) \geq 0$ $l = 1, 2...q$ (1)
 $L \leq x \leq Z$
 $f(x) : R^{n} \mapsto R, g(x) : R^{n} \mapsto R^{m}$
 $h(x) : R^{n} \mapsto R^{p}, d(x) : R^{n} \mapsto R^{p}$

The Lagrange function and KKT conditions for the formulation above in the complementarity form are written as

$$L(x, u, v, w) = f(x) - \langle u, g(x) \rangle - \langle v, h(x) \rangle - \langle w, d(x) \rangle$$

$$\nabla_x L \perp L_x \leq x \leq U_x$$

$$-\nabla_u L \perp u \geq 0$$

$$-\nabla_v L \perp v free$$

$$-\nabla_w L \perp w \leq 0$$
(2)

It should be noted that the gradient of Lagrangian w.r.t to the marginals from NLP result in the original inequality and equality constraints of the NLP.

Thus an NLP can be solved as an MCP using the KKT conditions. However, formulating the KKT conditions might prove difficult for complex systems, and require verification of their accuracy. In the following sections, we provide the framework for modeling the KKT conditions by using concept of dummy complementarity equations in the KKT formulation. The process includes the following steps:

1. Solve NLP formulation without explicit KKT conditions, and save the results

- 2. Restart the problem as an MCP with a system of dummy KKT conditions using solution from step 1 as initial point. The MCP should start at the solution itself
- 3. Replace one dummy equation at a time with one KKT condition. Resolve the NLP and save the results
- 4. Restart the problem as MCP. If MCP iteration count is > 0, there exists a problem with the KKT condition which was introduced.

Follow steps 3 and 4 until all KKT conditions have been successfully incorporated.

2 Example: Maximum Revenue- NLP formulation

Consider a simple case of a steel factory trying to maximize the revenue under budget constraints, with man-hours(h) and raw materials steel (s) as the decision variables. The revenue is a function of decision variables given by

$$R(h,s) = 200h^{(2/3)}s^{(1/3)}$$

where, budget = 20,000 cost of manpower = 20 /hr cost of raw material = 170 / tonn In it's standard form, the model can be written as :

min
$$R(h,s) = -200h^{2/3}s^{1/3}$$

s.t. $20h + 170s \le 20000$
 $L < h, s < U$ (3)

The GAMS program below gives the optimum values of

```
Maximum Revenue, R -51854.82
Man hours, h 666.67
Tons of raw material, s 39.22
```

```
$ontext
The model below showcases using GAMS to identify / modify the KKT conditions for a given
NLP formulation. Our starting point is a basic minimization NLP model.
$offtext
scalar
   labor 'cost of labor dollar per hour' /20/
   steel 'cost of steel per ton' /170/
   budget 'total budget for production' /20000/
variables
   h 'man hours in production' /lo 1, up 50000/
   s 'tons of raw material' /lo 1, up 50000/
   R 'Revenue'
Equations
   con1 'constraint on budget'
   obj 'objective function'
obj.. R = e = -200 * h**(2/3) * s**(1/3);
con1.. 20*h + 170*s =l= budget;
h.l=10;
s.1=10;
```

```
model khan /con1,obj/; solve khan using NLP minimizing R;
```

The above model is then written in form of an MCP, by explicitly adding the KKT conditions to the model. For the given system, the KKT conditions are given as

$$L = -200h^{2/3}s^{1/3} - con1_{m}[20h + 170s - 20000]$$

$$\nabla_{h}L = -200 * (2/3)h^{(-1/3)}s^{(1/3)} - con1_{-}m * (20)$$

$$\nabla_{s}L : -200 * (1/3)h^{(2/3)} * (1/3) * s^{(-2/3)} - con1_{-}m * (170)$$

$$\nabla_{con1_{-}m}L : 20 * h + 170 * s - 20000 = 0$$
(4)

It should be noted that the third KKT equation, result of differentiation w.r.t to the marginal, is the inequality budget constraint from original NLP model. The above equations are solved as an MCP model as shown below using the results saved in the initial run. In the model below, an error has been made in one of the KKT conditions. Execution of the model terminates due to the abort statement, with declaration 'we did not start at the solution' as shown in the subsequent log.

```
variables
    con1_m 'marginal value for con1' /up 0/
    ;
Equations
    dLdh 'gradL wrt h'
    dLds 'gradL wrt s'
    ;

con1_m.l=con1.m;
dLdh.. - 200*(2/3) * ([h**(2/3)]/h) * s**(1/3) - con1_m*(200) =n=0;
dLds.. - 200 * h**(2/3) * (1/3)*s**(-2/3) - con1_m*(170) =n=0;

model kkt /dLdh.h,dLds.s,con1.con1_m/;
kkt.iterlim=0;
solve kkt using MCP;

abort $(kkt.objval >1e-5) 'We should start at a solution';
```

```
--- Job sd_kkt.gms Start 07/26/18 15:56:02 25.1.1 r66732 WEX-WEI x86 64bit/MS Windows
GAMS 25.1.1 Copyright (C) 1987-2018 GAMS Development. All rights reserved
Licensee: Chintan Bhomia, Single User License G180612/0001CN-GEN
         GAMS Development, Fairfax DC14199
         cbhomia@gams.com
--- Starting continued compilation
--- Workfile was generated under GAMS version WEX251-251
--- sd_kkt.gms(17) 2 Mb
--- Starting execution: elapsed 0:00:00.008[LST:27]
--- sd_kkt.gms(42) 3 Mb
--- Generating MCP model kkt[LST:27]
--- sd_kkt.gms(43) 5 Mb
--- 3 rows 3 columns 8 non-zeroes
--- 25 nl-code 4 nl-non-zeroes
--- sd_kkt.gms(43) 3 Mb
--- Executing PATH: elapsed 0:00:00.015[LST:79]
Reading dictionary...
Reading row data...
Evaluating functions...
```

```
Checking model...
Calculating Jacobian...
PATH 25.1.1 r66732 Released May 19, 2018 WEI x86 64bit/MS Windows
3 row/cols, 8 non-zeros, 88.89% dense.
Path 4.7.04 (Sat May 19 15:07:52 2018)
Written by Todd Munson, Steven Dirkse, and Michael Ferris
Major Iteration Log
major minor func grad residual step type prox inorm (label)
   0 0 1 1 3.2033e+02 I 0.0e+00 3.2e+02 (dLdh)
FINAL STATISTICS
Inf-Norm of Complementarity . . 1.5533e+05 eqn: (dLdh)
Inf-Norm of Normal Map. . . . 4.6669e+02 eqn: (dLdh)
Inf-Norm of Minimum Map . . . 4.6669e+02 eqn: (dLdh)
Inf-Norm of Fischer Function. . 3.2033e+02 eqn: (dLdh)
Inf-Norm of Grad Fischer Fcn. . 2.7429e+04 eqn: (con1)
Two-Norm of Grad Fischer Fcn. . 2.7429e+04
** EXIT - iteration limit.
Major Iterations. . . . 0
Minor Iterations. . . 0
Restarts. . . . . . . 0
Crash Iterations. . . . 0
Gradient Steps. . . . 0
Function Evaluations. . 1
Gradient Evaluations. . 1
Basis Time. . . . . . 0.000000
Total Time. . . . . . 0.000000
Residual. . . . . . . 3.203316e+02
--- Restarting execution
--- sd_kkt.gms(43) 2 Mb
--- Reading solution for model kkt[LST:94]
--- Executing after solve: elapsed 0:00:00.085[LST:155]
--- sd_kkt.gms(45) 3 Mb
*** Error at line 45: Execution halted: abort$1 'We should start at a solution' [LST:160]
--- sd_kkt.gms(45) 3 Mb 1 Error
*** Status: Execution error(s)[LST:177]
--- Job sd_kkt.gms Stop 07/26/18 15:56:02 elapsed 0:00:00.087
```

The absence of *abort* statement results in a new solution to the MCP where the results do not match the desired values from the original NLP formulation, also indicating error in one of the KKT conditions. From simple observation, we can see that an error was made in typing out the multiplier for variable $con1_{-}m$ in equation dLdh, which when corrected provides results consistent with the NLP formulation.

However, mere observation does not help with larger, more complex systems. A strategy, as described in Section 1 is required to effectively correct the model. In the given case, the MCP formulation can be first solved using dummy KKT conditions described below. These conditions can then be replaced one at a time with the real KKT equations derived earlier.

```
dLdh.. 37 =n=0 ; h.fx=h.L;
```

```
dLds.. 37 + con1_m=n=0; s.fx=s.L; dummy
model kkt /dLdh.h,dLds.s,con1.con1_m/;
```

2.1 Rules for writing dummy KKT conditions

Writing dummy condition, as straightforward as it may seem requires consideration of few salient points to avoid errors from the GAMS compiler.

- 1. Number of dummy equations must equal number of marginal variables from the NLP formulation
- 2. Each dummy KKT condition must be accompanied by its differentiating variable (of Lagrangian)
- 3. The value to differentiating variable is fixed at the marginal values provided by NLP solution
- 4. Each KKT condition must be modeled as 'complimentary to' the differentiation variable for the condition. i.e. $dLdh \perp h$, and is modeled as dLdh.h in the model statement
- 5. Each variable representing the original constraint marginal (e.g con1_m) in the MCP model must appear in one of the KKT conditions.

Thus, all variables representing the marginals of NLP constraints can be incorporated in any one of the dummy equation. This equation should be replaced by KKT condition at the very end. However, in the current case, variable 'con1_m', representing marginal of constraint 'con1' from NLP formulation is part of both the KKT conditions. Thus, though incorporated in equation dLds, the order of replacing the dummy equation with KKT condition is irrelevant in the given case, but can be better understood in the example described in subsequent section

3 KKT Development for complex systems

In this section, we implement the proposed methodology and learnings from previous example to solve a more complex NLP problem as MCP. The NLP example has been designed as a minimization model, which helps maintaining the sign convention. The complexity applies the methodology over range of equations and contains leads/lags in the formulation. The NLP Model and the output is given below.

```
j 'set j' / j1 * j6 /
 j2(j) 'subset for j' / j2, j4*j6 /
 i 'set i' / i1 * i3 /
 i2(i) 'subset for i' / i1, i2 /
scalar
 eMin / 2.5 /
 sLow / -100 /
 vMax / 20 /
parameter
 c(j) /
   j1 2
   j2 -2
   j3 2
   j4 -2
   j5 2
   j6 -2
```

```
s0(i) /
   i1 10
   i2 20
   i3 -10
table A(i,j)
   j1 j2 j3 j4 j5 j6
i1 1 4 2 2
i2 4 1 2
i3 -2 -2 -1 4 ;
variable
 z 'objective var'
 ttt(j) 'variable over set j'
 sss(i) 'variable over set i'
positive variable
 x(j) 'positive variable over set j'
equation
 objDef
 sssdef(i)
 tttdef(j)
 eSum
 sSum
 allBnd
objDef.. sum{j, c(j)*x(j)} + sum{i, sqr(sss(i)-s0(i))} =E= z;
sssdef(i)...sss(i) = E = sum{j, A(i,j) * ttt(j)};
tttdef(j)...ttt(j) = E = 4*x(j) + x(j+1);
eSum.. sum{j2(j), exp(x(j)-1)} - eMin =G= 0;
sSum...sum{i2(i), sss(i)} - sLow = G = 0;
allBnd.. sum{j, x(j) + ttt(j)} + sum{i, sss(i)} -vMax =L= 0;
model nonlinear 'NLP model' / all /;
solve nonlinear using nlp min z;
file EX2 /EX2.txt/
put EX2;
put "Objective Function" , z.l / /;
put 'Var ttt(j)'/;
loop(j, put 'ttt(', @5,j.tl,@7')', @14, ttt.l(j)/);
put /;
put 'Var sss(i)' /;
loop(i, put 'sss(', @5,i.tl,@7')', @14, sss.l(i)/);
put /;
put 'Var x(j)' /;
loop(j, put 'x(', @3,j.tl,@5')', @14, x.l(j)/);
```

```
Objective Function 75.41
```

```
Var ttt(j)
ttt(j1) 0.18
ttt(j2) 0.85
ttt(j3) 0.54
ttt(j4) 1.28
ttt(j5) 5.13
ttt(j6) 0.00
Var sss(i)
sss(i1) 4.64
sss(i2) 13.69
sss(i3) -7.90
Var x(j)
x(j1) 0.00
x(j2) 0.18
x(j3) 0.14
x(j4) 0.00
x(j5) 1.28
x(j6) 0.00
```

As seen in the model, the problem consists of five constraints and one objective variable. We define multiplier variables per the convention for each equations as follows:

- p(i) for equation sssdef(i), free variable initialized at sssdef.m(i)
- q(j) for equation tttdef(i), free variable initialized at tttdef(i)
- r1 for equation esum, positive variable initialized at esum.m
- r2 for equation ssum, positive variable initialized at Ssum.m
- s1 for equation allbnd, negative variable initialized at allbnd.m

The Lagrangian (L) of the function is given as

$$L(sss,ttt,x,p,q,r1,r2,s) = obj - \sum_{i} p(i).sssdef(i) - \sum_{j} q(j).tttdef(j) - r1.esum - r2.ssum - s1.allbnd ~~(5)$$

The gradients of Lagrangian with respect to the marginals are

$$dLdttt(j) = \sum_{i} p(i)A(i,j) - q(j) - s1$$

$$dLdsss(i) = 2(sss(i) - s0(i)) - p(i) - r2 - s1, \quad r2\forall i2 \in i$$

$$dLdx(j) = c(j) + 4q(j) + q(j-1) - r1 \exp^{(x(j)-1)} - s1, \quad \exp^{(x(j)-1)} \forall j2 \in j$$
(6)

The gradients of Lagrangian with respect to the variables are the constraints themselves.

We save the results from the NLP formulation, and restart the following code with dummy KKT conditions shown in the code below. Since ∇L w.r.t to the variables are constraints themselves, no dummy equations are needed. Additionally, they need not be modeled with the other dummy equations under consideration.

```
variables
    p(i) 'multipler for equation sssdef(i)'
    q(j) 'multipler for equations tttdef(j)'
    r1 ' multipler for esum' /lo 0 /
    r2 ' multipler for ssum' /lo 0/
    s1 ' multipler for allbnd' /up 0/
equations
    dLdttt(j)
    dLdsss(i)
    dLdx(j)
*initializing the marginals/lagrangian multipliers
p.l(i) = sssdef.m(i);
q.l(j) =tttdef.m(j);
r1.1 = esum.m;
r2.1 = ssum.m;
s1.l = allbnd.m;
* dummy equations
dLdttt(j).. 37 =n= 0; ttt.fx(j)=ttt.l(j);
dLdsss(i)...p(i) + 37 = n = 0; sss.fx(i) = sss.l(i);
dLdx(j)...q(j)+r1+r2+s1=n=0; x.fx(j)=x.l(j);
model nlpkkt / dLdttt.ttt , dLdsss.sss, dLdx.x, sssdef.p , tttdef.q, esum.r1, ssum.r2,
   allbnd.s1 / ;
nlpkkt.iterlim=0;
solve nlpkkt using MCP;
abort $(nlpkkt.objval >1e-5) 'We should start at a solution';
```

The above model exits at iteration 0 with message "solution found' as shown by the log below.

```
--- Job EX2KKTO.gms Start 07/26/18 15:46:49 25.1.1 r66732 WEX-WEI x86 64bit/MS Windows GAMS 25.1.1 Copyright (C) 1987-2018 GAMS Development. All rights reserved Licensee: Chintan Bhomia, Single User License G180612/0001CN-GEN

GAMS Development, Fairfax DC14199

cbhomia@gams.com
--- Starting continued compilation
--- Workfile was generated under GAMS version WEX251-251
--- EX2KKTO.gms(37) 3 Mb
--- Starting execution: elapsed 0:00:00.004
--- EX2KKTO.gms(91) 4 Mb
--- Generating MCP model nlpkkt
--- EX2KKTO.gms(93) 6 Mb
```

```
--- 21 rows 27 columns 79 non-zeroes
--- 17 nl-code 4 nl-non-zeroes
--- EX2KKTO.gms(93) 4 Mb
--- Executing PATH: elapsed 0:00:00.011
Reading dictionary...
Reading row data...
Evaluating functions...
Checking model...
Calculating Jacobian...
PATH 25.1.1 r66732 Released May 19, 2018 WEI x86 64bit/MS Windows
12 row/cols, 0 non-zeros, 0.00% dense.
Path 4.7.04 (Sat May 19 15:07:52 2018)
Written by Todd Munson, Steven Dirkse, and Michael Ferris
Major Iteration Log
major minor func grad residual step type prox inorm (label)
   0 0 1 1 1.3422e-10 I 0.0e+00 1.3e-10 (eSum)
FINAL STATISTICS
Inf-Norm of Complementarity . . 4.1996e-09 eqn: (eSum)
Inf-Norm of Normal Map. . . . 1.3422e-10 eqn: (eSum)
Inf-Norm of Minimum Map . . . . 1.3422e-10 eqn: (eSum)
Inf-Norm of Fischer Function. . 1.3422e-10 eqn: (eSum)
Inf-Norm of Grad Fischer Fcn. . 0.0000e+00 eqn: (sssdef(i1))
Two-Norm of Grad Fischer Fcn. . 0.0000e+00
** EXIT - solution found.
Major Iterations. . . . 0
Minor Iterations. . . . 0
Restarts. . . . . . . 0
Crash Iterations. . . . 0
Gradient Steps. . . . 0
Function Evaluations. . 1
Gradient Evaluations. . 1
Basis Time. . . . . . 0.000000
Total Time. . . . . . 0.016000
Residual. . . . . . . 1.342206e-10
--- Restarting execution
--- EX2KKTO.gms(93) 2 Mb
--- Reading solution for model nlpkkt
--- Executing after solve: elapsed 0:00:00.193
--- EX2KKTO.gms(95) 3 Mb
*** Status: Normal completion
--- Job EX2KKTO.gms Stop 07/26/18 15:46:49 elapsed 0:00:00.194
```

3.1 Replacing Dummy Equations

The dummy KKT equations representing gradient w.r.t the marginals are replaced one at a time per the process described in previous section. We first replace the equation dLdttt(j) with the real KKT equation as shown in the model below (using restart feature). Also, the associated complementarity variable ttt(i) is no longer fixed, which is the key to switching dummy equation from inactive to active. Both the dummy equation and the has been commented. The output log return a normal completion, as shown indicating that we started at the solution, i.e. the KKT equation for dLttt(i) is correct.

It should be noted that the multiplier p(i), defined in equation dLdsss(i) is now removed as it is already part of the model in the new dLdttt(j) equation. However, keeping p(i) in the dummy equation would not affect the solution in any way because the multiplier sss(j) for the equation dLdsss(i) is still fixed, allowing the dummy equation to take any value in the LHS (attribute to =n= equality).

```
variables
    p(i) 'multipler for equation sssdef(i)'
    q(j) 'multipler for equations tttdef(j)'
    r1 ' multipler for esum' /lo 0 /
    r2 ' multipler for ssum' /lo 0/
    s1 ' multipler for allbnd' /up 0/
equations
    dLdttt(j)
    dLdsss(i)
    dLdx(j)
*assigning marginal(.m) from NLP result to variable marginal con1_m
p.l(i) = sssdef.m(i);
q.l(j) =tttdef.m(j);
r1.1 = esum.m;
r2.1 = ssum.m;
s1.l = allbnd.m;
*dLdttt(j).. 37 =n= 0;ttt.fx(j)=ttt.l(j);
dLdttt(j)...sum(i,p(i)*A(i,j)) - q(j) - s1 = n = 0;
* dummy equations
dLdsss(i)... 37 + p(i) =n= 0; sss.fx(i) = sss.l(i);
dLdx(j)...r1 + r2 + s1 = n = 0; x.fx(j) = x.l(j);
model nlpkkt / dLdttt.ttt , dLdsss.sss, dLdx.x, sssdef.p , tttdef.q, esum.r1, ssum.r2,
   allbnd.s1 / ;
nlpkkt.iterlim=20;
solve nlpkkt using MCP;
abort $(nlpkkt.objval >1e-5) 'We should start at a solution'
```

```
--- Job EX2KKT1.gms Start 07/26/18 16:32:20 25.1.1 r66732 WEX-WEI x86 64bit/MS Windows GAMS 25.1.1 Copyright (C) 1987-2018 GAMS Development. All rights reserved Licensee: Chintan Bhomia, Single User License G180612/0001CN-GEN GAMS Development, Fairfax DC14199
```

```
cbhomia@gams.com
--- Starting continued compilation
--- Workfile was generated under GAMS version WEX251-251
--- EX2KKT1.gms(36) 3 Mb
--- Starting execution: elapsed 0:00:00.009[LST:46]
--- EX2KKT1.gms(102) 4 Mb
--- Generating MCP model nlpkkt[LST:46]
--- EX2KKT1.gms(104) 6 Mb
--- 27 rows 27 columns 96 non-zeroes
--- 17 nl-code 4 nl-non-zeroes
--- EX2KKT1.gms(104) 4 Mb
--- Executing PATH: elapsed 0:00:00.016[LST:274]
Reading dictionary...
Reading row data...
Evaluating functions...
Checking model...
Calculating Jacobian...
PATH 25.1.1 r66732 Released May 19, 2018 WEI x86 64bit/MS Windows
18 row/cols, 46 non-zeros, 14.20% dense.
Path 4.7.04 (Sat May 19 15:07:52 2018)
Written by Todd Munson, Steven Dirkse, and Michael Ferris
Zero: 6 Single: 6 Double: 0
** EXIT - solution found.
Major Iterations. . . . 0
Minor Iterations. . . . 0
Restarts. . . . . . . 0
Crash Iterations. . . . 0
Gradient Steps. . . . 0
Function Evaluations. . 0
Gradient Evaluations. . 0
Basis Time. . . . . . 0.000000
Total Time. . . . . . 0.000000
Residual. . . . . . . 0.000000e+00
Postsolved residual: 8.8861e-16
--- Restarting execution
--- EX2KKT1.gms(104) 2 Mb
--- Reading solution for model nlpkkt[LST:289]
--- Executing after solve: elapsed 0:00:00.082[LST:433]
--- EX2KKT1.gms(106) 3 Mb
*** Status: Normal completion[LST:449]
--- Job EX2KKT1.gms Stop 07/26/18 16:32:20 elapsed 0:00:00.083
```

The remaining dummy equations are removed per the process described above, to obtain the final MCP model shown below. The model is initialized by the results obtained from solving it as an NLP.

```
variables
  p(i) 'multipler for equation sssdef(i)'
  q(j) 'multipler for equations tttdef(j)'
```

```
r1 ' multipler for esum' /lo 0 /
    r2 ' multipler for ssum' /lo 0/
    s1 ' multipler for allbnd' /up 0/
equations
    dLdttt(j)
    dLdsss(i)
    dLdx(j)
*assigning marginal(.m) from NLP result to variable marginal con1_m
p.l(i) = sssdef.m(i);
q.l(j) =tttdef.m(j);
r1.1 = esum.m;
r2.1 = ssum.m;
s1.l = allbnd.m;
*dLdttt(j).. 37 =n= 0; ttt.fx(j)=ttt.l(j);
dLdttt(j).. sum(i,p(i)*A(i,j)) - q(j) - s1 = n = 0;
*dLdsss(i).. 37 + p(i) =n= 0; sss.fx(i) = sss.l(i);
dLdsss(i)... 2*(sss(i)-s0(i)) - p(i) - r2$(i2(i)) -s1=n=0;
* r2 is active only for the equations where i2 is part of i
*dLdx(j).. r1 + r2 + s1 + q(j) = n = 0; x.fx(j) = x.l(j);
dLdx(j)..c(j) + 4*q(j) + q(j-1)-[r1*exp(x(j)-1)]$j2(j) - s1 = n= 0;
*exp over set j2. hence the differentiation term is over j2 as well
model nlpkkt / dLdttt.ttt , dLdsss.sss, dLdx.x, sssdef.p , tttdef.q, esum.r1, ssum.r2,
   allbnd.s1 / ;
nlpkkt.iterlim=0;
solve nlpkkt using MCP;
abort $(nlpkkt.objval >1e-5) 'We should start at a solution';
```