Implementation of Transportation Problem by Using the Method of Meta-Heuristics Approach

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Abstract

In this paper authors will present analysis and implementationof possiblesolutions ofvehicle routingproblem that is based onsimulated annealingmethod, which belongs to the category of meta-heuristic problem solving approaches.The described problemisrather complex linear programmingproblem from the field of operation research. Testing of developed applications in software package MATHEMATICA will be described. This application providesgreat possibilitieswhenit comes to workingwith numericalalgorithms,as well as inthe fieldof symbolicand algebraiccalculations.

Keywords: Transportation problem, linear optimization, Vehicle routing problem, met heuristics solving approach, simulated annealing

Introduction

In business economy mostly used methods arelinearoptimizationmethodsthat allowfindingthe most appropriate(optimal) solution to the problemin whichboth theobjective of a function(profit) andspending resources are linearlyproportional tothe values of independent variables. Transportation problemis one of theproblems in the fieldof operations research. The task is toprovide an arrayofbuyersandsuppliersof a commodityorganizetransportsothatpricesareoptimal. One of thetransportation problemswhichbelong toa linear programming problemis theproblem ofdetermining thebesttimesandthe vehiclerouting problemVRP(VehicleRoutingProblem). Inthe occasion that there is onlyone vehicle, and if there are noadditional restrictionsthen theVRP becomes a well-known traveling salesman problemTSP(Traveling SalesmanProblem) in that case you needa vehicleto reach everypoint ofthe graphwith theminimum cost (time).

Todefine theVRPfor distribution orcollectionof goods, it is necessary toprovide basicconstraints of the problem. Ata given time, a set of vehiclesservesset of users. Solving the problemis presented as a set ofroutes(roads). Each routehas astarting pointand an ending pointinwarehouse of all vehicles that usethe route.There is awarehouses andthe distancebetween consumers. Alluser requirementsmust be met,and allthe restrictions imposedrespected. The aim isthat the totaltransportation costis minimized.It is possible toimposedifferentconstraints andobjectivesthat may affect theconstruction ofroutesduringthe optimizationprocess.Information neededfor a gooddescription of theuserin solvingVRPis:

a) a startingpoint thatrepresents warehouse,
b) quantity of goodsthatneed to be collectedordelivered,
c) period(time frame) inwhich it is necessaryto servethe user,
d) timerequired to completedeliveryor collectionof goods at users,
e) time of unloadingorloading, which depends on the type ofvehicle andapplied technology,
f) subset ofthe availablevehicles thatcould be used byindividualusersdepending onpossibility toaccessfor loading and unloading.

The objectivein solvingthe problemis to findthe shortestroute thatstartsat a givennode,going through all theother nodesin the startingand endingnode.Variables to be optimizedmust not be onlydistances.Itmay betravel costs, travel timeor othervariables.Determining thebestroutes, that will be used by group of vehiclesserving set of customers will represent a generalvehiclerouting problem. For theconcrete implementationof this problem a software *Mathematica* has been applied, which hasmany applicationsin the fieldof symbolicand algebraiccalculations.*Mathematica* includes a great collectionof numerical algorithms, as well as a big number of constantsandfunction approximation.

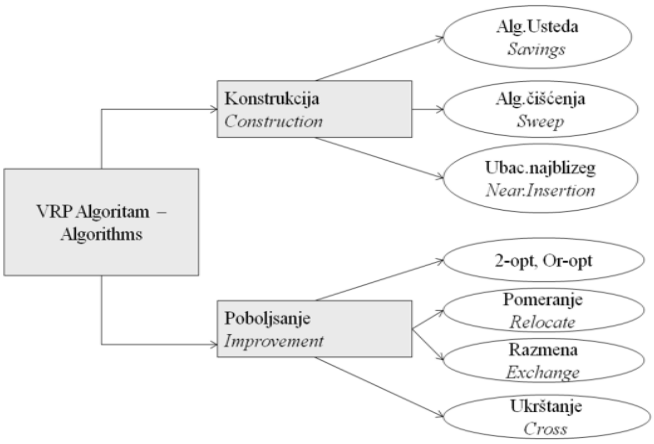
Approaches for Routing Problem Solving

The first approachto solvingproblems issearchforexact solutions of theproblem.The practicalapplicationof this approachis very limitedbecause theoptimalsolutioncan befound onlyina small numberof users.The number of possibleroutesfor the generalcase ofroutingvehiclesis growingquickly,so it is notpossible to expectthat this approachin the general casegeneratesusablesolutionsin real-timethat arerequired inpractice.

Heuristic approachrepresents a useof experience,intuition andyour ownestimationwhen solvinga problem.Unlikeexactmethods,heuristicmethods do notrepresentknowledgeabout the structureandrelationshipswithin the modeltosolvethe problem.

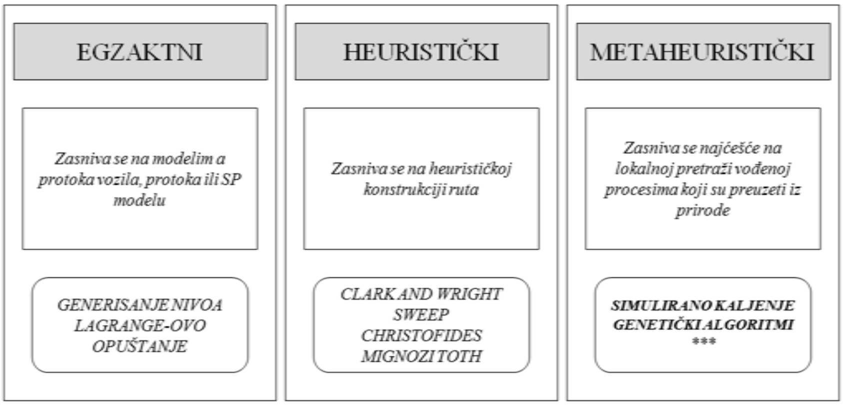
Some methodsof heuristicapproaches to solving theproblem ofroutingvehicles are: *methods of insertingthe nearestneighbors,addingthe farthestandnearestneighboradded two-pass sweepmethod, theClark-Wright method, etc.*
Heuristic methodsrepresent rule of choice; filtering and rejectingsolutions, and also help to reducethe number ofpossible waysin solvingproblems.Heuristicalgorithms areoften basedon the construction ofrouteswhere theconstruction andimprovement ofrouteswith respectto the targetfunction performediteratively.

Picture 1. Existing VRP algorithms



Metaheuristicsin practiceis a setof algorithms thatare usedin solvinga variety ofoptimization problemswhere thealgorithm itselfis very littlechanged depending on theproblembeing solved. Metaheuristicsapproach ofsolving the problem ofrouting of vehicles is oftenbasedon localsearchguidedprocesses that aretaken fromnature, such as *simulated annealing, genetic algorithms andant colony*.

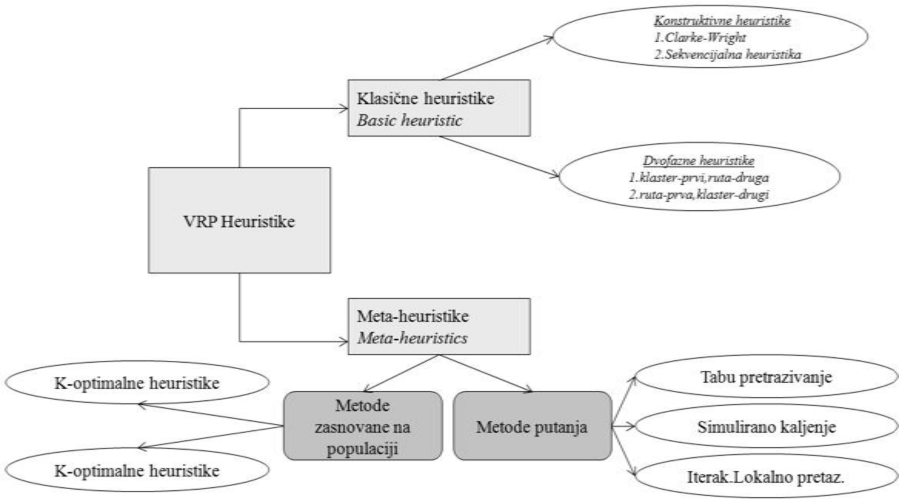
Picture 2. The main approaches tosolving problems



In solving problems by Metaheuristicsapproachfollowing methods are used:

- •Iterativelocalsearch (ILS)
- •simulated annealing(SA)
- •deterministichardening(YES)
- •tabusearch (TS)
- •Genetic Algorithms(GA)
- •ant colonies(AC) and
- •NeuralNetworks (NN).

Picture 3. Classification of VRPheuristicsfor solving problems



Metaheuristic Approach and Simulated Annealing

Classicaloptimizationprocedurestarts froman initialsolution,until the currentsolutionreplacesthe better from theimmediate surroundingsand alwaysfinds the closest*local optimum*.
Method of simulatedannealingis in the fieldof stochasticoptimization algorithms. Withthis method we start withone initialsolution,replacingthe existingsolutionbetter,butitcan be replaced also by the worse, with a certain probability ofacceptance.Probabilityof acceptingworsesolutionsdecreases asthe algorithmprogresses.Unlikeclassicaloptimizationprocedure with thesimulated annealingmethod*global optimum* is achieved.
Implementedalgorithm, used in this method,contains one parameter; *the temperature*, and the function that determines theglobal optimumcan be seen as: *energygrid*(ifwe determineminimum)or*negative energy of a grid*, if we determine themaximum.The algorithmstarts by choosingthe initial solution, and the initial temperature has arelatively largevalue(1step).Determining the initialc:

- determinethe initialacceptanceprobability(>50%) - p_0
- determinethe average increaseoffunctionsfor several neighboringsolutions- $\Delta C+$
- $c_0$is calculatedas:$c_0 = \Delta C+/\ln(1/ p_0)$

The currentsolutionis replaced bya better one,butit can be replacedwithworsewith a certainprobabilityof acceptance(step2).Thisprobabilityis determinedby selectingarandom numberfrom the interval[0,1], and the condition thata is less than:
exp(E(old) – E(new)/T,

where *E(x)* is a function for which itseeksa globalminimum, and*T* is the temperature.

Ifthe expression is truethe new solutionis accepted. The probability that worsesolution has been chosenis greaterwhen thehigher temperature. This meansthat in thebeginning of thesearchspace for obtaining solutions is big, and it will be smaller with temperature drop, and by the endof the process isnarrowlylocalized.The behavior ofthe function isspecified with its initialvalue ofthe temperature andspeed ofitsdrop.

Algoritham: *Metaheuristics – Simulated annealing*

Step 1. - initial solution, and objective function
$i{:=}i_0$; $c{:=}c_0$;
$C_i{:=}C(i)$;
Repetition

Step 2 - acceptance of the neighboring solution
j:=the neighboring solution(i);
$C_j{:=}C(j)$;
$\triangle C{:=}C_j{-}C_i$;
accepti:=FALSE;
  Step 2.1
  if $\triangle C<0$ than accept:=TRUE;
  Step 2.2
  if $\exp(-\triangle C/c)>random[0,1]$ than accept:=TRUE;
  if accept=TRUE then
  $i{:=}j$; $C_i{:=}C_j$;
  till thermal equilibrium
  Step 2.3.
  Decrease parameter c;
  Till freezing
end.

The finalvalue of$c_F$usuallywill not be presented, but the process is repeateda number oftimes.Cooling functionis usuallyimplemented bymultiplying*c* witha number less than1, while the number of repetitions ofthe innerloop(*thermalequilibrium*) is usually specified as anumericalvaluedepending onthe size (*complexity*) of the problem.

Testing of software design

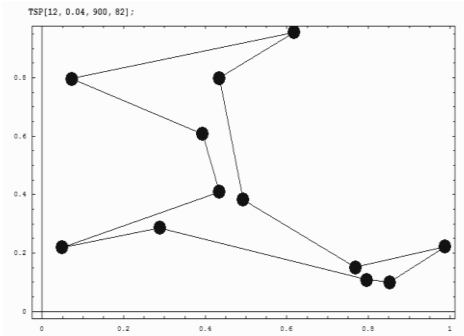
The application that was implementedin software package Mathematicacan bedownloaded fromthe link:http://muzafers.uninp.edu.rs/

Example 1. Test exampledeveloped applicationsfor thesimplerproblem, namelythetraveling salesmanproblem(TSP), using the describedmetaheuristics(simulated annealing).

Procedure TSP(N,S,p_0,α,KTL);
Input parameters:

- *N* – number of cities (100)
- *S* – number of repetition at external loop (10-100)
- p_0 – initial probabilityof acceptingbadsolutions (0.7-0.8)
- *α* – reduction factor of 'temperature' (0.5-0.99)
- *KTL* – coefficient ofthermal equilibrium (repeating cycles, *range 0.1-0.5*)

Picture 4. Testing the TSPproblemswith parameters [12,0.04,900,82]

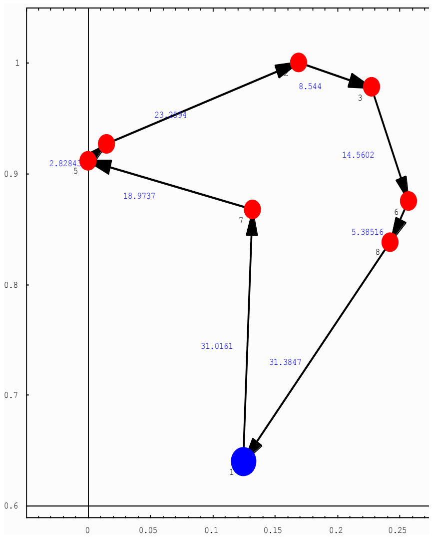


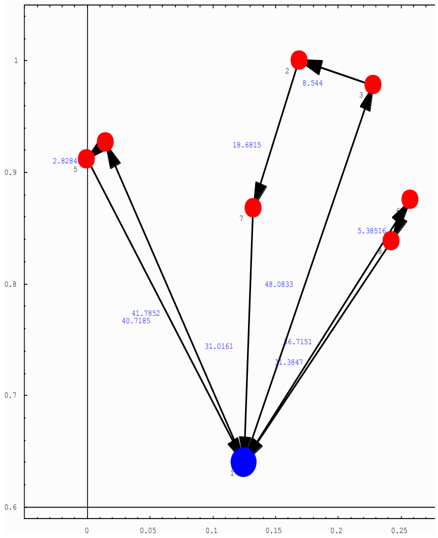
Example 2. Test exampledeveloped applications forcomplex problem(VRP-vehiclerouting problem), using the describedmetaheuristics(simulated annealing).

Numberofusers =8;
Coordinates={{145,215},{151,264},{159,261},{130,254},{128,252},{163,247},{146,246},{161,242}};
demand={0,10,7,8,14,20,40,8};
Capacityofvehicles=150;
P=VRP[Coordinates,demand,Capacityofvehicles]
TestVRP[Coordinates,demand,Capacityofvehicles,P]

Example 3. It is possibleto introduce a capacity constraints.Inthis example itwill decrease thecapacity (eg.Capacityofvehicles= 60).One type ofrestriction benefits is the requirement thatone useris used in a routethat containsa subsetof other users, and to servethecustomerbefore (or after) a subsetofusers. Limitation ofthis type is theproblemof collectingand shipping, where the goods that arecollectedata single usermustprovidethe same vehicleto another user.A commonrequirementisonewheretherouteservesseveral groupsof users,and it is knownthata group of userstobeserved.

Picture 5.TestingVRPproblemwith parameters,
forexample2 (left) and forexample3 (right)


23.7434
8.544
14.5602
2.82843
18.9737
5.38516
31.0161
31.3847


8.544
18.6815
2.82843
5.38516
48.0833
41.7852
40.7185
31.0161

Conclusion

Presentedmetaheuristicscan be considered asan effectivenaturalsupplement tomathematicalanalysis.The above methodmay beusefulwhen the system(business) or process is relativelycomplex (for example, when we do not disposeanalytical methodsforsolution of amathematical model). Also, themethod canbe usefulwhen it is notpossible toanalyze in detail thesystem ina real environment.

The above presented implementation ofsimulated annealingprovides manybenefitsto the givenproceduresof experimentation:

1. to a largeextent,can reduce the risk, depending on the reality thatis observed(eg, economic risk, the risk of attack anddefense),
2. time saving,
3. obtaininga clearerpicture of theprocesses, structure andfunction of the systemto be analyzed,
4. correctanalyses of complexindustrial andother systems.

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