InTraDE
Intelligent Transportation for Dynamic Environment

Identifying the Robust Number of Intelligent Autonomous Vehicles in Container Terminals

Date: 05/12/2014
Institution: Liverpool John Moores University

Shayan Kavakeb, Trung Thanh Nguyen, Zaili Yang and Ian Jenkinson

LAGIS UMR-CNRS 8219
Email: Z.Yang@ljmu.ac.uk

INTERREG IVB

Content

Liverpool Logistics
Offshore and Marine
Research Institute (LOOM)

I. Introduction
II. Improved Evolutionary Algorithm
III. Experimental Results
IV. Conclusion

Research Questions

Research questions:

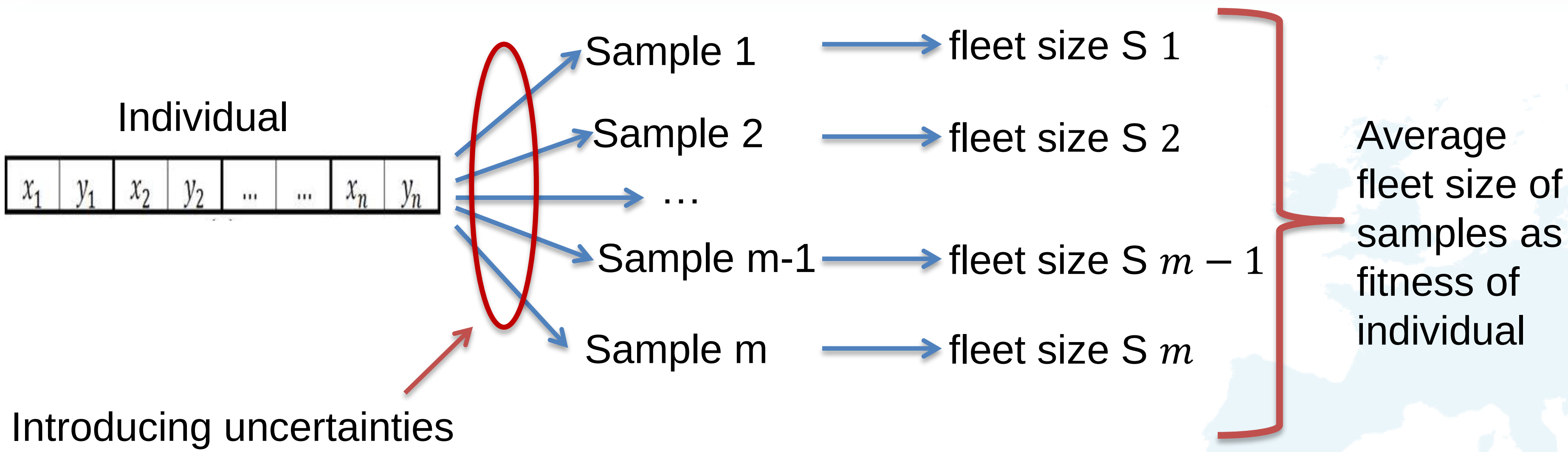
- Identifying the robust solutions in reasonable time?
- Different robust solutions for different requirements?

Solutions:

- An improved Evolutionary Algorithm (EA) combined with Monte Carlo simulation
- A dynamic sampling strategy to improve the performance of the EA
- Incorporating different robustness measures
- Statistical comparison of robust solutions

EA + Monte Carlo Simulation

- Evaluate robustness of individuals against uncertainty in travel time of vehicles
- The average fleet size of the samples is the fitness



New robustness measures

Why only considering the average of samples?

What would happen if other aggregation functions are used:

√ Minimum

√ Maximum

√ Mode

Results of the above robustness measures will be investigated

An improved sampling technique

In Monte Carlo simulation:

- The larger the number of replications, the more accurate the evaluation of individuals

Existing sampling technique:

- Disadvantages:
  - Very time consuming with a large number of samples
  - The same number of replications for poor and good individuals

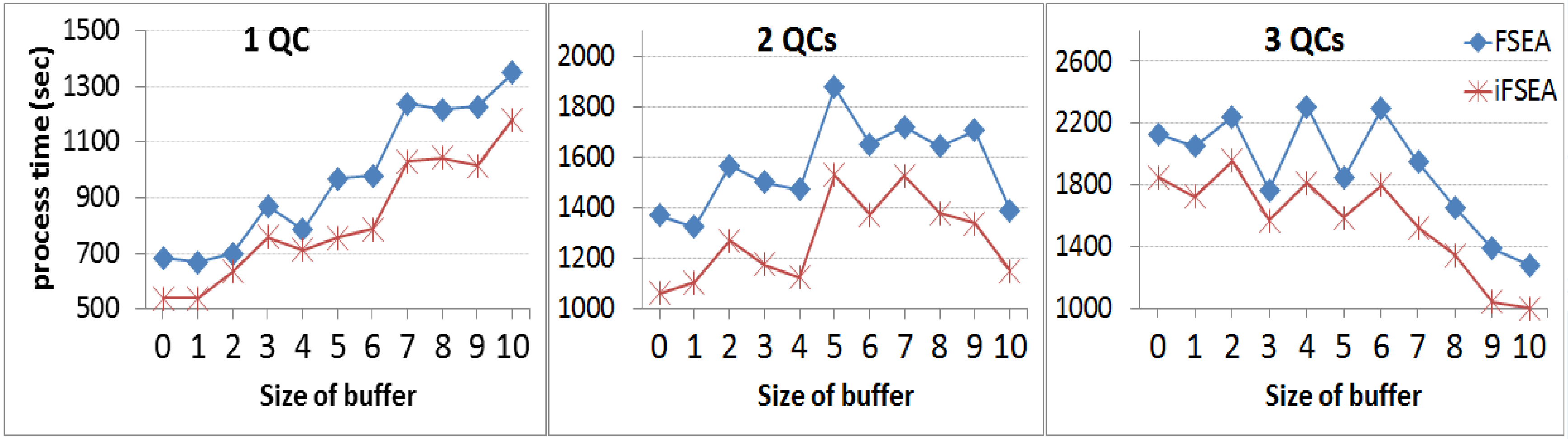
Improved sampling technique:

- Start with a low number of samples in the earlier generations
- Increase the number of samples during the evolution
- No wasting of the resources on poor solutions

Performance improvement

Using the improved sampling technique, the same results with better **performance.**

- **FSEA: the existing EA**
- **iFSEA: the improved EA**



Statistical test comparison

- Using Mann-Whitney U statistical test to compare robust solutions

Aggre. func.	1QC		2 QCs		3 QCs	
	sig. diff.	p-value	sig. diff.	p-value	sig. diff.	p-value
Min vs Max	+	0.0017	+	0.0354	-	0.0538
Min vs Avg	+	0.0011	+	0.0098	-	0.0790
Min vs Mod	+	0.0470	-	0.1252	-	0.1705
Max vs Min	+	0.0017	+	0.0354	-	0.0538
Max vs Avg	+	0.0409	-	0.2452	-	0.3347
Max vs Mod	-	0.3589	-	0.3347	-	0.2883
Avg vs Min	+	0.0011	+	0.0098	-	0.0790
Avg vs Max	+	0.0409	-	0.2452	-	0.3347
Avg vs Mod	-	0.6410	-	0.5130	-	0.3589
Mod vs Min	+	0.0470	-	0.1252	-	0.1705
Mod vs Max	-	0.3589	-	0.3347	-	0.2883
Mod vs Avg	-	0.6410	-	0.5130	-	0.3589

Summary

- Improving an existing EA
- Proposing an improved sampling technique to improve the performance of the EA
- Proposing new performance measures
- Comparing the results of different performance measures using a statistical test to find the most desired robust fleet size

InTraDE
Intelligent Transportation for Dynamic Environment

A TOPSIS Method for Vehicle Route Selection in Container Terminals

Date: 05/12/2014
Institution: Liverpool John Moores University

Michael Harrison, Zaili Yang, Trung Thanh Nguyen, Shayan Kavakeb and Jin Wang

LAGIS UMR-CNRS 8219
Email: Z.Yang@ljmu.ac.uk

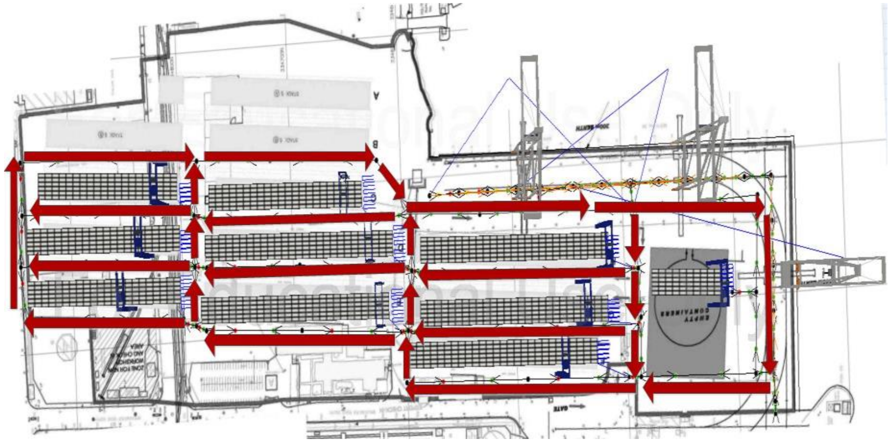
nwe
INTERREG IVB

Outline

- Research problem – research aims
- Literature – state of the art in optimal routing work
- Methodology – TOPSIS in route identification
- Case – application in small container terminal in NWE
- Conclusion – an easy solution to IAVs

Research question in routing in CTs

Complex mathematical algorithms when the routes are unknown



Adopting selection-based techniques when possible routes are known *a priori?*

Research aims

To examine the feasibility of using TOPSIS to create and organise a database of potential routes in container terminals

To demonstrate it with a real case study of the container terminal in North West European region.

To allow routes to be arranged in a ranked list to provide a real time on-demand response to a routing request by the system's controller.

To set out the desirability of a system, capable of reacting quickly to changes in circumstance, necessary in a dynamic real-life scenario.

The state of the art in routing

Existing work

Vehicle routing problems (VRPs)

- STravelling Salesman Problem (TSP), routing.
- logistics-based model, scheduling.

The state of the art

- Significant computational complexity
- High demands on computing and time resources
- less likely to be dynamic.

Available methods

- Ant Colony method
- Genetic Algorithm (GA)
- Tabu Search (TS)
- Dijkstra’s algorithm

Effectiveness

- Dropping off and collecting
- Computational demands, several nodes than a point-to-point network
- Overlapping two topologies, major and minor roads

Research methodology - TOPSIS

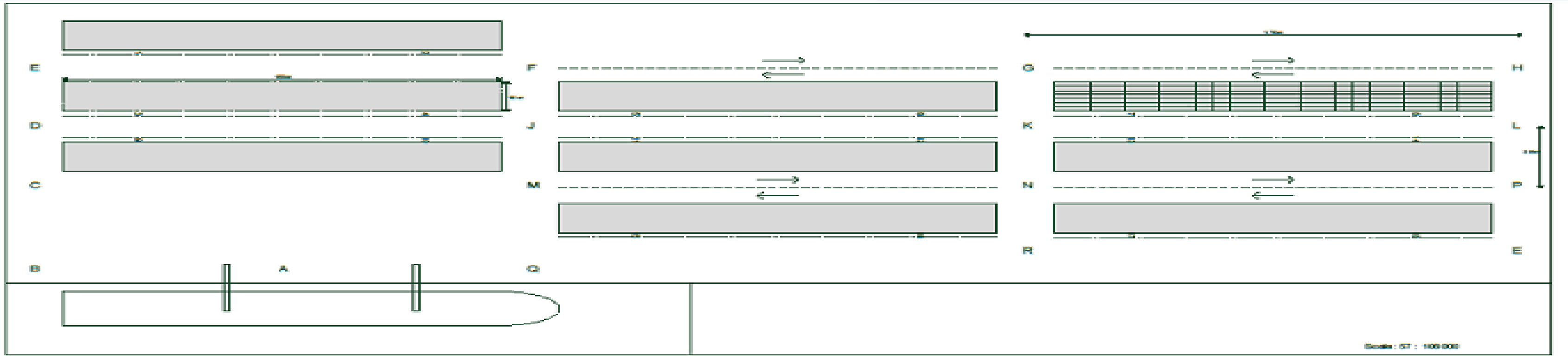
Car selection model

- BMW 5, the most expensive but very safe
- VW Golf, the most reliable but not cheap
- Fiat Punto, the cheapest, but less reliable and safe

Positive ideal solution –
BMW 5 safety, VW Golf reliability, Fiat Punto cost

Negative ideal solution –
Fiat Punto safety, Fiat Punto reliability, BMW 5 cost

TOPSIS in routing in container terminals



- Letters ‘A’ to ‘S’ represent ‘routing points’.
- Numbers 1 to 18 represent the ‘delivery points’ for containers
- Criteria F1-F6, Number of ‘express lanes’ traversed, Number of ‘service lanes’ traversed, Number of corners turned (into ‘Express’ lanes)
- Weight of F1-F6, the associated travel time. W_{F1} = 24.48s (170m/(25km/h)).
- Alternative routes with respect to the numbers 1-18.

Real case -alternative routes in a container terminal in NWE

Destination	Alternatives					
	A	B	C	D	E	F
1	BCDE	BCDJFE	QMJFE	QMJDE	QRNKGFE	QMNKGFE
2	BCDEF	BCDJF	QMJF	QRNKGF	QMNKGF	
3	BCD	QMJD				
4	BCDJ	QMJ	QMNKJ			
5	BCDJ	BCDEFJ	QMJ	QMNKJ	QRNKJ	
6	BCDJK	BCDEFGK	QMJK	QMNK	QRNK	QMJFGK
7	BCDEFGK	QMJK	QMNK	QRNK	QMJFGK	QMNPLK
8	BCDEFGHL	QMJKL	QMNKL	QRNKL	QMNPL	
9	BCD	QMJD				
10	BCDJ	QMJ	QMNKJ			
11	BCDJ	BCDEFJ	QMJ	QMNKJ	QRNKJ	
12	BCDJK	BCDEFGK	QMJK	QMNK	QRNK	QMJFGK
13	BCDEFGK	QMJK	QMNK	QRNK	QMJFGK	QMNPLK
14	BCDEFGHL	QMJKL	QMNKL	QRNKL	QMNPL	
15	Q					
16	QR	QMNR				
17	QR	QMNR	QMNPSR			
18	QRS	QMNRS	QMNPS			

Findings – best routes in the case study

Ranking and scores of routes from the origin point to destination 8

Ranking	Destination	Routes	Co-efficient
1	8E	QMNPL	0.62
2	8A	BCDEFGHL	0.55
3	8C	QMNKL	0.47
4=	8B	QMJKL	0.38
4=	8D	QRNKL	0.38

Conclusion

A new selection based route identification mechanism

Advantages (beyond the state of the art)

- **Alternative routes,** either failed vehicles or build-up of other vehicles delivering or collecting containers
- **Ranking** routes preference

Further work

- **Dynamic route calculation,** the vehicle finds itself after learning of a blockage as a new access point
- Operating system as a large static matrix of route hierarchies.

Thank You!