Artificial Intelligence in Train Scheduling Problems

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Project Motivation

Optimisation of train networks can provide return on all optimality factors; profit, timeliness or robustness. Train networks provide a unique problem where infrastructure expansions are complicated, expensive and disruptive. This leads to largely scheduling based problems, which this project is based upon.

Brief Introduction

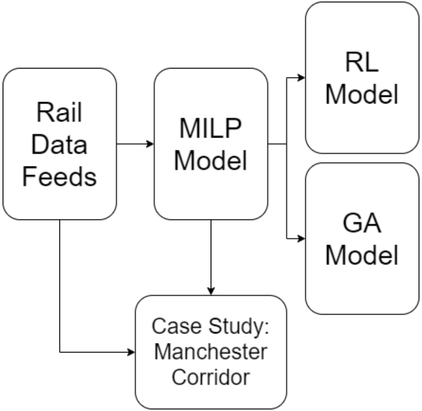

Figure: Project Outline

Brief Introduction

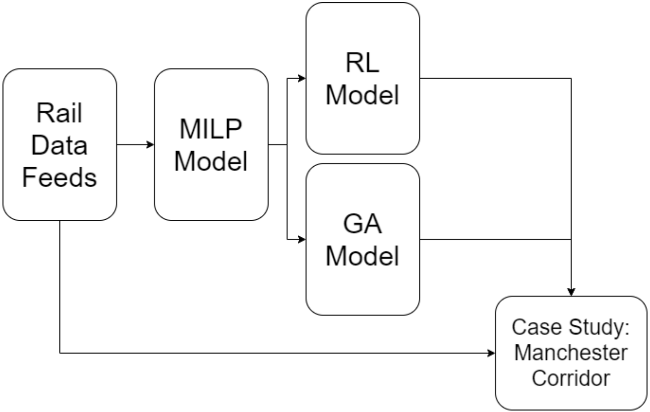

Figure: Intended Project Outline

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RDF - Implementation

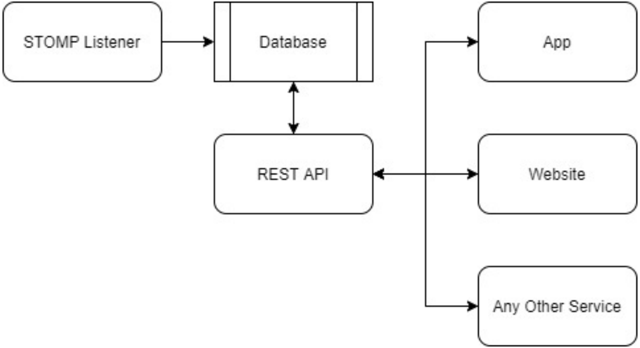

Figure: Rail Data Feeds Program Flow

RDF - Purpose

- View the Network Live
- Save Network Statistics
- Create Real World Test Sets

RDF - Outcomes

- Network Rail Listener
- Huxley Connector
- Network Rail Historic Database
- REST API
- Website

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MILP Model - TSP

Objective Function

$$\sum_{n=1}^{N} A^s_{n,M} - D^s_{n,0}$$

Example Constraints:

$$D^r_{n,m} \leq A^r_{n+1,m} - H$$

$$A^r_{n,m+1} \geq D^r_{n,m} + E_m$$

MILP Model - TRSP

Objective Function

$$\sum_{n=1}^{N} A^{r}_{n,M} - A^{o}_{n,M}$$

Example Constraints:

$$D^{r}_{n,m} = D^{0}_{n,m}$$

$$\delta_D > 1, \delta_t < D^{\delta_D - 1}_{\delta_n} + E_{\delta_D - 1} \rightarrow ...$$

$$A^{r}_{\delta_n,\delta_D} \geq D^{0}_{\delta_n,\delta_D - 1} + \delta_d + E_{\delta_d - 1}$$

MILP Model - TRSP (Passenger Weighted)

Objective Function

$$\sum_{n=1}^{N} P^{c}_{n,M} A^{r}_{n,M}$$

Example Constraints:

$$C - P^{l}_{n,m-1} < 100 \rightarrow P^{n,m}_{c} \leq 20\lambda_{n,m}$$
$$C - P^{l}_{n,m-1} \geq 100 \rightarrow P^{n,m}_{c} \leq 50\lambda_{n,m}$$
$$P^{c}_{n,m} \leq D + n, m^{r} - 50A^{r}_{n,m}$$

MILP Model - Outcomes

- MiniZinc TRSP Standard Model
- Series of Associated FlatZinc Data Files
- Minizinc TRSP Passenger Weighted Model
- Series of Assocaited FlatZinc Data Files

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GA - General Algorithm

```
P ← generatePopulation[100]                ▷ Get 100 random variables
while endCondition = false do
    P ← selection(P)
    P ← crossover(P)
    P ← mutation(P)
    B ← fitness(P)
    if B == optimal then
        endCondition ← true
return B,P
```

GA - TSP Framework

	Phenotype					
	toc	line	unit	origin	destination	intermediate
Bit Length	2	8	8	12	12	$12n$
Representations	4	256	256	4096	4096	$n(2^{12})$

GA - Basic Scenario

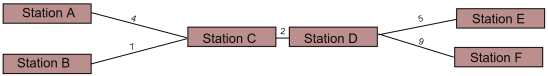
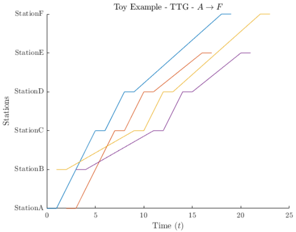
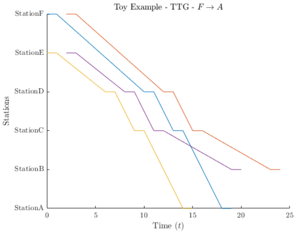


Figure: Toy Example Map

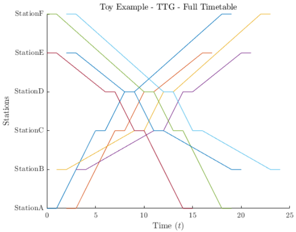
GA - Basic Scenario



(a) Stage 1



(b) Stage 2



(c) Stage 3

GA - Basic Scenario

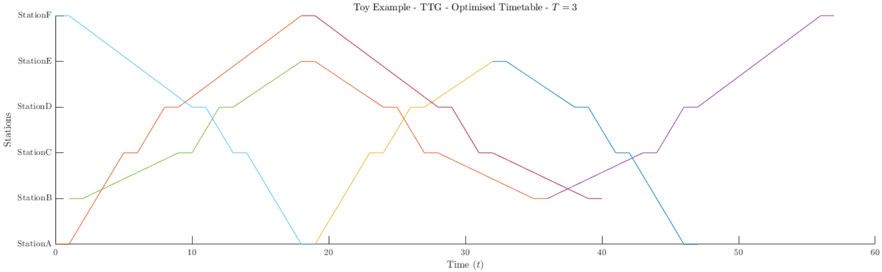


Figure: Toy Example Combined Stages

GA - Medium Scenario

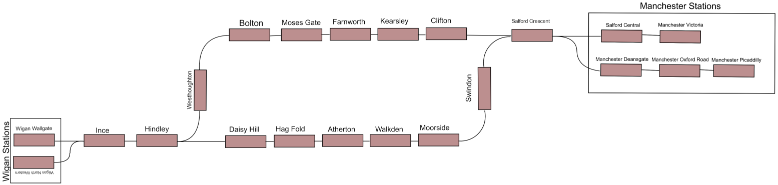


Figure: Small Example Map

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SBB Challenge

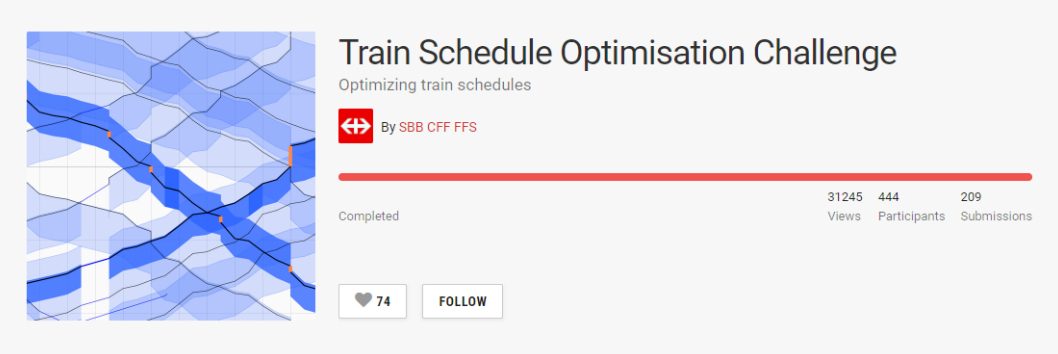


Figure: Crowd AI SBB Challenge

SBB Challenge

ID	Name	Trains	Routing	Difficulty		
01	dummy	4	V.Few	V.Simple		
02	a_little_less_dummy	58	Few	Simple		
03	FWA_0.125	143	Few	Simple		
04	V1.02_FWA_without_obstruction	148	Few	Medium		
05	V1.02_FWA_with_obstruction	149	Medium	Medium*		
06	V1.20_FWA	365	High	V.Hard		
07	V1.22_FWA	467	High	V.Hard		
08	V1.30_FWA	133	V.High	V.Hard		
09	ZUEZGCH_06001200			287	VV.High	VV.Hard

Table: Description of Problem Scenarios

RL - Delayed Q-Learning

Modelling a PACMDP
Update Function

$$Q_{t+1}(s,a) = \frac{1}{m}\sum_{i=1}^{m}(r_{k_i} + \gamma V_{k_i}(s_{k_i})) + \epsilon_1$$

Algorithm 1 Delayed Q-Learning

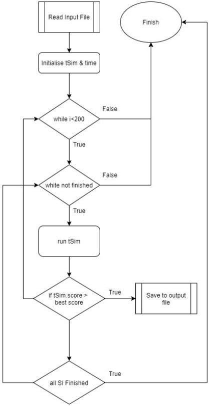
function DLQ(γ,S,A,M,ϵ_1)
    for all (s,a) **do**
        $Q(s,a) \leftarrow 1/(1-\gamma)$
        $U(s,a) \leftarrow 0)$
        $l(s,a) \leftarrow 0$
        $t(s,a) \leftarrow 0$
        $LEARN(s,a) \leftarrow TRUE$
    $t^* \leftarrow 0$
    while LEARN(s,a) =TRUE **do**
        $U(s,a) \leftarrow U(s,a) + r + \gamma \max_{a'} Q(s',a')$
        $l(s,a) \leftarrow l(s,a) + 1$
        if $l(s,a) = m$ **then**
            if $Q(s,a) - U(s,a)/m \geq 2\epsilon_1$ **then**
                $Q(s,a) - U(s,a)/m + \epsilon_1$
                $t^* \leftarrow t$
            else if $t(s,a) \geq t^*$ **then**
                LEARN$(s,a) \leftarrow FALSE$
            $t(s,a) \leftarrow t$
            $U(s,a) \leftarrow 0$
            $l(s,a) \leftarrow 0$
        if $t(s,a) < t^*$ **then** LEARN$(s,a) \leftarrow TRUE$

Figure: Delayed Q-Learning

RL SBB - Objective Function

$$\frac{1}{60} \times \left[\sum_{\mathcal{S},\mathcal{R},\mathcal{RS}} \mathit{weightIn}_{rs} \times \max\left(0, (t^{entry}_{s,r,rs} - \mathit{inLat}_{s,rs})\right) + \mathit{weightOut}_{rs} \times \max\left(0, (t^{exit}_{s,r,rs} - \mathit{outLat}_{s,rs})\right)\right] + \sum_{\mathcal{S},\mathcal{R},\mathcal{RS}} p_{s,rs} \times \beta_{s,rs}$$

RL SBB - Discrete Event Simulation



Algorithm 3 tSim Control Functions

procedure RUN(self)
    $t \leftarrow$minTime
    while $t <$ (maxTime+10) **do**
        for e **in** event[t] **do**
            runNextTrain[e]
        $t \leftarrow t + 1$
    return calculateScore()
procedure RUNNEXTTRAIN(self,e)
    if $e = type(Node)$ **then** runNode()
    else if $e = type(Resource)$ **then del** e.resource
    else if $e = type(Station)$ **then** $nextEvent \leftarrow$ **new**$event[e]$

RL SBB - Reinforcement Learning Applied Algorithm

Algorithm 5 tSim.QTable Class Functions

```
procedure GETACTION(self,o,s)          ▷ Getting Action for any option or state
    if length(o) = 1 return o[0] then
    if rand¡ϵ then                     ▷ Uniform Random Package, for better convergence
        a ← rand(o)
    else
        m ← −∞                         ▷ Maximum Q-Value
        a ← null                       ▷ Action to be performed
        for all o do
            v ← qval(s, o[i])          ▷ qval is predicted reward of action o[i]
            if v > m then
                a ← c
                m ← v
    return a
procedure UPDATE(self,S_n,S_{n−1},A,r) ▷ Updating Q-Values
    p ← qval(S_{n−1}, A)               ▷ Previous Value
    m ← 0
    if qval(S_n) > 0 then              ▷ If exists, update max
        m ← max(qval(S_n))
    v ← (1 − α) ∗ p + α ∗ (r + γ ∗ m)  ▷ New Value
    return v                           ▷ Update Q-Table with new Q-Value
```

RL SBB - Results

	Solving System					
ID	01		02		03	
	ObjVal	Time	*ObjVal*	Time	*ObjVal*	Time
01	0	5.452	0	4.296	0	7.590
02	0.43	87	0.43	72.087	0.43	77.042
03	0.86	45	0.96	198.273	0.11	200.234
04	24.94	430	24.94	439.121	024.94	435.945
05	n/a	1800	n/a	1800	n/a	1800
06	207.12	1355	207.12	1174.690	207.12	1750.154
07	456.60	1800	442.33	1800	467.10	1800
08	153.23	1800	122.70	1800	233.6	1800
09	138.95	1800	38.25	1800	43.95	1800

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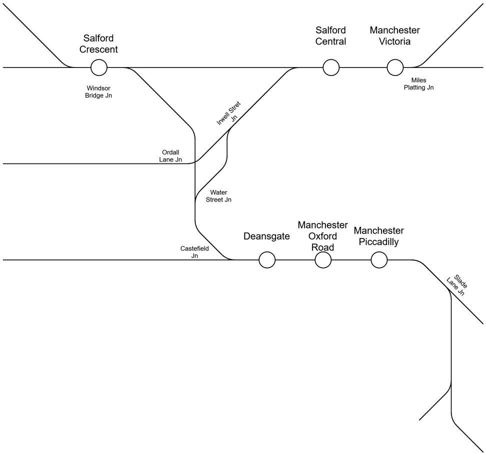
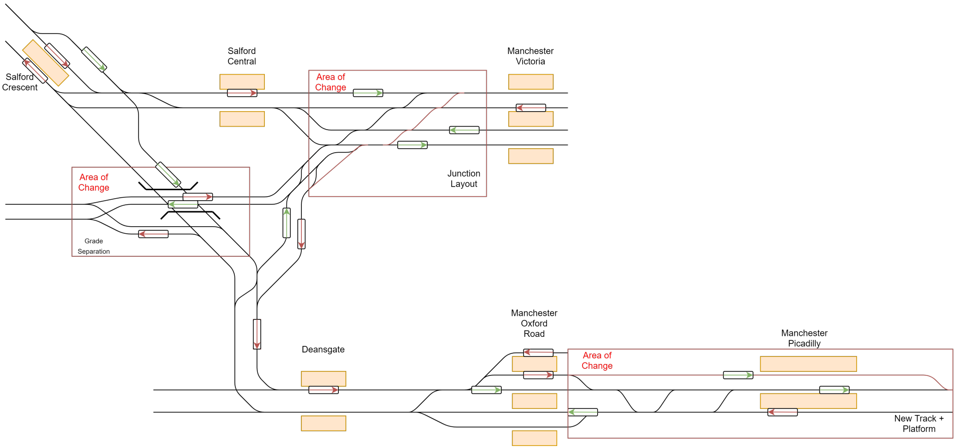
Manchester Case Study - Method

- Junction TPH Analysis
- Station Timing Data
- Previous Case Studies



Manchester Case Study - Key Outcomes



Final Words - Questions

Brief Discussion and Q&A

(a) Full Research Paper

(b) Full Slides

(c) Full Poster