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MODELLING OF EVOLUTIONARY ALGORITHMS FOR INTELLIGENT ELECTRIC TRANSPORT SYSTEM

EVOLŪCIJAS ALGORITMU MODELĒŠANA INTELEKTUĀLĀ ELEKTRISKĀ TRANSPORTA SISTĒMAI

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Introduction

This work is based on research in a field of intelligent agent systems, negotiation algorithm solving tasks of energy saving, optimal electric vehicle control and transport flow control in traffic jam.
Public electric transport should have higher priority than private cars, by criterion of transported passenger number, electric energy consumption and service level evaluated by schedule fulfillment. Public electric transport, such as trams and especially trolleybuses, which are more sensible to traffic jams, uses more electric energy during frequent acceleration and braking in traffic jam and infringe scheduled time. Also traffic lights are not synchronized and working independently from transport flow.
Evolutionary algorithm with dynamic input parameters can be very useful to synchronize traffic lights with each other, with transport flows and with public electric transport schedule to avoid idle time, directive term infringements and to provide faster service to passengers.
Paper presents a practical example to test proposed mathematical model and workability of evolutionary algorithm. The specific dynamic model of city transport system is created and results of evolutionary optimization are simulated.

Problem Formulation

The purpose of research is to develop new mathematical models and new algorithms for intelligent devices to control in electric transport system taking in account dynamic parameter of city transport system. Models and algorithms are proposed for multi-criteria optimization.
Main goal of research is energy saving for public electric transport. Mathematical model and evolutionary algorithm is proposed in the paper to solve multi-criteria optimization task minimizing idle time and electric energy used by public electric transport and maximize average speed of the flow in traffic jam.

- Set of electric transport vehicles: $T = \{t_1, t_2,...,t_n\}$
- Set of traffic lights: $L = \{l_1, l_2, ..., l_m\}$
- Intelligent control system : S
- Set of electric drives for each vehicle: $D_T = \{d_1, d_2 ..., d_n\}$
- Sets of sensors for transport and traffic lights - M_T, M_L
- Sets of transmitters for transport, traffic lights and control system: R_T, R_L, R_S
- Sets of actuators for transport and traffic light: A_T, A_L
- Electronic control devices for transport, traffic lights and control system : V_T, V_L, V_S
- Database for transport, traffic lights and control system: Db_T, Db_L, Db_S
- Software with artificial intelligence procedures for transport, traffic lights and control system: Pg_T, Pg_L, Pg_S
- Power supply for transport, traffic lights and control system: B_1, B_2, B_3

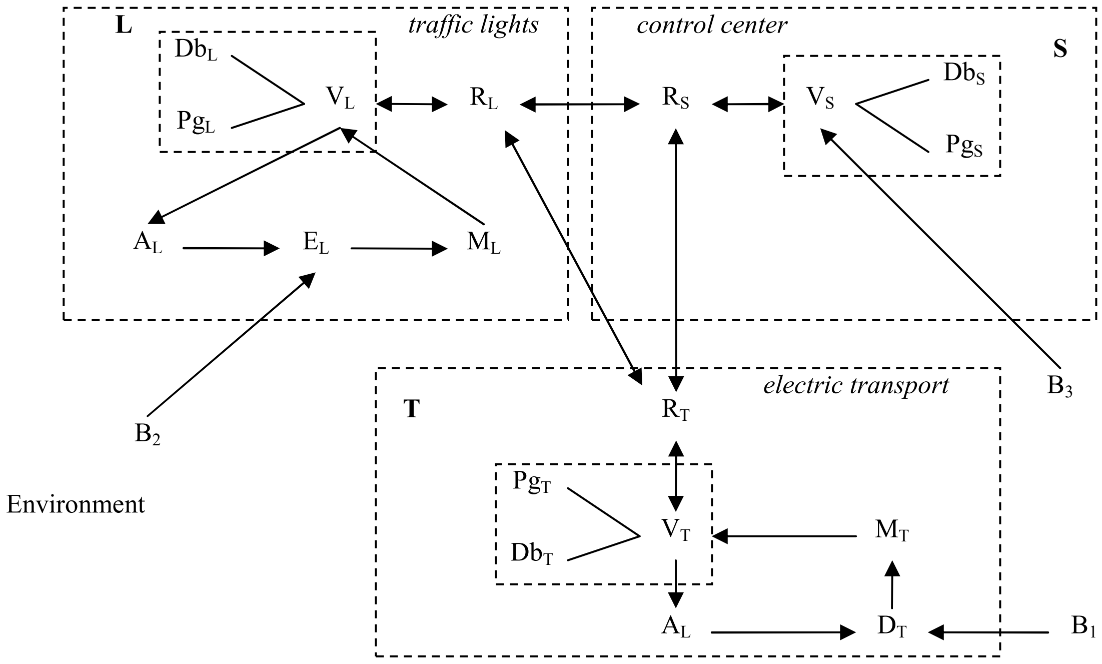

Figure 1. Structure of electric transport system with intelligent control

Mathematical Model

Mathematical model of public electric transport system has a set of dynamic parameters. Such parameters can be number of cars waiting on the crossroads, number of passengers waiting on passenger stops. Also number of lanes, which is very significant parameter for traffic jam problem solution, may be changed in case of breakdowns and crash of cars. All these variables are changing continuously. That is why evolutionary algorithm is necessary to adopt optimal solution to current input dynamic parameters.

A. Variables and functional dependences for for optimal control of electric transport

For transport task following mathematical model can be defined:

Set of processors P – stops, crossroads and streets, where $P = \{P^1, P^2, P^3\},\ P \in N,$ where

Stops: $P^1 = \{p_1^1, p_2^1, ..., p_s^1\} \subset P$

Streets without traffic lights: $P^2 = \{p_1^2, p_2^2, ..., p_c^2\} \subset P$

Streets with traffic lights and crossroads: $P^3 = \{p_1^3, p_2^3, ..., p_r^3\} \subset P$

Set of jobs Q – vehicles, where $Q = \{Q^1, Q^2\}$, where

Electric transport: $Q^1 = \{q_1^1, q_2^1, ..., q_n^1\}$

Non-electrical vehicles: $Q^2 = \{q_1^2, q_2^2, ..., q_m^2\}$

Each electric vehicle has fixed schedule, which defines directive terms for each passenger's stop: $q^1 \in Q^1,\quad \sigma_{q^1} : P^1 \to (D_{q^1}^{p_1^1}, D_{q^1}^{p_2^1}, ..., D_{q^1}^{p_s^1}) \subset Z^+$

Each electric vehicle $q^1 \in Q^1$ has processing time on each processor $p \in P$, $d_{q^1}^{p} \in Z^+$.

Let us define processing time for job $q^1 \in Q^1$ and $q \in Q$ on each type of processors:

- stop: $p^1 \in P^1$, $\quad t_{q^1}^{p^1} = d_{q^1}^{p^1}$,

  where

  $t_{q^1}^{p^1}$ - processing time, which depends on number of passengers;

- free street without traffic light and traffic jam $p^2 \in P^2$, $\quad t_q^{p^2} = \dfrac{l^{p^2}}{\bar{v}_q}$,

  where

  l^{p^2} - length of street;

  $\bar{v}_q$ - average moving speed on the street taking in account acceleration and braking

- traffic light (and street before crossroad): $p^3 \in P^3$, $\quad t_q^{p^3} = \dfrac{l^{p^3}}{x^{p^3}\bar{v}_{xq}}(x^{p^3} + y^{p^3})$,

  where

  x^{p^3} - time of green light;

  y^{p^3} - time of green light;

  l^{p^3} - length of street before traffic light;

  $\bar{v}_{xq}$ - average moving speed on the street in time interval x^{p^3}, taking in account acceleration and braking.

B. Definition of fitness function for optimal control of electric transport

Fitness function for optimization for all electric transport vehicles Q^1:

- Minimization of electrical energy:

$$E_{Q^1} = \sum_{q^1=q_1^1}^{q_n^1}\left(\sum_{j=1}^{r_{q^1}}\int_{\underline{t}_{q^1}^{p_j^2}}^{\bar{t}_{q^1}^{p_j^2}} i_{q^1}U'\,dt + \sum_{k=1}^{c_{q^1}}\int_{\underline{t}_{q^1}^{p_k^3}}^{\bar{t}_{q^1}^{p_k^3}} i_{q^1}U'\,dt\right) \to \min \quad (1)$$

where

U' – voltage of contact network;

$i_{q^1}(t)$ – current.

Total moving time minimization:

$$T_{Q^1} = \sum_{q^1=q_1^1}^{q_n^1}\left(\sum_{i=1}^{s_{q^1}} d_{q^1}^{p_i^1} + \sum_{j=1}^{r_{q^1}}\left(\frac{l^{p_j^2}}{\bar{v}_{q^1}}\right) + \sum_{k=1}^{c_{q^1}}\left(\frac{l^{p_k^3}}{x^{p_k^3}\bar{v}_{xq^1}}(x^{p_k^3} + y^{p_k^3})\right)\right) \to \min \quad (2)$$

with constraints:

$P_{q^1} = (p_1, p_2, ..., p_{s_{q^1}+r_{q^1}+c_{q^1}}),\quad p_i \in P^1 \cup P^2 \cup P^3$ - strictly defined route, which includes stops, streets and crossroads;

$\underline{t}_{q^1}^{p^1} + d_{q^1}^{p^1} \le D_{q^1}^{p^1}$ for all $p^1 \in P_{q^1}$ - schedule, where

$\underline{t}_{q^1}^{p^1}$ - time of arrival to passenger stop $p^1 \in P_{q^1}$.

Average speed maximization:

$$\bar{v}_{Q^1} = \sum_{q^1=q_1^1}^{q_n^1}\left(\sum_{j=1}^{r_{q^1}}\sum_{t=\underline{t}_{q^1}^{p_j^2}+1}^{\bar{t}_{q^1}^{p_j^2}}(v_{q^1}^{(t-1)} + a_{q^1}^{(t)}) + \sum_{k=1}^{c_{q^1}}\sum_{t=\underline{t}_{q^1}^{p_k^3}+1}^{\bar{t}_{q^1}^{p_k^3}}(v_{q^1}^{(t-1)} + a_{q^1}^{(t)})\right)\Big/ T_{Q^1} \to \max \quad (3)$$

where

$a_{q^1}^{(t)}$ - acceleration of a vehicle at time moment $t \in Z^+$

Also optimization functions for non-electric transport units Q^2 should be defined.:

- Total moving time minimization:

$$T_{Q^2} = \sum_{q^2=q_1^2}^{q_m^2}\left(\sum_{j=1}^{r_{q^2}}\left(\frac{l^{p_j^2}}{\bar{v}_{q^2}}\right) + \sum_{k=1}^{c_{q^2}}\left(\frac{l^{p_k^3}}{x^{p_k^3}\bar{v}_{xq^2}}(x^{p_k^3} + y^{p_k^3})\right)\right) \to \min \quad (4)$$

with constraint

$P_{q^2} = (p_1, p_2, ..., p_{r_{q^2}+c_{q^2}}),\quad p_i \in \cup P^2 \cup P^3$ - strictly defined route without passengers stops. Let us assume that it can not be changed.

- Average speed maximization:

$$\bar{v}_{Q^2} = \sum_{q^2=q_1^2}^{q_m^2}\left(\sum_{j=1}^{r_q}\sum_{t=\underline{t}_{q^2}^{p_j^2}+1}^{\bar{t}_{q^2}^{p_j^2}}(v_{q^2}^{(t-1)} + a_{q^2}^{(t)}) + \sum_{k=1}^{c_{q^2}}\sum_{t=\underline{t}_{q^2}^{p_k^3}+1}^{\bar{t}_{q^2}^{p_k^3}}(v_{q^2}^{(t-1)} + a_{q^2}^{(t)})\right)\Big/ T_{Q^2} \to \max \quad (5)$$

Using normalization formulas all optimization functions should be converted to common optimization target. As a result following function are defined:

$$E'_{Q^1} = \frac{E_{Q^1\max} - E_{Q^1}}{E_{Q^1\max}} \to \max \quad (6)$$

$$T'_{Q^1} = \frac{T_{Q^1\max} - T_{Q^1}}{T_{Q^1\max}} \to \max \quad (7)$$

$$\bar{v}'_{Q^1} = \frac{\bar{v}_{Q^1}}{\bar{v}_{Q^1\max}} \to \max \quad (8)$$

$$T'_{Q^2} = \frac{T_{Q^2\max} - T_{Q^2}}{T_{\max}} \to \max \quad (9)$$

$$\bar{v}'_{Q^2} = \frac{\bar{v}_{Q^2}}{\bar{v}_{Q^2\max}} \to \max \quad (10)$$

$E_{Q^1 \max}, T_{Q^1 \max}, \bar{v}_{Q^1 \max}, T_{Q^2 \max}, \bar{v}_{Q^2 \max} \in \Re^+$ are normalization values, which usually is maximal possible value of function. If maximal value is unknown any positive number may be used for normalization.
Using optimization criteria priorities $\alpha_{E_{Q^1}}, \alpha_{T_{Q^1}}, \alpha_{\bar{v}_{Q^1}}, \alpha_{T_{Q^2}}, \alpha_{\bar{v}_{Q^2}}$ fitness function is defined for evaluation of genetic algorithm population:

$$F = \alpha_{E_{Q^1}} E'_{Q^1} + \alpha_{T_{Q^1}} T'_{Q^1} +, \alpha_{\bar{v}_{Q^1}} \bar{v}'_{Q^1} + \alpha_{T_{Q^2}} T'_{Q^2} + \alpha_{\bar{v}_{Q^2}} \bar{v}'_{Q^2} \to \max \qquad (11)$$

C. Population mathematical definition for optimal control of electric transport

Let us assume, that population *S* is a set of traffic light schedules

$$S = \{s_1, s_2, ..., s_{s_{\max}}\}.$$

Each schedule $s \in S$ is vector containing optimization variables of traffic light time intervals:

$$s = (x_s^{p_1^3}, y_s^{p_1^3}, x_s^{p_2^3}, y_s^{p_2^3}, ..., x_s^{p_c^3}, y_s^{p_c^3}),$$

where
$x_s^{p_k^3} \in Z^+$ - *k*-th traffic light's green light time;
$y_s^{p_k^3} \in Z^+$ - *k*-th traffic light's red light time.

Initial population is generated with random numbers defined in predefined limits:

$$S^{(0)} = \{s_1^{(0)}, s_1^{(0)}, ..., s_{s_{\max}}^{(0)}\},$$

where

$$s = (x_{\min}^{p_1^3} \le x_s^{p_1^3} \le x_{\max}^{p_1^3}, y_{\min}^{p_1^3} \le y_s^{p_1^3} \le y_{\max}^{p_1^3}, ..., x_{\min}^{p_c^3} \le x_s^{p_c^3} \le x_{\max}^{p_c^3}, y_{\min}^{p_c^3} \le y_s^{p_c^3} \le y_{\max}^{p_c^3}),$$

$x_{\min}^{p_k^3}$ - *k*-th crossroad's traffic light's minimal time for green light;
$x_{\max}^{p_k^3}$ - *k*-th crossroad's traffic light's maximal time for green light;
$y_{\min}^{p_k^3}$ - *k*-th crossroad's traffic light's minimal time for red light;
$y_{\max}^{p_k^3}$ - *k*-th crossroad's traffic light's maximal time for red light.

Population should be evaluated and arranged by efficiency. Each schedule $s \in S$ is evaluated by function:

$$V_s = F(s) = \alpha_{E_{Q^1}} E'_{Q^1} + \alpha_{T_{Q^1}} T'_{Q^1} +, \alpha_{\bar{v}_{Q^1}} \bar{v}'_{Q^1} + \alpha_{T_{Q^2}} T'_{Q^2} + \alpha_{\bar{v}_{Q^2}} \bar{v}'_{Q^2}.$$

By evaluation of the whole population *S* a set of evaluations is defined:

$$V_s = \{V_{s_1}, V_{s_2}, ..., V_{s_{\max}}\}.$$

For arrangement of population following rule is used, according to optimization goal, which is maximization in this case. So, set *S* is arranged by $i < j, \quad ja \quad V(s_i) > V(s_j)$. In result arranged set is created:

$$\hat{S} = (\hat{s}_1, \hat{s}_2, ..., \hat{s}_{s_{\max}}),$$

where
$\hat{s}_1$ - the best (by target function) schedule of traffic lights in population *S*;
$\hat{s}_{s_{\max}}$ - the worth (by target function) schedule of traffic lights in population *S*.

A set of elite individuals is created to save the best results, which contains copies of β percents individuals from set $\hat{S}$. So, elite set is defined:

$$S_e = (\hat{s}_1, \hat{s}_2, ..., \hat{s}_{\beta \cdot s_{\max}}).$$

Algorithms for Problem Solution

D. Selection procedure for electric transport optimal control

Stochastic roulette individual selection procedure for task solution if defined.
1. step: For each state of traffic light $\hat{s} \in \hat{S}$ selection probability

$$P_{\hat{s}_i} = \frac{V(\hat{s})}{V_\Sigma(\hat{S})} = \frac{V(\hat{s})}{\sum_{j=1}^{s_{\max}} V(\hat{s}_j)}$$

and cumulative probability

$$C_{\hat{s}_i} = \sum_{k=1}^{i} P_k$$

are calculated.
2. step: Random number are generated

$$g \in [0,1] \in \Re.$$

3. step: Such $\hat{s}_i$ is selected, for which

$$C_{\hat{s}_i} \le g < C_{\hat{s}_{i+1}}.$$

4. step: Selected schedule is added to set of individuals for crossover and subtracted from the set $\hat{S}$: $\tilde{S} = \tilde{S} \cup \{\hat{s}_i\}, \quad \hat{S} = \hat{S} \setminus \{\hat{s}_i\}$
5. step: If $|K| = |S| \quad and \quad \hat{S} = \varnothing$, then end of selection procedure. Else repeat from 1. step.

Procedures result is arranged set where elements are grouped in pairs:

$\widetilde{S} = (<\widetilde{s}_1, \widetilde{s}_2>, <\widetilde{s}_3, \widetilde{s}_4>, ..., <\widetilde{s}_{s_{\max}-1}, \widetilde{s}_{s_{\max}}>)$

E. Crossover procedure for electric transport optimal control.

As $x_{\widetilde{s}}^{p_k^3}, y_{\widetilde{s}}^{p_k^3} \in Z^+, \quad \widetilde{s} \in \widetilde{S}$, are real numbers, for crossover operation by genetic algorithm weighted arithmetic crossover procedure is defined.

1. step: From set of traffic light schedules $\widetilde{S}^{(i)}$, where i – number of current generation pair is selected:

$<\widetilde{s}_j^{(i)}, \widetilde{s}_{j+1}^{(i)}>$.

2. step: Defining crossover weight

$w \in (0,1) \in \Re$.

3. step: Generating of new schedules for traffic lights by following rule:

$$s_j^{(i+1)} = w\widetilde{s}_j^{(i)} + (1-w)\widetilde{s}_{j+1}^{(i)} = (wx_{\widetilde{s}_j^{(i)}}^{p_1^3} + (1-w)x_{\widetilde{s}_{j+1}^{(i)}}^{p_1^3}, ..., wy_{\widetilde{s}_j^{(i)}}^{p_c^3} + (1-w)y_{\widetilde{s}_{j+1}^{(i)}}^{p_c^3})$$

$$s_{j+1}^{(i+1)} = w\widetilde{s}_{j+1}^{(i)} + (1-w)\widetilde{s}_j^{(i)} = (wx_{\widetilde{s}_{j+1}^{(i)}}^{p_1^3} + (1-w)x_{\widetilde{s}_j^{(i)}}^{p_1^3}, ..., wy_{\widetilde{s}_{j+1}^{(i)}}^{p_c^3} + (1-w)y_{\widetilde{s}_j^{(i)}}^{p_c^3}).$$

4. step: If $j+1 = s_{\max}$, then procedure ends with new (i+1) generation set of traffic light schedules: $S^{(i+1)} = \{s_1^{(i+1)}, s_2^{(i+1)}, ..., s_{s_{\max}}^{(i+1)}\}$, else $j = j+2$ and procedure repeated from step 1.

F. Mutation procedure for electric transport optimal control.

For mutation in traffic light scheduling task arithmetic mutation procedure is defined. Initialization: Mutation parameters are defined:

number of mutated schedules - $\bar{\gamma} \in [1, s_{\max}] \in \aleph$;

number of mutated variables in each schedule - $\bar{\lambda} \in [1, |s|] \in \aleph, \quad s \in S$;

value of mutation (usually small number) - $\upsilon \in Z$.

1. step: Generating of set of random numbers:

$\Gamma = \{\gamma_1, ... \gamma_{\bar{\gamma}}\}$, where $\gamma \in [1, s_{\max}] \in \aleph, \quad \gamma \in \Gamma$.

2. step: Selecting traffic light schedules from population *S*:

$S_\mu = \{s_{\gamma_1}, ..., s_{\gamma_{\bar{\gamma}}}\}, \quad S_\mu \subset S$.

3. step: Generating of random number set:

$\Lambda = \{\lambda_1, ..., \lambda_{\bar{\lambda}}\}$, where $\lambda \in [1, |s|/2] \in \aleph, \quad \lambda \in \Lambda, \quad s \in S_\mu$

4. step: In each schedule $s_j \in S_\mu$ variables mutation value is added, getting:

$$s_{\gamma_1} = \{..., x_{s_j}^{p_\lambda^3} + \upsilon, y_{s_j}^{p_\lambda^3} + \upsilon, ...\}, \quad \lambda \in \Lambda, \quad s_{\gamma_1} \in S_\mu \subset S$$

: ...

$$s_{\gamma_{\bar{\gamma}}} = \{..., x_{s_j}^{p_\lambda^3} + \upsilon, y_{s_j}^{p_\lambda^3} + \upsilon, ...\}, \quad \lambda \in \Lambda, \quad s_{\gamma_{\bar{\gamma}}} \in S_\mu \subset S$$

5. step: End of mutation procedure.

Computer Experiment

The specific environment is developed by authors for the dynamic modelling of intelligent system for energy saving algorithms. The interface is presented on figure 2.

This research presents results of traffic control using evolutionary optimization of traffic light working time.

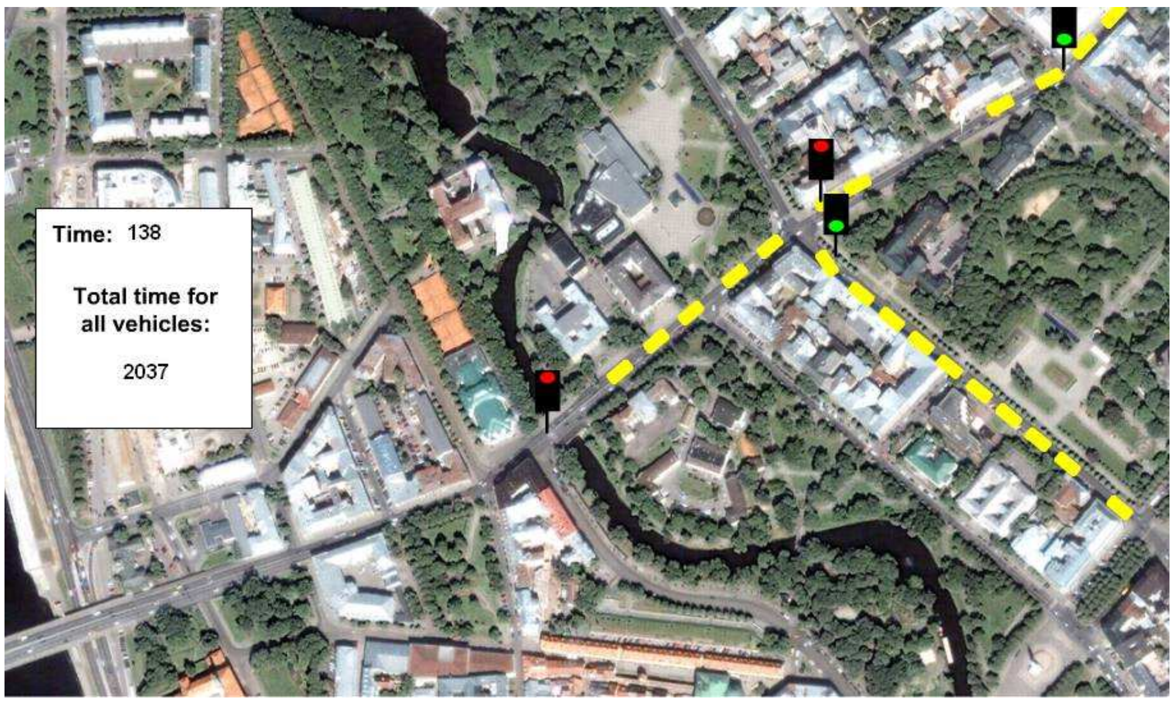

Figure 2. Computer model for traffic control

Figure 2 presents the model of traffic jam without evolutionary algorithm. Model shows current situation in Riga, where traffic jam is very actual problem.

Results of evolutionary algorithm show the necessity to set up maximal allowed time for green light.

Figure 3a show total waiting time for usual traffic light working mode. Figure 3b provides total waiting time with evolutionary algorithm results.

a)	b)
Time: 1538 Total time for all vehicles: 13784	Time: 1392 Total time for all vehicles: 12673

Figure 3. Results of simulation a) without optimization b) using evolutionary algorithm results

On current stage of research 8% of time is saved by using of evolutionary algorithm results.

Conclusions

The results of using algorithms of artificial intelligence in public electric transport systems show the possibility to avoid crashes and detect dangerous points on the way. They advance safety improvement, optimization of energy usage, profit increasing, idle time minimization and coordination. Simulation results prove the efficiency of provided algorithms in mechatronic systems. Usage of algorithms and models allow to reduce charges for energy consumption and to provide more safe service.

The additional value is the possibility of the developed systems to prevent accidents and to avoid different problems by intelligent diagnostic and coordination devices. General algorithm for diagnostics in intelligent agent systems gives possibility to detect the problem of electric vehicle immediately, to fix it in some cases without human intervention or inform all other participants about the problem.

Negotiations in intelligent agent systems give the possibility to coordinate actions of all participants in transport systems and to realize multi-criteria decision-making in control, diagnostic and scheduling for city electric transport.

Intelligent agents system based on the proposed models and algorithms are created using web-technologies, a database and the appropriate programming languages that allow to realize negotiation easy and effectively.

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References

1. Luger G. F. Artificial Intelligence. Structures and Strategies for Complex Problem Solving, Williams, 2003, 863. p

2. S. J. Russel, P. Norvig. Artificial Intelligence. A Modern Approach, 2nd edition. Prentice Hall, 2006, 1408 p.

3. Greivulis J., Levchenkov A., Gorobetz M. Modelling of Clustering Analysis with Special Grid Function in Mechatronics Systems for Safety Tasks. //In Proceedings of 6th International Conference on Engineering for Rural Development, Jelgava, Latvia, 2007.

4. Rankis I., Gorobetz M., Levchenkov A.. Optimal Electric Vehicle Speed Control By Intelligent Devices. Rīgas Tehniskās universitātes raksti. Enerģētika un Elektrotehnika. Sērija 4, sējums 16. 2006. 127-137. lpp.

5. Gorobetz M., Levchenkov A., Ribickis L. Intelligent Electric Vehicle Motion And Crossroad Control. //In Proceedings of 12th International Power Electronics and Motion Control Conference. Portoroz, Slovenia, 2006 – 1239 - 1246 p.

6. Levchenkov A., Gorobetz M.. The Algorithm of Negotiation for Software Agents for the Open Conveyor Schedule in Logistics Tasks. // In: HMS2003, Riga, Latvia, 142-148.

7. Rosin, M. Lehtla, T. Möller. Intelligent Control and Diagnostics System for Tallinn Trams. //In: EPE-PEMC2004, Riga, Latvia.

8. Reskó, P. T. Szemes, P. Korondi, P. Baranyi, H. Hashimoto. Camera Motion Control based on Ubiquitous Computing (Artificial Neural Network Based Adaptive Object Tracking in Intelligent Space) //In: EPE-PEMC2004, Riga, Latvia.

Gorobecs M., Ļevčenkovs A. Evolūcijas algoritmu modelēšana intelektuālā elektrotransporta sistēmai
Pētījuma mērķis ir izstrādāt jaunus matemātiskos modeļus un jaunus algoritmus intelektuālām iekārtām, lai vadītu elektro transporta sistēmu, ņemot vērā pilsētas transporta sistēmas dinamiku. Modeļi un algoritmi tiek piedāvāti daudzkritēriju optimizācijai.
Pētījuma galvenais mērķis ir samazināt pilsētas elektriskā transporta elektroenerģijas patēriņu. Matemātiskais modelis un evolūcijas algoritms tiek piedāvāts, lai atrisinātu daudzkritēriju optimizācijas uzdevumu elektroenerģijas patēriņa un stāvēšanas laika samazināšanai un vidējā transporta plūsmas kustības ātruma palielināšanai satiksmes sastrēgumos.
Sabiedriskā elektrotransporta sistēmas matemātiskajā modelī ir dinamisko parametru kopa. Visi mainīgie nepārtraukti mainās. Līdz ar to ir jāizmanto evolūcijas algoritms, lai adaptētu optimālo risinājumu aktuālo dinamisko parametru vērtībām. Evolūcijas algoritmu ar dinamiskajiem parametriem var izmantot, lai sinhronizētu luksoforus savā starpā, ar transporta plūsmu un ar sabiedriskā transporta sarakstu, tā izvairoties no dīkstāves, direktīvo termiņu pārkāpumiem un piedāvājot labāku servisu pasažieriem.
Rakstā tiek apskatīts arī praktiskais piemērs, lai pārbaudītu piedāvāto modeli un evolūcijas algoritma efektivitāti.

M. Gorobetz, A. Levchenkov. Modelling of Evolutionary Algorithms for Intelligent Electric Transport System
The purpose of research is to develop new mathematical models and new algorithms for intelligent devices to control in electric transport system taking in account dynamic parameter of city transport system. Models and algorithms are proposed for multi-criteria optimization.
Main goal of research is energy saving for public electric transport. Mathematical model and evolutionary algorithm is proposed in the paper to solve multi-criteria optimization task minimizing idle time and electric energy used by public electric transport and maximize average speed of the flow in traffic jam.
Mathematical model of public electric transport system has a set of dynamic parameters. All these variables are changing continuously. That is why evolutionary algorithm is necessary to adopt optimal solution to current input dynamic parameters. Evolutionary algorithm with dynamic input parameters can be very useful to synchronize traffic lights with each other, with transport flows and with public electric transport schedule to avoid idle time, directive term infringements and to provide faster service to passengers.
Paper presents a practical example to test proposed mathematical model and workability of evolutionary algorithm.

М. Горобец, А. Левченков. Моделирование эволюционных алгоритмов для интеллектуальной электротранспортной системы
Цель исследования разработать новые математические модели и алгоритмы для интеллектуальных устройств для управления системой электротранспорта, принимая во внимания динамику городского транспорта. Модели и алгоритмы предложены для многокритериальной оптимизации.
Главная цель исследования это уменьшение затрат электроэнергии для городского электротранспорта. Математическая модель и эволюционный алгоритм предложены для решения многокритериальной задачи оптимизации для минимизации затрат электроэнергии, минимизации времени простоя и максимизация средней скорости движения во время затора.
Математическая модель системы общественного электротранспорта содержит ряд динамических параметров, которые непрерывно изменяются. Поэтому возникает необходимость использовать эволюционный алгоритм для адаптации оптимального решения под текущее значение динамических параметров. Эволюционный алгоритм может быть применен для синхронизации работы светофоров друг с другом, с потоком транспорта и расписанием общественного транспорта, чтобы уменьшить время простоя, нарушения директивных сроков и предложить лучшее качество сервиса для пассажиров.
В статье рассмотрен также практический пример для проверки эффективности модели и эволюционного алгоритма