Fuzzy Modeling for Service Strategy and Operational Control of Loading Systems

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Abstract: Requirements, such as adaptive behavior, learning ability and self regulative features, that have to be met by modern logistic systems, need the construction of such control systems that are able to control the basic processes and also to develop and improve the material and information system by automating the control processes. For controlling the logistical systems focusing on loading systems the papers propose the application of LPV structure by which non-linear systems can be controlled on the basis of linear control theories. The proposal points out that the priorities of different states are of great importance when generating the logical rules of operation. For resolving the difficulties of constructing mathematical algorithms fuzzy sets are suggested, so in the control model a Takagi-Sugeno solution is proposed, that can describe multi-input multi-output, non-linear, dynamic systems like logistical systems.

Keywords: Takagi-Sugeno controller, loading system, fuzzy modeling, adaptive behavior

1. Introduction

For designing control systems of complex logistical processes the service strategy and operational algorithm of given system must be known. Service strategy is the set of procedures, rules that determine the direction, feature and measure of state transformation the system and its sub-systems for all possible situations and conditions. Since constructing operational algorithms for large scale logistic systems is of great difficulties we focus our research to the loading system which is one of the subsystems of logistic system.

There are many different design point of views for service strategies and operational algorithms of general stochastic demand and adaptive material handling systems , and the way of descriptions can be differ as well. The deployment of processes to operational elements, the interpretation of states and their transition are partly subjective. They depend on the features of actual system and the approaches of designers as well. Determination, description and representation of service strategy mean determination of states, specification and interpretation of transitions and definition of rules regarding the assignment of states and transitions. [13]

Many methods have been proposed to deal with multi-input, multi output systems, like logistics system by the literature. This paper describes a fuzzy modelling approach. For controlling the logistical systems focusing on loading systems we propose the application of LPV structure by which non-linear systems can be controlled on the basis of linear control theories. The proposal points out that the priorities of different states are of great importance when generating the logical rules of operation. For resolving the difficulties of constructing mathematical algorithms fuzzy sets are suggested, so in the control model a Takagi-Sugeno solution is recommended.

2. Strategy for loading systems

2.1. Elementary strategy for loading systems with adaptive behavior

In the case of stochastic loading systems linking two stochastic processes (such as inbound transportation - outbound transportation, transportation – internal material handling) is causeless to suppose the independency of onset and service, especially the system contains intermittent-duty, mobil, materiel handling machines. On that grounds developed models (eg. queuing models) are suitable for only approximate disquisitions. At the most part of loading systems the demand process has an effect on the service process, controls it, accelerates or slows down the executive process. (Fig. 1.)

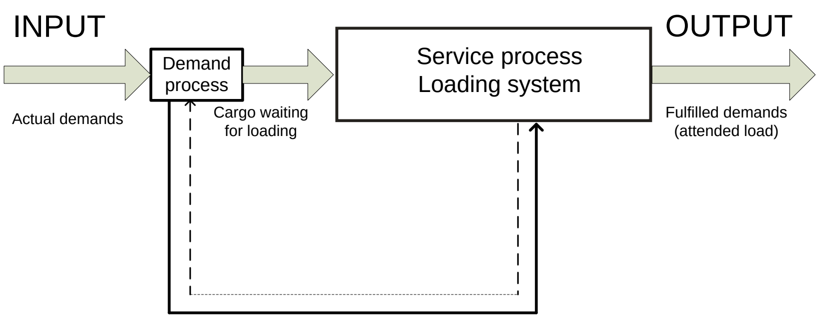

Figure 1. Scheme of relationship for demand and service processes

Those loading systems, in which the input influences the systems operational processes, are called loading systems with adaptive behavior.

The adaptivity can be shown in changing of

- service intensity (spontaneous adaptivity);
- number of elements being in the system (homotroph adaptivity);
- function of elements creating the system (heterotroph adaptivity);

or in any kind of combination of previous criterions [12].

The demand process can affect the service process through the arrival (eg. coming wagons, trucks, load-units) or changing the volume of queuing (eg. queuing wagons, trucks, load units). In practice the relationship between queuing and service occurs almost exclusively, arrival has an effect on service, if the system is refusal, which means: there are no room for waiting units.

Let be $x(t)$ the representative (differing only a bit from the expectation of value) realization of $\xi(t)$ stochastic demand process, $y(t)$ the representative realization of $\eta(t)$ stochastic service process, and C the capacity of loading system (maximum number of load units served by the loading system during a period of time).

In the systems behavior the next serving states can be distinguishable in function of time (Fig. 2.):

1. state: $x(t) > C$ and $y(t) < C$
2. state: $x(t) > C$ and $y(t) = C$
3. state: $x(t) \leq C$ and $y(t) = C$
4. state: $x(t) \leq C$ and $y(t) < C$.

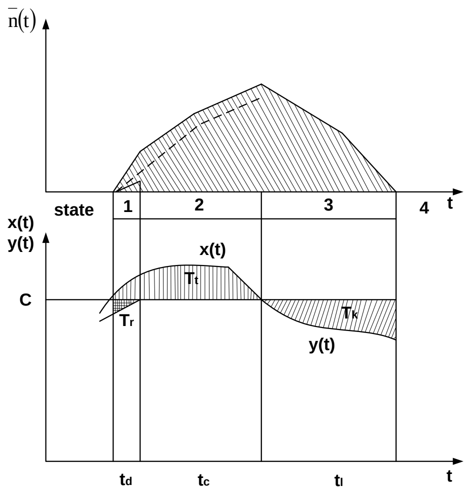

Figure 2. Scheme for demonstrating the temporal conformation of demand and service processes [12]

2.2. For the above mentioned states the strategic rules are the followings:

2.2.1. Strategy of the 1. state:

The system should endeavor to work on the capacity level as soon as possible if the demand process exceeds the capacity level. The system could complete the rules of service strategy with a delay of t_d duration because of the system's inflexibility. (Fig. 2.)

The darkest area in Fig. 2. demonstrates the demand numbers waiting because of the system's inflexibility. Function y(t), the realisation of service process as a stochastic process, is performed pushed left with the average service time. Characteristics of process realisations are denoted with continuous line.

2.2.2. Strategy of the 2. state:

The system should work on capacity level. The vertically striped area represents the demand numbers waiting because of overcharging.

2.2.3. Strategy of the 3. state:

The system should work on capacity level after the overcharged phase until satisfaction of waiting demands because of overcharging.

$$T_k \cong T_r + T_t \tag{1}$$

The upper part of Fig. 2. introduces the average numbers of waiting demands for states 1., 2. and 3., the creating and dissambly of waiting queues.

2.2.4. Strategy of the 4. state:

The system should endeavor to work flexibly under the capacity level after satisfaction of demands because of overcharging.

2.3. Description of service strategy for loading systems

The loading system and its sub-system go through state transition during the operation, since the external factors (type of vehicles and goods) and internal elements (such as material handling machinery, facilities) affects each others and induces a series of state transitions.

In our case the state is qualitative feature of a given process, an actual status, cross-section of complex loading process in time (e.g. the status of transport vehicle can be being loaded or waiting, status of handling machinery can be operable or out of order etc.). The transition parameters are qualitative features and logical variables of complex loading processes (e.g. priorities of loading, demand for loading capacity, maintenance time of machinery etc.)

In the framework of strategy the interactions between individual elements are not distinguished so machinery and facilities are not individualized only homogenous sets of machines and goods are considered. Thus service strategy can be generally determined and less vulnerable for changes than the operational algorithm. The description of operational algorithm of given actual system is more detailed than the above mentioned strategy. In the operational algorithm we distinguish and analyze the individual machinery and facilities, goods, vehicles, and states, state transitions by describing them quantitatively. The two objects, the service strategy and the operational algorithm have close connection to each other, so in the terminology we can use them in interrelation, that is service strategy is an overall, draft operational algorithm and the operational algorithm is a detailed service strategy.

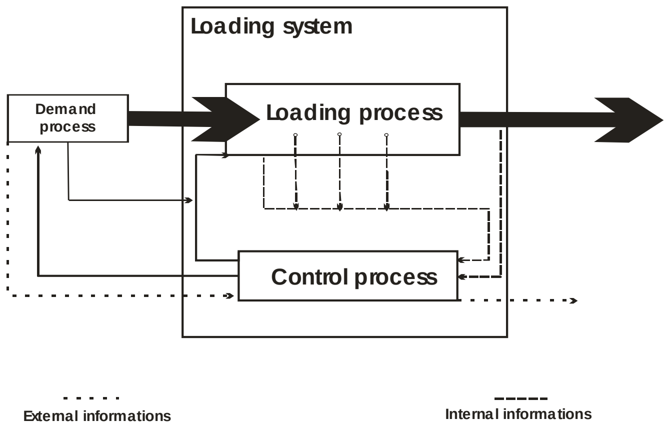

Figure 3. Extended structure model of general stochastic demand and adaptive material handling systems [13]

Fig. 4. demonstrates the schematized model of technical and technological process by complex loading systems. There are *n* type of goods loaded, unloaded and temporary stored in the analyzed system. The states of processes running in the system are shown as circles and rectangles, the transitions are directional arrows. External priority means the loading sequence based on the precedence information of goods on transportation vehicle arriving from outside the system [13].

2.3.1. Input

LI – Symbol for **loaded** transportation vehicle arriving occasionally. Parameters that have to be considered: arrival time, type of transported goods, quantity of arriving goods, demand of loading and dates of external priority. This information follows the transportation vehicle through the subsystem.

EI – Symbol for **empty** transportation vehicle. Parameters are the same as in the previous case.

2.3.2. Loading processes

WU – Symbol for transportation vehicle **waiting for unloading** ordered by preset priorities or by arriving sequence.

WL - Symbol for transportation vehicle **waiting for loading** ordered by preset priorities or by arriving sequence.

TS – Symbol for **temporary storing** or warehouse. The warehouse is divided into **n** parts for each type of goods to be stored. Parameters that have to be considered: coordinates, capacity and load of storing parts and possibility of conversion (exchange) between storing units.

SIU – Symbol for **interrupted state** of unloading because of failure of loading machine ordered to transportation vehicle (there is not free loading machine capacity) or appearing of loading demand in excess of critical priority (not enough loading machine capacity)

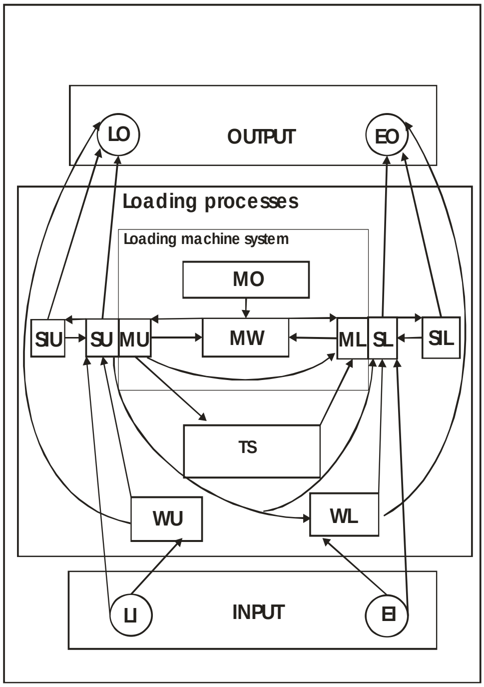

Figure 4. Subsystem realizing the basic process of a loading system

SU - Symbol for **state of unloading.** Transportation vehicle and loading machine are ordered together by type of transportation vehicle and transported goods. Parameters of loading are loading time and destination.

MU - Symbol for **unloading machine.**

MW - Symbol for **working loading machine** waiting for loading. Parameters that have to be considered: value of work capacity demanding on type of goods and transportation vehicle, kinetic characteristics.

ML - Symbol for **loading machine.**

SL - Symbol for **state of loading.**

SIL - Symbol for **interrupted state of loading**.

MO - Symbol for loading **machine out of work.**

2.3.3. Output

LO - Symbol for transportation vehicle leaving **loaded.** Parameters that have to be considered: leaving time, quantity of transported goods, type of transportation vehicle.

EO - Symbol for transportation vehicle leaving **empty.** Parameters that have to be considered: leaving time, type of transportation vehicle.

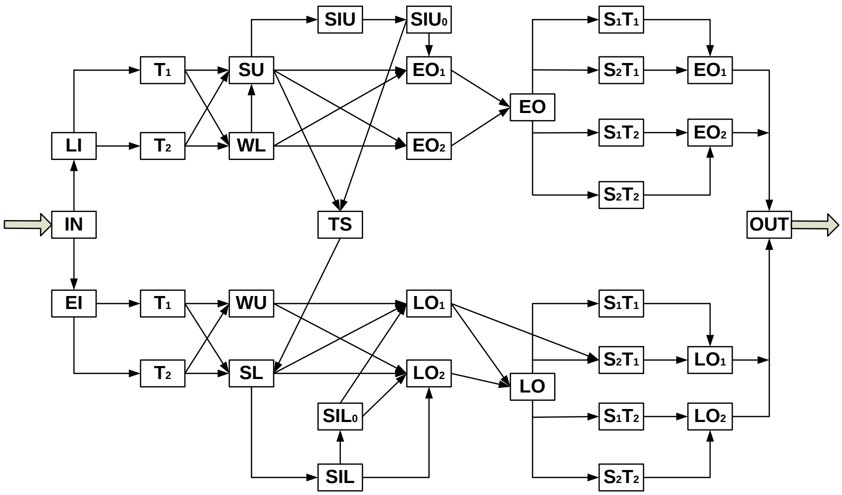

Figure 5. Graph of a loading system

3. Examples for multi input - multi output (MIMO) logistic system

3.1. The Port of Hamburg

The Port of Hamburg as one of the most important cargo handling sites in worldwide shipping is a suitable example for multi input multi output large scale logistic system. Logistical services must ensure that at any point along the transport chain the necessary goods are available in the right quantities, in the right place and at the right time. The port has capacities for forwarding the goods by feeder, ship, truck, rail and barge and also arrange the warehousing, the commissioning on behalf of foreign exporters. The same applies to exports from inland regions, i.e. for collecting, for interim storage and finally shipment to overseas destinations.

The in- and outflow of goods over longer distances is mainly affected with the environmentally friendly transport medium rail. Round 160 international and national container trains run per day from and to the port. It is not only containers but also project shipments, tubes, fruit, liquid cargoes (in tank wagons), ores, coal, grain, sugar and much more that are shipped by rail. Apart from the combined traffic terminals at the container terminals Hamburg can boast a handling station for combined freight traffic.

Although around 96 percent of Hamburg 's total general cargo turnover is now containerised the remaining quantities of "conventional cargo" are still of great significance to the port. This term includes crates and bags, wheeled cargo, heavy goods and bulk goods such as steel pipes etc. The port has specialist terminals for the conventional handling of vehicles, fruits/vegetables, paper/cardboard, cellulose, scrap, fertilizers, sugar, coffee and cocoa in sacks.

In many shipping regions Ro-Ro traffic plays an important role. Apart from pure car transport vessels very often con-ro ships are also used. These transport containers on deck while inside the ship itself cargoes are stowed that can be driven on board on their own wheels. These can be all types of vehicles and goods packed on trailers. The Hamburg port facilities are equipped with quay indentations or ro-ro ramps for the loading of these special ships.

As it has been turned out from this review, controlling such a difficult logistic system requires many kind of inputs in large quantities, for example type of transportation vehicle, of transported goods and of loading machine have to be ordered to the transportation vehicle, arriving time, priority. Situation is more complicated because of presence of combined traffic and each transport sector (rail, road, air and water).

3.2. Cross-docking depot at Wal-Mart Stores Inc, Home Depot, Tesco and Metro AG.

An other simple example for MIMO systems are the cross-docking depots. Cross-docking means unloading goods from a railcar, ship, or trailer, and quickly reloading the same goods in a similar or alternative source of transportation with little or no storage in between. It eliminates the need for warehousing and typically takes place at a transportation hub where goods are unloaded, sorted, and reloaded. Cross-docking may be done to change type of conveyance, to sort material intended for different destinations, or to combine material from different origins into transport vehicles (or containers) with the same, or similar destination. Direct trans-shipment of products to stores on an on-demand basis, (instead of delivery from stock) gets products to customers faster, and eliminates warehouse stock costs, material handling and personnel time.

The floor area of the depo is divided into a break up area and a build up area, where sorting and consolidation of consignment takes place, respectively. Customer order types can vary as well as the techniques for fulfilling them. The two main techniques for fulfilling orders are either through manual order picking operatives or automated order dispensers or on some occasions by both. A Cross-docking distribution centre system can exhibit some unpredictability in its behaviour which can influence its overall performance. For example, manual order picking operators can have different skill levels and familiarity with picking certain types of orders, while automated order picking machines failure are sometimes random occurrences. These arbitrary events amongst others can influence the overall volume of orders fulfilled through the Cross-docking distribution centre.

The center has two types of doors, receiving doors and shipping doors. The assignment of destinations to shipping doors, clustering of destinations to form groups, and determination of the number of groups are major operation problems directly related with the performance of the center.

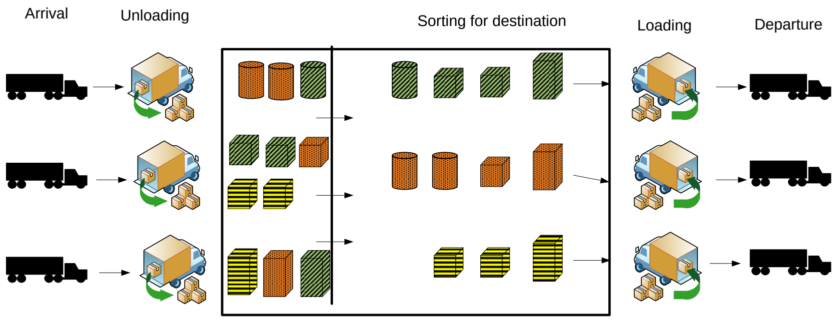

Figure 6. Scheme for cross-docking depots

4. Fuzzy modelling

The fuzzy sets based approach is suitable for describing (very) complex systems which cannot be modelled analytically. By fuzzy sets, operations and rules, inference systems may be created which imitate in some sense the ways of everyday human thinking. Such systems are referred to in the literature as fuzzy systems [9]. Fuzzy inference is the process of formulating the mapping from a given input to an output using fuzzy logic. The mapping then provides a basis from which decisions can be made, or patterns discerned. Two types of fuzzy inference systems can be implemented: Mamdani-type and Sugeno-type (Takagi.Sugeno). These two types of inference systems vary somewhat in the way outputs are determined.

„Because it is a more compact and computationally efficient representation than a Mamdani system, the Sugeno system lends itself to the use of adaptive techniques for constructing fuzzy models. These adaptive techniques can be used to customize the membership functions so that the fuzzy system best models the data." [16]

Comparison of Sugeno and Mamdani method

Advantages of the Sugeno Method:

- computationally efficient
- works well with linear techniques
- works well with optimization and adaptive techniques
- guarantees continuity of the output surface
- well suited to mathematical analysis

Advantages of the Mamdani Method:

- intuitive
- has widespread acceptance
- well suited to human input.

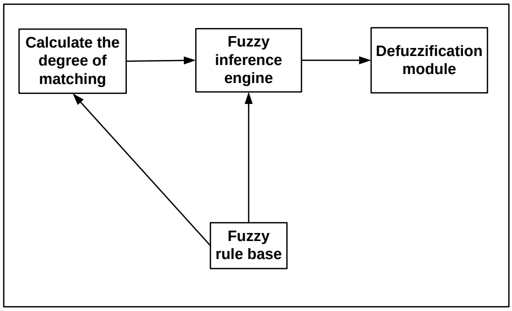

Figure 7. Structure of a typical fuzzy system [9]

4.1. Takagi-Sugeno(TS) fuzzy model

Takagi-Sugeno fuzzy models are suitable models for large class of nonlinear systems. In this section we give a brief review on the fundamental form of TS fuzzy models. A TS model consists a number of local linear models assigned to fuzzy regions, which are designed to approximate the dynamic features at the corresponding operating fuzzy points in vector space P. Fig. 5. shows the structure of a TS fuzzy model. The model varies according to vector $p \in \Re^N$, which may contain some values of the state vector x as well. The TS fuzzy inference engine is responsible for combining the local linear models according to vector p in order to find a proper model, which is assumed to be the momentary linear descriptor of the system capable of generating output vector y from state vector x and input vector u. A discrete time model varying on the parameter p:

$$\begin{aligned} x(k+1) &= \Phi(p)x(k) + \Gamma(p)u(k) \\ y(k) &= C(p)x(k) + D(p)u(k) \end{aligned} \tag{2}$$

Suppose that its system matrix

$$S(p) = \begin{pmatrix} \Phi(p)\Gamma(p) \\ C(p)D(p) \end{pmatrix} \tag{3}$$

is a parametrically varying object, which can be written as a convex combination of the system matrices $S_1,\ldots,S_N$. It means that for any $p \in \Re$ there exist coefficients $\mu_j(p) \in \Re$, $0 \le \mu_j(p) \le 1$ and $\sum_j \mu_j(p) = 1$, such that

$$S(p) = \sum_{j=1}^{V} \mu_j(p) S_j \tag{4}$$

where system matrices S_j are constans. Consequently, the original system is approximated by a convex combination of a number of local linear models assigned to regions defined by basis functions $\mu_j(p)$. In case of TS model approximations coefficients $\mu_j(p)$ are computed as the firing probability of the fuzzy rules, which based on the product operator t -norm.

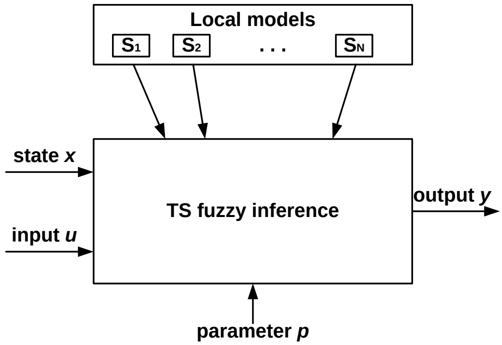

Figure 7. Scheme of the Takagi-Sugeno fuzzy inference model

4.1.1. Uncompleted TS Fuzzy Model

Assume $n-$varieble model consequent-based fuzzy rules as follows:

$$\text{IF } p_1 \text{ is } A_{1,i} \text{ AND} \dots \text{AND } p_N \text{ is } A_{N.i} \text{ THEN model } S_i$$

Here $A_{j,i} : \mu_{A_{j,i}}(p_j)$ is the $i-$th antecedent fuzzy set on the $j-$th input universe. The output of a rule is:

$$\hat{S}_i = S_i \prod_{j=1}^{N} \mu_{A_{j,i}}(p_j) \tag{5}$$

The approximated model is:

$$\hat{S}(p) = \frac{\sum_{i=1}^{V} \hat{S}_i}{\sum_{i=1}^{V} \prod_{j=1}^{N} \mu_{A_{j,i}}(p_j)} = \frac{\sum_{i=1}^{V} \prod_{j=1}^{N} \mu_{A_{j,i}}(p_j) S_i}{\sum_{i=1}^{V} \prod_{j=1}^{N} \mu_{A_{j,i}}(p_j)} \tag{6}$$

Usually the antecedent sets are given in Ruspini-partition, so for every $j : \sum_i \mu_{A_{j,i}}(p_j) = 1$. This implies that the denominator is equal to 1, so this can be taken out of consideration.

4.1.2. Completed TS Fuzzy Model

The completed fuzzy rules are formed by all combination of the antecedent sets. So a typical rule is:

IF p_1 is A_{1,i_1} AND . . . AND p_N is $A_{N.i_N}$ THEN model $S_{i_1 i_2 \ldots i_N}$

The range of indeces $i_n = 1 \ldots V_n$ where V_n denotes the number of antecedent sets in the $n-$th universe. The output of a rule is:

$$\hat{S}_{i_1, i_2, \ldots, i_N} = S_{i_1 i_2 \ldots i_N} \prod_{j=1}^{N} \mu_{A_{j,i_j}} \left(p_j \right) \tag{7}$$

The final conclusion is the weighted sum of the outputs:

$$\hat{S}(p) = \frac{\sum_{i_1=1}^{V_1} \cdots \sum_{i_N=1}^{V_N} \hat{S}_{i_1, i_2, \ldots, i_N}}{\sum_{i_1=1}^{V_1} \cdots \sum_{i_N=1}^{V_N} \prod_{j=1}^{N} \mu_{A_{j,i_j}} \left(p_j \right)} = \frac{\sum_{i_1=1}^{V_1} \cdots \sum_{i_N=1}^{V_N} \prod_{j=1}^{N} \mu_{A_{j,i_j}} \left(p_j \right) S_{i_i, i_2, \ldots, i_N}}{\sum_{i_1=1}^{V_1} \cdots \sum_{i_N=1}^{V_N} \prod_{j=1}^{N} \mu_{A_{j,i_j}} \left(p_j \right)} \tag{8}$$

If the antecedents sets are in Ruspini partition then

$$\sum_{i_1=1}^{V_1} \cdots \sum_{i_N=1}^{V_N} \prod_{j=1}^{N} \mu_{A_{j,i_j}} \left(p_j \right) = 1 \tag{9}$$

so the approximated model is

$$\hat{S}(p) = \sum_{i_1=1}^{V_1} \cdots \sum_{i_N=1}^{V_N} \prod_{j=1}^{N} \mu_{A_{j,i_j}} \left(p_j \right) S_{i_i, i_2, \ldots, i_N} \tag{10}$$

4.2. The Mamdani Method

The Mamdani method is the most commonly used one in practical applications [10]. The inference engine may be viewed as a special kind of generalised function generator as it maps the set of all possible input fuzzy sets into the set of all possible fuzzy outputs. The output is converted to a so-called “crisp” value by the defuzzification module. At the beginning of the inference the degree of matching between the observation and the rules is determined. Each component of the observation vector is compared to the same component of the antecedent of each rule. Let A^* be the *n*-dimensional observation vector. The degree of matching (firing) in the j^{th} dimension in the i^{th} rule can computed as:

$$w_{j,i} = \max \left\{ \min \left\{ A_j^* \left(x_j \right), A_{j,i} \left(x_j \right) \right\} \right\} \tag{11}$$

where $A_{j,i}$ is the membership function of the i^{th} rule in the j^{th} dimension. If the observation is a crisp vector then the above calculation is simpler: in case of state vector x^*, the degree of matching in the j^{th} dimension is:

$$w_{j,i} = A_{j,i}\left(x_j^*\right) \tag{12}$$

After the degree of matching was calculated in each dimension, the resultant for the whole antecedent is determined. The degree of applicability of a rule is affected by the degree of matching of its each dimension. Thus, the firing degree of the i^{th} rule can be computed by taking the minimum value of the degrees of matching of the rule's antecedents:

$$w_i = \min_{j=1}^{n} w_{j,i} \tag{13}$$

w_i shows that how important the role of rule R_i will be in the calculation of the conclusion for observation A^*. After the degree of firing was determined for each rule, each conclusion is separately calculated. This can be made by cutting the consequent fuzzy set of the rule at height w_i:

$$B_i^* = \min\left(w_i, B_i(y)\right). \tag{14}$$

The conclusion for the whole rule base can be computed by taking the union of the previously calculated sub-conclusions:

$$B^*(y) = \max_{i=1}^{r} B_i^*(y). \tag{15}$$

After the inference a $B^*(y)$ conclusion fuzzy set was obtained. However, in most cases, the expected conclusion is not a fuzzy set, but crisp value. Hence, the crisp value needs to be determined, wich describes the conclusion fuzzy set int he best way. This called defuzzification.[9]

4.3. Mixed method

For further research we decided to build a mixed (hybrid) method for resolving some problematics of control on loading systems. Because of different outputs of fuzzy methods this mixed method will use the Mamdani Method for resolving the inventory planning and control, as well as the Takagi-Sugeno Method for resolving the control of service strategy of loading systems. The next section entertains a proposal for introduction of service strategy using TS fuzzy modeling, which needs to be extended in the future. We also plan to match the next model with the Mamdani Method providing a complex solution for loading systems.

It is also worth considering, how can it be possible to get a fast solution to serve the loading and transportation tasks. When requiring inputs in such a great numbers as in our case, it is difficult to serve both quality characteristics of a control system: fastness and finding the optimal solution. It may be decided for the fast solution by description of operational algorithm, because a fast control system providing satisfying solution can be more effective then a slow one searching for the optimal solution.

5. Fuzzy modelling of a loading system based on TS method

5.1. Priorities and fuzzy sets

In serving systems, such as a loading system, one of the most important question is determining the order of importance between different demands. There are may be some exact, well-measurable features for ordering, but there are always uncertain, non well-defined features, for instance ”important”, ”perishable”, etc. Because of this uncertain information it is a difficult task to establish ordering between priority levels assigned to different kind of goods and transportation vehicles. In general, the priority level arises from different terms, for example:

$$P(t) = P_v + P_g + a(t)\frac{c_{req}}{c_{req} - c(t)} + b(t)\frac{n - n_{min}}{n_{max} - n} + c(t)t_w \tag{16}$$

where c_{req} is the required quantity of goods, $c(t)$ is the loaded quantity , n is the number of loading machines working with the vehicle, n_{min} is the minimal number of required loading machines, n_{max} is the maximal number of loading machines that could work with the vehicle, t_w is the waiting time, $a(t)$, $b(t)$ and $c(t)$ are proportionality terms, P_v and P_g are the priorities assigned to the transportation vehicles and to the goods, so the last two terms are usually not well-defined. As we seen, to every kind of goods and transportation vehicles can be ordered a priority value, which may be an uncertain measure. But these priority levels have exact meaning only if we compare them with the priority levels of goods and transportation facilities already being in the system, and with the priorities of the running processes in the system. For instance, perishable goods coming by a lorry handled in a different way if there is a loading in progress in the system and interrupting of the process or rearranging of the loading machines indicates too high cost, and in another way if there is enough available free loading capacity. So, priority values coming with the goods and the transportation vehicles are modified by the actual states of the system [7].

The duties in the system can be ordered using these modified priorities. Just a few example for modifier states: if a there is a load waiting for a long time , its priority level is increasing; if there is loading in progress, the priority level of the load is increasing; if a loading machine had worked a lot, priority level of its employment is decreasing. Priorities coming with goods and transportation vehicles, and priorities from the states of the system are usually uncertain, not crisp properties, so it seems reasonable to handle as fuzzy sets.

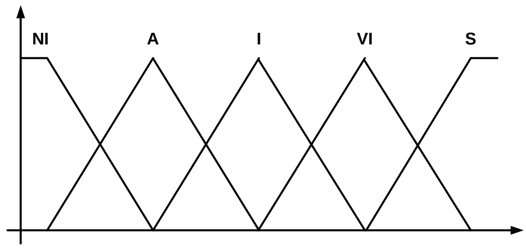

Figure 6. An example for fuzzy priority levels

In Fig. 4., there are some possible fuzzy sets for different priority levels, such as not important (NI), average (A), important (I), very important (VI) and super important (S).

5.2. Model description

As we mentioned in section 5, the model is essentially determined by the states of the system (state vector x) and the quantities, qualities and priorities of the incoming goods and transportation facilities (input vector u). The elements of the state vector x could be the following [7]:

- Number of incoming loaded and empty transportation vehicles (LI,EI)
- Number of available loading machines (separeted with respect to loading and unloading, kind of goods and type of transportation facilities) (MU,ML)
- Number of loading and unloading processes in progress (SL, SU)
- Number of waiting transportation vehicles in the system and their priority values (WL,WU, Pv)
- Quantity of waiting goods in the system and their priority values (Wg, Pg)
- Quantity of available goods for loading (C)
- Available storage capacity (TS)

Various states of the system (it means different values in the parameter vector p) indicate various local models. These type of models could vary in long term and short term, for example in short term different shifts in a day indicate different models or in long term different models valid for the seasons. Few example for rules describing the system operations:

$$\mathrm{IF}\left(\mathrm{ML}=0 \wedge \left(\mathrm{P_g} \wedge \mathrm{P_v} < \mathrm{P_{crit}}\right)\right) \vee \left(\mathrm{W_g}=0 \wedge \mathrm{SU}=0\right) \text{ THEN EI} \rightarrow \mathrm{WL}$$

$$\mathrm{IF}\left(\mathrm{MU}=0 \wedge \left(\mathrm{P_g} \wedge \mathrm{P_v} < \mathrm{P_{crit}}\right)\right) \vee \mathrm{W_g} > \mathrm{TS} \text{ THEN LI} \rightarrow \mathrm{WU}$$

$$\mathrm{IF}\left(\mathrm{W_g} < \mathrm{TS}\right) \wedge \left(\mathrm{MU} \neq 0\right) \text{ THEN LI} \rightarrow \mathrm{SU}$$

$$\text{IF } \mathrm{MU} \neq 0 \vee \mathrm{P(SU)} > \mathrm{P_{crit}} \text{ THEN SIU} \rightarrow \mathrm{SU}$$

$$\text{IF } \mathrm{ML} \neq 0 \vee \mathrm{P(SL)} > \mathrm{P_{crit}} \text{ THEN SIL} \rightarrow \mathrm{SL}$$

$$\text{IF } \mathrm{WL} \neq 0 \wedge \mathrm{SL} \neq 0 \wedge \mathrm{P}(\mathrm{SL}) > \mathrm{P}_{\mathrm{crit}} \text{ THEN MU} \rightarrow \mathrm{ML}$$

The complex entirety of these type of rules describe the behaviour of the whole system. To each micro-system (for example a day) of the global system assigned to the same model with different parameter values. In such a way, if a long term behaviour of the system (season) is approximated with an LPV model S, then the short term behaviour of this system is approximated with the same model changing the parameter values.

6. Conclusion

At the most part of loading systems the demand process has an effect on the service process, controls it, accelerates or slows down the executive process. The loading system and its sub-system go through state transition during the operation, since the external factors (type of vehicles and goods) and internal elements (such as material handling machinery, facilities) affects each others and induces a series of state transitions. Description of operational algorithm needs proper handling of priorities and composition of rules in relative small numbers to achieve the optimal function in the case of multi input multi output logistic system.

This study provides a fuzzy modelling approach for resolving the difficulties of constructing mathematical algorithms for loading system. The fuzzy sets based method is suitable for describing (very) complex systems which cannot be modelled analytically. In the control model a Takagi-Sugeno solution is proposed.

For further research our conception is to build a mixed (hybrid) method which contains the Mamdani Method for resolving the inventory planning and control, as well as the Takagi-Sugeno Method for resolving the control of service strategy of loading systems.

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