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(54) Title: SELF-LEARNING MACHINE SUPERVISING A SYSTEM FOR MANAGING AN INVENTORY OF GOODS

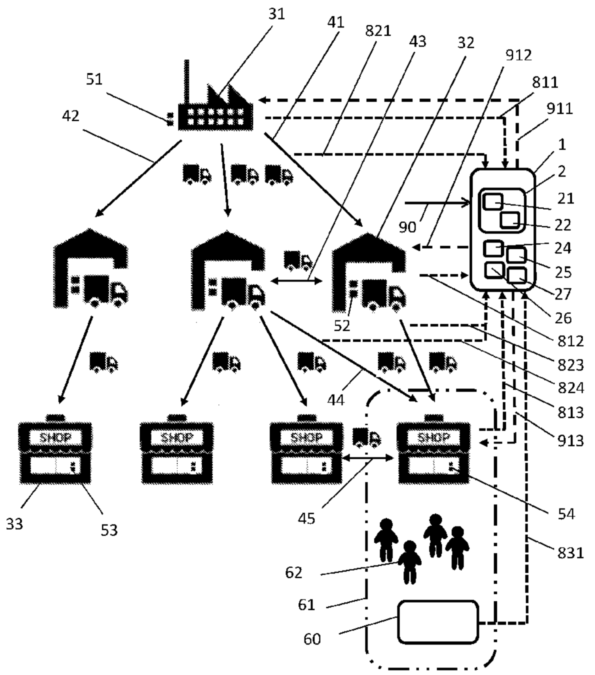

Figure 1

(57) Abstract: The invention concerns a method for training a self-learning machine (2) supervising a system (1) for managing an inventory (51, 52, 53, 54) of goods so as to infer a supplying order (91, 911, 912, 913) optimizing a given optimization function (90). The training of the self-learning machine (2) comprises a step of training a first self-learning unit (21) of the self-learning machine according to a first optimization function (90) being a sub-optimal approximation of said given optimization function. The training also comprises a step of training a second self-learning unit (22) using an output of the trained first self-learning unit (21) and/or according to a second optimization function being a sub-optimal approximation of said given optimization function (90).

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Self-learning machine supervising a system for managing an inventory of goods

Field of the invention

[0001] The present invention concerns a self-learning machine supervising an inventory management system for any kind of goods.

[0002] In particular, the present invention concerns a process for training the self-learning machine and a system comprising the trained self-learning machine.

Description of related art

[0003] Self-learning machines are used in many industries and services for predicting or supervising systems. As an example, the management of inventory systems already uses self-learning machines for predicting future needs and availabilities of goods in the inventory.

[0004] Inventory costs are directly related to the quantity of goods in inventory. Storing too few goods could cause shortages leading to losses. But storing too many goods implies increased inventory costs, such as immobilized capital, higher rents, or additional personnel expenses.

[0005] EP3311348 describes an inventory management apparatus configured to notify a product provider (e.g. food and drinks) about store inventory levels on a daily basis, to avoid product shortages and profit losses.

[0006] Moreover, there is a strong interest in systems that can not only react to inadequate inventory levels, but also anticipate future demand and adapt inventory levels pre-emptively.

[0007] US2016328724 describes a system and method for ordering products based on demand/sales forecasts provided by a set of dynamically weighted (using a sequential learning algorithm) predictive models.

[0008] WO2018/217954 describes an online marketplace system for online purchase of goods as well as for the efficient and expedient delivery of the goods purchased. The system comprises an artificial intelligence module having one or more learning platforms including a learning engine and an analytics or interference platform, including an interference engine. The interference engine may be configured for continuously running analytics on received data on a daily basis and/or with regard to one or more special or promotional events, such as prior to, during, and/or after the event, e.g. a shopping event, and functions with the purpose of improving the efficacity of the events results such as by improving the usefulness of producing, consuming, and/or delivery, of goods or services, being sold and purchased through the system.

[0009] Inventory systems often comprise large amounts of items whose availability needs to be monitored over long periods, often years or even decades, with a fine granularity, often days or even hours. As a consequence, the size of self-training systems that are required for supervising such a large inventory becomes very large. This results in large and expensive processing systems, and inefficient computation. Even worse, such a very large self-training system becomes very difficult to train, requires a large dataset, resulting in unreliable prediction or monitoring.

Brief summary of the invention

[0010] An aim of the invention is to provide a system capable of managing inventories of goods in a more cost-effective way than known systems.

[0011] Another aim of the invention is to provide a self-learning system for supervising an inventory that is more efficient when operational requirements are complex and/or datasets are large.

[0012] Another aim of the invention is to provide a solution for supervising an inventory that requires a smaller self-learning system and a smaller training dataset.

[0013] According to an aspect of the invention, these aims are achieved by means of a method for training a self-learning machine supervising a system for managing an inventory of goods, wherein the self-learning machine comprises a first and second distinct self-learning units; the first self-learning unit being trained with a first input dataset including a reference time set, and the second self-learning unit being trained with a second input dataset including one or many outputs of the trained first self-learning unit.

[0014] Surprisingly, this decomposition of the self-learning system in one first and one second unit may result in a partition of the required training dataset.

[0015] This partition is for example achieved when the first self-training unit is trained using a part of the training data set in order to achieve an approximation of a first optimization function, such as for example: reducing the amount of goods in the inventory, and the second self-training unit is trained using a part of the training data set in order to achieve another approximation of a second optimization function such as for example reducing the number of displacements.

[0016] This partition may also be achieved for example when the first self-training unit is trained according to a first time set (for example monthly variations of the inventory) while the second self-training unit is trained with the results of the first unit and according to a second time set (for example daily or hourly variations).

[0017] The first input dataset may include reference data representing observed amounts and/or observed variations of the inventory.

[0018] The first input dataset may include internal reference data representing observed human and/or mechanical events relevant to the inventory, such as for example changes in price, packaging, etc.

[0019] The reference time set may comprise reference times for: the goods reference data, the internal reference data, and/or the external reference data, for example times or dates of entries or exits from the inventory.

[0020] The first self-learning unit may infer one or a plurality of supplying orders in order to achieve a first given optimization function, for example a given cost function.

[0021] The first self-learning unit may be trained with a first optimization function that is a sub-optimal approximation of a given optimization function, for example a cost function. This approximation may for example be the approximation of a first inventory condition. The optimization function may be determined over a first period, for example over successive months.

[0022] The second self-learning unit may be trained with a second optimization function that is another sub-optimal approximation of a given optimization function, for example another cost function. This approximation may for example be the approximation of a second inventory condition. The optimization function may be determined over a second period, for example over successive hours or days.

[0023] Using different approximations of one or several optimization functions as input of successive self-learning units results in an efficient training of each self-learning unit, each being specialized in outputting orders to reach the corresponding approximation. Therefore, the size of the required dataset for each self-learning unit may be reduced.

[0024] According to another aspect of the invention, these aims are achieved by means of a method for training a self-learning machine supervising a system for managing an inventory of goods, wherein the self-learning machine comprises a first and second distinct self-learning units; the method comprising steps of:

A) Collecting an input dataset including, in any order:

collecting goods reference data representing observed amounts and/or observed variations of the inventory; and/or

collecting internal reference data representing observed human and/or mechanical events relevant to the inventory; and/or

collecting external reference data representing a human, natural, and/or environmental event affecting a given geographical region related to the inventory;

providing a reference time set comprising reference times for: the goods reference data, the internal reference data, and/or the external reference data;

B) Building a training dataset by pairing said goods reference data, said internal reference data and/or said external reference data with said reference time set;

C) Training the self-learning machine with said training dataset to infer a supplying order according to a given optimization function, for example a given cost function;

wherein said step of training the self-learning machine comprises steps of:

i) deriving a first optimization function that is a sub-optimal approximation of said given optimization function;

ii) training the first self-learning unit according to said first optimization function, and

iii) training the second self-learning unit using one or many output of the trained first self-learning unit and/or according to a second optimization function being another sub-optimal approximation of said given optimization function.

[0025] The proposed solution provides more accurate and cost-effective inventory management because it is configured to infer re-supplying orders from collected data, not only according to an optimization function, which can be for example a given cost function, but also by considering at least one approximation thereof.

[0026] In particular, splitting the inferring operation into at least two distinct inferring operations is more efficient when operational requirements are complex and/or datasets are large.

Brief Description of the Drawings

[0027] The invention will be better understood with an example of embodiments illustrated by the figures, in which:

Fig. 1 shows a schematic view of a system managing one or more inventories of goods diversely located between a factory and final clients, according to the invention;

Fig.2 and 3 show a self-learning machine for supervising the system of Figure 1, in self-learning mode (Fig. 2) and in operational mode (Fig.3);

Fig.4 shows a flow diagram of a method for training a self-learning machine, according to the invention;

Fig. 5 shows a self-learning machine comprising a plurality of self-learning units with different learning periods and/or predictive horizons.

Detailed Description of possible embodiments of the Invention

[0028] Figure 1 shows a system 1 for managing an inventory, notably a plurality of inventories 51, 52, 53, 54 of goods

[0029] The inventory can be the totality of the goods. Alternatively or complementarily, the inventory can be, or can comprise, a list or the aggregate value of the goods. The list can comprise an identifier (e.g. code number), a quantity, and/or a value for each good. The list can be physical and/or virtual (e.g. represented by digits and/or computer-readable data).

[0030] According to the invention, a good can be any physical object. The goods can be any mass of material, such as raw materials, semi-finished or finished products, consumer goods, foodstuffs or consumables. The goods can be rare materials, precious materials, and energy resources such as natural gas, electric energy, oil and refined products. Moreover, the goods can be (fixed or mobile) equipment or tools used for production or distribution, such as but not limited to: robots, machines, vehicles, containers, conveyors, engines.

[0031] The inventory can be located in a moveable storage unit, such as a moveable container, a shipping container, an intermodal container, the load bed of a vehicle (e.g. truck) and a trailer, or in a static storage unit (i.e. a storage unit not moving or not intended to be moved) such as a box, a safe or a bank vault. The inventory can also be located on an open or closed surface, such as a mine, a quarry, a plot of bare or cultivated land.

[0032] According to the invention, an asset can be, or can represent, any immaterial item that is/can be usable as a medium of exchange and/or as a medium of payment and/or that is convertible into a legal tender (e.g. cash) and/or into credit. The assets can be credentials providing the ownership of (a given amount or quantity of) such an immaterial item, such as credit and debit credentials, currencies, cryptocurrencies, shares, bonds, or stock options. The credentials can be physical and/or virtual (e.g. represented by digits and/or computer-readable data).

[0033] An asset can be, or can represent, any material item that is/can be usable as a medium of exchange and/or of payment, such as mediums of payment and legal tenders.

[0034] The inventory can thus be (alternatively or complementarily) located on a postal or bank account, in a portfolio of credentials (e.g. shares, bonds, notes), a database, and/or in a digital or physical wallet.

[0035] In the example of Figure 1, each of the inventories is located in a dedicated storing entity 32, such as a warehouse 32, a hangar, a depot, a basement or cellar or a storage closet in a (trading or commercial) building 33 or in a creating entity 31, such as a factory 31, a fabrication site, a power plant or an oil well.

[0036] The storing entities 32 can be interconnected, or connected to one or more creating entities 31 by means of distribution channels 41-45.

[0037] The illustrated system 1 comprises a goods data module 24, an internal data module 25, an external data module 26, a timestamping module 27 and a self-learning machine 2.

[0038] The goods data module 24 is configured to collect goods data 811, 812, 813 representing observed amounts and/or observed variations of the inventory 51, 52, 54, notably of the goods thereof. The observed amounts and/or variations can be related to the amounts of goods in the inventory. The observed amounts and/or variations are preferably observed, registered and/or determined at a specific time or within a specific time interval.

[0039] The internal data module 25 is configured to collect internal data 821, 822, 823, 824 representing observed human and/or mechanical events on the goods of the inventory. The observed human and/or mechanical events can notably relate to:

- the distribution of the goods such as transportation capabilities and/or availabilities;
- the production of the goods such as (current and/or forecasted) production capacities;
- storing capabilities of the goods for the inventory such as physical inventory capacities, personnel availabilities or working capital constraints;
- supply and demand for the good of the inventory;
- the cost of the inventory such as production, acquisition, managing, and/or sales costs of the goods;
- marketing and/or promotional activities.

[0040] The external data module 26 is configured to collect external data 831 representing human, natural, and/or environmental events affecting a given geographical region 61 having a relationship with and/or a connection to the inventory. The geographical region 61 can relate to:

a geographical region where the goods of the inventory are located; and/or

a geographical region where (a part of) the goods of the inventory are delivered.

[0041] The geographical region can be designed by a governmental and/or commercial organization. Alternatively or complementarily, the geographical region can be defined in relation to the inventory.

[0042] The human events can relate to human activities such as concerts, sports competitions, school and academic overtures and/or closures, holidays in the corresponding geographic region. Human activities can further concern the financial state and/or health of the geographical region 61, the purchasing power of residents and/or potential clients 62.

[0043] The environmental events can relate to temperature, weather, and/or season of the geographical region.

[0044] The natural events can relate to weather conditions, to a weather hazard (e.g. wind, thunderstorms, rain, snow, heat wave and frost hazards), natural disasters (e.g. floods) affecting the geographical region.

[0045] The system further comprises a timestamping module 27 configured to provide a consistent (i.e. unvarying, unmodifiable) time reference for the goods data, the external data, and/or to the internal data.

[0046] Each module can be a dedicated electronic circuit, a set of instructions executed on a (shared and/or common) processor of a device, and/or a combination thereof.

[0047] The self-learning machine 2 of the system 1 is configured to infer a supplying order 911, 912, 913 using a given optimization function 90 assigned to the inventory, notably by a manager or an operator of the system 1 in order to provide a more cost-effective solution for the management of an inventory.

[0048] In particular, as shown in Figure 3, the self-learning machine 2 is trained to provide the supplying order 91 in response to an input dataset 89 comprising:

the time reference set provided by the timestamping module 27; and

the goods data 811, 812, 813 provided by the goods data module 24, and/or

the internal data 821, 822, 823 provided by the internal data module 25, and/or

the external data 831 provided by external data module 26.

[0049] A supplying order 911, 912, 913 can be any (physical or virtual) order causing a modification of the goods of the inventory, notably by an increase or a reduction of the inventory.

[0050] The modification can relate to (at least a parameter of) the amount and/or value of the inventory, such as a quantity and a mass of goods of the inventory, notably by adding new goods to the inventory and/or by delivering (parts of) the goods of the inventory.

[0051] The modification can be immediate or short-term, i.e. within a short time interval from the execution of the inferred supplying order. The short interval can be a second, a minute, an hour, or a day.

[0052] Alternatively or complementarily, the modification can take effect, or being configured to take effect within a time interval that is delayed with respect to the execution of the inferred supplying order.

[0053] The supplying order 911, 912, 913 can also be an order potentially causing a modification of the inventory, in case the order is configured and/or destined to stabilize the inventory (e.g. amount and/or the value thereof), e.g. following a variation of:

a current and/or forecasted demand/sale related to the inventory, and/or

a current and/or forecasted production capacity, and/or

a current and/or forecasted inventory level.

[0054] The supplying order can be based (notably by a logical or mathematical function) on an inferred:

current and/or forecasted demand and/or sale related to the goods of the inventory; and/or

current and/or forecasted production capacity related, or potentially related to the goods of the inventory, and/or

current and/or forecasted inventory level, e.g. the goods and/or assets thereof.

[0055] The given optimization function 90 can include any element and/or combination of elements contributing to the cost of the inventory, such as related effort, material resources, time and utilities consumed, risk incurred, and opportunity forgone. Examples are: an economic inventory cost, immobilized capital, rents for storing the inventory, transportation cost and times, return-on-investment time, loss of sales and/or clients due to sold-outs, (economic) penalty.

[0056] The given optimization function 90 can also include any element and/or combination of elements generating an income related to the inventory, such as a profit, an excess of revenue, an opportunity. Examples are: a return-on-investment, an increase in sales and/or clients.

[0057] The given optimization function 90 can also include any element and/or combination of elements related to client satisfaction and promotions affecting the inventory.

[0058] The given optimization function can be related to a specific time horizon (i.e. a fixed point of time in the future at which point the optimization function is evaluated).

[0059] The given optimization function can be also related to (evaluated within) a specific time period (e.g. defined in one or more second(s), minute(s), hour(s), day(s), week(s), month(s), year(s), or by a combination thereof).

[0060] As illustrated in Figures 1-3, the self-learning machine 2 of the system 1 comprises a plurality of self-learning units 21, 22. Each of these self-learning units is configured (i.e. trained) to infer a specific output from a dataset according to a specific optimization function.

[0061] The self-learning machine 2 can comprise two or more self-learning units. In the illustrated embodiment of Figure 1 and 2, for the sake of simplicity, the self-learning machine 2 comprises a first and a second self-learning units 21, 22.

[0062] A plurality of self-learning units allows to split the inferring operation of the self-learning machine 2, into a plurality (i.e. equal number) of distinct inferring operations.

[0063] The applicant found that such a split allows to better infer and/or exploit patterns, trends, and associations within a potentially very large dataset, notably by:

feeding the results of one self-learning unit as the inputs of another self-learning unit; and/or

using an optimization function being different from the given optimization function 90 for a self-learning unit, notably by using a sub-optimal approximation of the given optimization function 90.

[0064] The self-learning machine 2 can thus be efficiently trained by collecting an input dataset including, in any order:

collecting goods reference data 81, 811, 812, 813 representing observed amounts and/or observed variations of the inventory; and/or

collecting internal reference data 82, 821, 822, 823, 824 representing observed human events relevant to the inventory; and/or

collecting external reference data 83, 831 representing a human, a natural, and/or an environmental event affecting the given geographical region 6;

[0065] The step of collecting an input dataset also includes a step of providing a reference time set 80 comprising reference times for: the goods reference data, and/or the internal reference data, and/or the external reference data.

[0066] The method for training the self-learning machine 2 further comprises a step of building a training dataset 88 by pairing the goods reference data 81 and/or the internal reference data 82 and/or the external reference data 83 with the reference time set 80.

[0067] The self-learning machine 2 can then be trained with the built training dataset 88 so as to infer the supplying order 91 optimizing the given optimization function 90.

[0068] The training of the self-learning machine 2 thus comprises steps of:

deriving a first optimization function 901 that is a sub-optimal approximation of said given optimization function; and

training a self-learning unit (e.g. the first self-learning unit 21) with a training database according to this first optimization function 901.

[0069] The training database used for training the first self-learning unit 21 can correspond to the entire, or to a (selected) portion, of the training database 88 provided to the self-learning machine 2.

[0070] The training can thus comprise a step of training another self-learning unit (e.g. the second self-learning unit 22) using an output 211 of the (already trained) first self-learning unit 21, i.e. the training dataset used for training the second self-learning unit 22 comprises this output 211. This training dataset can further comprise the entire, or a (selected) portion, of the training database 88 provided to the self-learning machine 2.

[0071] Alternatively or complementarily, the training of the second self-learning unit 22 can be executed, as shown in Figure 3, according to a second optimization function 902 which may be a (another) sub-optimal approximation of the given optimization function 90. The training dataset used for training the second self-learning unit 22 can comprise the entire, or a (selected) portion, of the training database 88 provided to the self-learning machine 2.

[0072] With references to Figures 2 and 3, the supplying order 91 can be based (e.g. inferred, calculated, mathematically or logically derived) from the output 211 of the first self-learning unit 21 and from the output 221 of the second self-learning unit 22, e.g. by means of an aggregating unit 23 and/or by means of one or more additional self-learning unit(s) of the self-learning machine 2.

[0073] The supplying order 91 can be obtained by aggregating the output 211 of the first self-learning unit 21 and the output 221 of the second self-learning unit 22 by means of an aggregating unit 23 being trained or configured to aggregate these results to optimize the given optimization function of the self-learning machine 2.

[0074] By aggregating it is meant forming an output by means of one or more logically, statistically and/or mathematically operations applied on inputs, such as:

logically, statistically and mathematically combination, notably sequentially combinations;

weighting;

voting.

[0075] The supplying order 91 can be obtained by providing one or both of the outputs 211, 221 of the first and second self-learning units 21, 22 to one or multiple other self-learning units of the self-learning machine 2, each unit being trained to optimize another (sub-optimal) approximation of the given optimization function and/or the given optimization function. The supplying order 91 can thus be obtained by training a (final) self-learning unit or by aggregating a set of outputs provided by two or more self-learning units by means of an aggregating unit, according to the given optimization function.

[0076] With respect to the embodiment of the Figures 1-3, the second self-learning unit 22 can be alternatively trained according to the given function of the self-learning machine 2. The second self-learning unit 22 acts as a final self-learning unit providing the supplying order 91.

[0077] A (sub-optimal) approximation of the given optimization function can be any optimization function:

valuing the same target in a similar but not identical manner as the given optimization function; and/or

valuing other costs/incomes related to the inventory than the given optimization function; and/or

being related to another time horizon than the given optimization function; and/or

being related to another time period than the given optimization function.

[0078] Alternatively or complementarily, the (sub-optimal) approximation of the given optimization function can be any optimization function related to:

a (current and/or forecasted) human and/or mechanical event relevant to the inventory;

a (current and/or forecasted) human, natural, and/or environmental event affecting a given geographical region related to the inventory.

[0079] Advantageously, each self-learning unit of the self-learning machine 2 comprises a set of distinct models 212- 214, 222- 224, each being individually trained according to the optimization function assigned to the self-learning unit, or according to any relevant and pre-specified optimization function related to the optimization function of the self-learning unit.

[0080] The output of the self-learning unit is provided by aggregating the (set of) outputs provided by the set of distinct models 215-217, 225-227. In particular, the aggregation can be provided by an aggregating unit 218, 228 being trained or configured to linearly combine with or without weighting the (set of) outputs to optimize the optimization function assigned to the self-learning unit.

[0081] The training of a self-learning unit 21, 22 of the self-learning machine 2 can thus comprise the steps of:

providing a set of models to the self-learning unit;

training each model of the set with the training dataset 88 and according to the optimization function 901, 902, or according to any relevant and pre-specified optimization function related to the optimization function 901, 902 assigned to the self-learning unit;

collecting a set of outputs 215-217, 225-227 individually provided by the models of the set; and

determining an aggregation (e.g. mathematical or logical combination, voting) 218 of the outputs of said first output set for optimizing the optimization function 901, 902 assigned to the self-learning unit.

[0082] The method can further include, after the determination of the aggregation, the steps of:

deleting a model from the (current) set so as to provide a new set of models, and

determining a new aggregation of the outputs of the new set of models, and

selecting either the current or the new set of models by comparing the accuracy (e.g. error) of the aggregation of the outputs of the current set of models with the accuracy (e.g. error) with the aggregation of the outputs of the new set of models.

[0083] Alternatively or complementarily, the method can comprise the steps of:

adding a new, different model to the set of models;

training the new model;

determining a new aggregation of the outputs of the set of models comprising the new model, and

deciding to add the new model to the set of models based on a comparison of the accuracies (e.g. errors) provided by the aggregation of the outputs of the set of models with and without the new model.

[0084] For example, the set of models can comprise one or more of the following models:

an exponential smoothing model;

a simple lag model, e.g. providing (a part of) the input dataset delayed by a given time interval (e.g. a day, a week or a year);

a regression model;

a ridge regression model;

a "zero" model, i.e. returning zero for every input dataset;

a neural network;

a Holt-Winters model;

a random forest model.

[0085] Figure 4 shows a flow diagram of an example method for configuring and training the self-learning machine 2 for supervising cost-optimally or cost effectively a system 1 managing an inventory 51, 52, 53, 54 of goods and/or assets.

[0086] The first step (S1) concerns the definition of one or more approximated optimization functions for the given optimization function. The approximated optimization function can be derived, extracted or identifying by

valuing the same target as the given optimization function in a similar but not identical way, e.g. by another mathematical or logical function;

valuing other costs/incomes related to the inventory; and/or

considering another time horizon than the given optimization function; and/or

considering another time period than the given optimization function; and/or

taking into consideration an observed and/or forecasted human and/or mechanical event relevant to the inventory; and/or

taking into consideration an observed and/or forecasted human, natural, and/or an environmental event affecting a given geographical region related to the inventory.

[0087] Each approximated optimization function is then assigned to a distinct self-learning unit. The self-learning machine comprises (at least) the same number of self-learning units as the number of defined approximated optimization functions.

[0088] The aim of the following step (S2) is the creation of a flow graph, which expresses the dependencies between the inputs and/or outputs of the self-learning units of the self-learning machine 2. For each of the self-learning unit, the input and the output are defined, notably according to the output provided by other self-learning units. The flow graph can comprise a final self-learning unit providing the supplying order 91 from an output or a set of outputs provided by (an)other self-learning unit(s).

[0089] For each self-learning unit, a dedicated set of models is selected (S3)

[0090] The training of the self-learning machine starts with the (individual) training of the independent self-learning unit (S4), i.e. the self-learning unit whose inputs are devoid of outputs from other self-learning units.

[0091] Once the outputs required as inputs for (an)other self-learning unit(s) are available (i.e. the related self-learning nodes have been trained), the dependent self-learning node can be (individually) trained (S5, S6).

[0092] The training then comprises a (final) aggregation or training (S7) for optimizing the given optimization function. This step involves the optimization of an aggregating unit processing a set of outputs or a training of the final self-learning unit.

[0093] The training of the self-learning unit and/or the definition of the approximated optimization functions can be preceded by a step of data loading and/or pre-processing, e.g. stationarization, de-seasonalization, denoising, and/or outlier filtering.

[0094] The step of training the self-learning units or of aggregating can comprise a step of modifying, cancelling and/or adding dependencies between self-learning units following observed training and/or aggregation results.

[0095] In particular, the applicant found that training self-learning units (with the given optimization function or with an approximated optimization function) that have different time horizons provides optimal inferring notably on large datasets.

[0096] A self-learning machine 2 comprising a plurality of self-learning units, at least one configured/trained with a shorter horizon and another with a longer time horizon, allows to aggregate and/or infer the supplying order 91 based on the short-term, mid-term, and long-term trends inferred by the self-learning units.

[0097] Fig. 5 shows a self-learning machine trained according to a given optimization function, e.g. for providing a buying order for a steel inventory optimizing a financial profit and loss (PnL) function, at a given time horizon, e.g. 1-day time horizon.

[0098] The self-learning machine comprises a plurality (a set) of self-learning units 28, 28', 28'', 28'''

[0099] A sub-set of the self-learning units 28-28'' is arranged as independent units, i.e. units non-depending on outputs provided by others units. Each of these units is configured to optimize the given optimization function (or another approximated optimization function) at:

a shorter time horizon, e.g. 12-hours; or

a similar or identical time horizon, e.g. 1-day time horizon; or

a longer time horizon, e.g. 3-day, 5-day, 10-day, 15-day and 20-day time horizons.

[00100] The self-learning machine 2 then comprises a final self-learning unit 28''' arranged to (sequentially) aggregate the outputs 281-281''' provided by the independent units 28-28'' (as input 280''') to provide the supplying order 91 according to the given optimization function (e.g. the PnL function) at the given time horizon (1-day time horizon).

[00101] The self-learning unit with a shorter time horizon provides an inferring of short-term up to mid-term trends permitting the self-learning machine to rapidly react to trend reversals.

[00102] Complementarily, the self-learning units with a longer time horizon provide an inferring of mid-term up to long-term trends to avoid overfitting effects.

[00103] The applicant also found that training the first and the second self-learning units, one by the optimization function related to a shorter time period and the other by the optimization function related to a longer time period can also provide an optimal inferring notably on very large datasets.

[00104] The applicant also found that training of distinct self-learning units with different learning periods can also provide an optimal inferring notably on very large datasets; in particular by, training one self-learning unit by the optimization function and with a shorter learning periods, and

another self-learning unit by the optimization function and with a longer learning periods.

Additional Features and Terminology

[00105] Depending on the embodiment, certain acts, events, or functions of any of the algorithms described herein can be performed in a different sequence, can be added, merged, or left out altogether (for example, not all described acts or events are necessary for the practice of the methods). Moreover, in certain embodiments, acts or events can be performed concurrently, for instance, through multi-threaded processing, interrupted processing, or on multiple processors or on processor cores or on other parallel architectures, rather than sequentially. In addition, different tasks or processes can be performed by different machines or computing systems that can function together.

[00106] The various illustrative logical blocks, modules, and algorithm steps described herein can be implemented as electronic hardware, computer software, or combinations of both. To clearly illustrate this interchangeability of hardware and software, various illustrative components, blocks, modules, and steps have been described above generally in terms of their functionality. Whether such functionality is implemented as hardware or software depends upon the particular application and design constraints imposed on the overall system. The described functionality can be implemented in varying ways for each particular application, but such implementation decisions should not be interpreted as causing a departure from the scope of the disclosure.

[00107] The various illustrative logical blocks and modules described in connection with the embodiments disclosed herein can be implemented or performed by a machine, a microprocessor, a state machine, a digital signal processor (DSP), an application specific integrated circuit (ASIC), a FPGA, or other programmable logic device, discrete gate or transistor logic, discrete hardware components, or any combination thereof designed to perform the functions described herein. A hardware processor can include electrical circuitry or digital logic circuitry configured to process computer-executable instructions. In another embodiment, a processor includes an FPGA or other programmable device that performs logic operations without processing computer-executable instructions. A processor can also be implemented as a combination of computing devices, e.g., a combination of a DSP and a microprocessor, a plurality of microprocessors, one or more microprocessors in conjunction with a DSP core, or any other such configuration. A computing environment can include any type of computer system, including, but not limited to, a computer system based on a microprocessor, a mainframe computer, a digital signal processor, a portable computing device, a device controller, or a computational engine within an appliance, to name a few.

[00108] The steps of a method, process, or algorithm described in connection with the embodiments disclosed herein can be embodied directly in hardware, in a software module stored in one or more memory devices and executed by one or more processors, or in a combination of the two. A software module can reside in RAM memory, flash memory, ROM memory, EPROM memory, EEPROM memory, registers, hard disk, a removable disk, a CD-ROM, or any other form of non-transitory computer-readable storage medium, media, or physical computer storage. An example storage medium can be coupled to the processor such that the processor can read information from, and write information to, the storage medium. In the alternative, the storage medium can be integral to the processor. The storage medium can be volatile or nonvolatile.

[00109] Self-learning units designate any computer system used to perform a task without using explicit instructions, relying on patterns and inference instead. The self-learning unit may be supervised or unsupervised. It may be implemented for example as a neural network. It may be implemented as a hardware, software or mixed solution. Reducing the size of a self-learning unit may include reducing the number of neurons, reducing the number of layers of the network, reducing the number of inputs, reducing the number of interconnexions, or any combination of those reductions.

[00110] A cost or optimization function may be implemented as a table or as a software module or function for representing a cost depending on certain input data. For example, a cost or optimization function may indicate the volume that is required for storing a number of items given as input.

[00111] Conditional language used herein, such as, among others, "can," "might," "may," "e.g.," and the like, unless specifically stated otherwise, or otherwise understood within the context as used, is generally intended to convey that certain embodiments include, while other embodiments do not include, certain features, elements or states. Thus, such conditional language is not generally intended to imply that features, elements or states are in any way required for one or more embodiments or that one or more embodiments necessarily include logic for deciding, with or without author input or prompting, whether these features, elements or states are included or are to be performed in any particular embodiment. The terms "comprising," "including," "having," and the like are synonymous and are used inclusively, in an open-ended fashion, and do not exclude additional elements, features, acts, operations, and so forth. Also, the term "or" is used in its inclusive sense (and not in its exclusive sense) so that when used, for example, to connect a list of elements, the term "or" means one, some, or all of the elements in the list. Further, the term "each," as used herein, in addition to having its ordinary meaning, can mean any subset of a set of elements to which the term "each" is applied.

<u>List of reference numerals</u>

1	System
2	(First) Self-learning machine
21	Self-learning unit
211	Output
212-214	Data model
215-217	Model output
218	Aggregation / Weighting unit
22	(Second) Self-learning unit
221	Output
222-224	Data model
225-227	Model output
228	Aggregation / Weighting unit
23	Aggregation / Weighting unit
24	Goods data module
25	Internal data module
26	External data module
27	Timestamping module
28-28'''	Self-learning unit
280-280'''	Input
281-281''	Output
31	Creating entity
32	Distribution platform
33	Distributing entity
41-45	Distribution channel
51-54	Inventory of goods and/or assets
60	Data provider
61	Geographical region
62	(End) client
80	Time reference
801	Global/common time reference

81	Goods reference data
811-813	Goods and/or inventory data
82	Internal reference data
821-824	Transporter and/or channel distribution data
83	External reference data
831	Regional Data
88	Training dataset
89	Input dataset
90	Cost function
901,902	Approximated cost function
91	Supplying order
911-913	Supplying Order
S1	Step of defining the approximated optimization functions and assignation of the approximated function to self-learning units
S2	Step of defining dependency between the approximated function, i.e. the self-learning units
S3	Step of selecting a set of models for each self-learning unit
S4	Training of independent self-learning unit, i.e. units non-requiring output from other self-learning units
S5	Step of training self-learning units depending uniquely from already trained self-learning units
S6	Conditional repetition of step S5
S7	Aggregating the outputs or training of a (final) self-learning unit with outputs provided by other units and according to the given optimization function

Claims

1. A method for training a self-learning machine (2) supervising a system (1) for managing an inventory (51, 52, 53, 54) of goods, wherein the self-learning machine (2) comprises a first and second distinct self-learning units (21, 22); the method comprising steps of:

A) Collecting an input dataset including, in any order:

collecting goods reference data (81, 811, 812, 813) representing observed amounts and/or observed variations of the inventory; and/or

collecting internal reference data (82, 821, 822, 823, 824) representing observed human and/or mechanical events relevant to the inventory; and/or

collecting external reference data (83, 831) representing a human, natural, and/or environmental event affecting a given geographical region (61) related to the inventory;

providing a reference time set (80) comprising reference times for: the goods reference data, the internal reference data, and/or the external reference data;

B) Building a training dataset (88) by pairing said goods reference data (81), said internal reference data (82) and/or said external reference data (83) with said reference time set (80);

C) Training the self-learning machine (2) with said training dataset (88) to infer a supplying order (91, 911, 912, 913) according to a given optimization function, for example a given cost function (90);

wherein said step of training the self-learning machine comprises steps of:

i) deriving a first optimization function (901) that is a sub-optimal approximation of said given optimization function;

ii) training the first self-learning unit (21) according to said first optimization function (901), and

iii) training the second self-learning unit (22)

using one or many outputs (211) of the trained first self-learning unit (21) and/or

according to a second optimization function (902) being another sub-optimal approximation of said given optimization function (90).

2. The method according to claim 1, wherein said step of training the self-learning machine (2) further comprises a step of aggregating one or many outputs (211, 221) of the trained first self-learning unit (21) and of the trained second self-learning unit (22), in order to optimize said given optimization function (90) or sub-optimal approximation of said given optimization (90).

3. The method according to claim 1 or 2, wherein the training of said first self-learning unit (21) comprises steps of:

providing a first set of distinct models (212, 213, 214);

training each model of said first set with the training dataset (88) and according to an optimization function, for example said first optimization function (901); and

collecting a first output set (215,216,217) comprising an output of each model of said first set of models; and

determining a first aggregation (218) of the outputs of said first output set so to optimize the first optimization function (901).

4. The method according to any one of claims 1 to 3, wherein the training of said second self-learning unit (22) comprises steps of:

providing a second set of distinct models (212, 213, 214);

training each model of said second set with said one or many outputs (211) of the trained first self-learning unit (21) and according to an optimization function, for example said second optimization function (902)

5. The method according to claim 4, wherein the training of said second self-learning unit (22) further comprises steps of:

collecting a second output set (225, 226, 227) comprising an output of each model of said second set of models; and

determining a second aggregation (228) of the outputs of said second output set in order to optimize the second optimization function (902) and/or the given optimization function (90).

6. The method according to any one of claims 3 to 5, wherein said training of the first self-learning unit (21) and/or of the second self-learning unit (22) comprises, after said step of determining the first and/or the second mathematical aggregation (218, 228), steps of:

deleting a model from the first and/or second set of distinct models to provide a first new set of models, and

determining a new aggregation of the outputs of the models of said first new set, and

evaluating the performance of said new aggregation.

7. The method according to any one of claims 3 to 6, wherein said training of the first self-learning unit (21) and/or of the second self-learning unit (22) comprises, after said step of determining the first and/or the second aggregation, steps of:

adding a new model to the first and/or second set of distinct models to provide a second new set of models, said new model being distinct from other models of said second new set;

training said new model;

determining a new aggregation of the outputs of models of said second new set, and

evaluating a performance of said new aggregation.

8. The method according to any one of claims 1 to 7, wherein the given optimization function (90) is related to a given time horizon, and wherein the first and/or the second optimization function (901, 902) is related to another time horizon;

in particular the time horizon of one of the first and second optimization functions being shorter than the given time horizon, and the other time horizon of the first and second optimization functions being longer than the given time horizon.

9. The method according to any one of claims 1 to 8, wherein the given optimization function (90) is related to a given time period, and wherein the first and/or the second optimization functions (901, 902) are related to a time period being different from the given time period;

in particular the time period of one of the first and second optimization functions being shorter than the given time period, and the other time period of the first and second optimization functions being longer than the given time period.

10. The method according to any one of claims 1 to 9, wherein said given geographical region (61) is:

a geographical region where the inventory and/or the goods of the inventory are located; and/or

a geographical region where the goods are delivered from said inventory.

11. A system (1) for managing an inventory (51, 52, 53, 54) of goods, the system comprising:

a goods data module (24) configured to collect goods data (811, 812, 813) representing observed amounts and/or observed variations of the goods of the inventory (51, 52, 53, 54); and/or

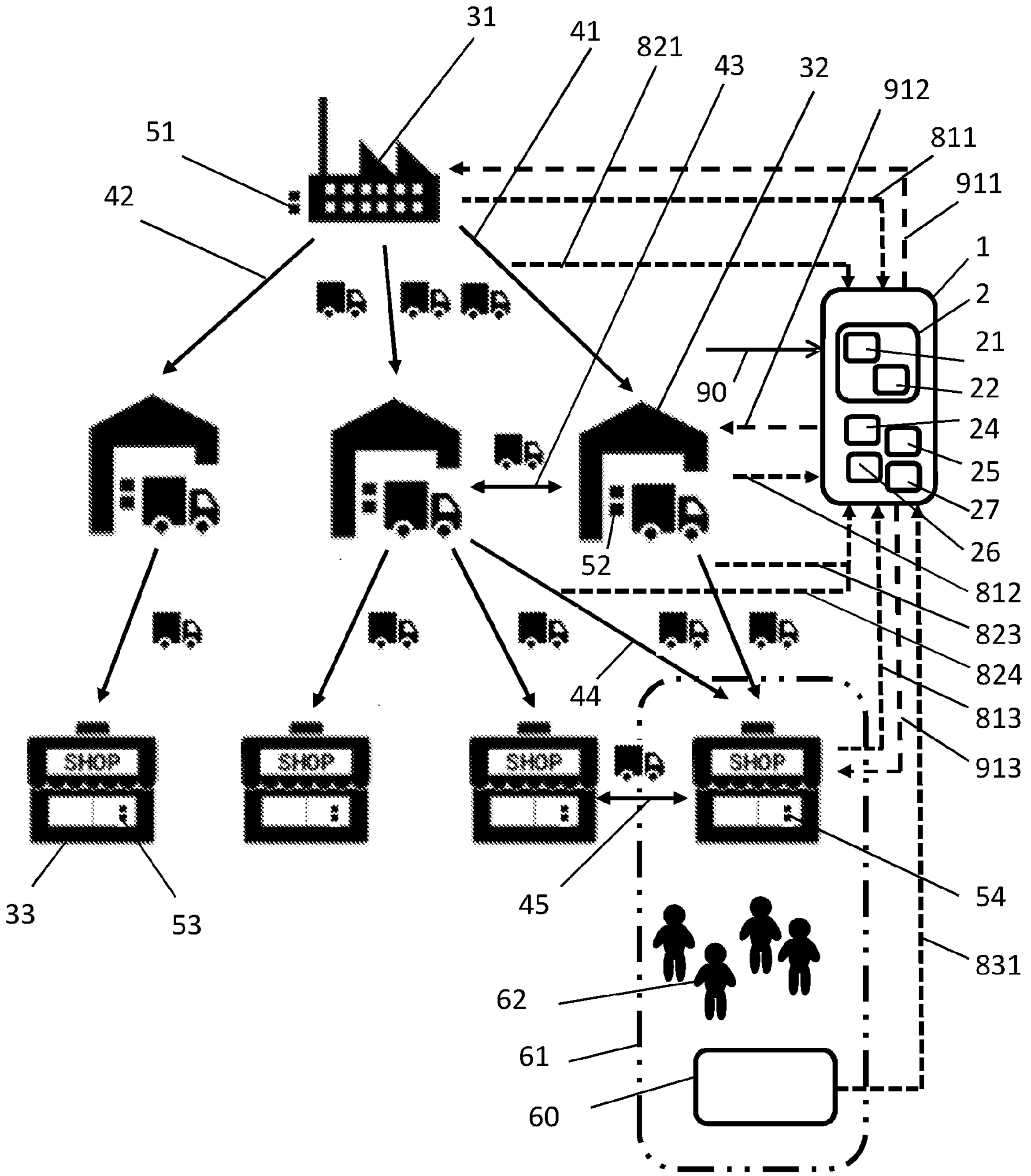
an internal data module (25) configured to collect internal data (821, 822, 823, 824) representing observed human events on the goods and/or on the inventory; and/or

an external data module (26) configured to collect external data (831) representing a human, natural, and/or environmental event affecting a given geographical region (61) where the inventory (54) is located and/or where the goods are delivered from said inventory and

a timestamping module (27) configured to provide a time reference set (801); the time reference set (801) comprising time references for the goods data, the external data, and/or the internal data; and

a self-learning machine (2) comprising a first and second distinct self-learning units (21,22); the self-learning machine (2) being trained by a process according to any one of claims 1 to 10 to provide a supplying order (911, 912, 913) in response to an input dataset (89) comprising the time reference set (801), the goods data (811, 812, 813), the internal data (821, 822, 823) and/or the external data (831).

12. A computer readable storage medium having recorded thereon a computer program, the computer program configured to perform the steps of the method according to any one of the claims 1 to 10 when the program is executed on a processor.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41
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911
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812
823
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SHOP
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SHOP
SHOP
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62
61
60
831

Figure 1

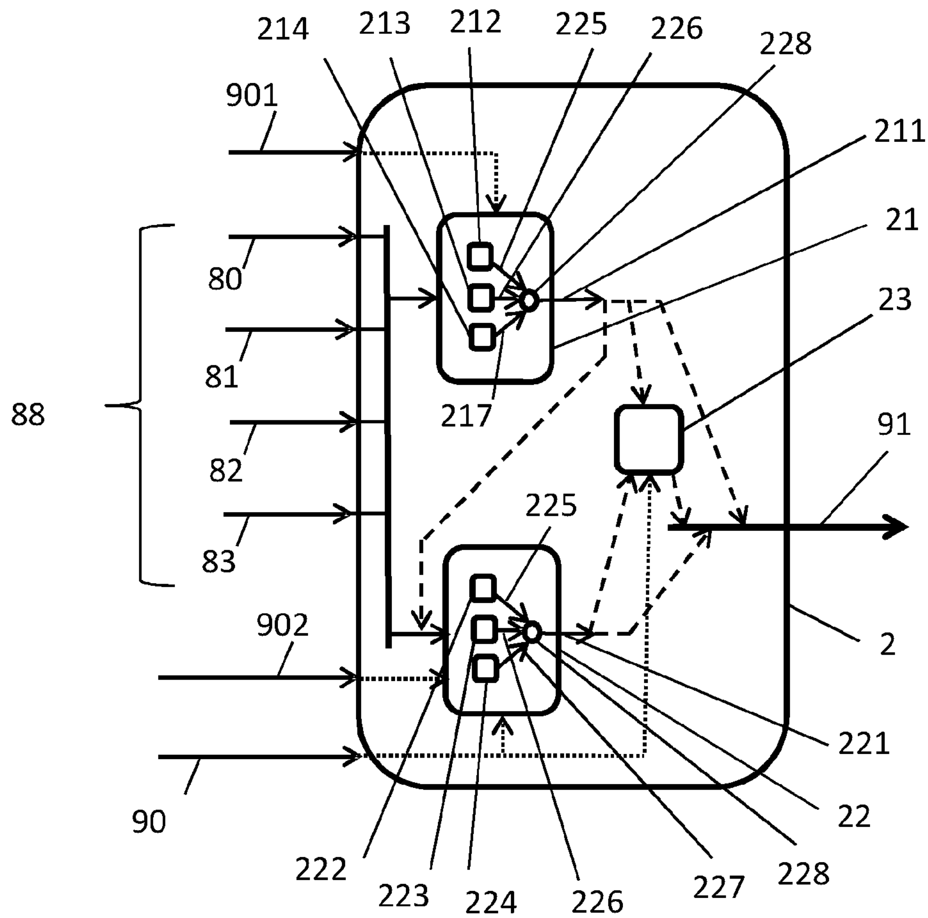

Figure 2

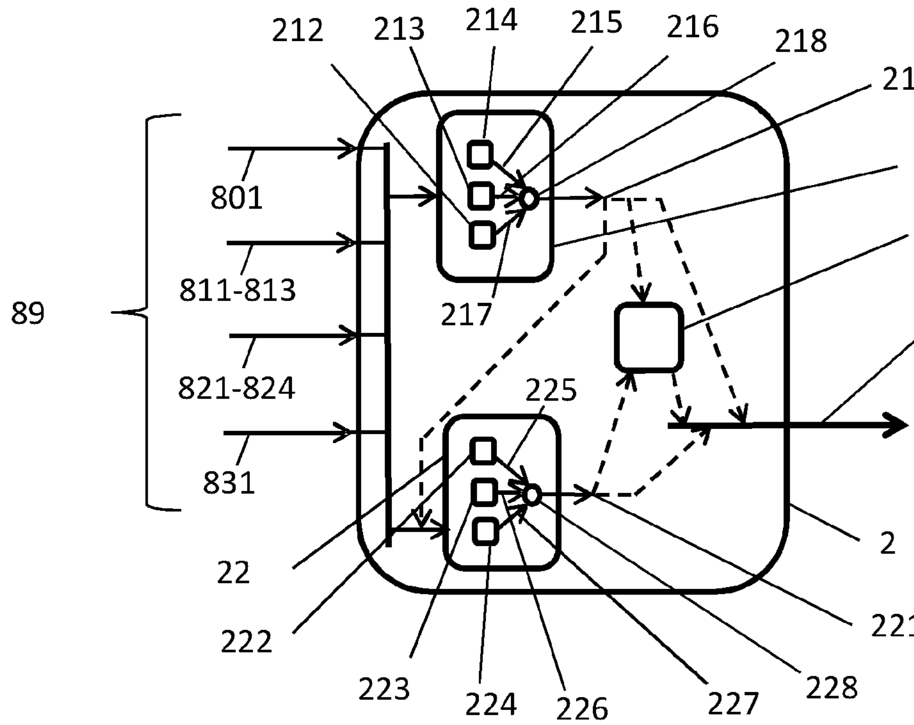

Figure 3

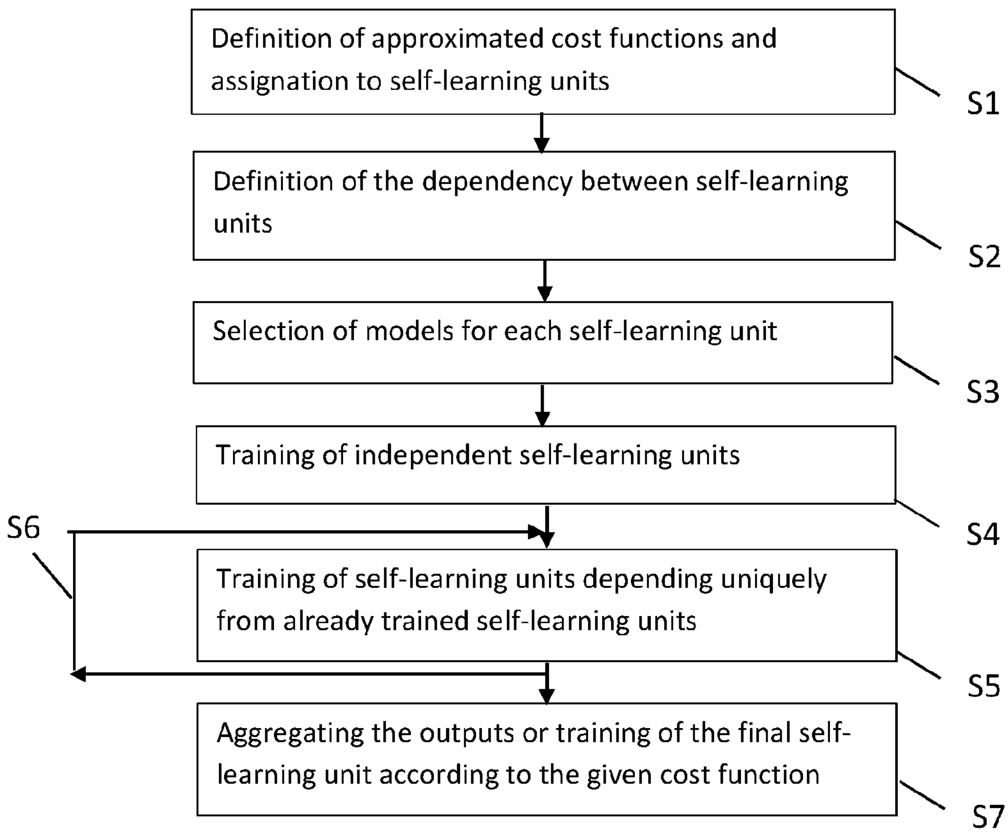

Figure 4

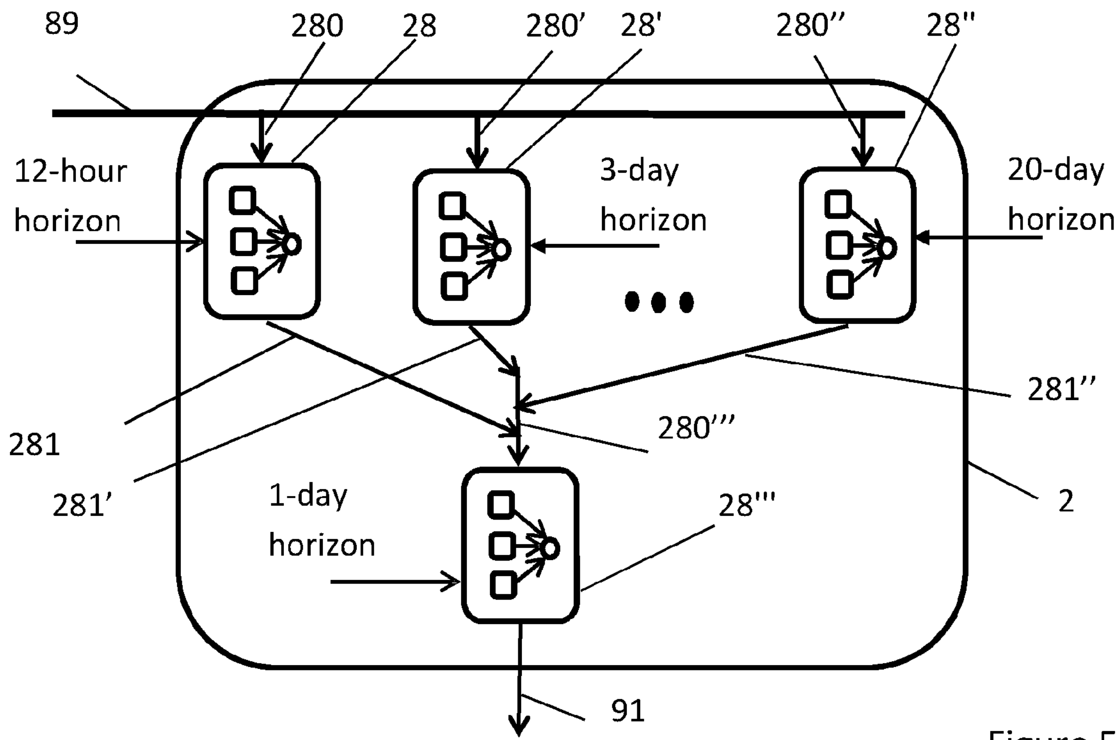

Figure 5

INTERNATIONAL SEARCH REPORT

International application No
PCT/IB2019/060561

A. CLASSIFICATION OF SUBJECT MATTER
INV. G06Q10/08
ADD.

According to International Patent Classification (IPC) or to both national classification and IPC

B. FIELDS SEARCHED

Minimum documentation searched (classification system followed by classification symbols)
G06Q

Documentation searched other than minimum documentation to the extent that such documents are included in the fields searched

Electronic data base consulted during the international search (name of data base and, where practicable, search terms used)

EPO-Internal

C. DOCUMENTS CONSIDERED TO BE RELEVANT

Category*	Citation of document, with indication, where appropriate, of the relevant passages	Relevant to claim No.
X	WO 2018/217954 A1 (MERCATO INC [US]) 29 November 2018 (2018-11-29) cited in the application abstract paragraph [0041] paragraph [0076] - paragraph [0139] -----	1-12

☐ Further documents are listed in the continuation of Box C.

☒ See patent family annex.

* Special categories of cited documents :

"A" document defining the general state of the art which is not considered to be of particular relevance

"E" earlier application or patent but published on or after the international filing date

"L" document which may throw doubts on priority claim(s) or which is cited to establish the publication date of another citation or other special reason (as specified)

"O" document referring to an oral disclosure, use, exhibition or other means

"P" document published prior to the international filing date but later than the priority date claimed

"T" later document published after the international filing date or priority date and not in conflict with the application but cited to understand the principle or theory underlying the invention

"X" document of particular relevance; the claimed invention cannot be considered novel or cannot be considered to involve an inventive step when the document is taken alone

"Y" document of particular relevance; the claimed invention cannot be considered to involve an inventive step when the document is combined with one or more other such documents, such combination being obvious to a person skilled in the art

"&" document member of the same patent family

Date of the actual completion of the international search	Date of mailing of the international search report
6 February 2020	21/02/2020

Name and mailing address of the ISA/	Authorized officer
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1

INTERNATIONAL SEARCH REPORT

Information on patent family members

International application No

PCT/IB2019/060561

Patent document cited in search report	Publication date	Patent family member(s)	Publication date
WO 2018217954 A1	29-11-2018	US 2018342007 A1	29-11-2018
		WO 2018217954 A1	29-11-2018