A model based estimator for inventory tracking with shrinkage detection in perishable supply chain

Beatrice Ietto [1] and Valentina Orsini [2]

***Abstract*— Accurate inventory tracking in the presence of shrinkage is a fundamental prerequisite for an efficient management of perishable Supply Chains (SC)s. In this paper we propose an effective low-cost alternative to the widespread use of Radio-Frequency IDentification (RFID) technology. The new presented method is based on the series connection of a physical low cost sensor with an estimator and on an outlier detector. Whenever the outlier reveals the presence of shrinkage, the internal state of the estimator is reinitialized to improve convergence towards the new value of the inventory level. We test our approach on a perishable SC governed by an Order-Up-To (OUT) policy.**

I. Introduction

Inventory shrinkage is the loss of inventory level due to a number of causes that are not immediately apparent (theft, damage, supplier fraud). The almost unavoidable presence of this invisible demand is the most preeminent factor of Inventory Record Inaccuracy (IRI) [1]. If this problem is not suitably faced it becomes a very difficult task to define an efficient replenishment policy, especially in the case of SCs with perishable goods [2]-[4]. Exploiting the information provided by a very precise sensor equipment like RFID is one of the most widespread methods to deal with this issue [5]. The main drawbacks of this approach are the large economic cost and the intrinsic impossibility of any sensor of providing exact measures.

The purpose of this paper is to propose a more efficient and cost-effective method to reduce IRI in the case of perishable SCs. We propose a method based on the use of a hybrid system and of an outlier detector. The hybrid system consists of the series connection of a physical and virtual sensor. This latter is an estimator designed on the basis of the information carried by the modelable part of the SC dynamics, i.e. the dynamics in the absence of shrinkage. In this ideal case, the estimate is asymptotically converging to the true value independently of the amount of noise introduced by the physical sensor. This noticeable result allows using a low cost sensor equipment.

The presence of shrinkage introduces the following problem: shrinkage is a disturbance signal resulting from many causes and is characterized by an unpredictable and unmodelable dynamics. This makes it impossible to endow the estimator with the necessary information to compensate for the effect of this disturbance on the current value of the inventory level. To face this problem we endow the estimator with an outlier detector. Its purpose is to identify the sharp discontinuities in the current estimated value of the inventory level caused by shrinkage. Whenever an outlier is detected, the current internal state of the estimator is reinitialized to speed up its convergence towards the new value of the inventory level. This greatly improves the efficiency of all the Inventory Replenishment Policies (IRP)s based on the comparison between the target inventory level and its actual value. We test our approach on a perishable SC governed by an updated version of OUT policy.

The rest of this paper is organized in the following way. The system model is defined in Section II. The robust estimator and the outlier detector are described in Section III and IV respectively. In Section V we show the application to the OUT policy. Numerical results on simulated data are reported on Section VI. Concluding remarks are given in Section VII. Acronyms and notation are summarized in Tables I and II respectively.

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[1]B. Ietto is with Weizenbaum Institute, Berlin, Germany beatrice.jetto@weizenbaum-institut.de

[2]V. Orsini (*Corresponding Author*) is with Department of Information Engineering, Universita' Politecnica delle Marche, Ancona, Italy vorsini@univpm.it

II. The dynamic uncertain model

We consider a periodically reviewed perishable SC given by the series connection of a retailer with a manufacturer. Its dynamical model is derived from the following standard assumptions:

A1) at the beginning of each review period $[kT_r, (k+1)T_r)$, $k \in Z^+$ of length T_r, the retailer performs the following operations: updates the recorded value of the inventory level, realizes the purchase order issued at time $(k-L)T_r$, delivers goods to the customer, places a new replenishment order to the manufacturer;

A2) the manufacturer fully satisfies each non null replenishment order issued by the retailer with a time delay $L = \ell T_r$, $\ell \in Z^+$;

A3) the goods arrive at the retailer new and deteriorate while kept in stock;

A4) the decay factor of the perishable stored between two consecutive review periods is $\rho \in [0,1)$;

A5) shrinkage may unpredictably occur inside some review periods;

A6) the measure $y(k)$ of the actual inventory level $x(k)$ is affected by a bounded error $v(k)$. The measure error is a zero mean bounded random sequence over the interval $[-\gamma x(k), \gamma x(k)]$, for some known $\gamma \in (0,1)$.

It follows that the true dynamics of the inventory level has the following discrete-time state space form, where the

TABLE I

ACRONYMS

SC	Supply Chain
IRI	Inventory Record Inaccuracy
IRP	Inventory Replenishment Policy
OUT	Order Up To
RFID	Radio-Frequency IDentification

TABLE II

NOTATION

$x(k)$	inventory level
$u(k)$	replenishment order
$s(k)$	shrinkage
$d(k)$	customer demand
$h(k)$	fulfilled customer demand
$g(k)$	unsatisfied customer demand
ρ	decay factor
$y(k)$	measured inventory level
$v(k)$	measurement noise
L	lead time
$\hat{x}(k)$	estimate of $x(k)$
$\hat{e}_x(k)$	inventory level estimate error
$\hat{v}(k)$	estimate of $v(k)$
$\hat{e}_v(k)$	measurement noise estimate error

explicit dependence on T_r has been omitted

$$x(k+1) = \rho\left[x(k) + u(k-L) - s(k) - h(k)\right] \tag{1}$$

$$y(k) = x(k) + v(k) \tag{2}$$

where:
- $x(0) = x_0$ is the unknown value of the initial inventory level;
- $x(k)$ is the inventory level at the end of the $(k-1)$-th review period;
- $s(k)$ is the unknown, possibly null amount of shrinkage. It is modeled as a random bounded sequence of discrete samples with values over $[0, x(k) + u(k-L)]$;
- $h(k)$ is the fulfilled part of the customer demand $d(k)$. It is given by

$$h(k) = d(k) - g(k) \tag{3}$$

where $g(k) \in [0, d(k)]$ is the amount of unsatisfied customer demand. As $h(k)$ is the actually delivered goods, it is assumed to be exactly known at each k.

III. The Robust Estimator

In this section we show that in the particular case of absence of shrinkage, it is possible to define a robust estimator that, exploiting the noisy measures provided by the physical sensor, yields an inventory level estimate asymptotically converging to the true $x(k)$, independently of the amount of the observation noise $v(k)$. This result is obtained using the notion of singular system [6].

Defining the extended state vector $\bar{x}(k) = \begin{bmatrix} x(k) & v(k) \end{bmatrix}^T$, the dynamics of inventory level (1)-(2) with $s(k) = 0$ can be rewritten in the form of the following singular system

$$\bar{T}\bar{x}(k+1) = \bar{A}\bar{x}(k) + \rho\left[u(k-L) - h(k)\right] \tag{4}$$

$$y(k) = \bar{C}\bar{x}(k) \tag{5}$$

where: $\bar{T} = \begin{bmatrix} 1 & 0 \end{bmatrix}$, $\bar{A} = \begin{bmatrix} \rho & 0 \end{bmatrix}$ and $\bar{C} = \begin{bmatrix} 1 & 1 \end{bmatrix}$.

An asymptotically exact estimate $\hat{\bar{x}}(k) \stackrel{\triangle}{=} \begin{bmatrix} \hat{x}(k) & \hat{v}(k) \end{bmatrix}^T$ of $\bar{x}(k)$ can be obtained through the following estimator

$$z(k+1) = G\bar{A}\hat{\bar{x}}(k) + G\rho\left[u(k-L) - h(k)\right] \tag{6}$$

$$\hat{\bar{x}}(k) = z(k) - Fy(k) \tag{7}$$

where G and F are the design matrices. The robust estimator is initialized with

$$\hat{\bar{x}}(0) = \begin{bmatrix} \hat{x}(0) \\ \hat{v}(0) \end{bmatrix} = \begin{bmatrix} y(0) \\ 0 \end{bmatrix} \tag{8}$$

Theorem The asymptotic convergence to zero of the estimation error

$$\hat{e}(k) \stackrel{\triangle}{=} \begin{bmatrix} \hat{e}_x(k) \\ \hat{e}_v(k) \end{bmatrix} = \begin{bmatrix} x(k) - \hat{x}(k) \\ v(k) - \hat{v}(k) \end{bmatrix} \stackrel{\triangle}{=} \bar{x}(k) - \hat{\bar{x}}(k) \tag{9}$$

given by the estimator (6), (7) is guaranteed if there exist two design matrices F and G such that the following conditions hold:

$$(I + F\bar{C}) = G\bar{T} \tag{10}$$

$$|\lambda_i\{G\bar{A}\}| < 1 \tag{11}$$

where $\lambda_i\{G\bar{A}\}$ denotes the i-th eigenvalue of $G\bar{A}$.

Proof By (5) and (7), the estimation error $\hat{e}(k+1)$ is given by

$$\begin{aligned} \hat{e}(k+1) &= \bar{x}(k+1) - z(k+1) + Fy(k+1) \\ &= \bar{x}(k+1) - z(k+1) + F\bar{C}\bar{x}(k+1) \\ &= (I + F\bar{C})\bar{x}(k+1) - z(k+1) \end{aligned}$$

If (10) holds, the error dynamics becomes

$$\hat{e}(k+1) = G\bar{T}\bar{x}(k+1) - z(k+1) \tag{12}$$

by (4) and (6), simple calculations show that

$$\hat{e}(k+1) = G\bar{A}\,\hat{e}(k) \tag{13}$$

and hence $\hat{e}(k) \to 0$ for $k \to \infty$ provided that (11) holds. $\triangle$
It is easily seen that the fulfillment of (10) and (11) is obtained choosing

$$G = \begin{bmatrix} 1 \\ -1 \end{bmatrix} \text{ and } F = \begin{bmatrix} 0 \\ -1 \end{bmatrix}$$

that give $G\bar{A} = \begin{bmatrix} \rho & 0 \\ -\rho & 0 \end{bmatrix}$, whose eigenvalues are $\lambda_1 = \rho < 1$ and $\lambda_2 = 0$.
The estimation errors go to zero as:

$$|\hat{e}_x(k)| = \rho^{(k-\bar{k})}|\hat{e}_x(\bar{k})| \tag{14}$$

$$|\hat{e}_v(k)| = \rho^{(k-\bar{k})}|\hat{e}_x(\bar{k})| \tag{15}$$

$$\forall k \geq \bar{k} \geq 0$$

Note that (8) and (9) imply

$$\hat{e}(0) = \begin{bmatrix} \hat{e}_x(0) \\ \hat{e}_v(0) \end{bmatrix} = \begin{bmatrix} -v(0) \\ v(0) \end{bmatrix}$$

so that

$$|\hat{e}_x(0)| = |v(0)|, \;\; |\hat{e}_v(0)| = |v(0)| \tag{16}$$

By A6 and (2) it follows $|v(0)| \leq \gamma x(0) \leq \frac{\gamma}{1-\gamma} y(0)$.

IV. The outlier detector

The asymptotic estimator is based on the assumption of an ideal inventory level dynamics without shrinkage, i.e. $s(k) = 0$, $k \in Z^+$. As long as no shrinkage occurs, the estimator guarantees that the actual inventory level $x(k)$ belongs to the uncertainty interval $I_{\hat{x}(k)}$ defined as

$$I_{\hat{x}(k)} \stackrel{\triangle}{=} [\hat{x}(k) - |\hat{e}_x(k)|, \hat{x}(k) + |\hat{e}_x(k)|] \tag{17}$$

where $|\hat{e}_x(k)|$ obeys (14).

On the other hand, by A6 and (2), it is surely true that

$$x(k) \in I_{y(k)} \stackrel{\triangle}{=} \left[\frac{y(k)}{1+\gamma}, \frac{y(k)}{1-\gamma}\right] \tag{18}$$

regardless of the presence or absence of shrinkage.

Hence, in the case of shrinkage, a discrepancy occurs between the information provided by the estimator and that one provided by the physical sensor. The outlier detector identifies this discrepancy through a continuous comparison between $I_{y(k)}$ and $I_{\hat{x}(k)}$. If

$$I_{y(\bar{k})} \cap I_{\hat{x}(\bar{k})} = \emptyset \tag{19}$$

for some $\bar{k}$, this means that a shrinkage has occurred at time $(\bar{k}-1)$: the prerequisite for the validity of the estimate provided by the estimator has ceased to exist and the only available information on $x(\bar{k})$ is $x(\bar{k}) \in I_{y(\bar{k})}$.

The time instant $\bar{k}$ is considered as the new origin of time and the robust estimator is reset starting from the new initial estimate:

$$\hat{\bar{x}}(\bar{k}) = \begin{bmatrix} \hat{x}(\bar{k}) \\ \hat{v}(\bar{k}) \end{bmatrix} = \begin{bmatrix} y(\bar{k}) \\ 0 \end{bmatrix} \tag{20}$$

Hence the estimation errors will go to zero according to (14) and (15) starting from

$$|\hat{e}_x(\bar{k})| \leq \frac{\gamma}{1-\gamma} y(\bar{k}).$$

The reinitialization procedure is repeated whenever condition (19) is satisfied.
The amount of shrinkage at time $(\bar{k}-1)$ belongs to the interval $[\underline{m}_{\bar{k}-1}, \bar{m}_{\bar{k}-1}]$ where $\underline{m}_{\bar{k}-1}$ and $\bar{m}_{\bar{k}-1}$ are the minimum and maximum distance respectively between $I_{y(\bar{k})}$ and $I_{\hat{x}(\bar{k})}$.

Remark The proposed robust estimator has a negligible computational cost as it only requires the on-line implementation of equations (6) and (7).

V. Application to the OUT policy

The inspiring principle of the OUT policy is issuing a purchase order to modify the current inventory level so as to attain a new reference value depending on the predicted customer demand. The actual computation of the purchase order is based on a model inversion procedure.

A. Assumption on the future customer demand

The frequently observed volatility of customer demand makes it very difficult to obtain an accurate prediction using mathematical models [7].
For this reason and similarly to our previous contributions ([8]-[15]), the demand forecast is based on the following assumptions:
A7) the customer demand $d(k)$ is uniformly bounded;
A8) at each k it is known that $d(k+j) \leq d^+(k+j)$, $j = 1, \cdots, L+1$, for a given $d^+(k+j)$.
A7 is based on the rather obvious consideration that in practice no customer demand diverges to infinite, A8 is based on empirical experience about the customer behavior over a short prediction interval.

B. The proposed OUT policy

We define a replenishment policy $u(k)$ based on the current estimate of the inventory level $\hat{x}(k)$ provided by the estimator. Every time the outlier detector recognizes the presence of shrinkage, the state estimate is reinitialized according to (20).
The inventory target is defined so as to guarantee a full customer demand satisfaction and a safety stock.
Assuming $s(k) = 0$, equation (1) gives the following predicted inventory level at the end of the $(k+L)$-th period.

$$x(k+L+1|k) = \rho^{L+1}x(k) + \sum_{\ell=0}^{L-1} \rho^{L+1-\ell} u(k+\ell-L)$$
$$+\rho u(k) - \rho^{L+1}h(k) - \sum_{\ell=1}^{L} \rho^{L+1-\ell} h(k+\ell|k) \tag{21}$$

To take into account the presence of perishable goods, of the time delay and of an uncertain future customer demand, we propose a version of the OUT policy where the predicted inventory level $x(k+L+1|k)$ coincides with the maximum value of the demand $d^+(k+L+1)$ defined in A8).
The computation is performed solving (21) with respect to $u(k)$ replacing both $x(k+L+1|k)$ and $x(k)$ with $d^+(k+L+1)$ and $\hat{x}(k)$ respectively. Moreover, according to a precautionary worst case approach, the replenishment order $u(k)$ is computed assuming: $h(k+\ell|k) = d(k+\ell) = d^+(k+\ell)$, $\ell = 1, \cdots, L$.
Defining

$$d^+(k+L+1) + \sum_{\ell=1}^{L} \rho^{L+1-\ell} d^+(k+\ell) + \rho^{L+1} h(k) \stackrel{\triangle}{=} \tilde{y}(k+L+1)$$

and

$$\tilde{y}(k+L+1) - \rho^{L+1}\hat{x}(k) - \sum_{\ell=0}^{L-1} \rho^{L+1-\ell} u(k+\ell-L) \stackrel{\triangle}{=} p(k) \tag{22}$$

the following value of $u(k)$ is obtained

$$u(k) = \max\left(0, \frac{p(k)}{\rho}\right) \tag{23}$$

The way the OUT policy is defined shows an intrinsic scalability property: the replenishment order $u(k)$ is continuously adjusted according to the maximum predicted customer demand and to the current estimated $\hat{x}(k)$ of the inventory level. If an unforeseen shrinkage occurs, $\hat{x}(k)$ is instantly reset as explained in Section IV.

VI. Numerical results

We consider a periodically reviewed perishable SC where the dynamics of inventory level (1)-(2) is characterized by a decay factor $\rho = 0.9$, a lead time $L = 2$, $x(0) = 10$ and an unknown measurement error $v(k) \in [-\gamma x(k), \gamma x(k)]$ with $\gamma = 0.1$.
The estimator is initialized with $\hat{\hat{x}}(0) = \begin{bmatrix} y(0) \\ 0 \end{bmatrix} = \begin{bmatrix} 10.62 \\ 0 \end{bmatrix}$.
According to A8), at any $k \in Z^+$, the future customer demand over a prediction interval of length $L+1 = 3$ is bounded above by the known trajectory $d^+(k+j)$, $j = 1, \cdots, L+1$. Figure 1 shows, the actual customer demand $d(k)$, $k \in Z^+$ and the upper boundary trajectory $d^+(k)$.

We carry out a simulation assuming the presence of three thefts worth 15% of the stock at times $k = 24$, $k = 47$ and $k = 75$ respectively. The simulation is stopped at time $k = 100$. Figure 2 shows how the inventory level drops sharply in the instant after the shrinkage and how the suitably reinitialized estimator, restarts tracking properly again the true inventory value. The unknown amount of shrinkage $s(k)$ at times $k = 24$, $k = 47$ and $k = 75$ is displayed in Figure 3 and the respective numerical value is reported in Table III. The same table also shows

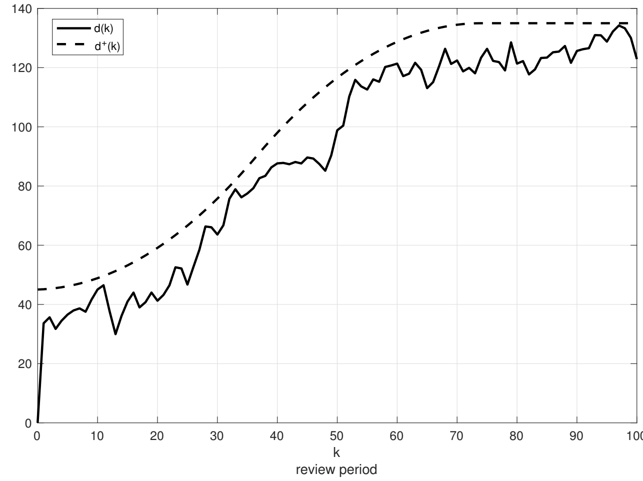

Fig. 1. The actual customer demand $d(k)$ (solid line). The dashed line represents the known boundary trajectory $d^+(k)$.

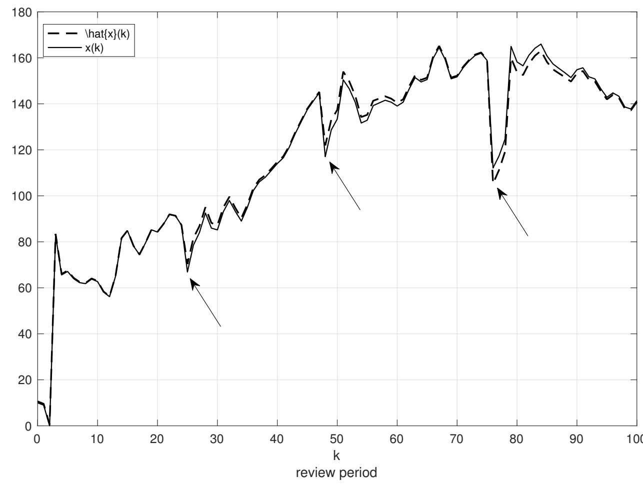

Fig. 2. The actual inventory level $x(k)$ (solid line) and the estimate $\hat{x}(k)$ provided by the robust estimator (dashed line).

how the outlier detector allows the manager to identify the uncertainty interval $I_{s(k)} \stackrel{\triangle}{=} [\underline{m}_k, \bar{m}_k]$ that contains the unknown $s(k)$. The numerical values of $\underline{m}_k$, and $\bar{m}_k$ are determined computing the minimum and maximum distance between $I_{y(k+1)}$ and $I_{\hat{x}(k+1)}$ respectively at time $k+1$ when condition (19) is verified. The intervals $I_{y(k+1)}$ and $I_{\hat{x}(k+1)}$ are reported in Table III.

The presence of shrinkage does not compromise the performance of the OUT policy. In fact, the consequent replenishment order $u(k)$, reported in Figure 4, yields a fulfilled demand $h(k)$ almost completely overlapped to the imposed demand $d(k)$ (namely $h(k) = d(k)$, $k \geq L$) as shown in Figure 5.

To numerically verify the robustness of the method against varying levels of measurement noise, we compute the following performance index:

$$IRI_{\%} \stackrel{\triangle}{=} \frac{\sum_{k=0}^{100} |x(k) - \hat{x}(k)|}{\sum_{k=0}^{100} x(k)} \times 100$$

TABLE III

IDENTIFICATION OF THE UNCERTAINTY INTERVAL $I_{s(k)} \triangleq [\underline{m}_k, \bar{m}_k]$ CONTAINING THE AMOUNT OF SHRINKAGE $s(k)$ OCCURRED AT TIME k. THE INTERVALS $I_{y(k+1)}$ AND $I_{\hat{x}(k+1)}$ THAT SATISFY CONDITION (19) AT TIME $k+1$.

	$k=24$	$k=47$	$k=75$
$s(k)$	22.32	38.38	44.28
$I_{s(k)}$	[8.7834, 23.1616]	[15.7070, 41.7229]	[34.5027, 57.1963]
$I_{y(k+1)}$	[63.9384, 78.147]	[110.8380, 135.4687]	[95.7404, 117.0161]
$I_{\hat{x}(k+1)}$	[86.9304, 87.1]	[151.1757, 152.5609]	[151.5188, 152.9367]

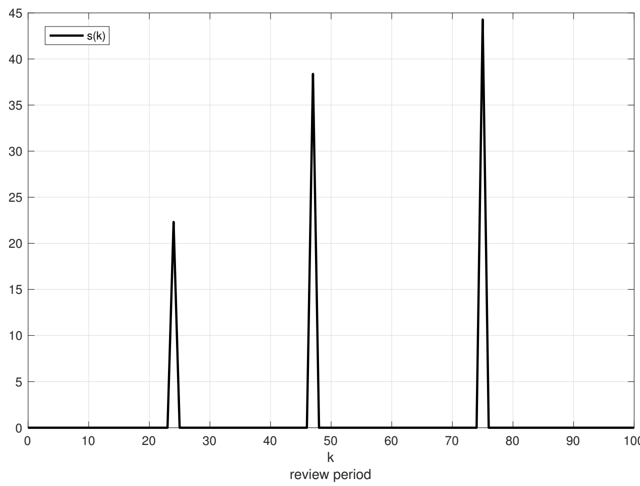

Fig. 3. The amount of shrinkage $s(k)$ at times: $k=24$, $k=47$ and $k=75$

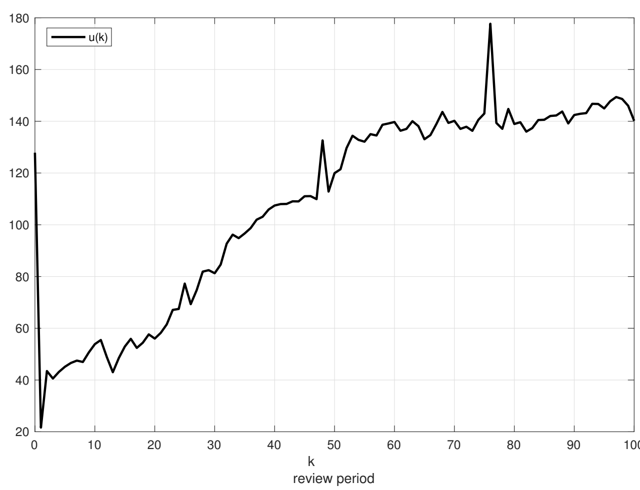

Fig. 4. The replenishment order $u(k)$ (solid line).

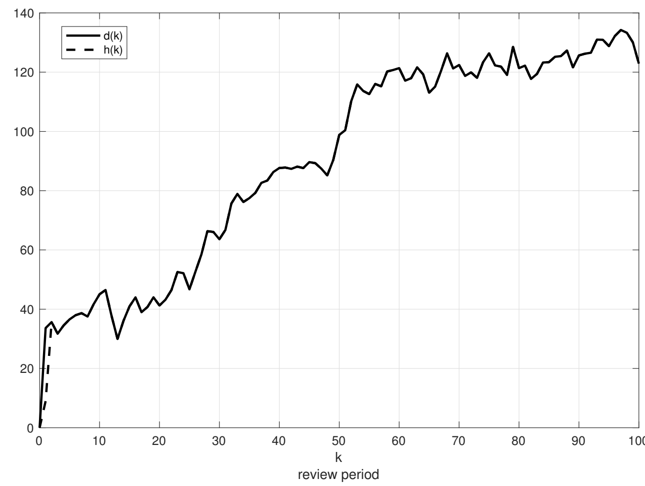

Fig. 5. The actual customer demand $d(k)$ (solid line) and the fulfilled customer demand $h(k)$ (dashed line).

for different values of γ.
The results are reported in Table IV.

VII. CONCLUSIONS

In this paper we have proposed a cost-effective alternative to expensive sensor technology for reducing IRI in perishable supply chains. The alternative consists of the aggregation of a physical and a virtual sensor. This latter is implemented as a state estimator. The two key points are:
1) in absence of shrinkage, the state estimate is monotonically and asymptotically converging towards the exact value despite the presence of measurement noise;
2) the possible failure of monotonic convergence is evidence of shrinkage and is recognized by an outlier detector. This information can be exploited to undertake two synergistic anti-shrinkage actions:
- reinitialize the state estimator to speed up its convergence towards the new inventory level,
- introduce the necessary anti-theft technology.

The methodological contribution of this work is clearly focused on point 2: the numerical simulations show how our approach is actually effective in compensating for the effect introduced by shrinkage. In conclusion the proposed smart sensor can be successfully applied to improve the performance of any cheap physical sensor already in use or as a tool to prevent the expense of sophisticated sensor instrumentation.

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TABLE IV

	$\gamma = 0.05$	$\gamma = 0.1$	$\gamma = 0.15$
$IRI_{\%}$	0.6175	1.23	1.2988

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